ECONOMIC DEVELOPMENT AND HEALTH IN INDIA: A HOUSEHOLD-LEVEL ANALYSIS

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IN ECONOMICS

BY

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DECLARATION

I, Rupali M. Tamuly, hereby declare that this thesis represents work which has been carried out by me and that it has not been submitted, either in part or full, to any other University or Institution for the award of any research degree.

Place: Taleigao Plateau.
Date:10-02-2024 Rupali M. Tamuly

CERTIFICATE

I hereby certify that the work was carried out under my supervision and may be placed for evaluation.

Prof Pranab Mukhopadhyay,
Goa Business School,
Goa University.

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I am a very late entrant to join this academically enriching and intellectually stimulating journey, and as this journey comes to an end bunch of humans to thank! Journey matters, not destination; as the saying goes, for me, both journey and destination mattered.

I am grateful to Shree Krishna for divine intervention and guidance. Our scriptures say the **‘Guru’** is an expert who possesses knowledge of the various scriptures that can answer all man's problems in daily life. Hence, tapping into and utilising this source of wisdom and knowledge would guide one to make the right decisions. As one should always consult with experts to make informed decisions, one can consult the Guru for help in applying solutions to any problem with which one may be confronted. One must be lucky to find a Guru with the above qualities, and I consider myself extremely lucky to have met one.

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I believe in magic and am an ardent fan of Harry Potter. I conclude with quotes from two of my favourite Professors.

To quote Prof. Albus Dumbledore, Headmaster of Hogwarts School of Magic & Wizardry, "Happiness can be found, even in the darkest of times, if one only remembers to turn on the light."

Professor Pranab says, "You need to ask the right question to get the right answer."

With Love and Prayers

Rupali

Offered at the lotus feet of Shree Krishna

Dedicated to Ba, Mamai, Ma, Pappa,

Moneesh, Raghavendra, Chetali,

Artham, Neil, Aruja

&

Nyke, Pita, Eli & Mia

Economic Development and Health in India: A Household Level Analysis

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INTRODUCTION

Chapter 1 is an introduction divided into 8 main sections. Section I is the introduction and is further divided into two sub-sections, each providing the perspective of health as human capital. Literature evidence is provided to establish empirical evidence between health and economic development globally. The next section provides background studies with 7 sub-sections. Each sub-section focuses on important aspects of evidence in the literature on economic development and health. The main section, 1.3, outlines the statement of the problem. The research gap is discussed in section 1.4, followed by objectives and research questions in the next section, 1.5. The materials and methods are discussed in section 1.6. Lastly, the chapter scheme is laid out in section 1.7, followed by a section on the conclusion.

1.1: Introduction:

Economic development aims to uplift and improve people's health and education levels(QuangDao,2008). Economic growth brings economic development, leading to improvement in income (Ranis, 2004). Income contributes to the population's health (Judge et al., 1998).In the early years of development planning, health was considered a consumption(Grosse & Harkavy, 1980). Still, it was later recognized as an asset with both intrinsicand instrumental value. Literature proves thathealth positively affects economic growth (Guisan & Aguayo, 2007; Strittmatter &Sunde, 2013).

1.1.1: Health As Human Capital: Theoretical Perspective:

Human capital is an important component of economic growth(Gunder, 1960; Galor & Tsiddon, 1997; Mincer, 1984). It comprises health, nutrition, and formal education (Quang Dao, 2008). Human capital theories focused on education and health have become interesting in development economics theories since the early 19th century(Pelinescu, 2015). We find an early reference to human capital in Schultz (1962). He mentions that men make self-investments to improve and upgrade their skills and capabilities as an indicator of human capital. The up-gradation of skills is likely to increase wages and income. These types of investments may become an engine of economic growth. Even though the focus of Schultz's work was on education, the framework could be used to understand investment in health and its proposed benefits.

Health was earlier considered a consumption expenditure as it satisfies human wants and enhances human welfare (Mushkin, 1962). Health needs can be reviewed as physical and emotional, which plays a role in labour productivity (Becker, 1962).Arrow(1963) suggests that the demand for health occurs when an agent needs to restore their original state of health. Those who demand health care are exposed to two pre- and post-treatment health risks. Individuals face pre-treatment risks since existing health status is determined by many exogenous factors, which are random. The second risk in demand for health care is unpredictable treatment outcomes. The individual cannot predict the number of days required to restore the health to the original status or some amount of recovery from ill health; expenditure incurred is also unpredictable (Koç, 2004). The stock of health is inherited once and depletes over an individual's life cycle. It can be replenished by investing in health. Increasing age and ill health can depreciate the stock of wealth. Possessing health helps the owner build other assets (Grossman, 1972).

1.1.2: Global Empirical Evidence Of Linkages Between Health And Economic Development:

One of the policy targets of developing countries is to reduce poverty and increase income. (Raghupathi & Raghupathi, 2020). Several studies have examined the relationship between health expenditure, economic growth and poverty reduction (Dinçer & Yuksel, 2019).For developing countries,one of the ways to attain an overall better economy is by achieving citizens' good health by investing in different areas related to health care (Raghupathi & Raghupathi, 2020).

Any health intervention works in income building for people experiencing poverty; hence, health interventions form a major part of health policies (Strauss et al., 1998). Health interventions on a larger scale are often responsible for the success of health programs in developing nations (Chowdhury et al., 2013). GDP per capita positively impacted health(Moayedfard et al., 2020). Building on the nation’s health infrastructure reflects adult survival rates (Bhargava et al., 2001). Poor nutrition in childhood may damage labour productivity, but if access to health care is provided, it will help improve the quality of life (Bhargava, 2001). One of the prominent causes of poverty for economies is the risk arising from health, and the channel through which health-related poverty could be tackled is health insurance (Liao et al., 2022). Some other mediums, like private investment in rural areas, enforcement of property rights and development expenditure, also helped to reduce differentials in economic growth at the sub-national level in India (Nandan & Mallick, 2022).

The literature also provides evidence that increased health expenditure in sub-Saharan Africa decreased poverty in the short run(Wang et al., 2022). For BRICS countries, the long-term positive impact on health was through investment in human capital coupled with technological innovations(Hu & Yao, 2021). From 1975 to 2018, Turkey exhibited a positive relationship between health expenditure and economic growth (Esen & Çelik Keçili, 2021). The demographic transition also favoured many developing countries to bring the desired outcome for health and economic growth (Ridhwan et al., 2022). Economies with better health outcomes exported complex and sophisticated products via employment channels for 103 countries between 1970 and 2015(Quang Dao, 2008; Vu, 2020). Asian countries have variations in health expenditure (Wu et al., 2021). Greater focus is on policies with regional characteristics and region-specific (Wang et al., 2022). The 1990 health reforms in New Zealand proved expensive due to neglect of the local situation (Cumming, 2015).

1.2: Background Studies:

1.2.1: Health And Health Expenditure: Macro And Micro Perspective:

Perception of well-being (well-being and welfare are used interchangeably in this thesis) is associated with good health (Helliwell & Putnam, 2004). Health is a consumption good that enhances well-being and an investment good that assists labour earnings (Rakodi, 1999). Health also enhances other forms of human capital, like education (Glewwe & Miguel, 2007). A healthy individual can spend more time learning skills and increasing productivity (Woodhall, 1987).

Similarly, job training is more likely to be given to healthy individuals. Health increases life span, and an increase in life span means a labourer will invest in retirement funds. These retirement funds are channelled into large-scale investment projects for many developing nations(Bloom & Canning, 2003). The study of macroeconomics, in general, requires incorporating studies on health(Cutler, 2006). At the macro level, health expenditure and healthcare facilities are important for the government. Several factors point to the need for government involvement. One argument is that health is human capital, and it aids in economic development (Bloom & Canning, 2003).

1.2.1.1: Role Of Government:

Government expenditure is also required because of the nature of health(Ferris, 1983). Illness is unpredictable and can occur at any point in the life cycle. All years of the life cycle are not subject to earnings(Glied, 1996). Expenditure associated with illness is also unpredictable. The health sector is generally affected by asymmetric information(Lu et al., 2010)and developing nations' health insurance and credit markets are also less developed (Bloom &Canning, 2003). Developing countries struggle to combat many other types of diseases, such as infectious diseases where preventive care is required on a massive scale, like Covid 19 recently and polio, cholera, and AIDS (Zaidi et al., 2004). These infectious diseases require clean drinking water and sanitation control, for which the government has special provisions(Watson et al., 2007). The poorest of the developing nations can also invest in basic health programs like antibiotics, vaccination, and primary health care (Bloom & Canning, 2003).

At the macro level, health expenditure by the government through planned outlays reflects the government's commitment to public health (Heller, 2006). The outlays in other sectors also indirectly help health attainment, like investment in employment-generating programs, clean water, sanitation, nutrition, housing, and female education. For most developing economies, allocating funds for the social sector has been challenging on two counts: insufficient empirical evidence and competing interests due to funding deficiency. Macro-level health spending has proved to be beneficial for developing nations (Farag et al., 2013).

1.2.2: Health And Developing Countries:

In developing countries, the stress is on manual work because of labour surplus. Poor face specific health issues over their life cycle, such as malnutrition (Pena & Bacallao, 2002). There may also be indirect constraints that reflect on the health of people experiencing poverty, like lack of credit availability or access to the credit market(Bayulgen, 2013). The linkages between health and productivity reflect patterns of allocation of poor household resources towards health expenditure (Strauss et al., 1998).

There was a systematic line of argument about health as human capital and individual ownership of health capital. The unidirectional relationship between wealth and health has dominated the literature for a long time (Chen & Goldman, 2016). Empirically also, it was proved that richer nations would automatically have healthy populations (Mirvis & Clay, 2008). The demographic transition theory also supported this view that medical advancement would occur only in industrialized nations(Cervellati & Sunde, 2007; Kirk, 2008). An alternative theory was that health drives economic development and acts as an engine of growth (Gruzina et al., 2021). More recent models focus on the contribution of health at a micro and macro level (Bloom et al., 2019). Improved health directly contributes to productivity, increasing the number of working years. This micro-level change also has an indirect effect on children and education. Macro effects include investment contributions and improved economic and demographic structure(Mirvis et al., 2008). Ample research was directed towards showing the linkages between population and economic growth (Peterson, 2017) and human capital and economic growth (Osiobe, 2019). The most used measures of human capital were education and health. The combined research of linkages between human capital, population and economic growth for MENA countries in 1980-2020 revealed that human capital (measured using education enrolment and life expectancy at birth) significantly influences the impact of demography on economic growth (Adeleye et al., 2022). Among the 67 developing countries during the period 1960-2014, it was observed that economic growth is much influenced by demographic transition and human capital (Ahmad & Khan, 2019).GDP is not an exclusive measure of economic growth, but beyond GDP is a more inclusive measure of economic growth (Costanza et al., 2009). Multiple factors determine the perception and measurement of well-being (Campbell, 1976). In a study between two groups for subjective well-being, confidence in institutions is one of the social cohesion indicators of well-being (Cavalletti & Corsi, 2018). Self-sufficiency and social cohesion, demography and non-relational use of time are related to higher subjective well-being. The physical effect of illness and pain on the body also determines individuals' subjective well-being (Collicelli, 2013).

Health spending is one monetary factor that affects health outcomes. Other non-monetary factors (elsewhere in the literature) include clean water (Jain, 2016), sanitation (Sclar et al., 2018), nutrition (Smith, 2005), food security (Jaron & Galal, 2009), housing (Bratt, 2002), female education (Heath & Jayachandran, 2016), and good governance (Helliwell et al., 2014). Along with these factors, the country's level of economic development also influences health. The lack of an empirical base in developing countries often challenges social sector policies that broadly guide investment. Resource scarcity puts a strong demand on evidence-based investments (Farag et al., 2013). The early evidence-based work was by Preston (1975), focusing on the correlation between measures of health and per capita income by Grossman (1972), Schultz (1979), and Schurke (2005).

The research and literature on health and wealth have exhibited a bi-dimensional relationship. Traditionally, the focus was on health as wealth (Meer et al., 2003); later, the focus shifted to 'Wealth is Health' for policies, and the health and income dimensions mattered(Semyonov et al., 2013). When the flow is from income to health, the policy focuses on people experiencing poverty and its eradication (OECD, 2003). If the movement is from health to income, the focus is on public expenditure and safeguarding people experiencing poverty from health expenditure by provisioning health insurance (Husain, 2010).

1.2.3:Health Shock:

Health shock is idiosyncratic and causes welfare loss to individuals and families (Dhanaraj, 2015). Health shocks are caused when a household member faces serious illness/ injury, often involving huge amounts of health expenditure(Ahmad & Aggarwal, 2017). Health issues or illness gets translated into health shock if it prevents the person from doing daily economic activity. Economic consequences of health shocks involve decreased labour earnings (García-Gómez et al., 2013), increased health payments (Alam & Mahal, 2014), and postponement of treatment due to the expenditure involved. Often, households resort to informal coping mechanisms without health insurance or inadequate coverage. These coping mechanisms, like self-insurance, involve running down assets, reduction in food and education expenditure and labour substitution within the family. All these actions eventually lead to a decline in economic welfare associated with health shocks (Onisanwa & Olaniyan, 2019).

1.2.4: Health And Social Capital:

Social capital at the micro level deals with cooperation in groups and networks within groups of people (Paldam, 2000; Paldam & Svendsen, 2000). The early literature in economics focuses on health-related literature on health discussions from an individualistic perspective. According to Bourdieu (1985), social capital was accumulated human labour. It helps the participants access economic, cultural, and institutional capital. There was a reference to social capital, mostly in sociology literature (Portes, 2000; Alejandro, 1998). Social capital is important in maintaining the individual's health (Turner, 2003). The everyday interaction of the individual with others on various platforms like family, social, religious, and culture creates a network. This network is more voluntary and informal, based on trust, mutual respect, and cooperation with a common goal of altruism. The stronger these networks are, the more information related to health and healthcare will be trustworthy (Ferlander, 2007).

Social capital contributes toward investment in health (Nutbeam & Muscat, 2021). Social capital linkages positively affect individuals' health through three mechanisms: trustworthy health-related information which benefits the members, informal health care such as care giving and support groups and group lobbying. The prerequisite for individual members to benefit from the social capital on health is a community with high social capital. In those regions with high community social capital, that would benefit individual health(Roco et al., 2014; Roco & Engler, 2012). Social networks are stronger for those individuals who are highly educated as they can achieve higher levels of social integration and are well-connected to the community (Alpaslan & Yildirim, 2020).

1.2.5: Measurement Of Health:

Health is a multidimensional concept that incorporates nutrition, disability, and short and major morbidity. Therefore, health indicators are used to measure health, such as general health status, self-reported morbidity and normal activity, self-reported physical functioning, and nutrition-based indicators. Broadly, the quality of life is related to health and influenced by disease, injury, treatment, or health policy is measured using broader categories like duration of life, disabilities, functional status, and perceptions about health and opportunities (Patrick & Bergner, 1990). There are individual measures and composite summary measures.

The individual measurements are given by Bloom & Canning(2003).

1. Physical measurements could include height (Steckel, 2009), weight (Panagiotakos, 2009) and BMI(Breslow, 2006).
2. Economic measures could be recording differences in wages of a representative individual visa -a-vis the one who is ill(Prados, 2012).
3. Demographic structures of the population like life expectancy(Stiefel et al., 2010), infant mortality rate(Reidpath & Allotey, 2003), morbidity(Kivimäki et al., 2003), and mortality(Vahtera, 2004).

A connected theme is the burden of disease (Population Council, 1999). The disease's economic burden can also be measured as direct and indirect costs on the household (Rice, 1967). The direct cost for the household is the cost of prevention and treatment (Segel, 2006). Labour time and productivity lost due to illness are indirect costs (Koopmanschap & Rutten, 1993). Social cost is the increased public health expenditure (McGuire et al., 2002). There is a sizeable loss of labour input and school days lost. A study in Jamaica reflected on illness-related early retirement (Willie-Tyndale et al., 2016).
The composite summary measures are categorised as measuring health gaps and health expectations. The measures focus on time lost due to disability or death as a deviation from a healthy life. The health gap is measured using Health life years (HEALYs)(Santé et al., 2002), Disability-adjusted life years (DALYs)(Devleesschauwer et al., 2014), and Quality-adjusted life years(QALYs)(Sassi, 2006). The health expectancy measures are disability-free life expectancy (DFLE) or health-adjusted life expectancy (HALE)(Hyder et al., 2012; Wolfson, 1996).

Health is also considered preventive and curative, although these are not measurements. As a choice between preventive and curative health expenditure, the US and OECD nations' health policy focus on preventive health care has helped increase human capital(Mohan & Mirmirani, 2007). For Taiwan, higher economic growth and social welfare were linked to higher expenditure on preventive health care, which showed better results for health(Wang, 2018). Public health policies had a significant role in economic development, which was empirically tested for Western European countries from 1820 to 2010 (Strittmatter & Sunde, 2013). The widened scope of health interventions needs to be incorporated into public policies. It helps in drawing support from society towards health improvement. Due to the complexity of health gains, health promotion may be one of the solutions for poverty, among many others (Mirvis & Clay, 2008). One also must tackle the systematic errors that may crop up in measuring health (Strauss & Duncan, 1998).

1.2.6: Health And Sustainable Development Goals: World Health Organisation(WHO), Millenuim Development Goals(MDG), Sustainable Development Goals(SDG):

Numerous international actions have recorded the importance of health as a global target. WHO advocates the right to health. According to WHO, health is a complete state of well-being, not just the absence of diseases. The right to health is considered the most fundamental right of every citizen. Health access helps every individual lead a productive life on the social and economic front(Nutbeam & Muscat, 2021). The first systematic step in this direction was taken in 1978 by accepting primary health care as an important mechanism in health care(WHO, 1978). There was a shift in approach by diverting focus from provider to end consumer(Catford, 2011). Subsequently, the major resolution passed by WHO was for health education (1981). In 1980, 'Health promotion', a more holistic word, got wide acceptance among member nations (Catford, 2011). Health promotion facilitated people's engagement by providing them control over their health and helped the improvement of health(WHO, 1986).

Member countries of the World Health Organisation (WHO) met in Ottawa(1986) and pledged a common goal, 'Health for all by 2000'(World Health, 1987). There were 12 targets to be achieved.

WHO Commission on Macroeconomics and Health (2001) asserted that health is important for economic development and poverty reduction, mostly for poorer nations (WHO, 2001). The commission enforced the need for directed investment in health for developing nations(Mirvis & Clay, 2008).In 2001, the UN member countries agreed to fulfil 8 Millennium Development Goals(MDG) to be achieved by 2015, and health was not explicitly mentioned; it overarched all the MDG(Fehling et al., 2013). The focus was on poverty reduction globally(Hulme, 2009). With all its shortcomings, MDG helped to steer the focus of the international community and donor countries to important areas of health globally(Fryatt et al., 2010). At the end of the MDG target year 2015, the UN member countries again pledged to fulfil 17 Sustainable Development Goals (SDG) by 2030. And thus, SDG superseded MDG(Buse & Hawkes, 2015). SDG agenda resulted from the United Nations Conference on Sustainable Development, 2012(WHO, 2015). Health was now explicitly mentioned in SDG3: 'Ensure healthy lives and promote well-being for all ages(Macassa, 2021). The WHO member states signed a resolution towards developing a financial system to provide Universal Health Coverage(UHC) in 2005(Gupta, 2009). UHC means everyone can obtain health services without financial hardships(Fukuda-Parr, 2004; Fukuda-Parr et al., 2013).

The health in all policies (HiAp) concept was incorporated into the WHO agenda in 2006(Calloway, 2019; Oneka et al., 2017). The steps taken by nations in achieving the

SDG would have their reflections on health. Attainment of SDG3 requires a well-coordinated focus on HiAP(Mauti et al., 2020; Nutbeam & Muscat, 2021).

A review of recent trends in research on sustainable development goals found that SDG 3 was the second most frequently researched goal for Africa, Eastern Mediterranean, and South-Eastern Asian regions and under SDG 3, goal number 3.8, UHC was the frequently researched sub-goal(Endalamaw et al., 2022).

1.2.7: Economic Development And Health In India:

In post-independence India, the importance of health and healthcare investment was self-recognised (Chakravarthi et al., 2017). Given the low per capita income and high poverty levels at the time of independence, the government played a significant role through systematic expenditures in the health sector(Kadekodi & Kulkarni, 2008.). The growing population also greatly strained the health infrastructure(Dey et al., 2013). India developed a three-tier healthcare system: a primary healthcare system followed by secondary and tertiary throughout the length and breadth of the country(Ghosh& Dinda, 2018).

India experienced demographic and epidemiological transition with regional variations(Yadav & Arokiasamy, 2014). Demographic transition altered the structure of the population pyramid with an increase in life expectancy and a reduction in infant and child mortality(Bhagat, 2014). The challenge of epidemiological transition involved a shift from communicable to non-communicable disease. The interstate variations aggravated the situation further since some regions (BIMARU) were still fighting killer communicable diseases, whereas some regions experienced the onset of lifestyle diseases (Bose, 1996; James, 2008). The need for health infrastructure to cater to the demand for health care posed a major challenge(Ramani & Mavalankar, 2006). The expensive nature of treatments forced the ill to spend their savings on the treatment (without insurance) or go without it. The increase in life expectancy posed issues for the elder population having age-related health issues. Thus, the economy had to deal with communicable and non-communicable diseases and geriatric issues(Bloom et al., 2013; Pati et al., 2014; Verma et al., 2021).

There was a tectonic shift in the global agenda for health, and nations moved from providing state-sponsored health facilities to more market-oriented health facilities through the provisioning of health insurance using semi-laissez-faire market forces(Hernández-Álvarez et al., 2020). The model of health care underwent several structural changes over time. In the 1990s, with market-oriented reforms, there was a phase-wise liberalization of insurance, the pharma sector and medical care, which impacted the health sector. The health sector moved from primarily government-sponsored to market-oriented (Purohit, 2001).

Soon after the independence in 1952, the organized sector employees benefited from the Employment Insurance Scheme (Mehta, 1961). Central Government Health Insurance (CGHI) was introduced in 1954(Ahlin et al., 2016). In the mid-1980s, the World Bank's World Development Report initiated health investment and guided health sector reforms. In the mid-1980s, the government encouraged the entry of the formal private sector in health care. Direct and indirect concessions were given to private investors to supplement the public sector(Baru, 2013). In 1986, the health insurance market opened for private players to sell only health insurance policies (medical claims) (Ellis et al., 2000). The 1990 market reforms saw a paradigm shift in the health sector(Bisht, 2017).

The state government initiated the withdrawal of support to provide health care(Duggal, 2007). The role of the government was reversed from tax-based support to financial protection (Sen, 2012). The patients had to pay for health care and then be reimbursed for full coverage or cashless hospitalization. The 8th five-year plan witnessed an important structural change with the introduction of user fees. Different states administered user fees in stages from the mid to late 1990s. Around the same time, states initiated World Bank-sponsored health system reforms, increasing user fees in government hospitals. However, the user fee for households living below the poverty line was waived(Thakur et al., 2009).

Reforms in the health sector emphasized the need for user fees on one side and compulsory enrolment of health insurance(Sharma, 2012). The shying away of the masses from health insurance due to premium payment, non-renewal due to documentation hassles and different premiums being charged by different companies worsened the situation(Anita, 2008). The population below the poverty line had to be insulated with government-sponsored health insurance, which involved minimum payment and maximum coverage(La Forgia & Nagpal, 2012a, 2012b, 2012c). However, cashless hospitalization was still not a common feature of all policies, and wider coverage of diseases and diagnostics was also uncommon (Mavalankar & Bhat, 2000). The population was presented with many government-sponsored insurance policies and private insurance (Hooda, 2017a, 2017b, 2020).

The central and State government employees were insured with ESI / CGHIS(Gupta & Trivedi, 2005). The question was of the remaining population who was not covered under this. In 2005 National Rural Health Mission was introduced by the government of India (Kapil& Choudhury, 2005). 2008, the Rashtriya Swastha Bima Yojana (RSBY) was introduced by the central government, and many state governments followed the pursuit(Dror & Vellakkal, 2012).

The various structural and market reforms led households to finance their health payment from their pockets: out-of-pocket health expenditure (OOPHE)(Ghosh, 2011, 2014).OOPHE has drawn attention internationally and nationally due to its dual effects on households: catastrophe and impoverishment(Reshmi et al., 2017; Reshmi et al., 2021) and hence a matter of concern because of its financial implications for the masses. According to the WHO report on UHC 2013, an estimated 150 million people suffer economic catastrophe yearly because they must pay out of pocket for health services.OOPHE in India in 2004-05 was more than 2/3 of total health spending, which is high compared to global standards (NHA, 2007).OOPHE compared male and female rural-urban expenditure at the primary and hospital levels, and for childbirth and hospitalization was more than double in the private sector under all categories (NSS, 2014).

In the next section, we present data on health expenditure and health insurance for India from different sources such as Economic Surveys, National Health Accounts (NHA), National Family and Health Survey (NFHS), World Bank Data and data from the National sample survey(NSS). This data is compiled by us and presented using descriptive statistics. One of the important macroeconomic indicators is health expenditure incurred by the government (Table 1). In Table 1, the first row is health expenditure as a percentage of Gross Domestic Product (GDP); the second is health expenditure as a percentage of total expenditure; and the third is health expenditure as a percentage of social service. Health expenditure as a percentage of GDP is between 1.2% to 1.8%. Budgetary estimates for 2021-22 health expenditure were predicted to be 2%. As a percentage of social expenditure, health expenditure is between 4% to 5%. A quarter of the share is allocated to health expenditure as a percentage of social service.

TABLE 1: INDIA'S HEALTH EXPENDITURE

Variables	2014-15	2015-16	2016-17	2017-18	2018-19	2019-20	202021(RE)	2021-22(BE)
As % of GDP	1.2	1.2	1.4	1.4	1.4	1.3	1.8	2.1
As % of Total expenditure	4.5	4.7	5	5.4	5.3	5	5.4	6.6
As % of social service	19.4	19.1	20.5	21.4	20.8	20	21.4	24.7

Source: Compiled by author from Economic survey 2021-22.

1.2.7.1: Health Expenditure And Health Insurance Data For India:

Table 2 summarises the different components of health expenditure sources from the National Health Accounts(NHA). The first row is Total Health Expenditure (THE) as a percentage of GDP. THE is made up of two components: current and capital expenditure. The government and private sources, including external/donor funds, incur these expenditures. THE is expressed as a percentage of the GDP and is an important indicator that reflects and measures the nation's economic development. It also reflects the expenditure incurred on health per person. For 2017-18, the average health expenditure was Rs 4297.

The next row is Current Health Expenditure (CHE). CHE comprises the expenditure which is repeatedly incurred on health care. When CHE is expressed as a percentage of total health expenditure, it indicates effective expenditure. This expenditure provides direction to the population's health outcomes and is expressed as the expenditure expressed in one year. The next row is Government Health Expenditure (GHE), which comprises all spending done by the government (Central, State, and Local).

Further, it includes the expenditure incurred by all quasi-government organizations and donations spent on health but channelled through the government. GHE is a very important indicator for understanding the amount of expenditure incurred by the government on health. A higher percentage of this expenditure indicates that households will spend less from their funds to avail of health care.

The next row is OOPHE: OOPHE are payments households incur when availing of health care facilities. These are the payments that households incur outright when accessing health care. A high OOPHE means that the households do not have financial protection against health payments.

Social Security Expenditure (SSE) comprises finance used to make payments for premiums of RSBY state health insurance schemes and employee benefit schemes. This expenditure denotes pooled funds available for making payments for insurance premiums for a specific category of people.

Households also opt for voluntary health insurance, and the premiums employers pay for coverage to employees under health plans are covered under this. Private Health Insurance Expenditure (PHIE) indicates health insurance premium payments from households and employers. PHIE is given as a percent of total health expenditure.

THE as a % of GDP has reduced from 4.2% in 2004-05 to 3.3% in 2017-18(Table 2). There is an increase in per capita total health expenditure. The CHE and GHE have also reduced, but there is an increase in SSE as % of THE. There is also a four times increase in PHIE as % of THE.

The most important indicator of health care expenditure is Current Health Expenditure (CHE). CHE is the share of each country's spending on health to the size of the economy. It portrays the efforts made by a given country in achieving its health care in monetary terms. CHE in PPP is the core of health financing, facilitating international comparison. This indicator contributes to understanding the total expenditure on health relative to the beneficiary population. CHE per capita PPP is also consistently increasing during the same period.

TABLE 2: **HEALTH EXPENDITURE COMPONENTS IN INDIA**

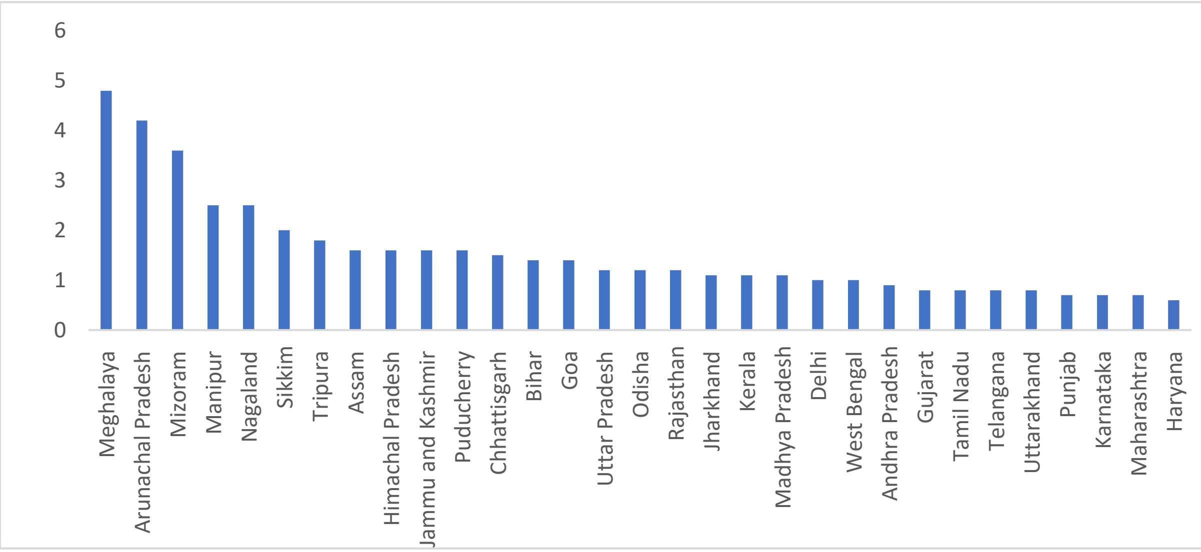
Years	2017-18	2016-17	2015-16	2014-15	2013-14	2004-05
THE % GDP	3.3	3.8	3.8	3.9	4	4.2
THE per capita (Rs)	3333	3503	3405	3231	3174	2066
CHE% THE	88.5	92.8	93.7	93.4	93	98.9
GHE%THE	40.8	58.7	60.6	62.6	64.2	69.4
OOPE%THE	48.8	58.7	60.6	62.6	64.2	69.4
SSE%THE	9	7.3	6.3	5.7	6	4.2
PHIE %THE	5.8	4.7	4.2	3.7	3.4	1.6

Source: Compiled by author from National Health Accounts, 2017-18.

We present an analysis of total government health financing expressed as GHE as a percentage of GSDP by states (see Graph 1) and per capita GHE in Rs by states (see Graph 2). The North-Eastern states of Meghalaya, Arunachal Pradesh, Mizoram, Manipur, Nagaland, and Sikkim have spent 2% and more than 2 % of GSDP on GHE. The states that have spent less than 1 % are Andhra Pradesh, Gujarat, Tamil Nadu, Telangana, Uttarakhand, Punjab, Karnataka, Maharashtra, and Haryana.

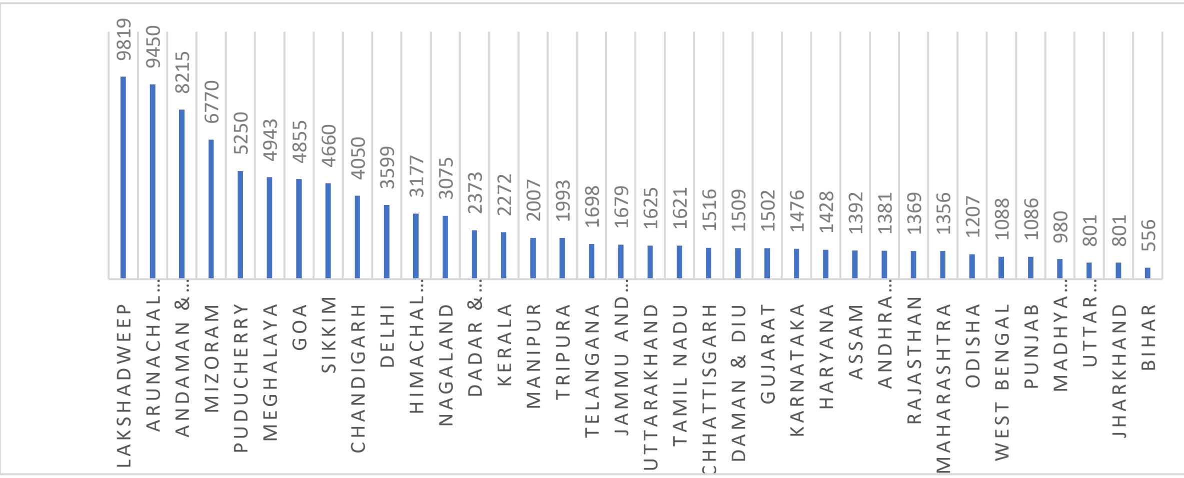
The five states with the highest per capita GHE(Rs) are Arunachal Pradesh, Mizoram, Meghalaya, Goa, and Sikkim. The five states with the least per capita total health expenditure are Bihar, Jharkhand, Uttar Pradesh, Madhya Pradesh, Punjab and West Bengal (Graph 2).

GRAPH 1: **State-Wise Government Health Financing: Government Health Expenditure As A % Of Gross State Domestic Product (GHE AS % OF GSDP)**



Source: Compiled by author from NHA, 2017-18.

Graph 2:**State-Wise Total Government Health Expenditure (Rs)(Per Capita The)**



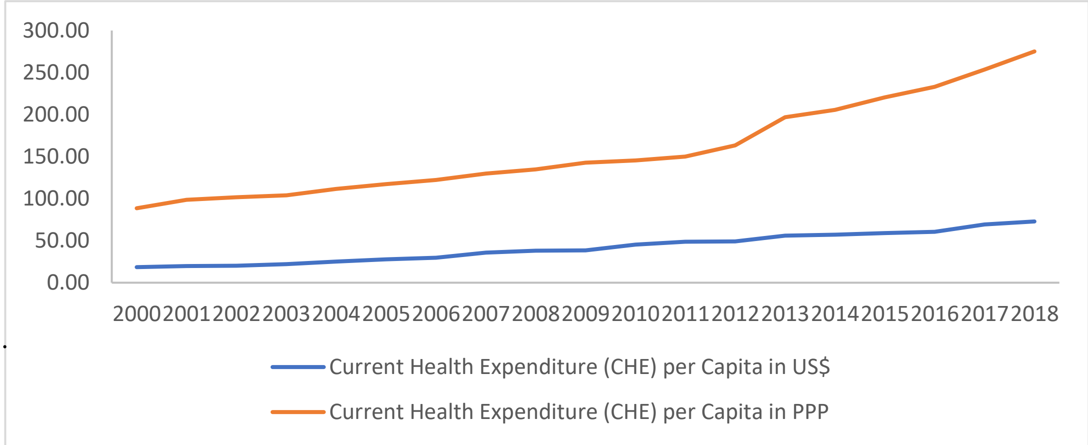
Source: Compiled by authors from NHA, 2017-18

World Bank provides open access data on the Global Health Expenditure Database (GHED). This data is comparable across 192 countries for the last two decades. The focus of this data is on health expenditure. It captures the expenditure-related information on aggregates, financing sources, financing schemes, primary health care, revenues, disease and conditions, age, capital expenditure, consumption, and health care functions. Some of the findings from this data are presented below.

The current health expenditure (CHE) in US $ and in PPP $ has increased between 2000 to 2018 for India(Graph 3). The domestic general government health expenditure comprises public sources that include internal transfers and grants, subsidies to voluntary health insurance beneficiaries, and social health insurance contributions. All these transfers and subsidies represent public sources for health and indicate the overall share of government funding for health. In 2019, this share was 0.99 % (Graph 4). This share is very low. In India, the private health expenditure per capita in USD is relatively higher than the general government expenditure in USD.

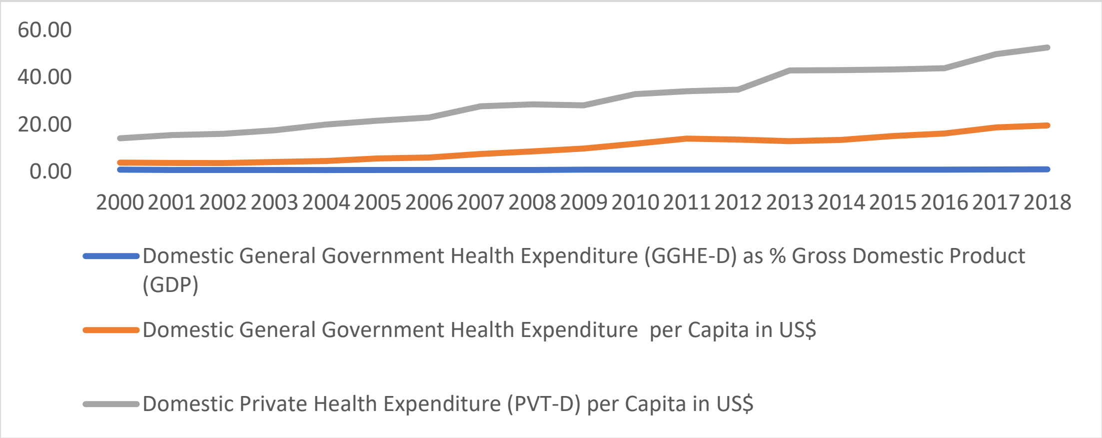
Health system financing arrangements are either compulsory or voluntary. These financing arrangements are meant to provide for health care costs. Some countries provide full coverage to their citizens via government financing. Also, compulsory health insurance schemes are linked to the payment of social contributions. In addition, there is voluntary health insurance. In India, compulsory financing arrangements are higher than government financing arrangements (Graph 5). In India, voluntary financing arrangements are higher than government and compulsory financing arrangements.

GRAPH 3:**International Comparison Of Current Health Expenditure For India 2000-2018**



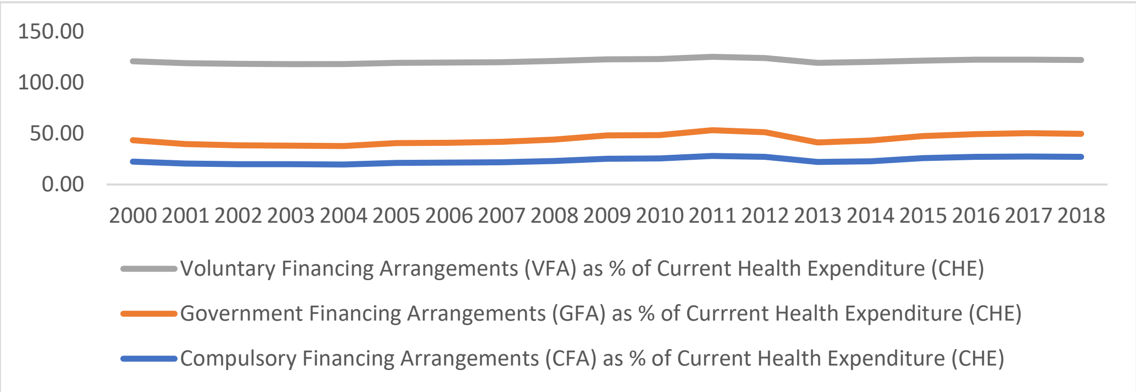
Source: Compiled by authors from World Bank data / https://apps.who.int/nha/database.

GRAPH 4: **Domestic General Government Health Expenditure**



Source: Compiled by author from World Bank data / https://apps.who.int/nha/database.

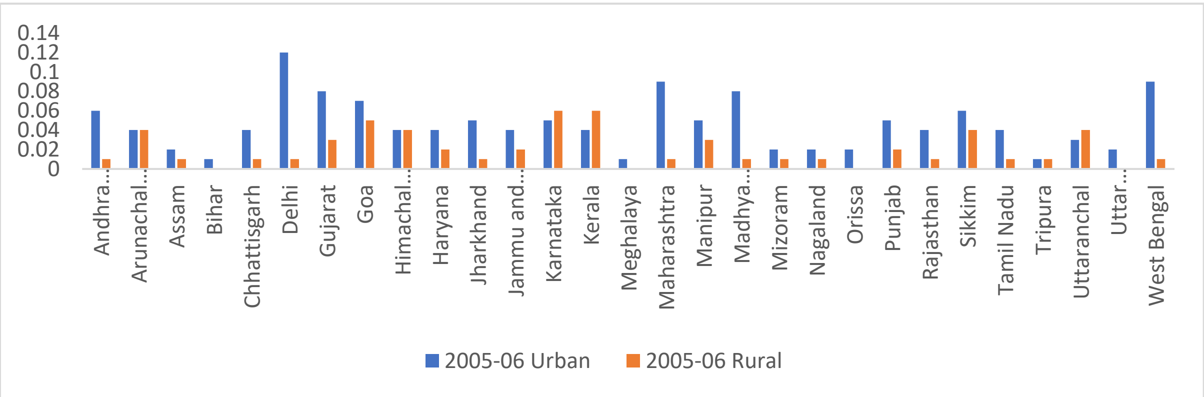
GRAPH 5: **Compulsory, Government And Voluntary Financing Arrangements.**



Source: Compiled by author from World Bank data / https://apps.who.int/nha/database.

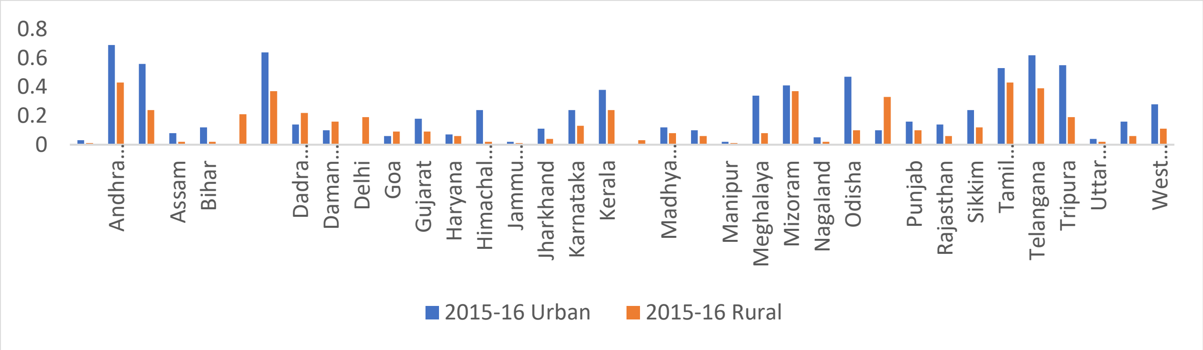
This section presents findings from NFHS data of two rounds for state-wise health insurance (Graph 6 and Graph 7). Almost all the States that reported very low insurance coverage in 2005-06 had higher coverage in 2015-16(Graph 6 and Graph 7).

GRAPH 6: **Distribution Of Health Insurance By States (NFHS 2005-06)**



Source: Author's calculation from NFHS 3 and NFHS 4.

GRAPH 7:**Distribution Of Health Insurance By States (NFHS, 2015-16)**



Source: Author's calculation from NFHS 3 and NFHS 4.

Summary statistics of health insurance by socioeconomic categories from NFHS 05-06 and NFHS 2015-16 are presented in Table 3. The population covered by health insurance in round 3 was highest for urban, non-SC/ST/OBC, Hindus and the richest wealth quintile. In round 4, the rural population, OBC, Hindus and middle-income wealth quintile had more health insurance coverage (Table 3).

TABLE 3: Insurance Coverage By Socio-Economic Status

Variables	**NFHS 2005-06**					**NFHS 2015-16**			
Place of Residence	**Not covered**	**Covered**	**Don't know**	**Missing Values**	**Total**	**Not covered**	**Covered**	**Don't know**	**Total**
Urban	43.91	74.57	53	50	46.07	29.28	28.99	36.21	29.25
Rural	56.09	25.43	47	50	53.93	70.72	71.01	63.79	70.75
Total	100	100	100	100	100	100	100	100	100
Caste of Head of Household									
Scheduled caste	17.77	11.88	15.62	13.51	17.34	17.8	18.76	14.11	18.03
Scheduled tribe	14.63	6.71	8.55	18.92	13.98	16.99	24.54	21.36	18.97
Other Backward Class	33.29	26.21	28.67	13.51	32.72	37.62	37.56	32.56	37.57
None of above	33.48	54.36	45.99	51.35	35.12	22.39	16.27	25.59	20.82
Don't know	0.44	0.72	0.68	0	0.47	0.63	0.39	2.41	0.58
MV	0.39	0.12	0.49	2.7	0.38	4.57	2.49	3.98	4.03
Total	100	100	100	100	100	100	100	100	100
Religion of Head of Household									
Hindu	73.78	76.6	80.44		74.55	73.78	76.6	80.44	74.55
Muslim	14.08	6.76	7.47		12.15	14.08	6.76	7.47	12.15
Christian	7.1	11.18	8.33		8.16	7.1	11.18	8.33	8.16
Sikh	2.29	1.8	0.66		2.15	2.29	1.8	0.66	2.15
Buddhist/neo-Buddhist	1.42	1.53	1.58		1.45	1.42	1.53	1.58	1.45
Jain	0.17	0.14	0.39		0.17	0.17	0.14	0.39	0.17
Jewish	0	0	0		0	0	0	0	0

Parsi/Zoroastrian	0.03	0.02	0.03		0.02	0.03	0.02	0.03	0.02
No religion	0.05	0.18	0.06		0.08	0.05	0.18	0.06	0.08
Other	1.09	1.78	1.05		1.27	1.09	1.78	1.05	1.27
Total	100	100	100		100	100	100	100	100
Wealth Index									
Poorest	14.43	0.38	9.9	10.53	13.43	23.12	18.57	15.05	15.05
Poorer	16.27	1.99	9.79	7.89	15.2	21.83	21.12	15.66	15.66
Middle	20.19	6.96	14.34	31.58	19.21	19.72	21.88	18.01	18.01
Richer	23.83	18.05	20.74	10.53	23.38	18.22	19.97	20.86	20.86
Richest	25.28	72.62	45.23	39.47	28.77	17.11	18.47	30.43	30.43
Total	100	100	100	100	100	100	100	100	100

Source: Author's calculation from NFHS 3 and NFHS 4.

According to the National Sample Survey (2017-2018), some key findings were that 30% use government public hospitals, but the % of health service providers are private doctors/ private clinics at 43%. Among the states, Kerala had the highest proportion of persons treated as an inpatient in private hospitals. Private hospitals have the highest share of hospitalization as well. The percentage share of government hospitals in hospitalization cases was highest for rural Assam and Urban Odisha and the lowest for rural Telangana and urban Karnataka and Telangana.

Household savings and borrowings are still the highest sources of finance for expenditure towards hospitalization. The urban households' coverage was more than rural for health insurance, but the coverage was below 20 % for urban and 14 % for rural (86 % population from the rural and 80 % of the urban were not covered). For health insurance owned by households in rural areas, government-sponsored was highest, followed by Government/Public Sector Undertaking(PSU) as an employer. Government sponsoring was highest in urban areas but lower than in rural areas. Government/PSU as an employer-sponsored was also higher for urban households, which was higher than rural. The health insurance arranged by the households with insurance companies was also higher.

The average expenditure incurred on hospitalization in private was almost seven times more than Government/ public expenditure per hospitalization. The highest expenditure incurred was for cancer, followed by cardiovascular. Cancer treatment in private hospitals was almost four times more than in public hospitals. For cardiovascular diseases, private treatment was nine times more than public.

For any ailment, private sector hospitalization costs seven times more than public. Among the health expenditures, the highest share was taken by medicines charges in both public and private hospitals, but in public hospitals, the rest, including doctor Fees, diagnostic tests, and bed charges, were relatively expensive. Medicine costs in the private sector were almost three times more than in the public sector.

The findings from the data presented above highlight that in India, some striking features of the health sector are high health expenditure to access private health care, low coverage of health insurance, and relatively lower government expenditure on health than private health expenditure.

In the next section, 1.3, we present our statement of the problem, research gap, objectives, and research questions.

1.3: Statement Of The Problem:

With 2030 as a target year set for the achievement of SDG, member countries raised concerns about UHC(Babu & Yadlapalli, 2016; Pandey et al., 2018). The concerns were more specific for developing nations. Empirical evidence across the developing nations provided evidence about the financial hardship people face when seeking health care. India coordinated to achieve UHC by 2022 (Devadasan et al., 2013; Sen, 2012).

India has a three-tier healthcare system (Chokshi et al., 2016; Kumar, 2021): the primary health centre, the community health centre at the secondary level and district hospitals at the tertiary level(Chokshi et al., 2016). Reforms led to changes that impacted the manufacturing of drugs, the health insurance market and the introduction of user fees(Ghosh, 2014; Shewade & Aggarwal, 2012). It led to several structural changes in the healthcare sector(Anand et al., 2020). Reforms expected that entry to private players would help end consumers in terms of better facilities and competitive prices for health care(Bennett, 1992; Bhat, 1996; Chakravarthi et al., 2017). After the reforms, studies questioned its impact(Bali & Ramesh, 2015).

The NRHM was introduced to strengthen the health infrastructure in rural areas. The RSBY was expected to reduce the burden of health expenditure. The outcome of these flagship programs is a matter of debate (Acharya, 2018; Bose & Dutta, 2018; Jayakrishnan et al., 2016). Health sector reforms affected households with different socioeconomic and demographic characteristics differently(Dhak, 2015; Mathiyazhagan, 2007). There emerged interstate and intrastate variations(Haddad et al., 2012). The health sector's most researched and debatable area was household expenditure for seeking health care(Thakur et al., 2018). High levels of health expenditure compelled households to avoid seeking treatment, leading to worsening ailments (Alam & Mahal, 2014). Poor households were pushed further below the poverty line(Alam & Mahal, 2014; Duggal, 2007; Garg & Karan, 2009). The health insurance only covered inpatient hospitalization expenses(Sriram & Khan, 2020). The outpatient expenditure and the expenditure incurred to procure medicine and to avail of diagnostic services remained a considerable component of expenditure incurred by the households(Selvaraj & Karan, 2009, 2012; Singh et al., 2016). The reimbursement from health insurance did not cover some indirect costs related to health treatment, such as travel expenses and lodging and boarding expenses by the caretakers(Kastor & Mohanty, 2018; Mahapatro et al., 2018). The issue from the demand side of the health sector was the OOPHE (O'Donnell, 2007; Xu et al.,2003); from the supply side, it was ill-equipped health infrastructure (Purohit, 2004).

1.4 Research Gap:

In this study, an attempt is made to examine economic development and health in India, which has a two-way causal relationship. The literature on economic development and health is rich with the contribution that has looked at both micro and macro aspects.

At the micro level, studies have examined the allocation of household consumption expenditure(Dinçer et al., 2019), consumption expenditure shocks(O'Donnell, 2019) and household well-being(Berg,2010).

While macro studies have focused on issues of allocation for health (Goel, 2021; Malhi et al., 2020), the impact of health on development(RMCMEH, 2004; Finlay, 2007; Guisan & Aguayo, 2007; Guisan & Exposito, 2008; Strittmatter & Sunde, 2013) and economic growth(Adeleye et al., 2022; Ahmad & Khan, 2019; Costanza et al., 2009; Gruzina et al., 2021; Osiobe, 2019; Peterson, 2017)both at the national level and sub-national level(Nandan & Mallick, 2022). We contribute to the literature by examining the micro and macro aspects.

The micro aspect is examined using household consumption expenditure data. Several studies have also looked at household-level allocations(Asfaw & Braun, 2004; Calvo, 2008; Dhanaraj, 2015; Heltberg et al., 2015; McIntyre et al., 2006; Nguyet & Mangyo, 2010; Stephens, 2001)and outcomes(Gertler & Gruber, 2002; Meyer & Mok, 2019; Patnaik et al., 2016; Simeu & Mitra, 2019; Sultana et al., 2012). However, almost all these studies have used cross-sectional data from NSS(Bhageerathy et al., 2016; Chakravarthi et al., 2017; Fan et al., 2012; S. Garg et al., 2019; Johnson & Krishnaswamy, 2012; Mukhopadhyay, 2017; Ramprakash & Lingam, 2021; Ranjan et al., 2018; Selvaraj &

Karan, 2012); from NFHS(Farahani et al., 2010; Joe et al., 2008; Saha et al., 2022), and IHDS(Ahmad & Aggarwal, 2017; Azam, 2018; Barik & Thorat, 2015; Bhattacharjee & Mohanty, 2022; Bradshaw et al., 2019; Gebremedhin et al., 2020; George et al., 2021; Hooda, 2020; Khan, 2018; Kumar et al., 2016; Ojha, 2022; Panikkassery, 2020; Patnaik et al., 2016; Sahoo & Madheswaran, 2014; Saikia, 2014). or do their data collection (Aggarwal, 2010; Bahuguna et al., 2019; Das & Leino, 2022; Dasgupta et al., 2013; Dwivedi & Pradhan, 2017; Fan et al., 2012; Ghosh, 2014; Nandi & Schneider, 2020; Patel et al., 2013); We fill a research gap in this domain by looking at households/individuals using a panel data set constructed from IHDS using multiple schedules and available in the public domain.

We have looked at changes in household consumption expenditure and its impact on household well-being. We have examined three unanticipated shocks affecting household consumption: a) Disability, b) Health Expenditure and c) Natural Disasters. These shocks are examined on different types of household expenditures. We fill the research gap in this domain by studying multiple shocks to household well-being.

We have used adjusted consumption expenditure(derived from consumption expenditure by making adjustments for health expenditure) and other unique variables like Activity of daily living intensity, Natural disaster intensity, publicly funded health insurance intensity, membership intensity and Village health infrastructure index constructed for this thesis.

We cover the macro aspect by evaluating the effectiveness of two national-level policies: the National Rural Health Mission (NRHM) and RSBY(publicly funded health insurance).

We fill the larger gap by studying micro and macro aspects using the same longitudinal data.

1.5: Objectives and Research Questions:

1.5.1: Objectives:

The primary objective of this study is to examine how different groups of India's population deal with unanticipated consumption expenditure shocks. We have looked at two types of shocks: idiosyncratic and covariate. We specifically study the impact of idiosyncratic shocks: disability and health expenditure on household well-being. We study the covariate shock natural disaster and its impact on household well-being. Health insurance is propounded as a worldwide remedial method to meet the unanticipated health expenditure. We examine health insurance's role in India and how this has changed over time. We examine this in the context of India’s health policies in the light of UHC. Specifically, we evaluate the effectiveness of NRHM.

The specific objectives of this study are:

1. To examine the impact of unanticipated idiosyncratic shocks on household well-being.
2. To investigate the effect of covariate shocks on household consumption expenditure.
3. To study the impact of health expenditure on household consumption expenditure.
4. To study if Health insurance helped in household consumption smoothing.
5. To assess the extent to which India's Health policy enhances household well-being.

1.5.2: Research Questions:

We address three specific questions in this thesis.

1. How much do unanticipated shocks impact adjusted consumption expenditure?
2. What has been the role of public and private insurance financing on the health expenditure of households?
3. Whether health policy like NRHM have achieved their targets at the household level?

1.6: Materials and Methods:

1.6.1: Materials:

We have used the India Human Development Survey (IHDS) data. IHDS is conducted by the University of Maryland USA and the National Council for Applied Economic Research (NCEAR) in New Delhi. This data is available in the public domain through the Inter-University Consortium for Political and Social Research (ICPSR) at household and individual levels and can be downloaded in different formats, making it very researcher-friendly. IHDS, 2004-05(here onwards IHDS 1) consists of data collected from 41554 households (937 variables) and 215754 individuals (211 variables) in 1503 villages and 971 urban neighbourhoods in 33 States and Union territories. IHDS, 2011-12(here onwards IHDS 2) is a multi-topic and multi-design survey covering 42512 households

(872 variables) and 204568 individuals (502 variables) with 14 different datasets in 384 districts, 1420 villages and 1042 urban neighbourhoods. In IHDS 2, the households covered in IHDS 1 were surveyed with a re-contact rate of 84%. Researchers widely use this data for analyzing various aspects using households and individual schedules (see Chapter 3 for details).

1.6.2: Methods:

Descriptive statistics are used to arrive at averages and their meaningful interpretations. Multiple regression with fixed effects, Instrumental variable approach with two-stage least square, the difference in differences regression with continuous and binary treatment, catastrophic, incidence and impoverishment impact of health expenditure is calculated (see Chapter 3 for details).

1.7: Chapter Scheme:

There are 9 chapters in this thesis. Chapter 1 is the introduction. In the introduction, we provide a theoretical perspective, empirical evidence from past literature and a rationale for our study.

Chapter 2 is a Review of the literature. In this chapter, we discuss theoretical and empirical studies, followed by a review of methodologies used for data analysis. We discuss large data sets available in India for analysing household consumption expenditure and provide comparative analysis. We justify the use of IHDS data for this thesis.

Chapter 3 discusses Materials and Methods. It describes the data processing and methods used. The various stages of data processing are discussed at length. We provide the stepwise procedure for merging 2 IHDS rounds using different schedules. We describe variables we constructed from IHDS data and variables used from the data.

We provide details of methodologies used to analyse the data, such as the test of significance, regression with fixed effects, methods for calculation of catastrophic and impoverishment impact of health expenditure, the instrumental variable approach using two-stage least square, Difference in Differences (DID) with continuous and binary treatment and finally, principal component analysis (PCA) for the index construction.

Chapter 4 is 'Consumption Expenditure and household well-being: analysis of disability as an idiosyncratic shock'. This chapter exclusively deals with the first objective, which examines the impact of unanticipated idiosyncratic shocks on household well-being.

We have discussed two types of household disabilities: a) Duration and Disease-specific disability and b) Activity of Daily Living Intensity (ADLI). We have used different measures of consumption expenditure to examine the impact of the disability of a household member on household well-being. We have used cross-sectional IHDS data from both rounds to analyse the duration and morbidity-specific disability. We have provided results for different types of household consumption expenditure for IHDS 1 and IHDS 2 separately. This analysis is done at a disaggregated level for rural and urban areas.

Using a regression model in household individual panel data, we have analysed the impact of ADLI on household well-being. ADLI is used as one of the independent variables to examine the changes in consumption expenditure and adjusted consumption expenditure. Seven models are used with different types of household expenditures as dependent variables. These analyses are presented for socioeconomic categories for rural and urban areas.

Chapter 5, titled 'Impact of natural disasters as covariate shock on household consumption expenditure'. This chapter deals with the second objective, which investigates the effect of covariate shocks on household consumption expenditure.

The impact is studied using two distinct methodologies, IV2SLS and DID, using household village panel data. Natural disaster intensity and confidence intensity are used as the instruments (exogenous) that influence the endogenous regressor, i.e., household assets. The second methodology is the DID. Natural disaster intensity is the continuous treatment given to households. Two models with consumption expenditure and adjusted consumption expenditure as dependent variables are used with socioeconomic categories.

Chapter 6 deals with health expenditure as an idiosyncratic shock, titled 'Health expenditure analysis at household and individual level'. The third objective that studies health expenditure's impact on household consumption is dealt with exclusively in this chapter. The health expenditure is analysed for the households and individuals from IHDS data. A descriptive analysis is done for different types of health expenditure for rural and urban areas. The shock of health expenditure is examined by measuring the catastrophic health expenditure and impoverishment effect of health expenditure for rural and urban areas.

Chapter 7 evaluates 'Universal health coverage and health insurance in India '. The fourth objective, which examines the role of health insurance in household consumption smoothing, is dealt with in this chapter. We have used household village panel data. Impact evaluation of health insurance is done using DID with continuous and binary treatment. The analysis is done separately for rural and urban areas for socioeconomic categories.

Chapter 8 is 'Evaluation of National Rural Health Mission Policy 2005-2012 and Health Infrastructure in Villages' and covers the last objective, which assesses how India's Health policy has enhanced household well-being. The VHII is constructed using principal component analysis (PCA). Different variables that measure the availability of health infrastructure at the village level are used for constructing the index. Merged data of households and individuals at the village level is used. The constructed index has five categories that measure different levels of infrastructure development. Descriptive statistics of index values using Statewise and expenditure quintiles are provided.

Chapter 9 is the concluding chapter. This chapter summarises the thesis findings and matches them with the objectives and research questions set out earlier. This thesis tried to examine the impact of economic development on health in India at the household level by analysing the consumption expenditure of households. This chapter also provides policy implications and the future scope for research.

1.8: Conclusion:

Health is human capital, and its contribution to economic development is documented in the literature. Economic development and health have a causal relationship. This causal relationship is examined in the literature using indicators such as life expectancy, infant mortality, and body mass index. The reverse causality of the impact of health on economic development is also examined using labour productivity, days unable to work due to illness. Achieving SDG 3 is very crucial for India. Largely, the health policies of the last 1.5 decades reflect India's intention to do so. The provisioning of publicly funded financial protection to households and strengthening of health infrastructure is articulated in the health policy. The achieved targets and milestones are also documented and available in the public domain.

This thesis focuses on examining the unanticipated shocks that affect household well-being. Changes in health status via health shocks affect the household's well-being. Well-being is affected at two levels: the onset of illness reduces productivity at work (due to disability) and health expenditure that the households incur on the members to restore their health. Households use various productive and unproductive strategies to smoothen consumption. These actions cumulatively are responsible for loss in consumption expenditure, affecting the household's well-being. Loss in well-being affects economic development because households postpone consumption decisions during unprecedented health shocks. Besides these shocks, climate-related adversaries in the form of natural disasters also impact household well-being, and it is well documented in the literature. Natural disasters are covariate shocks that may affect more than one household and are localized in nature. Coping strategies for consumption smoothing may vary depending on the localized impact. Thus, disability, health expenditure and natural disasters are unanticipated shocks that impact consumption and household well-being.

This research has policy bearing. The two existing government policies, i.e. Publicly Funded Health Insurance and National Health Rural Mission, are evaluated to study the impact of the same. These policies are also directly related to the well-being of the households. Health insurance provides financial protection against OOPHE to access health care as a formal coping strategy. The provisioning of health infrastructure gives a boost to public health infrastructure. Utilization of public health infrastructure reduces the health expenditure of the household.

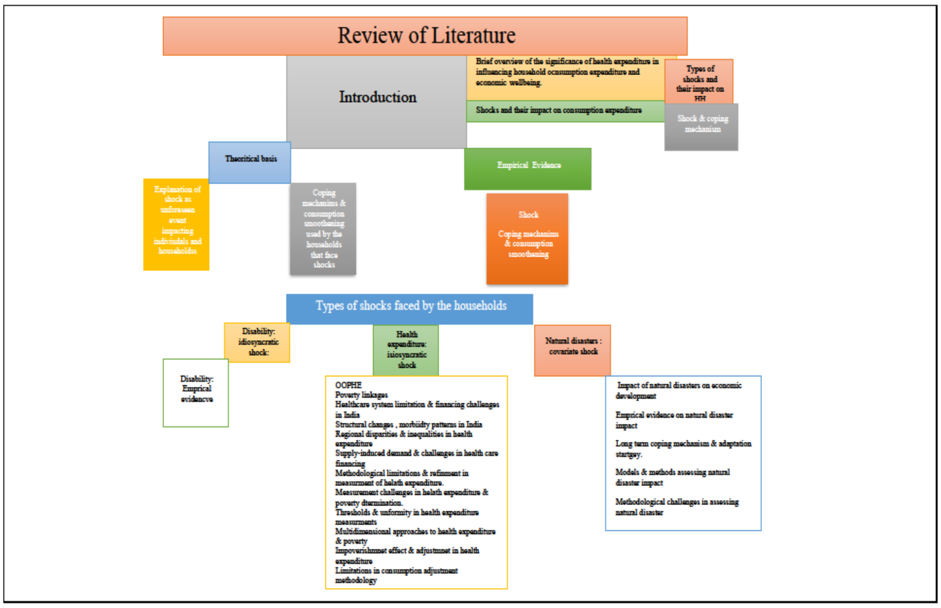
The next chapter, 2, reviews literature that builds a strong theoretical and empirical background for understanding Economic Development and Health in India. The theoretical and empirical background of unanticipated shocks is discussed at length. A section on large-scale data covers various aspects of data collected from households. Limitations of such data are also discussed.

CHAPTER 2:

REVIEW OF LITERATURE

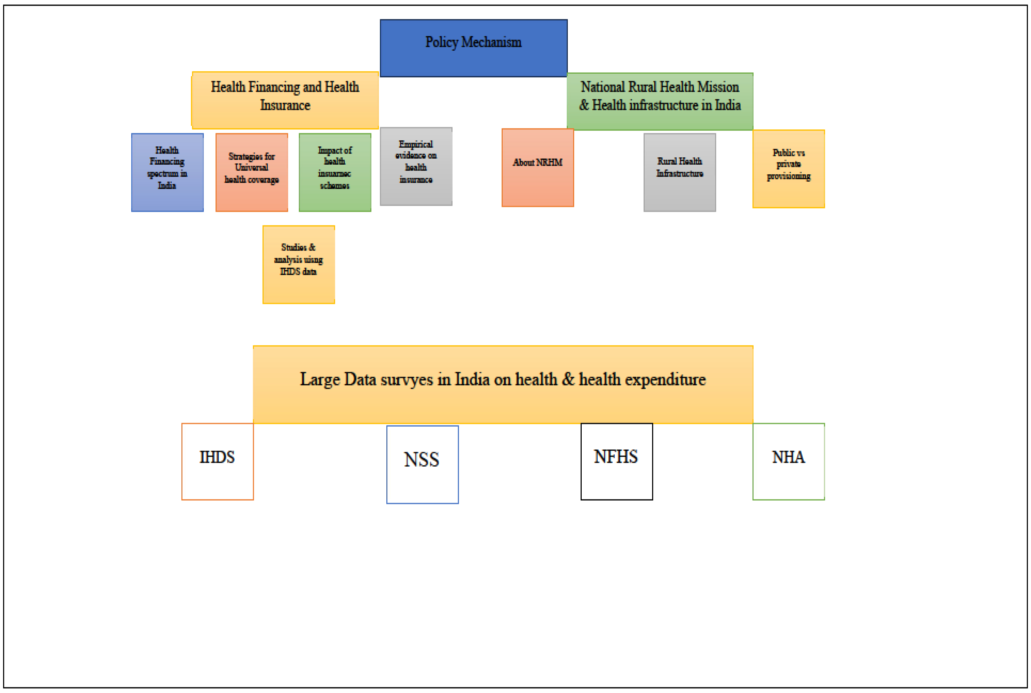
The previous chapter, 1, provides a theoretical background to linkages between human capital and economic development and growth. The empirical evidence builds up a strong case for the existing linkages. Chapter 2 is a Review of the literature. It covers the theoretical and empirical background for various unanticipated shocks and is divided into 8 sub-sections. We first provide an infographic layout of this chapter for better readability and comprehension, followed by an in-depth literature analysis. The first section, 2.1, is the introduction. Sections 2.2, 2.3, 2.4, 2.5 and 2.6 deal with background studies and theoretical background, disability, health expenditure, natural disasters, health insurance and NRHM, respectively. The next section, 2.7, is on large data surveys in India. These subsections broadly cover descriptions of the different large-scale surveys in India, such as the India Human Development Survey (IHDS), Consumption expenditure and social consumption surveys of NSS, National family health surveys, and National health accounts. The chapter is concluded in section 2.8.

Images 1: Schematic Diagram Of Review Of Literature



Source: Infographics created by the Author based on the review of literature.

Images 2: Schematic Diagram Of Review Of Literature



Source: Infographics created by the Author based on the review of literature.

2.1: Introduction:

According to the International Monetary Fund (IMF), India retains its rank as the world's fastest-growing major economy, tying with China, with a projected growth rate of 6.1% for the fiscal year 2019. Regarding the Human Development Index, India ranked 132 in 2020-21 (Human Development Report, 2021-22). However, India hosts the second largest population in the world, with about 30% below the poverty line (Subramanian, 2012). According to the Multidimensional Poverty Index of 2020-21, India's value is 0.123, with a headcount of 28 % and 44 % intensity of deprivation. The percentage of the population living below the poverty line (National) was 22%, and those below the international poverty line were 22.5 % (PPP $ 1.90 a day) (HDR, 2021-22).

2.1.1.Brief Overview of the Significance Of Health Expenditure in Influencing Household Consumption Expenditure And Economic Wellbeing:

In India, the health policy shifted from providing health through the public health network to financing health coverage (Ghosh, 2011). In India, the status of public health expenditure is abysmally low, and private health cost/payment is exorbitant(Ellis et al., 2000; Gumber et al., 2012; Gupta & Chowdhury, 2015; Rao & Choudhury, 2012). The government health expenditure was 1.28 % of GDP, Rs 1,1815 per capita in 2018-19. The OOPHE is 1.52 % of GDP(National Health Estimates, 2018-19).

Inter-state variations in healthcare utilisation between the public and private sector, rural and urban, and rich and poor health expenditure burdens arise from direct and indirect health payments(Ellis et al., 2000). There is an increase in average healthcare costs featuring OOPHE on health in India (Ghosh, 2011; Gupta & Chowdhury, 2015; Rao & Choudhury, 2012). A concern is raised about low levels of UHC and private insurance(Ghosh, 2011). Despite coordinated efforts toward providing health for all, the disabled population remains vulnerable(Guets & Behera, 2022).

Therefore, to provide theoretical background, we have looked at literature that provides the basis for forming the theoretical framework, delving into households' health and economic well-being. We looked at literature that provides concepts and definitions about those health-related issues mainly responsible for disruption in economic well-being. We also have collated the empirical evidence for external cushioning provided by the government to reduce the hardships caused by health-related issues. We have invested and provided a great deal of literature for the reader to look into the data sets and their scope available for India in the public domain.

2.2:Shocks And Their Impact On Consumption Expenditure:

This section discusses the shocks and their impact on household consumption.

2.2.1: Importance Of Understanding Different Types Of Shocks And Their Impact On Household :

Shock is any adverse event the household faces that negatively affect household income, decrease in consumption or even loss of productive assets(Ansah et al., 2019a, 2021b, 2022c, 2023d). Shock is unanticipated and has detrimental effects on a household's current well-being and affects the household's ability to cope with future shocks(Bufe et al., 2022). We adopt this concept of shock for our study.

Shocks are divided into many broad categories, such as climatic, economic, political/social/legal, crime and health(Dercon et al., 2005). Shocks faced by households are of two types: the one faced by the given household in isolation, such as chronic illness/death/ disability of head of the household/earning member, damage to a physical asset such as land and livestock calamity. Such shocks are idiosyncratic in literature(Gertler & Gruber, 2002; Mitra et al., 2016). We have used this concept of idiosyncratic shock in our thesis.

There are geographically localised shocks, such as climatic shocks or spurted from economic crises or epidemics, which affect clusters of households, entire localities/communities, or sometimes the whole economy. Such shocks are called covariate shocks(Shehu & Sidique, 2015; Yilma et al., 2014). Our thesis uses the concept of covariate shock based on this meaning.

When households face shocks, consumption adjustments eventually affect economic welfare (Asfaw & Braun, 2004; Calvo, 2008; Dhanaraj, 2015; Stephens, 2001). The micro effect of these shocks is on consumption, savings, and productive assets(Heltberg et al., 2015), and the macro-economic impact is on the economy’s human capital via health and education(Bleakley, 2010). There is growing evidence about the linkages between shock and poverty(McIntyre et al., 2006; Nguyet & Mangyo, 2010). Therefore, the pathways through which these shocks affect household well-being and economic development are important from a macroeconomic point of view(Stevenson & Wolfers, 2008). Studying the welfare impact of these shocks on households and individuals is important. The most common ones are idiosyncratic health shocks (illness and disability) (Mitra et al., 2017), the most sizeable and least predictable(Gertler & Gruber, 2002). These shocks originate from economic disturbances, political turmoil, and health imbalance(Wolf, 2014). If the household cannot insure fully against the shock, it may witness welfare loss(Gertler & Gruber, 2002) . We study the impact of idiosyncratic and covariate shocks on household consumption expenditure. The source of shock and household response to it are also important.

Consumption expenditure is more stable than income. Individuals derive material well-being from consumer goods, reflecting living standards better(Morattii & Natali, 2012). Using income as a welfare indicator or as a variable for analysis may lead to errors (Anand & Harris, 1994; Cabral et al., 2020; Moore et al., 2000; Sumarto et al., 2007). From an empirical perspective, in the United States, the household's income was susceptible to under-reporting compared to expenditure(Brewer et al., 2017). Moreover, the questions included in the survey for collecting information about household expenditure are perceived as less sensitive than their counterpart income (Ali, 2019). Thus, consumption expenditure is a proxy for household well-being(Rentschler, 2013). We have used consumption expenditure and adjusted consumption expenditure in our thesis.

Health shock is among the most critical(Lindeboom et al., 2016). Health shock faced by the household in the form of illness or disability generates two types of costs: cost in the form of lost productivity due to ill health, which affects income earned and the expenditure incurred for treatment is often borne by the households is OOPHE(Gertler & Gruber, 2002) and is the direct effect of shock(Simeu & Mitra, 2019). This effect may be temporary and not affect the households' consumption compared to permanent hardships (Patnaik et al., 2016; Sultana et al., 2012). Those that are more permanent are the ones that arise due to chronic illness and disability(Meyer & Mok, 2019). Examining the effect of shocks and situations in which these shocks create temporary or permanent hardships may provide insights into a better understanding of a household's economic dynamics.

2.2.2: Shocks And The Coping Mechanism Used By The Households:

Households use different coping mechanisms to mitigate the loss of consumption. The transition of households into poverty due to shocks and the mitigation strategies used by the households is constantly the focal point of research and more so for developed economies (Carter & Barett, 2006). Consumption smoothening due to shocks reveals enormous information about a household's coping mechanisms(Patnaik et al., 2016). According to Townsend (1995), the measures taken by the household to mitigate shocks depend upon the nature of the shock. The impact of idiosyncratic shocks on households is minimal, and the mitigation strategies that households use more often serve as insurance(Ajefu, 2017). When the shock is idiosyncratic, like health shock, households borrow and sell assets. However, those that face covariate shocks, such as natural disasters, lead to a reduction in consumption and dissaving(Yilma et al., 2014). Households often insure against those illness shocks that are recurrent and small over large and rare(Gertler & Gruber, 2002). Household socioeconomic characteristics may also influence the coping mechanism(Alderman & Paxson, 1994; Mitra et al., 2016; Morduch, 1995).

Households use two types of coping mechanisms:

a) Formal mechanisms like health insurance(Cohen & Young, 2007) .

b) Informal mechanisms such as self-insurance(Patnaik & Narayanan, 2010)or Local insurance(Townsend, 1995) .

The empirical literature has evidence for households using informal mechanisms over formal mechanisms. The most used informal mechanisms are:

a) Physical capital: accumulation of assets and livestock(Cohen & Young, 2007); selling productive assets(Pradhan & Mukherjee, 2016) .

b)Economic capital: Diversification of crops(Pandey et al., 2000); land fragmentation(Townsend, 1995); gifts and remittances(Ajefu, 2017); loans from a formal source such as credit societies and banks(Pradhan & Mukherjee, 2016; Townsend, 1995) and informal source(Pradhan & Mukherjee, 2018) such as rice banks or even money lenders (Townsend, 1995).

c)Human capital: Reduction in investment in children's education and labour substitution by bringing more family members as labourers (Ajefu, 2017; Pradhan & Mukherjee, 2016).

d) Social capital: help from the community(Townsend, 1995).

Despite all these coping mechanisms, households may not be able to get to the level of full insurance, and this may lead to a reduced standard of living (Meyer & Mok, 2019).

When the head of the household falls sick, the household engages in labour substitution, reduced leisure time, and decreased school days(Sauerborn et al., 1996). Irrespective of the duration and severity of the illness, households may still face the risk of a loan for health expenditure(Yilma et al., 2021). Poor households may not have savings, or small family sizes may be unable to use labour substitution (Mitra et al., 2016). The inability of households to smoothen consumption may be due to limitations related to the quantity and price of assets and limitations on those markets that provide formal mechanisms for smoothing, such as financial, credit and insurance markets (Alderman & Paxson, 1994; Morduch, 1995).

The issue with self-insurance mechanisms is that they can be expensive (Liu, 2016). When health insurance comes into the picture, it leads to substitution with self-insurance (Pannequin et al., 2020). When households fully insure themselves using self-insurance, social insurance may provide fewer marginal benefits. Thus, social insurance may eventually crowd out self-insurance (Liu, 2016).

2.3: Theoretical Basis:

In the following section, we provide the theoretical basis from the literature for shocks, household expenditure and consumption smoothening. We have mainly discussed four important theories: The Life Cycle hypothesis, The Permanent Income Hypothesis, The Complete Market hypothesis and the Full insurance theory.

2.3.1:Explanation of Shocks as Unforeseen Events Impacting Individuals Or Households: Theoretical Basis:

Unanticipated shocks faced by households create responses to mitigate these shocks. The theories on consumption smoothing proceed with the broad assumption that any smoothing that happens for consumption against shock only if households feel that this shock is permanent (Meghir & Pistaferri, 2011).

There are two popular theoretical approaches to predicting consumption behaviour – the Life-Cycle Hypothesis (Ando & Modigliani, 1963; Modigliani & Brumberg, 1954) and the Permanent Income Hypothesis (Friedman, 1957). In both these hypotheses, consumption is predicted by income. The life cycle hypothesis relies on an inter-temporal smoothing of consumption, which is adjusted by changes in wealth (borrowing in the early periods and saving in the later periods). The change in the net asset value smooths consumption in the life cycle hypothesis.

On the other hand, the permanent income hypothesis predicts that consumption is not based on current income but on future expectations(Friedman, 1957). According to the permanent income hypothesis, consumption responds to a change in income only if the change is permanent. Income has two components: one is steady (or permanent) income, and the other (transitory) fluctuates. The fluctuations in income are temporary, which is transitory income. Consumption smoothing is done by the households against income shocks that are transitory.

These hypotheses use the idea that agents smoothen consumption by using some notion of income earned over pre-defined periods or a lifetime. The inherent assumption is that income itself is contingent on intertemporal asset ownership choices of economic agents who distribute their flows (income) and stocks (wealth) to maintain certain levels of target consumption (Arrow et al., 2012; Mayer, 1972). Therefore, if agents wanted to smoothen consumption, they would stabilise incomes by inter-temporal stock-flow choices between holding assets or monetising them to overcome temporary fluctuations in the flow of consumption and incomes (Dasgupta, 2009; Onuma et al., 2020; Sundaresan, 1989). The income shock that damages household assets may be permanent and prompts households to smoothen assets(Hoddinott, 2006). Literature supports that households from developing economies use productive assets and livestock to smoothen consumption against income shocks(Islam & Maitra, 2012).

The complete market hypothesis(Cochrane, 1991)and Full Insurance theory (Townsend, 1995)discuss the smoothing of consumption due to idiosyncratic income shocks (permanent and transitory) but not covariate shocks. These adjustments take place through both formal and informal channels of risk-sharing. Empirically, these theories were challenged by the Asset smoothing theory (Zimmerman & Carter, 2003). The theory helped the households to distinguish between productive and unproductive assets and stated that economically less affluent households would choose to smoothen productive assets. The households may sacrifice consumption to build productive assets (Barrett & Carter, 2008). The empirical support drawn by these theories was mixed. The households did not smoothen consumption against transitory income shocks, but smoothing happened for idiosyncratic shock (health shock)(Onisanwa & Olaniyan, 2019). Households that face shocks also smoothen consumption by diversifying economic activities, especially activities that may be exposed to seasonal income shock (Reardon et al., 2007). Productive assets may not have a role to play in consumption smoothing (Nguyen et al., 2019).

2.3.2: Coping Mechanism And Consumption Smoothening Used By The Households That Face Shocks :

Households respond to shocks in many ways, but assets are households' most important coping mechanisms(Heltberg et al., 2015; Nikoloski & Mossialos, 2018). Productive assets lead to income generation(Berloffa & Modena, 2013). In this situation, shocks may generate different consequences. The household decision often involves a trade-off between the choices related to assets and consumption (Ansah et al., 2020). Investment in assets may involve consumption sacrifice (Rusell, 1996).

Similarly, selling productive assets or incurring less investment in accumulating assets may lead to a future income decrease(Berloffa & Modena, 2013). Thus, when households experience shocks leading to a loss in income, and if this loss gets translated into drastic decisions concerning asset investment, there may be some consequences of such shock in the long run, even if the shock was temporary (Carter et al., 2007). Households are often found to maintain the asset level even at the cost of consumption.

2.3.3: Empirical Evidence: Shocks, Coping Mechanisms And Consumption Smoothening:

For villages in India, Thailand, and Cote-d-Ivoire (West Africa), the households used crop inventory (buffer stock), currency and credit for consumption insurance (Townsend, 1995). In rural Nigeria, the transfer of resources was from those individuals who were not facing shocks to those who were facing shocks (idiosyncratic) through community transfer of resources(Shehu & Sidique, 2015). For Korea, it was found that those not engaged in any economic activity were likely to face catastrophic health expenditure, but the relationship between economic activity and catastrophic health expenditure was more valid for people with disabilities (Lee et al., 2020). Among many shocks faced by Ethiopia, drought and illness were more long-lasting than others, and they reduced consumption (Dercon & Krishnan, 2000). These two shocks were also significant for female-headed households and when the head of the household was uneducated (Hill & Porter, 2017). In Kenya, households were more affected by natural disasters followed by illness. Those households that were engaged in subsistence farming were affected by the shock. Many poor households had to forgo healthcare(Bonfrer & Gustafsson-Wright, 2017). Households in Uganda that had no exposure to any credit facilities had a reduction in productivity that they experienced due to health shock (Isoto et al., 2017).

According to Sauerborn et al. (1996), in Burkina Faso, households that face illness use intra-household labour substitution. Labour substitution is better in rural areas(Wagstaff et al., 2007). Remittance from relatives helped households to smoothen consumption in Indonesia(Genoni, 2012). Also, poor Indonesian households use borrowing and family savings and assets(Sparrow et al., 2014). In Bangladesh, households used the sale of livestock and microcredit as coping mechanisms(Islam & Maitra, 2012). Vietnam's rural households took loans or reduced food consumption to pay for illness treatment(Nguyen et al., 2019). In another study by Mitra et al. (2015) in Vietnam, households could smoothen consumption by reducing education expenditure, increasing loans, and running down on assets, but health expenditure increased. Different coping mechanisms are used in Ethiopia for different categories of shocks: the natural and economic shock, which is dissaving and reducing food consumption.; health shock is reduced savings, asset sales and borrowing from informal sources(Yilma et al., 2014). Further, in Indonesia, in an experiment, an unconditional cash transfer was done for ten months, and the poor households managed to increase their food consumption (Tiwari, 2019).
For covariate shocks in a study in Japan, precautionary motive in the life cycle framework was analysed to study the impact of natural disasters. An increase in the saving rate is linked to the occurrence of earthquakes. The frequency of earthquakes is very high in Japan. This study provided evidence in support of the precautionary motive as an important determinant of household savings. The savings act as self-insurance, an indicator of non-functional insurance markets (Skidmore, 2001).In a study in Nawairuku, Fiji, households used tangible assets like land and intangible assets like motivation and sustainable agricultural practices, which helped adapt to climatic changes(Currenti et al., 2019).

In India, households rely on informal coping mechanisms for idiosyncratic shocks (Jha et al., 2011), such as savings, remittances, institutional loans, and loans from moneylenders. For covariate shocks, the reliance is more on the welfare schemes of the government(Jha et al., 2011; Pradhan & Mukherjee, 2016). Extremely poor households may suffer a complete loss in consumption during shocks without an informal coping mechanism (Pradhan & Mukherjee, 2016).

2.4: Types Of Shocks Faced By The Households:

In the following section, we focus on 3 types of shocks and their impact on household consumption expenditure.

2.4.1: Disability As An Idiosyncratic Shock:

Linkages between health shocks and poverty have many pathways, and one of the pathways is disability (Mitra et al., 2011). The literature provides the impact of disability on a household's well-being at the micro and macro levels:

a) Disability and Human Capital:
   a. Miss out on schooling due to a lack of facilities or attendance(Kuper et al., 2014).
   b. Lack of access to financial resources may worsen the disability or delay treatment (Batavia & Beaulaurier, 2001).
   c. When a child is disabled and in poverty, malnutrition may affect further physical development (Parnes et al., 2009).

b) Disability and economic impact:
   a. Lack of opportunity to upgrade skills due to lack of / less investment in education(Palmer et al., 2019; Parnes et al., 2009).
   b. Limited earning capacity due to disability(Palmer et al., 2015); Low wage employment(Batavia & Beaulaurier, 2001).
   c. Unequal distribution of resources within the household and under-weighted disabled members (Huang et al., 2010).
   d. Households with disabled members are likely to witness multi-dimensional poverty(Banks et al., 2022; Groce et al., 2011).

The impact of disability, particularly on the labour market in developing economies, is important since this may be a major pathway for households with disabled members to slip into poverty(Mitra et al., 2011). There is growing evidence of this in the literature (Mani et al., 2018). Households suffer income loss on account of the physical disability of their working members, but the loss is greater when there is mental illness(Babiarz & Yilmazer, 2017). Economic development increases life expectancy, but also there is an increase in disabilities (Wiman et al., 2002).

The literature reveals that the cross-section data for poverty for households with a disability may not be able to identify the poor or poorer households(Dercon & Krishnan, 2000).

For poor households, there is a two-way relationship between income and disability(Pandey, 2012). When the household is poor, they often have a chance of facing disability(Lwanga-Ntale, 2003). Due to limited access to resources, the household may not be able to support a member with a disability(Asuman et al., 2021; Palmer et al., 2015). This disability, which originates as a health-related disability, becomes a social disability(Mitra, 2006). Households who are also into caregiving for disabled members spend much time looking after the disabled members(Loyalka et al., 2014). Thus, poverty can be a cause and consequence of disability(Ali, 2014). Therefore, studying disability and its impact on household consumption using longitudinal data becomes important.

A disability may have direct and indirect costs. Direct cost is the institutional cost of disability care and the cost that family members incur despite receiving disability monetary benefits(Banks et al., 2022). The households may incur additional expenditures to maintain the standard of living(Morris & Zaidi, 2020). The indirect cost measures the loss in productivity of disabled members and the cost of time spent by other household members to support and take care of disabled members(Ali, 2014).

2.4.1.1: Disability And Empirical Evidence:

Literature provides evidence from developing nations for linkages between disability, health expenditure, and household well-being. Those households with disabilities faced higher health expenditures than those without(Hong et al., 2022). In Vietnam, disabled members had a higher share of OOPHE and a higher frequency of hospitalisation (Palmer et al., 2015). A study in Bangladesh on disability recorded that more than 40 % of the population had at least one side disability; those with a disability had to incur higher OOPHE (Sultana et al., 2021). A systematic literature review using 38 studies found that households with OOPHE had at least one disabled member(Azzani et al., 2019). In Ethiopia, household members with a disability and chronic illnesses incur high OOPHE

(Mekonen et al., 2018). In Turkey, poor households with disabled members and chronic illnesses were strong contenders for receiving protection against OOPHE (Yilmaz et al., 2009). In Nigeria, households resorted to community sharing and consumption against illness and disability (Onisanwa & Olaniyan, 2019). A study using longitudinal data in Indonesia revealed that households with disabled members experience additional costs for health expenditure, but the non-medical consumption in the short run was safeguarded (Simeu & Mitra, 2019).

Using the Indonesian Family Life Survey and ADL Index, Lim (2017)found that:

a) Households with major morbidity shocks need to be provided with subsidies and may enjoy greater welfare with disability insurance.

b) The households used labour substitution as a coping mechanism but only for minor illnesses.

c)The workers in the informal sector incurred huge indirect health expenditures and income loss from disability. Disability also impacted self-employed workers compared to salaried workers(Mani et al., 2018).

In China, earlier policies did not consider disability but gained importance only after de-collectivisation, and causal linkages between disability and poverty were found (Eide & Ingstad, 2011). In Indonesia, household consumption was less affected and depended on the ADL effect(Nguyet & Mangyo, 2010). A composite standard of living index was used in a UK study that found a negative correlation between disability and standard of living(Schuelke et al., 2022). A study in Indonesia found that the onset of disability makes individuals more vulnerable to moving out of the employment market, but at the same time, recovery from a disability also increases the chances of an individual returning to work(Mani et al., 2018). Those households that faced illness shocks could insure them fully as against ADL(Gertler & Gruber, 2002).

Studies on disability are uncommon in developing economies (Raut et al., 2014). In India, the research on disabilities and their impact on household welfare are mostly related to the impact of disability on health expenditure(Dhanaraj, 2015; Flores et al., 2008). A study using the disability module of NSS data (2002) for India reports that consumption loss is higher in urban areas for those with speech disabilities and highest for Sikkim, followed by Maharashtra. This study used household consumption expenditure to find the impact of job loss due to disability onset (Raut et al., 2014). Menon et al. (2014), in their study, point out that in comparison to other developed economies, disability policies in India are better. Despite this, the disabled population faces numerous challenges. In their study, they further observe that households with disabled members, male adults, and disabled children from poor states belonging to urban areas have low expenditures compared to non-disabled households.

2.4.2: Health Expenditure As An Idiosyncratic Shock:

Health and human development are integral to a nation's overall socioeconomic development (Nair & Durairaj, 2007). The shock households receive due to health expenditure in general and health expenditure without financial protection are idiosyncratic shocks(O'Donnell, 2019). Large inequities in health and access to healthcare services are pointed out in the literature(Baru et al., 2010).

Some of the features of health expenditure in India, as documented in the literature:

a) High outpatient expenditure (Johnson & Krishnaswamy, 2012).
b) High cost of medicine and diagnostics and preference for private health care despite the higher cost (Barik & Desai,2014; Barik & Thorat, 2015; Johnson & Krishnaswamy, 2012).
c) Prejudices against public health care for providing inferior services (Sahoo & Madheswaran, 2014).
d) Inequalities among rural & urban areas and socioeconomic differentials (Barik & Thorat, 2015); Dalit and Adivasis (Lampietti & Stalker, 2000).
e) Rural households face a higher probability of catastrophic expenditure(Sahoo & Madheswaran, 2014).
f) Higher regional variation in OOPHE (Wagstaff et al., 2020).
g) Lack of all-inclusive financial protection for health (Johnson & Krishnaswamy, 2012).
h) The households affected due to catastrophic expenditure have reduced access to health insurance(Xu et al., 2003).

2.4.2.1:Health Expenditure And Empirical Evidence:

The following section provides empirical evidence from the literature :

2.4.2.1.1: Health Expenditure And Out-Of-Pocket Expenditure On Health(OOPHE) And Its Impact:

There is growing evidence and available literature suggesting the detrimental effects of OOPHE, especially on poor households (Jalali et al., 2021). The literature around OOPHE and its impact on household economic status has grown tremendously. OOPHE have a striking impact on increasing poverty ratios in the country (Wagstaff & Van Doorslaer, 2003).

Impoverishment effects of health expenditure are decomposed into transient poverty and hidden poverty. Transient poverty arises because households adjust their consumption needs by shifting resources from basic needs towards health care, and hidden poverty arises when households live below the poverty line (Coudouel et al., 2002). To meet the health expenditure, borrowings, savings, and the sale of assets are used; this helps to increase the consumption expenditure of poor households above the threshold. Therefore, these households are not counted as those living below the poverty line as per conventional measures(Flores et al., 2008). Estimates of the poverty impact of health payments can be considered conservative because poor people from rural areas do not have access to health. Due to poverty, cultural barriers, and the price elasticity of demand for health, some households may opt out of health care (Bonu et al., 2007).

In the literature, a threshold of 10 % is commonly used to measure the catastrophic impact of health expenditure with the rationale that above this, the households may be forced to sacrifice other basic needs, sell productive assets, incur debts or become impoverished (Gupta et al., 2020; Ranson, 2002; Russell, 2004; Wagstaff & Van Doorslaer, 2003).

2.4.2.1.2: Health Expenditure Impact On Household Well-Being And Poverty Linkages In Different Countries :

Health expenditure is non-discretionary and does not contribute to the household's well-being like spending on other goods and services(Berman et al., 2010). Health shock made rural households in China vulnerable to financial bankruptcy (He & Zhou, 2022), and members with chronic diseases faced the risk of medical poverty (Ma et al., 2022).

A study of catastrophic health expenditure in 59 countries by Xu et al. (2003) revealed wide variations in the proportion of households facing catastrophic payments from OOPHE and identified three key preconditions for catastrophic payments:

a) Availability of health services requiring payment.

b) Low capacity to pay.

c) Lack of prepayment of health insurance.

Another study on determinants of catastrophic health expenditure in Iran pointed out that the rate of OOPE was nearly the same or greater than the rate of total health expenditure (Abolhallaje et al., 2013). In Myanmar, poor households use the public health sector infrequently compared to the rich(Htet et al., 2015). Rural households in Uganda face catastrophic expenditure, of which few are covered with health insurance (Guets & Behera, 2022). In rural Kenya, although health shocks affect the quantity of food purchased, the households smooth total food consumption with the help of food gifts received by the households from friends and relatives. Social networks help smooth consumption(Mbugua et al., 2020). Microfinance may have a larger role in mitigating health shocks (Isoto et al., 2017).

2.4.2.1.3:Healthcare Systems Limitations And Financing Challenges In India:

The important limitations of the healthcare system and its financing in India are exceptionally high healthcare expenditures, over three-fourths of which are private OOPHE(Flores et al., 2008). The outcomes of these expenses are unsatisfactory; households with low income and health insurance experience growing inefficiencies and low-quality services (Ellis et al., 2000). Millions of households incur catastrophic payments and are pushed below the poverty line yearly(Selvaraj & Karan, 2009). The poverty impact of health payments is greater in the poorer states, especially in rural areas (Garg & Karan, 2009). For the remaining, there is evidence of an increased burden of health care and increased average expenditure incurred per episode of illness (Sanyal, 1996).

Inequitable access to healthcare occurs due to myriad factors but is rooted in low overall healthcare financing by the state(Bahuguna et al., 2019; Mukherjee & Karmakar, 2008). India spends only 5% annual gross domestic product (GDP) on health care. Most of the expenditure (about 80%) is private and OOPHE. Households are the main contributor to financing health care in India; this expenditure is reimbursed for a small proportion of households(Garg & Karan, 2009). As OOPHE poses a heavy financial burden on families, the Government of India is considering a variety of financing and delivery options to universalize healthcare services(Prinja et al. 2012). Only 5% of households in India were covered under any health insurance(Shijith & Sekher, 2013). According to NFHS 3, despite the emergence of several health insurance programs and health schemes, only 5% of households reported that any health insurance covers any member.

Health insurance schemes provide partial protection against catastrophic health expenditure, and households finance more than 72% of health expenditure in India during illness through OOPHE(Devadasan et al., 2007).

2.4.2.1.4: Structural Changes, Morbidity And Mortality Patterns In India:

There are marked structural changes in India's morbidity and mortality age patterns (Yadav & Arokiasamy, 2014). High OOPHE makes health services inaccessible to many Indian households. High private healthcare and OOPHE place a considerable financial burden on households in India (Berman et al., 2010). There are social class-related inequalities in household health expenditure. In India (Kerala), high levels of private healthcare expenditure and OOPHE placed a considerable financial burden on households with lower caste (Mukherjee et al. 2011). High OOPHE resulted in 34% of poor households losing all their savings, 30% borrowing with interest, and 2% selling their assets(Mondal, 2013).

Poverty estimates need to consider OOPHE, and poverty will likely increase if OOPHE adjustments are made as much as 3.6% and 2.9% for rural and urban India, respectively(Gupta, 2009).

Road traffic injuries are increasing public health problems in urban India, where OOPHE on health are among the highest in the world (Dandona et al., 2008). This study outlined the burden of out-of-pocket medical and total expenditures associated with road traffic injuries in India.

The odds of experiencing catastrophic health expenditure and impoverishment among households with non-communicable disease patients were 3.2 and 2.3 times greater than that of other households in rural Vietnam (Minh & Tran, 2012). In India, non-communicable diseases and injuries account for an estimated 62% of the total age-standardised burden of forgone disability(Engelgau et al. 2012).

2.4.2.1.5: Regional Disparities And Inequalities In Health Expenditure:

Studies have also found regional disparities in health expenditure in India across states and subgroups (Ladusingh & Pandey, 2013). Spending on healthcare was comparatively lower among all the backward or isolated states(Dwivedi & Pradhan, 2017). The class-based inequalities in access to health services have worsened for both men and women. Of all inequities, gender inequity in untreated morbidity is worse (Sen & Iyer, 2012).

The interstate variation in treatment-seeking from public providers has declined, and preference for private providers has increased(Gumber et al., 2012; Sanyal, 1996). The gap is widened within interstate, rural-urban and communities. Preliminary results of an analysis of data sets on morbidity and healthcare utilization from two NSS surveys in the 1980s and 1990s, together with empirical results of other studies, point to the worsening of class-based inequalities in access to health services for both men and women (Sen, 2012).

2.4.2.1.6: Supply-Induced Demand And Challenges In Health Care Financing:

An increase in OOPHE in India was also due to demand and supply. Due to supply-induced demand, morbidity and cost per illness episode have inevitably increased in the last decade in India(Jayakrishnan et al., 2016). Public and private financing of clinical services to reduce non-communicable diseases is a major challenge. Inpatient care costs of decedents are much higher than survivors, particularly those residing in rural areas, staying longer in hospitals, utilising private health facilities and suffering from non-communicable diseases in India (Ladusingh & Pandey, 2013).

2.4.2.2: Methodological Limitations And Refinement In The Measurement Of Health Expenditure:

The following section provides various methodological limitations and refinement in the measurement of health expenditures:

2.4.2.2.1: Measurement Challenges In Health Expenditure And Poverty Determination:

The poverty line is the main determining factor in household well-being, but it does not include any health expenditure, essential or otherwise. There are issues with the measurement of health expenditure. The households that spend on acute or chronic illness will change their expenditure patterns. Accordingly, the reference period of 15 days, 30 days, and 365 days will also give differential results. Further, inpatient visits are more expensive than outpatient, and different types of health expenditure may carry different weights in calculating health expenditure(Gupta, 2009).

Households' health spending needs to be adjusted for financial borrowing to meet health spending (Flores et al., 2008). OOPHE is catastrophic if it leads to a reduction in non-health expenditure to a level that is lower than the required level. Cereal consumption deprivation is another measure that is used. This approach considers household preferences to determine the required consumption of necessities(Pal, 2009).

2.4.2.2.2: Thresholds And Uniformity In Health Expenditure Measurements:

Studies have used a threshold level that is arbitrarily set up. The thresholds ranged from 5%, 10%, 15%, 25% and 40%. They also heavily rely on the poverty line when applied in India's case. As such, this method fails to capture whether the health expenditure incurred is complete and takes care of all health needs. The issue is also for all those who cannot receive any treatment. Household compromises their consumption of necessities by reducing the consumption expenditure over a period to mitigate health expenditure incurred by them or to incur the same. However, a common threshold remains a contentious issue for the research community. Uniform thresholds for households with different consumption expenditures may give different results. Economically affluent households may compromise trivial expenditures, and economically marginalised households may sacrifice actual consumption to support their health spending needs (Rusell, 1996). Literature has also suggested using a lower threshold for developing economies and households living below the poverty line since a slight disruption may bring noticeable changes in their budget (Xu et al., 2003).

Studies have used health expenditure as a proportion of total household and non-food expenditure to understand the threshold. The household coping mechanisms are not reflected in these methods; hence, this can lead to a miscalculation of poverty. Some attempts were made to adjust for these coping mechanisms that may temporarily change the consumption of expenditure and health expenditure (Flores et al., 2008; Pal, 2009).

2.4.2.2.3: Multidimensional Approaches To Health Expenditure And Poverty:

The multidimensional poverty method considers other factors that reflect poverty besides the poverty line, such as education, caste, and type of housing, reflecting on non-income factors that drive the household into poverty or out of poverty. This method adjusts the household's financing sources of health expenditure and non-monetary poverty influencers such as education, type of housing and sanitary facilities and caste as a social group(Gupta & Joe, 2013). However, other factors could also influence health expenditure measurements, such as a) an increase in the recall period and b) the number of items on which data is collected (Heijink et al., 2011).

The effect of health expenditure that makes households face poverty only after incurring health expenditure is the impoverishment effect and is calculated based on the assumption that the nature of the health expenditure is not voluntary. If the households did not incur the health expenditure, this amount would be available for the household to spend for other non-health purposes. The non-health expenditure increase is measured as an increase in households' well-being. There is also a situation where households must supplement their income with external sources to meet their health expenditures by borrowing or selling their assets.

2.4.2.2.4: Impoverishment Effect And Adjustment In Health Expenditure:

In calculating impoverishment due to health expenditure, the adjustment of the financial borrowings is important. Hence, borrowings used for sponsoring health expenditure are adjusted from total health expenditure by subtracting the same way insurance reimbursements are adjusted (Berman et al., 2010).

2.4.2.2.5: Recall Period And Its Impact On Health Expenditure Analysis:

One of the important methods of data collection is asking the households direct questions on health expenditure incurred in a fixed duration preceding the survey. The items included vary, from expenditure incurred on inpatient and outpatient as done in NSS and IHDS and on short morbidity and major morbidity (IHDS). The recall period can be 15 days, 30 days (social consumption expenditure round of NSS), 365 days (consumption expenditure round) or 30 days and 365 days (IHDS) and recall period matters. The items that capture the health expenditure and recall period affect the analysis for measuring health expenditure (OOPHE and catastrophic)(Lu et al., 2009).

2.4.2.2.6: Limitations In Consumption Adjustment Methodology:

Another issue with the consumption adjustment methodology is that it does not capture lost earnings resulting from the inability to work due to illness, injury or death. This lost income may be more critical to household well-being. The methodology also assumes that out-of-pocket payments are involuntary; they hinder the household from using these funds for other welfare activities. Unanticipated health shocks drive health payments. Health care expenditure is not regular consumption spending but are non-discretionary payments. Households borrow or use savings to finance healthcare payments and smooth current consumption at the expense of future consumption. Health payment-related impoverishment may not consider these households as impoverished. Similarly, those households who cannot afford to pay due to higher costs will also be not considered (Rashad & Sharaf, 2015).

The studies that are carried out using the NSS consumption round for estimating expenditure on health and its effects on households give lower estimates (fewer questions on health expenditure) than the social consumption rounds(Mohanty et al., 2016).

2.4.3: Natural Disasters As A Covariate Shock:

The following section deals with natural disasters, which is a covariate shock:

2.4.3.1: Impact Of Natural Disasters On Economic Development:

There is growing evidence of the impact of climate-related damages on household well-being across different extreme events (Schmidhuber & Qiao, 2020). Natural disasters have a long-lasting effect on poverty and the overall economic development of those affected (Baez & Santos, 2008).

Natural disasters negatively impact economic growth, especially in developing countries (Klomp & Valckx, 2014). The country's size and population density make natural disasters reduce per capita income in the short term(Cavallo & Noy, 2009). The long-term effects suggest that these disasters reduce economic growth for several years(Botzen et al., 2019; Noy, 2009).

2.4.3.2: Empirical Evidence On Natural Disaster Impact:

There is considerable empirical literature analysing direct and indirect losses arising from natural disasters(Meyer et al., 2013). Direct damage is an immediate impact, like destroying physical assets(Kliesen & Mill, 1994). Indirect damages are deprived production and substandard consumption (Cavallo & Noy, 2009). The distinction is made between direct market loss (damages to those goods whose price can be ascertained in the market) and direct non-market loss (loss of life, destruction of protected sites)(Hallegatte & Przyluski, 2010). Assessment of the impact of a natural disaster involves both direct and indirect effects (Thomas et al., 2010). Direct losses have increased over time, and economic and population growth are two key factors responsible for increased losses. The direct effect on households is felt in reduced income and households being pushed into poverty(Hallegatte & Przyluski, 2010). Indirect effects have more magnitude regarding the dislocation of people experiencing poverty, those politically less connected deprived of relief, the rise of conflicts, women-headed households, and minorities more affected(Israel & Briones, 2013).

2.4.3.3:Long Term Coping Mechanism And Adaptation Strategies:

There is substantial evidence in the literature about coping mechanisms used by households that face natural disasters. Frequent natural disasters negatively affect the household's standard of living. In Vietnam, droughts are mitigated through irrigation(Thomas et al., 2010). Asia Pacific region has witnessed a substantial impact of natural disasters and, in certain cases, even amounting to the loss of lives, and hydrometeorological events have more impact in comparison to other disasters(Cavallo et al., 2010). Drought caused by El Nino contributed to the largest share of poverty(Skoufias, 2003). A study in Indonesia pointed out that the impact of earthquakes (more damaging) leads to income shifts among households from non-poor to poor. Droughts and forest fires also significantly impacted those households dependent on agriculture (Dartanto, 2022). In Vietnam, storms, floods, and droughts negatively affected household well-being. Frequent exposure to disasters also reduces immediate shock due to better household preparedness(Thomas et al., 2010).

Households use insufficient and informal coping strategies to deal with the natural disaster shock. Households often use self-insurance without a formal mechanism(Baez et al., 2013).

Households use self-insurance mechanisms like:

a) Borrowings, running down on assets or compromising children's education(Baez et al., 2013; Sawada & Takasaki, 2017) ,
b) Migration to safer places(Loebach, 2016; Maharjan et al., 2021; McLeman & Hunter, 2010),
c) Seeking jobs in the non-agricultural sector(Baez et al., 2013),
d) Change in occupation(Marotzke et al., 2020),
e) Altered land use patterns, adjusted crop choices, and built protective infrastructure (Brown et al., 2018).

This informal coping mechanism gives temporary relief but is also responsible for decreasing household well-being(Van den Berg, 2010). However, this self-insurance mechanism may not be enough(Arouri et al., 2015). As pointed out in a study in Guyana, the issue with self-insurance is maladaptation. In the absence of proactive infrastructural investment by the govt, household insurance may lead to maladaptation. The reason was the inability of the state to solve a range of societal issues, including environmental, forced households to maladaptation (Mycoo, 2014).

The household witnessing natural disasters shock smoothens consumption, and as a long-term strategy, households look for a permanent source of income(Baez et al., 2013). As a long-term coping mechanism, households that face repeated disasters shift from high risk – high return activity to low risk- low return. The shift is from optimal to sub-optimal outcomes on investment and employment(Baez et al., 2013; McElwee et al., 2017; Rentschler, 2013). Households may often use low-risk investments for low returns in future to reduce exposure to natural disasters(Heltberg et al., 2009). The support system used by the households in the event of natural disasters may also help the households to compensate monetarily for the loss involved. A natural disaster becomes a shock only when a huge monetary loss is involved. All this may lead to an underestimation of the welfare impact of natural disasters on households (Thomas et al., 2010).

Even without government support, households adapt to perceived climatic changes (Heltberg et al., 2009). Households that witnessed floods in Vietnam (Red River Delta) took some low-cost, basic natural disaster prevention actions, and there was also community support in terms of monetary donations and labour support for reconstruction(McElwee et al., 2017).

Households are vulnerable to natural disaster shocks in many ways. The vulnerability could be due to physical exposure to floods. The sensitivity of the households to impacts also makes them vulnerable. Both rich and poor households are vulnerable. Poor people suffer higher relative income damage, and the rich experience absolute damage(McElwee et al., 2017). Poverty increases because of natural disasters since the assets and savings of households are wiped out(Hallegatte & Przyluski, 2010). Households that face repeated weather shocks have the highest negative effect on consumption, which is felt more by poor households with fewer assets (Baez et al., 2013). Households are ill-equipped to deal with shocks. Without any public safety net, households may fight a lengthy battle with poverty. In uncommon situations, this poverty also burdens the next generation(Skoufias, 2003). Households living below or very close to poverty often sell assets to meet basic consumption requirements. Before the household can reach its pre-disaster level of consumption, and if the same household faces another disaster, it gets into the poverty trap (Rentschler, 2013). The impact is also felt on psychological well-being and may eventually affect labour productivity(Yamamura, 2012). Another factor that may affect labour productivity is the postponement of health treatment by people experiencing poverty(Baez et al., 2013; Israel & Briones, 2013).

The effect of natural disasters on the poor is marginal compared to the rich and may not get captured in statistical analysis, but the impact is disproportionately large on the poor (Cohen & Werker, 2008; Kellenberg & Mobarak, 2008). Poor households are affected at two levels: damages to assets and livelihood and the socioeconomic environment (Shameem et al., 2014). Poor households bear the brunt of natural disasters regarding human capital, malnutrition, and education(Rentschler, 2013). Poorer households are worst regarding consumer protection, and cash transfers may act as a rapid mechanism for helping households (Skoufias, 2003).

Credit played a significant role for the households that faced the Tsunami in India, but poor households had no access to credit, and subsidised loans would help(Sawada & Sawada, 2006). Social capital played a significant role during the cyclone in Sundarbans, India (Sanyal & Routray, 2016). Micro credits and transfers help households increase income and reduce consumption fluctuation(Arouri et al., 2015). The community-based coping mechanism may prove less effective if it is a covariate shock(Skoufias, 2003).

2.4.3.4: Models And Methods For Assessing Natural Disaster Impact:

Some models used for assessing the impact of natural disasters are:

a) Social Accounting Matrices(Okuyama, 2007).

b) Neoclassical Growth Theory (Felbermayr & Gröschl, 2013).

c)Endogenous Productivity (Hallegatte & Dumas, 2009).

d)Regional Models(Botzen et al., 2019) .

e) Simulating the effects of Disasters and Catastrophe Models (Pita, 2022).

Some macroeconomic models quantify the indirect economic effects of natural disasters using the following :

a) The Input-Output model (Sieg et al., 2019; Wydra, 2012).
b) Computable General Equilibrium (CEG)model (Kazimi & Mackenzie, 2016).

c) Integrated Assessment Models(IAMs) of climate change impacts(Frame et al., 2020)on economic outcome GDP(Toya & Skidmore, 2007), trade flows(Oh & Reuveny, 2010), death counts (Kahn, 2005), employment(Xiao, 2011), migration (Boustan et al., 2012).
d) Regression of aggregate variables at the economic level(Miranda et al., 2020; Tamuly & Mukhopadhyay, 2022).
e) Measurement of monetary damages (Wirtz et al., 2014).

Past studies have aggregated panel data at the country-year level(Botzen et al., 2019). Damage caused by the earthquake in Haiti was estimated using data on past natural disasters and damage estimates(Cavallo et al., 2010).

Datasets that are widely used in analysing the impact of natural disasters are:

a) EMDAT (estimated monetary damage)(Botzen et al., 2019; Cavallo & Noy, 2009; Felbermayr & Gröschl, 2014).The total number of people affected (those who lost life), which is non-monetary, may be more appropriate for measuring disaster intensity (Panwar & Sen, 2019).

b) Geo-met Data is recorded based on the physical strength of natural disasters (Felbermayr & Gröschl, 2014).

2.4.3.5:Methodological Challenges In Assessing Natural Disasters:

The most common ways of reporting disasters are self-reporting by the households and tracing the geographical characteristics of the natural disaster in terms of its location to match it with households(Edwards et al., 2019; Nguyen & Nguyen, 2020).

Self-reporting holds merit since most of the disasters are geospatially localised. However, it is affected by the household’s economic and health status. Edwards and Gray (2021) used a longitudinal cohort study of children in Filipino and improvised on self-reporting disasters by households. They used neighbourhood disaster exposure and community-level measures.

Furthermore, aggregating weather shocks at the community level may not greatly help (Nguyen & Nguyen, 2020). A study in Bangladesh on households' response to persistent natural disasters used self-reported and non-self-reported data. Self-reporting of natural disasters by households facilitates impact assessment more precisely. However, a mere binary response regarding the impact of natural disasters may not be all-encompassing(Karim, 2018).

Vietnam household living standard survey collected information on natural disaster shock self-reported by households, and the same was used for studying the impact of natural disasters on per capita income and expenditure(Bui et al., 2014). The location of the household may influence the consumption expenditure since the location may have the possibility of natural disaster occurrence. When a natural disaster repeatedly hits households, the families adapt themselves. This adaptation may lead to an endogeneity issue and is dealt with using fixed effects at the district level to yield consistent results. The household surveys conducted recently have a module on natural disasters in the Philippines(Israel & Briones, 2013). Although natural disasters are self-reported(Mottaleb et al., 2013), they are exogenous variables. Natural disasters as a covariate shock have localised effects, and as such, self-reporting may help to capture the impact better(Edwards et al., 2021).

The self-reported or subjective measure of natural disasters also has another methodological issue. For a household to consider an event disaster depends on its exposure to preparedness (ex-ante exposure) and capacity to deal with the aftermath (Ex-post capacity). At the same time, the disaster data poses difficulty regarding space and time limitations regarding its impact. For a study in Vietnam, a repeated cross-section household survey was used with mapped disaster data (Thomas et al., 2010).
Impact evaluation studies use different terminologies and methodologies, giving different outcomes for assessing damages(Hallegatte & Przyluski, 2010). Measurement and assessment of damages from natural disasters must be assessed using welfare-based criteria over asset criteria(Verschuur et al., 2020). Continuous and binary measures of disaster intensity help separate the impact of severe to moderate natural disasters(Panwar & Sen, 2019). Results from studies on natural disasters are ambiguous since some have quoted negative, positive, and no effects in the short and long term about the impact of natural disasters on economic growth(Loyalka et al., 2014).

2.5 Health Financing And Health Insurance :

The following section deals with health financing and the role played by health insurance:

2.5.1: Health Financing Spectrum In India:

Health financing in India has a large spectrum ranging from revenues based on one hand to sourcing through external funds at the other end(Sahoo & Madheswaran, 2014). Global evidence on countries sponsoring health expenditure via risk pooling/ sharing mechanisms, such as social health insurance, has a low share of OOPHE and a higher share if financed from GDP(Wagstaff et al., 2020). The entry of private health insurance companies and user fees in the public health sector were two major structural changes in India during the Eighth five-year plan(Sahoo & Madheswaran, 2014). User fees exposed households from rural areas and workers from the informal sector to the cost of accessing health care in the primary sector (Donfouet & Mahieu, 2012).

India has three types of health insurance schemes: tax-funded (RSBY), mandatory social and government insurance schemes and voluntary private health insurance(Bahuguna et al., 2019). In India, about 85.9 % of rural and 80.9 % of urban areas are not covered by health insurance (NSS, 2017-18).) Further, among those covered, about 12.9 % in rural and 8.9 % in urban areas are covered by government-sponsored health insurance schemes. The average medical expenditure is about Rs 20135, with Rs 31845 in private and Rs 4452 in government health care facilities. Only 8.6% of hospitalised cases involve reimbursement. This reimbursement is highest at 12% for urban areas in private hospitals(NSS, 2017-18).

2.5.2: Strategies For Universal Health Covergae(UHC):

SDG advocate for providing financial cushioning to mitigate the risk of expenditure on health (Hooda, 2020). India has designed systematic strategies for attaining UHC(Lahariya et al., 2016). Two important such strategies were the National Rural Health Mission launched in 2008 (now it is the National Health Mission with the added component of NUHM) for health system strengthening (NRHM mission document, 2005-2012, nhm.gov.in) and Rashtriya Swasth Bima Yojana, 2008 (https://www.india.gov.in/spotlight/rashtriya-swasthya-bima-yojana#rsby1). In a constant pursuit to achieve SDG 2030, Ayushman Bharat was introduced in 2018 under National Health Policy 2017 in line with universal health coverage(https://nha.gov.in/PM-JAY). The schemes launched were the health and wellness centre for strengthening existing health infrastructure and the Pradhan Mantri Jan Arogya Yojana (PM-JAY) for financial protection. The PMJAY (subsumed RSBY) is the largest in the world. (https://pmjay.gov.in/about/pmjay).

RSBY was initially launched for BPL households and extended to NREGA workers(Azam, 2018), beedi workers, and street vendors(Palacios et al., 2011). In 2011, it was expanded to seven more unorganised sectors, including rag pickers, rickshaw pullers, taxi and autorickshaw drivers, miners, sanitation workers and toddy workers(Taneja &

Taneja, 2016). The three state governments, the government of Andhra Pradesh (Rajiv Aroygyahsree and RSBY in 26 districts), Karnataka and (Kalaignar)Tamil Nadu, implemented through private health insurers. Kerala and Karnataka targeted all vulnerable populations(Palacios et al., 2011). Yeshaswini scheme covered outpatient and diagnostic & lab tests at discounted rates when ill and for inpatients (Aggarwal, 2010).

By 2012, states with zero district participation in RSBY were Andhra Pradesh, Goa, Madhya Pradesh, Sikkim, Tamil Nadu, Chhattisgarh, Dadra Nagar Haveli, Daman and Diu, Delhi, Lakshadweep, Puducherry. The states with the highest district participation were Bihar, Chhattisgarh, Gujarat, Haryana, Jharkhand, Karnataka, Maharashtra, Orissa, Punjab, Uttar Pradesh, Uttarakhand, West Bengal, Chandigarh(Nandi et al., 2013). In May 2012, 412 districts and 25 states & UT had already implemented RSBY(Taneja & Taneja, 2016), and 27 million households and 3.1 million hospitalisation cases were covered by February 2012(Johnson & Krishnaswamy, 2012).

2.5.3: Impact Of Health Insurance Schemes:

The regional studies by Fan et al. (2012) in Andhra Pradesh explored the state impact of health insurance provided by the state on OOPHE. The study findings were that those households insured in the first phase led to a significant decline in inpatient expenditure and an increased probability of having no outpatient spending. However, the increase in per capita spending was lesser than the average decline in OOPHE for inpatient spending per person.

One of the studies pointed out that the higher reporting of illness and increase in the health-seeking behaviour of the population may be an unintended consequence of one of India's major publicly funded health insurance programs. RSBY may strengthen private healthcare providers(Selvaraj & Karan, 2009).

The impact of social, voluntary, and government-financed health insurance schemes is different(Hooda, 2020). Government health insurance is target-oriented, and the question often raised in the literature is about the promotion of health care and reduction in the cost of access to health care among the target population, which is, by and large, the poor population (Hooda, 2015). There are also doubts about the effectiveness of social & voluntary health insurance in promoting health care and providing financial protection against health expenditure(Ahuja, 2004; Bhat, 1996; Joumard & Kumar,2015).

India has undertaken different health insurance (typically meant for the better-off and people experiencing poverty) models to facilitate health service access in the country(Mavalankar & Bhat, 2000). International experiences reveal that the insurance-based system may have adverse consequences if governments do not strictly regulate and oversee insurers and health providers(Hooda, 2015). Implementing publicly funded health insurance schemes has proved very expensive, and rising premiums have squeezed fiscal space. Government Spending on primary care is reduced to pay insurance companies focusing on tertiary care(Ghosh & Gupta, 2017).

2.5.4: Empirical Evidence On the Impact Of Health Insurance On Households:

The risk associated with health for households is centripetal towards enormous expenditure. If this expenditure receives a cushion of insurance, it will have a welfare impact on healthcare utilisation at the household level and may further get transposed into improvised consumption patterns of households(Wagstaff & Pradhan, 2005). The literature has questioned household benefits, specifically regarding protection from OOPHE on health payments(Dwivedi & Pradhan, 2020). The empirical evidence has provided divided evidence about health insurance helping households to reduce health expenditure, which crosses a certain level (Wagstaff & Doorslaer, 2003). Health insurance is responsible for increasing household health expenditures as OOPHE(Sahoo & Madheswaran, 2014).

2.5.5: Studies And Analysis Using IHDS Data:

Some studies have used a national sample survey to analyse the impact of RSBY using different rounds (Fan et al., 2012; Johnson & Krishnaswamy, 2012). Studies on publicly funded health insurance programmes (Garg et al., 2019; Ranjan et al., 2018) are done using IHDS. There are studies exclusively on RSBY using IHDs data: a) using IHDS 1(Sahoo & Madheswaran, 2014), b) using IHDS 2(Khan, 2018), c) Using both rounds and an HDPI round 1992-93(Azam, 2018), d) Both rounds were used by(Gebremedhin et al., 2020; Hooda, 2020; Ojha, 2022).

There were studies analysing the linkages between health expenditure and health insurance using IHDS data: a)IHDS 1(Barik & Thorat, 2015), b)IHDS 2(Kulshreshtha & Sharma, n.d.; Panikkassery, 2020), c) Both rounds (Ahmad & Aggarwal, 2017; Bhattacharjee & Mohanty, 2022; George et al., 2021; Goli et al., 2021; Saikia et al., 2016). There are other studies on PFHI(Bhageerathy et al., 2016; Chakravarthi et al., 2017; Mukhopadhyay, 2017; Ramprakash & Lingam, 2021; Unnikrishnan, et al., 2021; Selvaraj & Karan, 2012).

Substantial regional studies are available on: RSBY & GFHI for Odisha(Dwivedi & Pradhan, 2017), Chhattisgarh(Dasgupta et al., 2013; Nandi & Schneider, 2020);

Maharashtra(Ghosh, 2014), Delhi(Das & Leino, 2022), Ahmedabad(Patel et al., 2013); Gujarat, Haryana & Uttar Pradesh(Bahuguna et al., 2019)Karnataka(Rajasekhar et al., 2011) (Agarwal, 2010), Andhra Pradesh(Fan et al., 2012).

2.6: National Rural Health Mission (NRHM) And Health Infrastructure In India:

The following sections provide a literature analysis of NRHM and health infrastructure in India.

2.6.1: Introduction To NRHM:

The decline of public health expenditure from 1.3% of GDP to 0.9 % in 1999, curative health services were biased towards the rich, and health expenditure related to poverty provided a rationale for launching NRHM(Bajpai et al., 2009). NRHM's mission was to provision health care to rural populations with a focus on 18 states and to increase the public health expenditure to 2%-3% of GDP(Berman, 2015). The 18 states chosen to receive funding for key components were Uttar Pradesh, Bihar, Rajasthan, Madhya Pradesh, Orissa, Uttaranchal, Jharkhand, Chhattisgarh, Assam, Sikkim, Arunachal Pradesh, Manipur, Meghalaya, Tripura, Nagaland, Mizoram, Himachal Pradesh, and Jammu & Kashmir. Panchayat and NGOs also had designated roles (NRHM 2005-2012, mission document).

2.6.2: Rural Health Infrastructure:

According to Rural Health statistics (2020-21), India has a three-tier rural health infrastructure. Each tier serves a certain population distinguished based on the geographical location as plain area and non-plain area. Sub-centres serve a population of 5000 in plain areas and 3000 in hilly, tribal, and difficult areas. Sub-centres are the first referrals for patients. They provide health services for patients suffering from communicable and non-communicable diseases, maternal and child health, nutrition, and family welfare. Since 2005, there has been a significant increase in sub-centres to 156101 functional units. Rajasthan, Gujarat, Madhya Pradesh, and Chhattisgarh witnessed remarkable sub-centre growth (Rural Health Statistics, 2020-21)(Government of India, 2020).

Primary health centre (PHC) serves 30000 population in plains and 20000 in hilly areas. PHC provides curative and preventive health care and is maintained by state governments under a minimum-need programme. Jammu & Kashmir, Karnataka, Rajasthan, Gujarat, and Assam witnessed a considerable increase in PHCs, with 25140 functioning PHCs nationally.

Community health centres serve as referral centres for primary health centres. From 2005 to 2021, the number of CHCs increased to 5481. Compared to 2005, the increase in sub-centres was 6.9 %; primary and community health centres increased by 8,2 % and 63.8 %, respectively (Rural Health Statistics, 2020-21) (Government of India, 2020).

2.6.3: Public Vs PrivateHealth Provisioning:

India's extensive public sector health delivery system complements a sizeable private health provision system(Ladusingh & Pandey, 2013). Rural people report a lack of medical facilities. Critical patients are handled only by the public health sector. Better public health provisioning would reduce the loss of several working hours and days (Gumber et al., 2012). Studies have also pointed out that the reasons cited by people for being unsatisfied with the public sector are three-fold: lack of infrastructure, indifference, and rude behaviour of health personnel (Baru et al., 2010).

2.7: Large Data Surveys In India:

In this section, we describe large data surveys available in India. The information compiled is sourced from NSS consumption expenditure and social consumption rounds, the National Family Health Survey, the India Human Development Survey, and the National Health Accounts. The development and progress in the field of any discipline are guided by data availability and data accessibility. For valid findings and implications for policy, one needs not only all country-level unit data (household/Individual) data sets but also substantial sample data. In India, few large available datasets are NSS's Consumption Expenditure Surveys (CES) and Social Consumption (SC) rounds, the National Family Health Survey (NFHS) and the India Human Development Survey (IHDS), which contains specific information on health-related parameters for households and individuals.

2.7.1: Overview Of Major Indian Surveys That Capture Data On Health And Health Expenditure:

NSS is critical in Indian policy, providing poverty and employment status estimates through repeated cross-sections. NFHS survey is a major source of household data (modelled after demographic & health surveys. However, NSS and NFHS have limited focus with repeated cross-sectional design. They are excellent sources of data on poverty and child health. NSS& IHDS are the most important because they provide information on health expenditure and financial protection(Saikia & Kulkarni, 2016).

2.7.2: IHDS, NSS, NFHS: Key Data Sources:

We now describe the key data sources in the given section.

2.7.2.1: INDIA HUMAN DEVELOPMENT SURVEY:

The IHDS data is collected by the University of Maryland USA & National Council for Applied Economic Research (NCEAR) New Delhi. This data is available in the public domain through the Inter-University Consortium for Political and Social Research (ICPSR) at household and individual levels and can be downloaded in STATA, SPSS, and Excel format, making it very researcher-friendly. IHDS 1, 2004-05(Fieldwork: November 04-October 05) consisting of 41554 households (937 variables) and 215754 individuals (211 variables) in 1503 villages and 971 urban neighbourhoods across India. This survey has four features that make it unique among Indian surveys: Breadth of topics, Depth of human development indicators, panel component and rich contextual measures. Only those variables that capture health expenditure are detailed. It comprises household-level information on medical inpatient expenditure (365 days reference period) and medical outpatient expenditure (30 days reference period).

At the individual level, it includes detailed information on short-term morbidity (30 days reference period), major morbidity (365 days reference period), and associated costs. The information was asked to the respondent about his family member’s health status. Short-term morbidity included three illnesses, namely fever, cough, and diarrhoea. Major morbidity included ailments like Cataracts, Tuberculosis, High blood pressure, Heart disease, Diabetes, Leprosy, Cancer, Asthma, Polio, Paralysis, Epilepsy, Mental illness, STD or AIDS and other long-term morbidities. The information related to treatment taken, number of days disabled due to illness and whether hospitalised was sought. Treatment cost is combined for inpatients and outpatients. The question was asked that collected the following inputs: expenditure on doctor, hospital and surgery(combined)(Rs); Expenditure on medicine and test included in fees(dummy); Expenditure on medicine and tests not included in doctor and hospital fees (Rs); expenditure on bus train or lodging related to treatment (Rs). Hospitalisation and doctor's costs are not separated but combined in a single question, and therefore difficult to ascertain the split-up cost separately for hospitalisation.

IHDS 2, 2011-12(released in 2015), a survey carried (out between November 2011-October 2012) is a multi-topic and multi-design survey with coverage of 42512 households (872 variables) and 204568 individuals (502 variables) with 14 different datasets in 384 districts, 1420 villages and 1042 urban neighbourhood. IHDS 1 covered 41554 households in 33 States and Union territories. In IHDS 2, each of these (split household) was re-interviewed with a re-contact rate of 84%. Fifty-two questions about household consumption are designed to estimate total household expenditure (39 items captured for a 30-day frame and 14 items for an annual frame); it gives the calculation of below-poverty-line households using both the Tendulkar committee poverty line and the planning commission poverty line.

Thus, it can be converted into panel data. Panel data can be created at households and individuals, and households can be linked to individuals. The researcher gets a unique opportunity to capture the changes in health expenditure over half a decade. It can be used as cross-sectional data as well. In the case of cross-sectional data, one can merge the households with individuals and, in turn, merge with village-level data.

2.7.2.1.1: Insights From IHDS Data:

IHDS 2 covers the same health expenditure information as IHDS 1 for the individual level. Still, it has information on the type of health insurance (government/ private) for households and health expenditure covered by the insurance such as Medi-claim or RSBY (expenditure covered everything) and if not received but expected to receive for both short-term and major morbidity.

IHDS 1 does not capture any insurance information; however, post-NRHM and RSBY changes can be very well captured in cross-sectional data about health insurance in IHDS 2 for almost all the Indian states. (Except Andhra Pradesh and Tamil Nadu did not implement RSBY till the survey period). This data can be disseminated to the village level; the changes can be tracked and compared with state-level reports. Whereas the changes in health expenditure can be tracked using panel data. The health expenditure at the household level on inpatient and outpatient and the detailed split of health expenditure at the individual level allow the researcher to understand the extent of health expenditure. However, there is no direct question on OOPHE; one can estimate it by adding all the health expenditures and subtracting the amount reimbursed from health insurance. Further, all this can be studied using available background variables such as socioeconomic status, educational status, number of family members, age-sex composition, and ownership of assets.

According to Desai (2007), IHDS data is not suitable for estimating inequality in health indicators but only for testing the association between socioeconomic factors and health indicators (Saikia & Kulkarni, 2016).

2.7.2.1.2: Studies Levraging IHDS Data:

IHDS panel data is used to study gender differences in healthcare expenditure (Saikia & Bora, 2015). OOPHE and catastrophic health expenditure (Kumar, 2010; Ladusingh & Pandey, 2013) RSBY(Azam, 2018)(See Chapter 7 for details).

IHDS is available in the public domain, and the longitudinal data is sparingly used for studies in health expenditure compared to NSS.

2.7.2.2: Understanding NATIONAL SAMPLE SURVEY (NSS):

NSS is cross-sectional data covering the length and breadth of the country. It has a Quinquennial round on consumption expenditure and decadal rounds on social consumption expenditure, including morbidity and health care.

2.7.2.2.1: Historical Evolution Of NSS And Its Morbidity Surveys:

Since the 1950s, there have been 11 occasions on which morbidity issues were dealt with but in an exploratory nature. There were conceptual changes in these experimental rounds concerning the recall period, the use of proxy respondents, and the definition of illness (Dilip, 2005). The first round on morbidity was carried out between October 1953 to March 1954 (7th round). This round was followed by an exploratory round in 1956-58(11th& 13th)). In the 17th round, a pilot survey was carried out. The exploratory survey helped to carry a full-fledged morbidity survey in 1973-1974 (28th round). An India-level survey on social consumption was carried out in the 35th round (July1980-June1981). This covered topics of the public distribution system and health services, including mass communication and family welfare programs (71st NSS document). 1986-1987 was the second survey on social consumption (42nd round), but it was one of the first enquiries. The second one was during post-liberalisation in 1995-96 (the 52nd round), soon after the formulation of the National Health Policy. However, this was a too-early enquiry. Therefore, a survey conducted in 2004 (60th round) became a very important reference point.

2.7.2.2.2: Importance Of NSS Rounds In Capturing Health Expenditure Trends:

Health surveys use self-reporting by taking a 365-day recall period for institutional ailments and a 15-day recall period for non-institutional ailments. These surveys cover detailed information on ailments and the expenditure incurred thereof, using Schedule 25.

The 52nd round of morbidity was a nationwide survey that covered the utilisation of the curative healthcare system, the morbidity profile of the population and the expenditure incurred thereof. Stratified 2-stage sampling was used. It captured information on 19 short-duration ailments consisting of Diarrhoea and Gastroenteritis (including cholera), Tetanus, Diphtheria, Whooping cough, Meningitis and Viral encephalitis, Fevers of short duration, Chickenpox, Measles, Mumps, Diseases of the eye, Acute disease of the ear, Heart failure, Cerebral stroke, Cough and acute bronchitis; Acute respiratory infection (including pneumonia), Diseases of the mouth, Teeth & gum, Injury due to accident and violence, Other diagnosed ailment(up to 30 days); Undiagnosed ailment(up to 30 days).

Thirty-eight long-duration ailments include Chronic amebiasis, Pulmonary tuberculosis, STD, Leprosy, Jaundice, Guinea worm, Filarial(elephantiasis); Cancer, Other tumours, Anaemia, Goitre & Thyroid disorders, Diabetes, Beriberi Rickets; Other Malnutrition diseases; Mental & Behavioural diseases, Epilepsy, Other diseases of nerves, Cataract, Other Visual disabilities, Other diseases of the eye, Hearing disabilities, Other diseases of the ear, diseases of the heart, High/low blood pressure, Piles, Speech disability, Diseases of the mouth, teeth & gum, Gastritis hyperacidity/ gastric/peptic/duodenal Ulcer, Diseases of the kidney/urinary system, Prostrate disorders, Hydrocele, Pain in joints, Other disorders of bones & joints, locomotor disability, Other congenital deformities(excluding disability), Other diagnosed ailment(up to 30 days), Undiagnosed ailment(more than 30 days).

It consisted of 71284 rural and 49658 urban households. It was carried out in 4 sub rounds comprising three months from July 1995 to June 1996.

It contained four main topics: Utilisation of maternity & child health care services, morbidity & utilisation of medical services, the problem of aged persons, and participation in education.

A set of probing questions was put to all the individuals of the sample household to find out about the illness they suffered and the medical treatment taken during the reference period. All the adult male members were interviewed, and for female members, it was a proxy in some cases. However, a large part of the data was obtained from proxy respondents.

The data on medical expenditure was sought for every spell of ailment for hospitalised and non-hospitalised cases separately. For hospitalised cases, data was sought on every event of hospitalisation, including the deceased person, for 365 days. For non-hospitalised, it was 15-day recall period for every ailment suffered, whether hospitalised or not. The following information on health and morbidity was collected: Insurance premium (life, medical and accident); hospitalisation during last year; the ailment last 15 days, duration of stay in the hospital; medical services received; source of treatment if treatment availed before hospitalisation, duration of treatment and whether treatment continued after discharge. Further, it collected information on expenses incurred for treatment, including hospital charges paid, the total medical expenditure amount, and particulars of other expenses incurred (transport, lodging, charges of escorts. Attending charges, personal medical appliance). Sources of finance for medical expenditure included current income, past savings, sale of animals, ornaments, other physical assets, borrowing and other sources, and reimbursement by employers.

2.7.2.2.3: Comparing Different Rounds Of NSS: Methodological Changes And Insights:

Sixtieth round (2004) included the curative aspect of the health care system in India & utilisation of health care services provided by the public and private sectors together with expenditure incurred by the household for availing these services. It included topics on morbidity & utilisation of health care services, including immunisation and maternity care, the problem of aged persons, and the expenditure of households for availing health care services. It covered 47302 rural and 26566 urban households.

The data on health expenditure was collected separately as the cost of non-hospitalised and hospitalised treatment. For medical treatment, the information was collected separately for each case of hospitalisation for institutional treatment. For non-institutional, treatment was considered consolidated for the ailing person despite several ailments and spells. Other expenses were recorded separately. Medical expenses included expenditure on items like medicines, bandages, and plaster, fees paid for medical and para-medical services, charges for diagnostic tests, charges for operations and therapies, charges for an ambulance, and the cost of oxygen and blood. It also included doctor's fees, bed charges, medicines and other materials and services supplied by the hospital, and charges for diagnostics tests done at the hospital for all hospitalised treatment. The other expense constituted all expenses relating to treating an ailment, such as transport, lodging, attendant charges, and personal medical appliances purchased. The total expenditure estimate is calculated as medical and other expenditures.

The ailments included:

a) Gastrointestinal (Code 1 to 5), b)Cardio-vascular diseases (Code 6 to 07), c) Respiratory including ear, d) Nose and throat ailments(Code 08), e) Tuberculosis(Code 09), f) Bronchial asthma(Code 10), g) Disorders of joints and bones(Code 11), h) Diseases of kidney/ urinary system(Code 12), i) Prostatic disorders(Code 13), j) Gynaecological disorder(Code 14), k) Neurological disorder(Code 15), l)Psychiatric disorder(Code 16), m) Eye ailments(Code 17 to 19), n)Diseases of the skin(Code 20), o) Goitre(Code 21), p) Diabetes Mellitus(Code 22),q) Under Nutrition(Code 23), r)Anaemia(Code 24), s) STD(Code 25), t) Febrile illness(Code 26 to 33), u) Disability(Code 34 to 37), v) Diseases of the mouth, teeth/gum (Code 38), w) Accidents/injuries/burns/fractures/poisoning(Code 39), x)Cancer and other tumours(Code 40), y)Other diagnosed ailments(Code 41),z)Other diagnosed ailments(Code 99)(NSS), 2004).

The 71st round (2014) aimed to collect basic quantitative information on the health sector. The special focus was on hospitalisation, including treatment for inpatient ailments, utilisation of public health care, health expenditure in public and private health sectors, and break up of inpatient and outpatient and OOPHE. It used multistage stratified sampling consisting of 36840 rural and 29452 urban households.

It sought information on:

a) The morbidity prevalence rate among various age-sex groups in different country regions.

b) The measurement of the extent of use of health services provided by the government.

c) Hospitalisation or medical care received as an inpatient of the medical institution; ailment for which such medical care was sought.

d) The extent of use of govt hospitals and expenditure incurred on treatment received from the public and private sector.

e) Break up of expenditure by various heads to be estimated for expenses on medical care received as inpatient and otherwise.

There are important changes in coverage and differences in concepts and definitions of important parameters in this round. Therefore, the results of this round are not comparable with the previous round. In the earlier surveys, a disabled person (pre-existing disability) was treated as an ailing person against the present round, where pre-existing disability is considered a chronic ailment. Disabilities acquired during the reference period were treated as an ailment. Further, in the earlier round, only medical treatment on medical advice was treated as treatment. Self-medication (on the advice of a chemist) is not considered medical treatment. The medication taken for such an ailment was treated as an untreated ailment. Health expenditure was dealt with using the paid approach.

The main ailments(reported diagnosis / main symptoms) covered: a) Infection(Code 1 to 12), b)Cancers(Code 13), c) Blood diseases(Code 14-15), d) Endocrine, metabolic, nutritional(Code 16 to19), e) Psychiatric & neurological(Code 20 to 26), f)Eye(Code 27 to 31), g) Ear(Code 32 to 33), h) Cardio-vascular(Code 34 to 35), i) Respiratory(Code 36 to 38, j) Gastro-intestinal(Code 39 to 42), k) Skin(Code 43), l)Musculo- skeletal(Code 44), m)Genito-urinary(Code 46 to 48), n) Obstetric(Code 49 to 51, o) Injuries(Code 52 to 88).

The thirtieth round was the third quinquennial conducted from January to December 1983. It collected information on household consumption expenditure, which was the total monetary value of all the items (goods & services) consumed by the household for domestic purposes during the reference period. This survey consisted of 12 blocks. This survey had no questions on medical expenditure.

The 43rd round, the 4th Quinquennial round, collected information on domestic consumption for the last month before the survey. Compared to the 38th round, changes in the sample were made to incorporate more households from the upper-income bracket. No information was collected on health expenditure.

The 50th round was conducted from July 1993 to June 1994. It consisted of 18 items of medical and educational expenditure. This survey had 14 blocks. Block 8 sought information on medical goods and services, 8.1 was on expenditures incurred in the last 30 & 365 days, and block 11 sought information on insurance details.

Schedule 1: Quinquennial survey: schedule 1 for consumption expenditure collects information on consumption expenditure for those goods with monthly consumption and yearly consumption of nine durable goods, clothing and footwear is collected using the same schedule.

Health expenditure is recorded as both institutional and non-institutional expenditure. Health expenditures on institutional expenditure are captured in five items, including the purchase of drugs and medicines and the expenditure incurred on clinical tests such as X-rays, ECG, and pathological tests. Fees to doctors and surgeons, payments made to hospitals and nursing homes for medical treatment, and 'other health expenditures' not recorded above. For non-institutional, it is nine items captured as allopathic medicines, homoeopathic medicines, ayurvedic medicines, Unani medicines, other medicines, X-ray, ECG, pathological tests, fees to doctors or surgeons, family planning appliances including IUD (intra-uterine device), oral pills, condoms, diaphragm, spermicide, and other fees (Fan et al., 2012).

2.7.2.3: Methodological Consideration In Large Scale Surveys: Choice Between Consumption Expenditure Survey (CES) And Social Consumption (SC) Rounds For Analysing Health Expenditure:

In social consumption rounds, medical expenditure is calculated from those respondents who report ailment based on self-perceived illness & for only those who report ailment. CES records the same based on the recall period and as a part of household expenditure. Although the recall period for institutional treatment is 365 days, for non-institutional treatment in CES rounds, the recall period is 30 days, and in SC rounds, it is 15 days. A longer recall period captures larger aspects of non-institutional treatment and, hence, more health expenditure. In social consumption surveys, households will get accounted for incurring medical expenditure only when they report ailment (25% of households report in morbidity surveys). Therefore, there is a tendency to report higher OOPHE on health out of the total household expenditure.

The recall period of non-institutional expenses of 15 days tends to underreport medical expenditures. In CES surveys, 70% of households report medical expenditures. One must consider the large difference between reported medical expenditure in CES and SC. The question on health expenditure in both surveys also adds to the difference. Expenditure on self-medication is not included. There are differences in recall period for expenditure and ailment. In accounting for household expenditure, there is a mixed recall period. For institutional expenditure on health, the recall period is common for both types of surveys, but for non-institutional expenditure, the CES survey has a recall period of 30 days as against the 15-day recall period for the SC. Morbidity surveys do not record drug expenditure separately concerning the institutional expenditure. Hospitalisation reflected a large chunk of medical expenditure. In CES data, drug expenditures can be separated into institutional and non-institutional expenditures. Drug expenditure is reported to be the highest among medical expenditures. Another issue in CES is that the proportion of OOPHE payments spent on drugs for non-institutional may be slightly higher in rural areas since many doctors club their consultation fees and medicines (Garg & Karan, 2009).

2.7.2.3.1: Methodological Issues And Challenges With Large-Scale Surveys On Health Expenditure And Morbidities:

A study was done using two different rounds of NSS: a social consumption (SC)round (60^{th} round) and a Consumption expenditure survey (CES) round(61^{st}) to check the variation in health expenditure data. The social consumption round has detailed health expenditure and brief consumer expenditure. However, the CES round has detailed consumer expenditure but brief health expenditure. The recall period for a non-institutional ailment is 30 days in CES rounds and 15 days in SC rounds. The poverty line is used to estimate the poverty-related impact of health expenditure. In a morbidity survey, detailed item-wise consumption expenditure is not collected and therefore, reported monthly per capita expenditure needs to be used with an updated poverty line. Poverty estimates and health expenditures must come from the same survey. Poverty calculations are based on monthly rupees per capita, and one must take only health expenditures closer to the average monthly expenditure (Gupta, 2009).

Further, since part of the sample will report ailments, an average expenditure of the ailing persons (reported) will upscale, and this cannot be used as a norm for the rest of the population. If one tries to use the entire population (respondents reporting ailment + not reporting ailment) to arrive at average health expenditure will lead to underestimation. The ideal approach would be to consider total health expenditure reported only over 365 days.

Planning commission figures are based on the uniform recall period, and health expenditure is based on a mixed recall period(Gupta, 2009). Cross-sectional data is inadequate for measuring the long-term effect of household impoverishment on health spending(Berman et al., 2010). The comparability of health expenditure with the poverty line needs to be validated.

2.7.2.3.2: Implications Of Data Biases And Limitations In NSS Surveys:

Health survey uses a direct interview approach, and questions are non-sensitive. Reporting health and morbidity information varies across the surveys due to the respondent's psychological mindset, which in turn depends on notions& beliefs about one's health. It also depends on the financial protection available at the time of illness and the crispiness of the questionnaire. The unavoidable biases in NSS surveys in India are due to the level of literacy and health awareness of the household chosen as the sample and the respondent from whom the information is sought (Self /proxy) (Dilip, 2005).

Impact assessment of health insurance is sensitive to the methodology and data used for analysis. The issue with NSS data is that the information collected is on household expenditure on health. Although it is recorded as medical and non-medical, this expenditure is not bifurcated as OOPHE and reimbursement from health insurance companies, and such bifurcation is important for impact assessment. Further, there is no record of cashless reimbursement. The reported expenditure in CES rounds comprises out-of-pocket spending and payments received by households from insurance companies and other sources. Therefore, the CES round of 2009-10 was invalid for making an impact assessment of the health insurance scheme (Vellakkal & Ebrahim, 2013).

To achieve universal health coverage in line with SDG goal 3.8, one of the important requirements is the availability of data and the quality of the available data. One of the requirements is that the national data needs to be consistent with international data; communication of updated health information on national websites and a high level of leadership and coordination are important to avoid overlap (Garg, 2014).

The data collected is based on respondents' self-assessment of their medical status rather than on medical examination (self-perceived morbidity) (NSS). The information was sought from all adults/women/ mothers of children in the household. However, data was also collected from proxy respondents, which often leads to understating the illness of the respondents for whom the proxy is given.

2.7.2.4: NATIONAL HEALTH ACCOUNTS (NHA), 2004-05: Overview:

NHA is a comprehensive and consolidated statistic about various aspects of health expenditure. One of the important subtopics handled by NHA is OOPHE by households. The latest one is NHA 2018-19(https://nhsrcindia.org/national-health-accounts-records).

2.7.2.5: NATIONAL FAMILY AND HEALTH SURVEY (NFHS):

NFHS, under the flagship of the Ministry of Health and Family Welfare, is a national-level cross-sectional survey carried out in five rounds now. It is very comprehensive in terms of information collected on health and morbidity. NFHS 3, NFHS 4 and NFHS 5 have one question on the household status concerning health schemes or insurance and the type. The replies sought to include options of Employee State Insurance Scheme, Central government health scheme, community health insurance, other health insurance through an employer, medical reimbursement from an employer, or another privately purchased reimbursement from health insurance.

2.7.3: Comparison Between NSS And IHDS:

The following sections deal with a meaningful comparison between the two large data sets available in India on health and health expenditure:

2.7.3.1: Contrast Between NSS And IHDS Data Structures And Health Expenditure Details:

The basic difference between the two large datasets of NSS and IHDS is that NSS data can also be longitudinal data, but the panel will consist of states and variables, unlike IHDS, where a panel will consist of households and individuals. In NSS, the latest round, the 71st, is not comparable to the previous 52nd and 61st. Whereas IHDS, both rounds are comparable, and even a round (HDPI)before IHDS I of NCEAR 1992 is comparable. In NSS, all health expenditures are distinguished based on hospitalised and non-hospitalised treatment with a recall period of 15 days and 365 days. In IHDS, the health expenditure is distinguished based on short and major morbidity, with a recall period of 30 days and 365 days, respectively. However, the surveys do not give the extent of OOPHE, which needs to be estimated from the given data.

2.7.3.2: Analysing The Distinctions And Overlaps Between NSS And IHDS:

NSS does not record the cost of medicine, whereas IHDS questions whether doctor fees include the cost of medicine and, if not, specify the amount. In CES proportion of pocket payments spent on drugs for non-institutional care may be slightly overestimated cause, in rural areas, the doctor fees are inclusive of medicine as well (Garg & Karan, 2009). Given the current scenario, these two data sets serve most of the needs of the researchers around health expenditure. It is evident from literature studies that health expenditure needs further exploration and probing.

2.7.3.3: Current Status And Utilisation Of Available Large Datasets For Health Expenditure Studies In India:

The IHDS data, which is longitudinal, is sparingly used for health expenditure. In India, the major research gap is that the available data on health expenditure is not fully exploited to explore various facets of health expenditure.

2.8: Conclusion:

Households experience shocks that affect the consumption expenditure of the households. The consumption expenditure is the proxy for household well-being. Shocks related to health, such as morbidity, disability and health expenditure, are peculiar to households. Some shocks like natural disasters affect the households and the entire community/village. The household uses strategies to mitigate these shocks. Some strategies are sustainable, and some are not. The reforms in the health sector were mainly responsible for introducing user fees, and in the absence of any financial protection, the households incured OOPHE.

The SDG insisted on providing UHC to people so that there are no financial hardships in accessing health care. In India, publicly funded health insurance, Rashtriya Swasth Bima Yojana (now PMAJAY), is widely used to provide financial protection to specific categories of people likely to experience catastrophic health expenditure and impoverishment effects. This policy intervention is from the demand side. From the supply side, the NRHM policy (Now NHM, Ayushman Bharat) was launched to build the health infrastructure. Policy analysis of these two policies is crucial to deciding the future course of action. The existing literature review has provided mixed responses about the benefits of health insurance, mostly publicly funded to households, in terms of reducing health expenditure and utilising government health facilities.

The studies on disability as a shock require socioeconomic analysis of households on different types of consumption expenditure. Disabilities vary by duration and morbidities.
Although numerous studies on health expenditure in India use NSS data, very few studies have explored IHDS data. For that matter, longitudinal data that uses information about consumption and health expenditure sourced from the same households may provide different findings over cross-sectional data. It's also important to study the demand and supply issues of the health sector sourced from the same data.

The existing studies have sparingly used self-reported data collected from households to study the impact of natural disasters. Although household-level information about monetary damages is not available in the public domain, using household consumption expenditure and other measures of consumption expenditure may give an idea about the loss in household well-being for those affected by the disasters. No known studies have examined different types of natural disasters in India. Using longitudinal data to examine the loss in household welfare may further add to the existing research gap.

No known studies have combined ESIS, CGHI and RSBY data to study the impact evaluation of health insurance on households. Few studies provide the impact of private health insurance on household consumption and adjusted consumption expenditure using longitudinal data and differences in differences.
From the supply side, its ill-equipped tertiary sector, skewed distribution of PHC and lack of medical facilities force people to seek health care from the private sector despite OOPHE. For evaluation of NRHM, the data from which household consumption expenditure is sourced may give deeper insights into the utilisation of public health infrastructure and changes in household well-being, if any.

From a research point of view, it is important to understand the linkages between health expenditure and the economic status of households. The data in question should cover various aspects of health expenditure. The various aspects of health expenditure would be household and individual level health expenditure, monthly & annual health expenditure, inpatient and outpatient expenditure, short and long-term morbidity expenditure, indirect costs related to health such as health-related travel and food and lodging expenditure, loss in income due to illness, health insurance and types, ailments covered and reimbursed.

Also, the nature of the data is important. For household expenditure analysis, panel data is very useful compared to cross-sectional or pooled data. Data coverage in terms of geographical area and variables covered is also important.

In the next chapter 3, the methodology is discussed. It comprises data merging, the construction of variables for the analysis, the definition of important concepts and the methodology used for the analysis in the thesis.

CHAPTER 3:

MATERIALS AND METHODS

The theoretical and empirical background of the topic, ‘Economic development and health in India,’ is discussed in Chapter 2. The third chapter, ‘Methodology’, deals with materials and methods. This chapter is divided into 5 main sections with several subsections. Section 3.1 is the introduction, describing the database; sections 3. 2 and 3.3 describe the variables used. Section3. 4 gives details of the various methodologies used. The last section concludes the chapter.

3.1: Introduction:

In this section, we describe the data used and the process used for data extraction.

3.1.1: Description Of The Database:

We use a nationally representative dataset from the India Human Development Survey from two rounds: IHDS 1, 2004-5(IHDS 1 from here onwards) and IHDS 2011-12(IHDS 2 from here onwards). It is a multi-topic survey produced by the National Council of Applied Economic Research (NCAER), New Delhi, and the University of Maryland for India. IHDS 1 covered 41,554 households in 1,503 villages and 971 urban neighbourhoods. 27,010 rural and 13,216 urban households are covered in 382 districts (from 612 districts in 2001). This data covers India's states and union territories (except Andaman/Nicobar and Lakshadweep). IHDS 2 covered 42,152 households across 1,503 villages and 971 urban neighbourhoods in India. The households(individuals) from IHDS 1 were re-interviewed in IHDS 2 with an 86% recontact rate.

The IHDS data is available in the public domain for two rounds (or waves). The raw data for IHDS 1 is available in eight schedules: individual, household, medical, non-resident, primary school, birth history, village, and crops. It's available as a documentation file, code book, and questionnaire. For each schedule, there is a code book. There are five questionnaires: Income and social capital questionnaire, education and health questionnaire, learning tests, medical facility questionnaire, and school questionnaire. The individual schedule has collected data on 211 variables and 215,754 observations; the household schedule has collected data on 937 variables and 41554 observations. Village data has 378 variables and 1501 observations. We have used household data, individual data, and village data.

The data for IHDS 2 is available in fourteen schedules: individual, household, eligible women, birth history, medical staff, medical facilities, non-resident, school staff, school facilities, wage and salary, tracking, village, village panchayat, and village respondent. The household schedule has 42152 observations and 872 variables; the individual schedule has 204568 observations and 502 variables. We have used individual, household and village data.

The unique property of this dataset is that it allows for merging the data: a) with different schedules of the same round and b) with the same schedule in two separate rounds. Multiple combinations of longitudinal data can be formed.

Next comes the panel or longitudinal data formation at household and individual levels. IHDS has uniquely reinterviewed the same households in both rounds (86% recontact rate). It further merges and links files to household and individual data. Therefore, this data can be combined in multiple ways. After merging the different schedules, we get multiple combinations of panel data. These combinations are as follows: Firstly, 1) Household data from IHDS 1 can be merged with household data from IHDS 2; 2) Individual data from IHDS 1 can be merged with IHDS 2; 3) Village data from IHDS 1 can be merged with IHDS 2(village identifiers are anonymous). The second way this data can be linked is that the Household Individual-matched data from IHDS 1 can relate to Household Individual-matched data from IHDS 2. Lastly, Household Individual Village data from IHDS 1 can be merged with Household Individual Village data from IHDS 2. The merging of Household, Individual and Village-level data from IHDS 1 and IHDS 2 or Household Individual data from IHDS 1 and IHDS 2 gives the master panel data set. We have used 1) a Household-Individual panel, 2) a Household-Village panel, and 3) a Household-Individual-Village panel.

3.1.2: Description Of Data Extraction And Arrangement:

The first task was downloading the data after registering on the IHDS website. After downloading the data in *STATA* format, we began examining the data for data cleaning. Two processes were involved for data cleaning and editing. After going through the Frequently Asked Question (FAQ) provided on the official IHDS website (https://ihds.umd.edu/faq), the data was treated for missing values/entries. The missing values were given as '**.**' in the original dataset. The missing values were replaced with '0'. Missing values create problems when new variables are created in *STATA*. The observations with missing values were not deleted because it would lead to losing some important observations.

The following steps were taken before processing the data:

1. Checking for missing observations.: this is a three-step procedure. In the first step summary(STATA *command: sum/tab*), statistics of the variable of interest were performed. The second step was to replace the missing values. The missing values can be found in *STATA* by browsing the variables or counting the missing observations(STATA *command: be varname or count varname*=.). Once the missing observations are treated, it is important to summarise another time to match the results with pre and post-treatment. This step is helpful since it avoids any carry-over mistakes in data analysis later.

2. Next, the variables of interest were summarised and cross-checked with the code book provided by the survey. We found that coding was erroneous for caste, income, and toilets. The same was rectified before proceeding with merging.

3. The variables in the data set were numeric and string, indicating the type of storage used in *STATA*. To process them further in regression, we converted the string to numeric (STATA Command: *detsringvarname force replace*) (https://www.stata.com/ manuals/ddatatypes.pdf).

4. Renaming the variable of interest was the third step before merging the data. A step to ensure data is not lost when household data is merged with individual data*(STATA Command: rename, old-varname,new-var name)*. When the variable of interest for both rounds has similar names, some variables may go missing. We added the suffix of year to distinguish them, one of the data requirements for converting a wide panel into a long panel.

5. Creation of the new variables: some new variables were created based on the requirement(STATA *command: gen varname; egenvarname)*. After the formation of the new variable, the variable label must be changed*(STATA: command: label*)

Each schedule was provided with a data file *(STATA)*, code book, questionnaire, and supplemental syntax for both rounds. We downloaded the STATA files(data, link and supplemental syntax). These allowed observations in IHDS 2 to match those in IHDS 1.

IHDS also provides a user manual for merging the data (https://ihds.umd.edu/merging-guide). Recently, the website has provided a ready panel for downloading with a limited number of variables (https://ihds.umd.edu/data).

3.1.3:Description Of Households:

The household data is provided in Schedule 2 in both rounds. There are 41,544 households in IHDS 1 and 42,152 households in IHDS 2. The linking file gives IHDS 1 identification codes for all the households from IHDS 2 that were reinterviewed.

All the variables were named with the suffix 2005 and 2012 for rounds 1 and 2 of households, respectively, before the file merger. This step facilitated the identification of households based on rounds after merging. Care was taken not to rename the variables used as identifiers based on which merging was done. These variables are the identifiers of rounds 1 and 2, like *STATEID, DISTID, PSUID, HHID and HHSPLITID*. These are unique identifiers. These were retained with the original name(without adding any prefixes or suffixes).

3.1.4: Merging Households From Rounds 1and 2:

The first step was to run supplemental syntax given by IHDS as a 'do file' independently for both rounds. The linking file matched the households from IHDS 1 with IHDS 2. This merger gave 42,152 matching household observations.

The second step was to merge the data of household IHDS 2 with IHDS 1 household data. After merging, the number of matching households in both rounds was 40,018 and formed the panel for household analysis combining IHDS1 and IHDS 2.

3.1.5: Merging Individuals From Rounds 1 And 2:

The individual data from IHDS 1 and IHDS 2 were also merged using the ready manual provided by the IHDS. In the IHDS 1 215, 754 individuals were interviewed; in the IHDS 2, 205,468 individuals were interviewed. There is a supplemental syntax to be used for both rounds. The linking file matched the individuals from IHDS 1 with IHDS 2. The same steps for household mergers were used for individual schedules, forming the panel of 150988 observations of individuals in IHDS 1 and IHDS 2.

3.1.6: Merging The Panel Of Households With The Panel Of Individuals:

As a next step, we merged the household and individual panels. '*IDHH'* (a nine-digit identifier) is used for this merging, which exists in both IHDS 1 and IHDS 2. This merger gives 190,047 observations combined with household and individual panels.

3.1.7: Merging Of Individual Household Panels With Villages:

IHDS provides village-level information in Schedule 7 of IHDS 1 and Schedule 12 of IHDS 2. In the next step, village data from IHDS 1 is merged with village data from IHDS 2 to create a village panel. Both these rounds have supplemental syntax to be run independently. The matched number of villages is 1407.

The individual household panel is merged with the village panel. This master file aggregates 179,048 observations. The data is further processed to ensure that only those individuals in the same households in IHDS1 and IHDS 2 are retained. This data processing retains 101,900 observations. When we did the village-level analysis, all urban observations were also dropped, leaving 99,028 observations in the final panel of individuals(households) residing in villages.

3.1.8:Converting Wide Panel To Long Panel:

Once the data is merged to form a panel data set (longitudinal data), it could be used in two formats—wide and long. To convert the panel from wide to long, the *STATA* command '*reshape*' is used(https://stats.oarc.ucla.edu/stata/modules/reshaping-data-wide-to-long/)

3.1.8.1: Advantages Of Panel Data:

Panel data has several advantages compared to cross-sectional data.

1. When the same individuals are observed during a given period, the variables that cannot be observed or measured, panel data provides control of those variables.

2. Variables change over time, but the observations on whom they produce the effect remain the same. The effect of change in these variables on those observations can be studied (Torres-Reyna, 2007, http://www.princeton.edu/~otorres/).

Once the panel is transformed from wide to long, before any model is run, it is important to prepare it for manoeuvring. When wide data is converted to long data, two identifiers are crucial: the panel and time identifiers. The panel identifier identifies the observations to be converted (matched) and the time identifier identifies the year for which this data will be matched. It is executed in *STATA* using *xtset* (*xtsetpanlvartimevar).* A strongly balanced panel is one where all observations have data for all years. If any observations are missing for any year, the panel is unbalanced. Ideally, a balanced panel is required.

3.2: Description Of Constructed Variables:

We constructed variables from households and individual and village schedules. This section provides details of all such constructed variables and the variables used from the survey with minor or no modifications.

3.2.1: Disability By Duration And Morbidity-Specific Disability:

Disability is an idiosyncratic shock, as discussed in Chapter 2. This shock affects the household's well-being through changes in consumption expenditure. These changes occur for two reasons: firstly, the onset of illness leads to higher health expenditure. If this expenditure is financially unprotected, it compromises other important expenditures. It could also compromise on treatment by delaying or skipping it altogether. In this regard, we examine the household's consumption expenditure changes. Disability-related shocks were measured using the individuals' self-reported days of inability to work. We measured the Activity of Daily Living Intensity (ADLI).

Types of disability:

1. Morbidity-specific disability: The IHDS data provides short and major morbidity data by type of morbidity.
2. Disability by duration: data on the number of days disabled is collected from those individuals who were unable to work due to illness.
3. Disability due to ADL: data on six parameters of activity of daily living is collected from the individuals who were finding it difficult to perform the given activity.

IHDS provides data on days disabled due to short morbidity (30 days) and major morbidity (365 days). We reconstructed these variables by grouping them based on the duration of the disability. The days disabled were grouped based on the duration of the illness to capture changes caused by the illness (Table 4).

The specific question asked during the IHDS survey for short morbidity was, "How long has (respondent Name) been unable to do usual activities (including work, school, and domestic work) in the last 30 days?" For major morbidity, the specific question asked was, "In the last 12 months, how many days he/she has not been able to do normal/ usual activities?". We created two new categorical variables to record all those individuals who were never disabled due to illness from short and major morbidity, respectively. Those who could not do daily activities for 30/365 days were regrouped as days disabled due to short and major morbidity, respectively. Accordingly, dummy variables were constructed separately for short and major morbidity disability by duration. Those disabled were grouped with value = 1, and those not disabled with value =0.

For constructing morbidity-specific disability, information from individual rounds about different short and major morbidities reported was used. The variable that captured disability by duration in the data was given for 30 days and 365 days. Accordingly, short morbidity and major morbidity disability by duration were grouped into five mutually exclusive groups comparable across both rounds of IHDS. For short morbidity, the duration-specific disability was grouped into five groups (Table 4).

a)Never disabled.

b)Disabled for one week.

c) Disabled for two weeks.

d) Disabled for three weeks.

e) Disabled for four weeks.

For major morbidity, the groups created were (Table 4):

a)Never disabled

b)Disabled for three months.

c)Disabled for six months.

d) Disabled for nine months.

e)Disabled for twelve months.

IHDS 1 and 2 also provide data on the types of short morbidity and specific diseases classified as major morbidity. The short morbidity included cough, fever, and diarrhoea in IHDS 1 and IHDS 2. IHDS 1 has defined 14 types of diseases, and IHDS 2 has defined 15 diseases as major morbidities. IHDS 1 lists 14 major morbidities: Cataracts, Tuberculosis, High blood pressure, Heart disease, Diabetes, Leprosy, Cancer, Asthma, Polio, Paralysis, Epilepsy, Mental illness, STD, AIDS, and Other long-term diseases. IHDS 2, in addition to 14 ailments, included information on Accidents. Many individuals indicated that they did not contract any disease/disability. The data collected on ailments was originally coded into three categories (No=0, Cured=1, Yes=2). We re-coded this in a new variable with two categories: currently ill (Yes =1) to cover those who were cured and those who were ill from the original variable and (No =0) for all ailments. These binary responses were mapped against short and major morbidity to examine the morbidity-specific disability.

The information on days disabled and disability due to disease-specific morbidity was used from the individual round.

TABLE 4: Category Of Disabilities Based On Duration

Group	Category	Number of days disabled
	Major morbidity	
1	Individuals were never disabled due to illness.	0 days disabled
2	Individuals were disabled for 3 months or less.	More than 0 days and less than 91 days
3	Individuals were disabled for 3 to 6 months.	More than 90 days and less than 181 days
4	Individuals were disabled for 6 to 9 months.	More than 180 days and less than 271 days
5	Individuals were disabled for nine to 12 months.	More than 271 days
	Short morbidity	
1	Individuals are never disabled due to illness.	Disabled for 0 days
2	Individuals were disabled for 1 week or less	More than 1 day and less than 8 days.
3	Individuals were disabled for 1 to 2 weeks.	More than 7 days and less than 15 days.
4	Individuals were disabled for 2 to 3 weeks.	More than 14 and less than 22 days
5	Individuals were disabled for 3to 4 weeks	More than 21 days.

Source: Authors' calculations based on IHDS 1 and IHDS 2.

3.2.2: The Activity Of Daily Living Intensity (ADLI):

ADLI was constructed using the information provided in individual rounds of IHDS 1 and IHDS 2. In the module on Activities of Daily Living (ADL), the question was about the physical difficulty that people above the age of 7 in the household might have (including handicapped, disabled, and elderly above 7). The disability module comprised seven activities/ functions on which responses were collected.

The disabilities that were measured were:

a) Walking 1 km.

b) Going to the toilet without help.

c) Dressing without help.

d) Hearing a normal conversation.

e) Seeing distant things (with glasses, if any).

f) Seeing near objects, such as reading.

g)Sewing (with glasses).

The options for the ADL module were: can still do with some trouble or cannot do it, and had three options:

a)No difficulty (=0).

b) Can do it with difficulty (=1).

c) Unable to do it(=2).

The options for each question were added row-wise for individuals to construct ADLI.

3.2.3: Days Disabled Due To Major Morbidity:

This variable measures the disability caused due to major morbidity. IHDS 1 and IHDS 2 from the individual module collected information on the number of days an individual could not work due to illness. For individuals suffering from an illness (major morbidity), the exact question was, “How long the household member was unable to do a usual activity like school, work or domestic work in the last 12 months?”. The original replies sought measured the number of days.

The ordered categorical variable was constructed from this variable using the options: those never disabled were=0, those disabled for three months were = 1, those disabled for six months =2, those disabled for nine months=3, and those disabled for 12 months =4.

3.2.4:Consumption Expenditure Per Capita (COPC):

COPC is given in IHDS 1 and reported monthly, while IHDS 2 reports COPC annually. We divided the COPC from IHDS 2 by 12 to make it a monthly expenditure, and this was done after the clarification was received from the IHDS help desk. The COPC data from IHDS 1 and IHDS 2 were now comparable at the monthly level.

IHDS 1 had 47 consumption items, and IHDS 2 had 52. These included rice, wheat, sugar, kerosene, other cereals, pulses, meat, sweeteners, edible oil, eggs, milk, milk products, vegetables, salt/ spices, tea/coffee, processed food, paan/tobacco/ intoxicants, fruits and nuts, eating out, fuel, light, entertainment, telephone, cosmetic, toiletries, household items, soaps/detergent, conveyance, diesel/petrol/CNG/ house/other rents(home loan, other rent, consumer tax/fees, services servants, medical outpatient, medical inpatient, school/ college/ fees, private tuition, school books, clothing/bedding, footwear, furniture/ fixture, crockery utensils, household appliances, recreation goods, jewellery, transport equipment, therapeutic appliances, personal care, other personal, repair maintenance, insurance premium, vacations, social functions.

Self-reported income may have issues regarding the accuracy of reporting. Consumption of items is truthfully reported. However, many studies have used asset/asset-based and consumption quintiles for household well-being analysis. Household well-being is measured in multiple ways in the literature (see Chapter 2 for details). IHDS provides a quantitative measure of monetary value for consumption. It also provides a quantitative measure of assets but does not provide a monetary value. It just provides the number of assets owned by a household. Both comparisons over time and across the households provide insightful information. IHDS also collected income information. However, this was self-reported; it has not been used for our study.

IHDS provides COPC as a constructed variable. Thirty items with repetitive consumption and fulfilling daily nutritional requirements and other needs were calculated using a monthly time frame (30 days). There were also 17 items meant for long-term consumption, having a 365-day frame. Households usually sourced their consumption from 3 sources: a) purchased from the public distribution system, b)market and c) cultivation for self-consumption (excluding kerosene). The commodities purchased from the public distribution system(PDS) were treated as reported by households. The market price was used for self-consumption cultivation and items purchased from the market. The quantities of market and self-consumption cultivation were calculated based on adjustments between the PDS purchase and the total consumption of such goods. Items like other cereals, cereal products, pulses, meat, sweeteners, edible oil, eggs, milk, milk products, and vegetables were also considered with the option of self-consumption cultivation or market purchase. The items of annual consumption were converted from annual to monthly for the construction of monthly per capita consumption.

IHDS 1 collected data on 47 items, and IHDS 2 collected data on 52 items. The difference between IHDS 1 and IHDS 2 concerning information collected on consumption expenditure items was as follows:

1. Additional items like Tea/coffee processed food, eating out, soaps/detergents, Diesel/petrol/CNG, and private tuition were added in IHDS 2.
2. Fuel and Light were separated in IHDS 2 as compared to IHDS 1.

3.2.5: Adjusted Consumption Expenditure(Consumption Expenditure Adjusted for Health Expenditure):

We constructed a variable: Adjusted Consumption Expenditure(used interchangeably as consumption expenditure adjusted for health expenditure in this thesis). It was constructed from the household schedule by subtracting health expenditure from COPC. Since there is no additional information on OOPHE, we consider the measurement provided of health expenditure as equivalent to OOPHE(See Section 3.2.8 for details). Information on health expenditure is provided in both household schedules and individual schedules of IHDS 1 and IHDS 2. We get total health expenditure as a sum of inpatient and outpatient expenditures from the household schedule and total health expenditure as the sum of short and major morbidity expenditures from the individual schedule. The details of the construction of variable health expenditure are provided in the following sections.

3.2.6: Food And Non-Food Expenditures:

Monthly and Annual food and non-food expenditures were constructed from IHDS 1 and IHDS 2. This variable is constructed from household schedules excluding medical inpatient and outpatient. Bifurcation of consumption expenditure into food and non-food expenditure was done by constructing a) Monthly food expenditure, b) Monthly non-food expenditure, c) Annual food expenditure, and d) Annual non-food expenditure, separately for rounds 1 and 2 (comparable across both rounds).

IHDS 1 used 47 items for constructing COPC, and they were bifurcated as follows:

a. **Monthly Food Expenditure**: The 17 1items: rice, wheat, sugar, kerosene, other cereals, cereal, pulses, meat, sweeteners, edible oil, eggs, milk, milk products, vegetables, salt/ spices, other food, fruit and nuts were added directly. These items were directly added to get the monthly food expenditure. We used the deflator provided in IHDS 2 to deflate the monthly food expenditure from IHDS1.

b. **Annual Food Expenditure**: This was constructed by multiplying the monthly food expenditure by 12(deflated).

c. **Monthly Non-Food Expenditure:** Constructed using 30 items: Paan/ tobacco/ intoxicants, eating out, fuel/light, entertainment, telephone, personal care, toiletries, household item, conveyance, house, other rent, consumer/ tax fees, services servants were added directly on account of their monthly consumption. This variable was Non-food expenditure group 1. The remaining items that were consumed annually: school fees, school book, clothing and bedding, footwear, furniture/fixtures, crockery/utensils, household appliances, recreation goods, jewellery, transport equipment, therapeutic appliances, other personal, repair maintenance, insurance premium, vacation and social function were added and divided by 12 to get monthly non-food expenditure group 2. Both groups of non-food expenditure were added to get the monthly non-food expenditure. Monthly non-food expenditure was also deflated using the deflator.

d) **Annual Non-Food Expenditure**: constructed from monthly non-food expenditure by multiplying by 12(deflated).

IHDS 2 has collected information on 52 items that have gone into monthly consumption per capita construction. The food and non-food expenditures from IHDS 2 were constructed as follows:

a) **Monthly Food Expenditure**: 18 items were used for calculating food expenditure: rice, wheat, sugar, kerosene, other cereals, pulses, meat, sweeteners, edible oil, eggs, milk, milk products, cereal products, vegetables, salt/ spices, tea/coffee, processed food, fruits and nuts. These were directly added to get monthly food expenditure.

b) **Annual Food Expenditure**: This was constructed by multiplying the monthly food expenditure by 12.

c) **Monthly Non-Food Expenditure**: For the calculation of COPC, the IHDS converts all items of monthly consumption for the final calculation. However, for specifically calculating non-food expenditures, certain adjustments were made. The items with annual time frames were added and divided by 12. Items with monthly time frames were added separately. Both these variables were added to get monthly non-food expenditure. 34 items are used for constructing non-food expenditures. 15 items consisting of paan/tobacco/intoxicants, eating out, fuel, light, entertainment, telephone, cosmetic/ toiletries, household items, soaps/detergents, conveyance, diesel/petrol/CNG, house /other rents (home loan, other rent), consumer tax/fees, services servants, with monthly time frame were directly added as monthly non-food expenditure group 1. 19 items having annual frames were added separately: school/colleges/fees, private tuition, schoolbooks, clothing/bedding, footwear, furniture/fixture, crockery utensil, household appliances, recreation goods, jewellery, transport equipment, therapeutic appliances, personal care, other personal, repair maintenance, insurance premium, vacations, social functions) were divided by 12 to form another group 2. These groups of non-food expenditures were added together to get monthly non-food expenditures.

d) **Annual Non-Food Expenditure** was calculated by multiplying the monthly non-food expenditure by 12.

Variables of food and non-food expenditures were converted to per capita. They were divided by the number of persons in the household for comparability.

3.2.7: Adjustments In Consumption Expenditure:

1. Adjustment using health expenditure
2. Adjustment in COPC using deflator.

COPC is adjusted for health expenditure by constructing a variable-adjusted consumption expenditure. The household schedule provided information on the following:

a) Medical Inpatient expenditure (365 days).
b) Medical outpatient expenditure (30 days).

We constructed the following variables.

a) Monthly Inpatient Expenditure: The medical inpatient expenditure was divided by 12 to get monthly inpatient expenditure.
b) Annual Outpatient Expenditure: The Medical outpatient expenditure was multiplied by 12 to get the annual outpatient expenditure.
c) Total monthly health expenditures include medical outpatient and monthly inpatient expenditures(added together).
d) Total annual health expenditure is derived by adding outpatient(annual) and medical inpatient expenditures.

From the household round, the total monthly/annual health expenditure is also treated as equal to OOPHE without further information.

For COPC to be comparable between IHDS 1 and IHDS 2, the latter provides a deflator and the methodology for its use. All the expenditure variables from IHDS 1 measured in money terms are deflated using the deflator (variable divided by the deflator). The mean value of the deflator provided is 0.5453441. For IHDS 1, the total monthly/annual health expenditure was deflated(All the variables measured in Rs from IHDS 1 were deflated using the deflator provided in IHDS2).

3.2.8: Out-of-pocket Expenditure On Health (OOPHE):

According to National Health Accounts (NHA) accounts 2017-18, any expenditure incurred by the household/individual at the point of receiving health service is accounted as the out-of-pocket health expenditure (OOPHE)(NHA, 2017-18). We constructed a variable accordingly. The individual schedule from IHDS 1 and IHDS 2 provides variables on different items of health expenditure for short(30 days) and major morbidities(365 days). The OOPHE was constructed using data from individual schedules from IHDS 1 and IHDS 2. IHDS 1 provides health expenditure incurred on various items. Additionally, IHDS 2 provides information on insurance reimbursement, if any.

The following questions collected information on health expenditures incurred by the respondent from the individual schedule. The questions were: “What was the total cost of the treatment for outpatient and inpatient expenditure?” This question was split into:

a) For doctors, hospital surgery

b) Whether tests or medicine included in the fees?

c) For medicine, tests, and expenses not included in the doctor and hospital fees.

d) For tips, bus/train/taxi fare or lodging while getting treatment?

The responses for question numbers ‘a’ and ‘c’ ‘d’ were in monetary terms. In addition, insurance reimbursement information was collected only in IHDS 2. The specific question was: “Were any of these expenditures covered by insurance such as Mediclaim/RSBY?”. The response was:” If yes, how much did the insurance pay?” (include everything?) (If not received but expected to receive, was also recorded. This information was collected in monetary terms.

From individual schedules, for IHDS 1, the OOPHE was estimated by adding the expenditure incurred on doctor fees and procedures, cost of medicine, and travel combined for both inpatient and outpatient for short morbidity. Similar information was captured for major morbidity. Health expenditure on short morbidity was added(deflated) to get the OOPHE.

The expenditure on major morbidity was also added(deflated) to get OOPHE divided by 12 to convert this expenditure from annual to monthly. Monthly OOPHE on short and major morbidity was added to get the total monthly OOPHE. This expenditure was subtracted from the monthly COPC to get the monthly COPC adjusted for OOPHE; we call this variable interchangeably adjusted consumption expenditure in the thesis(In the literature, it’s also referred to as non-health expenditure). Adjusted consumption expenditure for OOPHE was divided by the number of persons in the household to get per capita estimates.

For IHDS 2, there were two separate variables of OOPHE constructed:

a) Monthly COPC adjusted for OOPHE without insurance reimbursement (Adjusted consumption expenditure without insurance reimbursement).

b) Monthly COPC adjusted for OOPHE with insurance reimbursement (Adjusted consumption expenditure with insurance reimbursement).

To construct the variable as mentioned in a), monthly COPC was adjusted for OOPHE without insurance reimbursement; the same steps were followed as IHDS1. This variable is comparable with IHDS 1.

To construct variable b), insurance reimbursement from major morbidity was divided by 12 to get monthly insurance reimbursement from major morbidity. Insurance reimbursement from short morbidity and monthly insurance reimbursement from major morbidity were summed up to get the total monthly insurance reimbursement. Total monthly insurance reimbursement was subtracted from the total monthly OOPHE to get the adjusted total monthly OOPHE. For constructing an adjusted COPC with insurance reimbursement, we subtracted the adjusted total monthly OOPHE from the COPC. This variable is not comparable with IHDS 1.

Thus, from the household schedule, the following consumption expenditure variables were constructed:

a) Monthly/ Annual consumption expenditure per capita,

b) Monthly/ Annual consumption expenditure adjusted for total health expenditure (OOPHE)

c)Monthly/ Annual food expenditure,

d)Monthly/Annual non-food expenditure

e) Monthly/Annual outpatient expenditure

f) Monthly/Annual inpatient expenditure

g)Monthly/Annual total health expenditure) (OOPHE).

From the individual schedule, the following consumption expenditure variables were constructed:

a) Monthly/annual OOPHE on short morbidity without insurance reimbursement for IHDS1 and IHDS2.

b) Monthly/ annual OOPHE on major morbidity without insurance reimbursement for IHDS 1 and IHDS 2.

c) Monthly/annual OOPHE on short morbidity with insurance reimbursement for IHDS 2.

d) Monthly/annual OOPHE on major morbidity with insurance reimbursement for IHDS 2.

e) Monthly/annual adjusted consumption expenditure without insurance reimbursement for IHDS 1 and IHDS 2.

f) Monthly/annual adjusted consumption expenditure with insurance reimbursement for IHDS 2.

The difference between health expenditure and OOPHE provided in household schedule and individual schedule is as follows:

a) The household schedule has data on medical inpatient and outpatient medical expenditures.
b) The individual schedules contain the data on short morbidity and major morbidity expenditure.
c) OOPHE from the household schedule is total health expenditure (the sum of inpatient and outpatient health expenditures).
d) OOPHE from the individual schedule is total health expenditure (sum of short and major morbidity expenditure).

To determine whether health expenditure incurred by the household had catastrophic and impoverishment effects, we constructed the following variables from household and individual rounds.

a) Household Capacity To Pay: we calculate household capacity to pay (household's non-subsistence expenditure) as the difference between a COPC and the poverty line. In households whose food expenditure is below the poverty line, household capacity to pay is calculated as the difference between households' COPC and food expenditure.

b) OOPHE As A Share Of Household Capacity To PAY: OOPHE as a share of households' capacity to pay is calculated as OOPHE divided by the capacity to pay.

c) Catastrophic Health Expenditure: Calculated Using Two Threshold Levels:

1. When health expenditure exceeds 10 % or more than consumption expenditure adjusted for health expenditure (Household's non-health spending).
2. When health expenditure exceeds 40% or more than the household's capacity to pay.

d) Impoverishment: A household is impoverished if the COPC falls below the poverty line after making health payments.

Difference Between The Household Capacity To Pay And Adjusted Consumption Expenditure:

Household capacity to pay is calculated using XU's (2005) methodology: subsistence expenditure is calculated as the difference between consumption expenditure and the poverty line. Or the difference between consumption expenditure and food expenditure if food expenditure is less than the poverty line. Adjusted consumption expenditure is calculated as the difference between consumption expenditure and health expenditure.

3.2.9: Disability Pension Received By The Households:

A dummy variable was created using the information collected on the amount of pension received as a disability pension by assigning value =1 to all those households who received the disability pension and =0 otherwise.

3.2.10: Health Insurance:

We constructed 3 variables to measure health insurance:

a) Health insurance
b) PFHII
c) VPHI

IHDS1 and IHDS 2 recorded the household's health insurance coverage. The household schedule of the IHDS 1 contains information on whether households have purchased private health insurance /government insurance.IHDS 2 has additional details and records on whether households had private or government health insurance through the household schedule.IHDS 1 has included a question, “Does anybody in the household have health insurance?” IHDS 2 elaborates on distinguishing between government and private health insurance, and two insurance categories were added to make one category (binary variable). It helped to make data comparable with IHDS 1.

Health insurance is a dummy variable; those without insurance are marked as = 0, and those with insurance are marked as =1(Comparable across both rounds).

There was an additional question in IHDS 2 on household ownership of the Rashtriya Swasth Bima Yojana (RSBY) card. Information from household ownership of health insurance by source and RSBY were combined to create variable Publicly Funded Health Insurance Intensity (PFHII). PFHII had three ordered categories.

a) Category 1: PFHII=0

b) Category 2: PFHII=1whether household had any PFHII- Government insurance or RSBY

c)Category 3: PFHII=3 Whether household had both types of PFHII- Government and RSBY.

We excluded the ownership of private health insurance from the construction of PFHII.

PFHII is not comparable with IHDS 1.

In IHDS 2, the household schedule has information from the source on voluntarily purchased health insurance (VPHI). VPHI of the households was constructed as a dummy variable: The households that did not own private health insurance =0; households that owned private health insurance =1. VPHI is not comparable with IHDS 1.

3.2.11: Developed Village:

We constructed variable-developed villages from the IHDS 1 and IHDS 2 village schedules. This variable described the geographical status of the households in terms of their location. The categories in the original variable were Metro urban=0; Other urban=1; More developed village=2; Less developed village =3. A dummy variable was constructed as a Developed Village. The developed village was =0 if the location was a less developed village and =1 if the location was a more developed village. The newly constructed variable developed village had two categories now: less developed and more developed. This variable is comparable across both rounds of IHDS.

3.2.12: Village Health Infrastructure Index(VHII):

An index measuring the access and availability of health infrastructure at the village level was constructed, and we named it as Village Health Infrastructure Index (VHII). VHII is created using Principal component analysis (See Chapter 8 for details). This variable is constructed using individual and village schedules of IHDS 1 and IHDS 2. The individual schedule provided data on short and major morbidity, place of first and second advice, and place of the first and second treatment. The IHDS data at the village level has collected information on variables that capture the availability of health infrastructures like PHC, CHC sub-centre, and district hospital and their availability in the village and nearby villages. (Only government health facilities are considered in the construction of the index) Besides this, there is information on the availability of transport infrastructure in the village, such as distance to the nearest railway station, bus stop, and pucca road. New variables constructed using PCA were short and major morbidity places of advice and treatment, health infrastructure available in the village, health infrastructure available nearby and infrastructure facilities. This index is constructed based on a five-point scale: Very low, Low, Average, High and Very high. This index is comparable across both rounds of IHDS.

3.2.13: Households Without Toilets:

The toilet information is taken from the household schedule of IHDS 1 and IHDS 2. The status of household toilets was provided in the original variable with four options:

a) None/open fields.

b) Traditional latrine

c)VIP latrine

d)Flush toilet

The dummy variable for Households without toilets was constructed. Those households were assigned value=0 if the original option was none/open fields. Households that opted for the remaining categories were assigned value=1. This variable is comparable across both rounds of IHDS.

3.2.14: Membership Intensity:

The IHDS records membership in various associations (like caste-based associations, micro-finance groups, and village committees). This data is given in the household schedule. These associations help build cooperation and resilience against adversities. The question asked during the survey was: Membership and political activity: “Now I would like to know about the groups or organisations to which you and others in the households belong”. The options included membership to:

a) Mahila Mandal.
b) Youth club.
c) Sports group or reading room.
d) Employee union, trade union, business, or professional group.
e) Self-help groups.
f) Credit or savings groups/ committee/ chit fund.

g) Religious or social group or festival society.

h) Caste association.

i) Development group or NGO.

j) Agricultural, milk or other cooperatives.

k) Political party.

l) Lions/Rotary Club and other similar clubs.

The original variable was recorded as a dummy variable separately for each option. The household could be a member of more than one association. Therefore, we added row-wise options to construct a variable membership intensity. This newly constructed variable captured household members of more than one such organisation. This variable is comparable across both rounds of IHDS.

3.2.15: The Proportion Of Children 0-14 And The Proportion Of Adults 60+:

The age given in single years was used from individual rounds to calculate the proportion of children. The number of children in the age group 0-14 was calculated first. The same was divided by family size (the number of persons in the households). The proportion of adults 60+ was calculated as the number of adults 60 + divided by the family size. This variable is comparable across both rounds of IHDS.

3.2.16: Remittances Received By The Households:

The remittances received by the household were from non-resident family members. This information was collected from the individual schedule. IHDS 1 has asked a specific question: 'How much money has been sent/received by the household in the past 12 months? IHDS 2 has a specific question, 'Rupees received by the household from a non-resident last year.' The original variables have sought information in terms of money received. We constructed a dummy variable based on this variable. We name this dummy variable as remittances received by the household. Those households that received any money in the last year were coded =1, and those who did not receive =0. This constructed variable is comparable across both rounds of IHDS.

3.2.17: Caste:

Variable caste is provided in the household schedule in six categories, namely (a) Brahmin, (b) Forward/General (except Brahmin), (c) Other Backward Caste, (d) Scheduled Caste (SC), (e) Scheduled Tribe (ST), and (f) Others. For IHDS1, the question on caste was: "Is this Brahmin (=1), OBC (=2), SC (=3), ST (=4) and others (=5)? IHDS-2 had categories of Brahmin (=1), forward/general (except Brahmin=2), OBC (=3), SC (=4), ST (5) and others (=6).

Since caste is time-invariant and there is a possible non-sampling coding error (since summary statistics were not matching), we adjusted the data originally given in the IHDS 1 and 2. For IHDS 1, categories 1 and 5 were merged to get category 1 Brahmin and forward caste. The remaining categories were retained as they were. For IHDS 2, categories 1, 2 and 6 were merged and added to get category 1 Brahmin and forward caste; the rest were retained as they were.

After these adjustments, the percentage of brahmins and forward caste was 26%, OBC was 40%, SC was 23, and ST was 11%. We have used their stated category in IHDS 1 while constructing the panel and used by Bhattacharjee & Mohanty (2022). The variable caste constructed by us is comparable across both rounds.

3.2.18: Natural Disaster Intensity:

The information collected on natural disasters is available only in IHDS 2 in the village schedule. The question asked to collect this information was, 'The difficulties that might have occurred in the past six years in this village. This information was collected from 2006 to 2012. The information was collected for all years as a dummy variable if faced difficulties =1 or otherwise =0. The natural disasters on which information was collected were Drought, Floods, Epidemics, Earthquakes, Cyclones, Tsunamis, Hailstorms, and Others. The variable others were not included since it had many categories that could not be summarised into meaningful categories. We had a choice to construct the variable natural disaster as a dummy variable. But instead, we constructed natural disaster intensity.

The variable natural disaster intensity was constructed as follows: The individual dummy variables were first summed up for 2006 -2012 as dummy variables, and those who faced a natural disaster between 2006 and 2012 were coded as '1' and otherwise '0', which was constructed to capture the repeated disasters faced for years. Variable flood now was Flood2006-2012 and so on. All these summed variables were added row-wise: Drought2006-2012; Flood2006-2012; Epidemic2006-2012; Earthquake2006-2012; Cyclone 2006-2012; Tsunami 2006-2012; Hailstorm 2006-2012 to get Natural disaster intensity (NDI).NDI captured the repeated disasters in different years and cumulatively all disasters. This information was compiled only for the year 2012. Another dummy variable was created to match the households in IHDS 1. These households did not face any natural disasters in 2005 but faced the same in subsequent years from 2006 to 2012. This information is only available at the village level. The variable natural disaster intensity is not comparable across both rounds.

3.2.19: Confidence Intensity:

The IHDS had a single question that captured information on ten institutions ranging from police to schools on confidence in the household schedule of IHDS 1 and IHDS 2. The dataset for IHDS 1 and IHDS 2 captures the information on confidence by asking: ‘I am going to name some institutions in the country, as far as the people running these institutions are concerned’.

This data was collected by asking questions about confidence in:

a) Politicians - to fulfil promises.

b) Military - to defend the country.

c) Police – to enforce the law.

d) State government – to look after the people.

e) Newspapers/News media – to print/broadcast the truth.

f) Village Panchayats / Nagarpalika / Nagar Panchayat – to implement public projects.

g) Government Schools – to provide good education.

h) Private Schools – to provide good education, Government Hospitals, and doctors to provide good treatment.

i) Private Hospitals and doctors – to provide good treatment.

j) Courts – to deliver justice.

k) Banks to keep money safe.

The original responses were:

a)No confidence =0.

b)A Great deal of confidence =1

c) Only some confidence =2.

d) Hardly any confidence at all=3.

This variable was constructed by adding row-wise responses from the original variable that households had reported for different institutions. The construction of confidence intensity helped to capture the different levels of confidence expressed by the households in multiple institutions. This constructed variable is comparable across both rounds of IHDS.

3.2.20: Conflict Intensity:

IHDS collected information from the household schedule on village/ neighbourhood conflicts. Two questions were asked about local trust and conflict: one was about general conflict, and another was specific to inter-community (*jati*) conflict. The specific questions asked were, 'In the village/neighbourhood, do people generally get along with each other, or is there some conflict or much conflict'? The subsequent question was: 'In this village/neighbourhood, how much conflict would you say there is among the communities/ jatis that live here?'. Options included a) many conflicts, b) some conflicts, and c) getting along. Conflict intensity was created by adding the options to these two questions row-wise. This variable is comparable across both rounds.

3.2.21: Public Project Intensity:

IHDS 1 and IHDS 2 have collected information using the village schedule on implementing public programmes in villages (in the last five years preceding the survey). The specific question was: 'Are there any public programmes promoting [PROGRAM] in this village?

IHDS 1 had the following options:

a) Old Age Pension Scheme.

b) Widows' Pension Scheme.

c) National Maternity Scheme.

d) National Disability Pension; Annapurna.

e) Safe Drinking water.

f) Sanitation/latrines.

g) Housing.

h) Improved stoves.

i) Agricultural extension.

g) Forestry.

h) Small loans- micro-credit.

i) Revolving credit.

j) Anganwadi (ICDS) Programs for Immunization.

k) Health Check-up, Food / Meals.

l) Growth monitoring (weighing the child).

l) Early childhood/preschool education.

m) Street and Light Program.

n) Others.

IHDS 2 included a specific question on public programs implemented in the village: Were any programs implemented in this village in the last five years?

Additionally, IHDS-2 provided the following options:

a) Skill development program.

b) Janani Suraksha Yojana.

c) Other women's welfare schemes.

d) Antodaya.

e) Housing (Indira Awas Yojana).

f) Crop insurance scheme.

g) Kisan credit card.

h) Street light programme.

i) Health insurance (RSBY).

j) Life insurance scheme for BPL.

k) Ambulance.

l) Mobile medical van.

m) Any other public program.

n) Anganwadi: adolescent girl's programme.

By adding the number of such programs, we constructed a variable that captured the extent of public programs/ projects in a village. The constructed variable is called public project intensity. This variable captures multiple projects implemented in the village. The information captured under every response was added row-wise to get public project intensity.

3.2.22: Rural Poor:

IHDS gives information on the poverty line in the household schedule. IHDS 1 uses the poverty line Tendulkar method 2005, and IHDS 2 uses the poverty line Tendulkar method adjusted for the interview date 2012. IHDS provides the original variable poor (Poor=1 and otherwise=0) and urban(urban=1, rural=0). The poverty line is given for individuals, and when using it for households, it needs to be multiplied by the number of persons and, accordingly, if used as annual, then multiplied by 12 (Sahoo & Madheswaran, 2014). The average poverty line for IHDS 2 was Rs 808, and for IHDS 1, it was Rs 797.15.

Using the poverty line provided in IHDS 1 and IHDS 2 variable poor (dummy variable) was constructed for rural and urban. This poverty line for IHDS 1 was adjusted using the deflator provided in IHDS 2. With the help of the poverty line, the dummy variable poor rural was constructed. Rural poor (Urban=0 and Poor=1) was constructed as poor residing in rural areas coded as =1 and otherwise =0.

3.2.23: Urban Poor:

Urban poor (Urban=1 and Poor=1) was constructed as Poor residing in urban areas coded as = 1 and otherwise. Both Rural Poor and Urban Poor are comparable across both rounds.

3.2.24: Consumption Expenditure And Adjusted Consumption Expenditure Quintiles:

We created an expenditure quintile using the following:

a) Monthly consumption expenditure per capita

b) Adjusted consumption expenditure.

Consumption expenditure quintiles were constructed for those above the poverty line with 5 categories: APL1, APL 2, APL 3, APL4, and APL 5 using the *STATA* command *xtile*. Category BPL was derived from the poverty line and added separately to the quintile(Choudhury et al., 2019; Hooda, 2015; Mehta, 2008). The construction and use of consumption expenditure quintile aligns with existing literature (Arouri et al., 2015; Bhattacharjee & Mohanty, 2022; Edwards et al., 2021; Shahrawat & Rao, 2012; Xu, 2005).

Similarly, the adjusted consumption expenditure quintiles were constructed as 5 quintiles above the poverty line and one BPL quintile below the poverty line.

Household quintile: Household quintiles were created for rural and urban from consumption expenditure and consumption expenditure adjusted for total health expenditure(comprising medical outpatient and inpatient expenditure) in IHDS 1 and IHDS 2 separately.

Individual quintile: Individual quintiles were also constructed for rural and urban areas for COPC; COPC adjusted for out-of-pocket health expenditure (together for short morbidity and major morbidity)without insurance reimbursement and with insurance reimbursement separately.

3.3: Description Of Variables Used From IHDS 1 And IHDS 2:

We have used variables from the household, individual schedule, and village schedule from IHDS 1 and IHDS 2 without any modifications to the original variable and have renamed them. The following sections provide details of those variables.

3.3.1: Assets Owned By The Households:

Information about assets owned by the household was provided in IHDS 1 and IHDS 2. IHDS 1 and IHDS 2 provided information on 30 and 33 different types of household assets for the survey year, respectively. This information was elicited from the household round.

The assets included: vehicle, bicycle, sewing machine, generator set mixer/grinder, motor vehicle, motorcycle/ scooter, television (black and white or colour), air cooler, clock/watch, electric fan, chair or table, cot, telephone, mobile phone, fridge/refrigerator, pressure cooker, cable/dish tv, car, air-conditioner, washing machine, computer, laptop, credit card, microwave oven,)clothes, footwear, electricity, LPG, indoor piped drinking water, separate kitchen, flush toilet, pucca roof, pucca wall, pucca floor.

The survey did not record the monetary values of assets but recorded the number of assets. To make the survey data compatible for comparison, IHDS 2 provides data on 30 assets from IHDS 1. We have used the latter information in our study. The household asset scale would sum to a maximum of 30 in both rounds of IHDS 1 and IHDS 2 if any house owned all the assets and a minimum of zero if they owned none of the assets listed for the survey. This variable was used as it is by renaming the same to follow a standard order of renaming.

3.3.2: Urban:

Variable Urban is a dummy variable that distinguishes between rural and urban households. Urban households were given the value of one (=1) and rural values of zero (=0).

3.3.3: Highest Completed Adult Education:

This variable captured information on the years of completed education by the adult members of the households.

3.3.4: The Number Of Married Females:

The number of married females in the household was the original variable used as provided in the data.

3.3.5: Family Size:

This variable is used as it is from the data, indicating the number of persons in the family.

3.4: Methodology:

In this section, we describe the methods used to analyse the data.

3.4.1: The Choice Between Fixed And Random Effects:

Panel data can be examined using fixed effects or random effects. In panel data, the behaviour of the same observation is observed over a period (more than once). This behaviour could be social or economic**.** The data collected this way is also referred to in the literature as longitudinal data.

Fixed effects: Each observation unit (household and individual) has observed and unobserved characteristics. These characteristics may influence the independent (predictor) variable. Fixed effects study the relationship between predictor and outcome variables within the observations. The variables change characteristics over time.

The assumption of fixed effect is the correlation between the observation error term and predictor variable. It is assumed that the observations have changed (observed or latent) over some time. These changes may influence or generate bias in the outcome or predictor variable. Fixed effects help to control these changes. Fixed effects help to control for time-invariant changes. Hence, the results produced from any model with fixed effects help to assess the net effect. The second assumption with fixed effects is that the characteristics of observations that change over time are unique to that individual. These characteristics differ from individual to individual. Therefore, the error terms generated from the observations and the constant are orthogonal. Any correlation between these error terms will lead to bias.

The equation for fixed effects:

$$Y_{it}= \beta_1 X_{it} +\alpha_i+\mu_{it} \qquad (1)$$

In equation 1 (assuming there is a single independent variable for representation purposes), $\alpha_i(i=1,\ldots,n)$ unknown intercept for each observation; Y_{it} is the outcome variable for 'i' observation in 't' time-periods; $\beta_1 X_{it}$: X is the independent variable and β_1 coefficient of the independent variable; μ_{it} exogenous error term.

STATA xtreg command is used to produce regression with fixed effects. (*xtreg* Y X, fe). This command controls for fixed effects within the regression. If there is multicollinearity, the *STATA* drops those variables automatically. The given command controls for the heteroskedasticity with option robust (robust option is also known as Huber/ White or sandwich estimators).

Thus, fixed effects control for all differences between observations that are time-invariant. Furthermore, these time-invariant variables are absorbed by the intercept. Thus, the coefficient produced is unbiased (the coefficient takes care of omitted invariant characteristics). One of the fixed effect's limitations is that it cannot examine the time-invariant characteristic of the dependent variable.

Random effects: In the random effect model, it is assumed that there are variations in the observations, which are random. These variations are also not correlated with the independent variables in the model. Random effects can be used when the theoretical literature provides the background that the differences in observation influence the dependent variable. Time-invariant variables like gender and caste can be plugged into the model.

$$Y_{it}= \beta_1 X_{it} +\alpha+ U_{it}+ \varepsilon_{it} \qquad (2)$$

In equation 2, 'U_{it}; represents between entity error and 'ε_{it}' within entity error.

The random effect assumption is that the error term of individual observations is not correlated with the independent variables; hence, the time-invariant variables also act as explanatory variables. Sometimes, some variables may not be available, leading to omitted variable bias. *STATA* command *xtreg* is used with '*re'* (random effect) as a suffix to get random effects.

3.4.1.1: Hausman Test For A Decision On Fixed And Random Effects:

Which data type is required to examine the changes in household economic behaviour over a while? The longitudinal study examines the behaviour of the same individual/ household across different periods. In doing so, any change in economic behaviour can be observed. For many surveys, the unit of observation is the household. Household undergoes many changes, such as family size and composition, economic gain, or losses in consumption expenditure. These changes are captured in the longitudinal data (Koen, 1999). Hausman test is used to decide on using fixed or random effects.

The null hypothesis is as follows: The model in question can be considered a random effect model. Alternative hypothesis: The model in question is fixed effects—the Hausman test tests whether the unique errors are correlated with regressors. As per the null hypothesis, they are not correlated (this is the assumption of fixed effects that they are correlated).

Steps followed:

1. A model with fixed effects can be run first, and the output will be stored in STATA.
2. A model with random effects will be run, and results will be saved.
3. The Hausman test will be run using the output from the fixed and random effects model run earlier (since the results are stored, it is easy to get them together).

3.4.1.2: Interpretation of Results Produced In *STATA:*

1. The null hypothesis is that the difference in coefficients is not systematic. The results produce a Chi-square. If the p-value of the chi-square is less than 0.5 (significant), the null hypothesis is rejected, hence the alternate hypothesis that the model is fit for using fixed effects (Torres-Reyna,2007).

3.4.2: Disability And Household Consumption Expenditure (See Chapter 4 For Details):

In this section, we describe the measurement of disability using IHDS data.

3.4.2.1: Disability By Duration And Morbidity-Specific Disability:

This analysis was done to study the difference in consumption expenditure for those who were never disabled and those who were disabled. Test of significance was done using Two-tailed tests at a significance level of 5%. From these test results, the number of observations, mean, and standard deviation were used to test the significance of household expenditure between the group that was never disabled and those disabled for different durations of short and major morbidities(See Chapter 4 for details). Furthermore, the same procedure was repeated for testing all the hypotheses for all categories across rural and urban areas. Different consumption expenditures were analysed to examine the differences between different categories of disabilities by duration. This analysis was done using the merged Household Individual panel for IHDS1 and IHDS 2 separately.

We tested for the following null hypothesis.

1. The consumption expenditure of those never disabled does not differ significantly from those disabled with morbidity-specific disabilities.
2. The consumption expenditure of those never disabled does not differ significantly from those disabled by duration.
3. The adjusted consumption expenditure of those never disabled does not differ significantly from those disabled with morbidity-specific disabilities.
4. The adjusted consumption expenditure of those never disabled does not differ significantly from those disabled by duration.
5. The non-food expenditure of those who were never disabled does not differ significantly from those of disabled people with morbidity-specific disabilities.
6. The non-food expenditure of those never disabled does not differ significantly from those disabled by duration.
7. The food expenditure of those never disabled does not differ significantly from those disabled with morbidity-specific disabilities.
8. The food expenditure of those who were never disabled does not differ significantly from those disabled by duration.

For IHDS 2, additionally, we tested for differences in outcomes in adjusted consumption expenditure without insurance reimbursement and with insurance reimbursement(see Chapter 4 for results).

3.4.2.2: The Activity Of Daily Living Intensity(ADLI) As A Shock On Household Consumption Expenditure:

The shock that is caused due to disability may alter the consumption expenditure of the households. The study of consumption expenditure per capita concerning health shocks is the main focus of this analysis.

We have used equations 1 and 2 for the decision about fixed effects. In the regression model, the activity of daily living intensity (ADLI)and disability caused due to major morbidity as the covariate is used. These two variables capture the possible effect of disability on various consumption expenditure measures. The ADLI was constructed using the information provided in individual rounds (explained in detail in the later section of this chapter).

The causal effects of disability from ADLI and major morbidities on household consumption expenditure were examined using different regression models.

Below is **Model 1** with the outcome variable Monthly consumption expenditure per capita.

$$Y_{it}=\alpha + \beta X_{it} + \varepsilon_{it} \tag{3}$$

Where Y is the monthly consumption expenditure per capita, X is a vector of independent variables and $\varepsilon$is the error term in equation 3.

The expanded form of this equation is equation 4.

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it} \tag{4}$$

Y_{it} = Outcome variable: Monthly consumption expenditure per capita

$\beta_1 \ldots \beta_{12}$ = Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

In equation 4, the outcome variable $Y_{it,}$ in model 1, is Monthly consumption expenditure. Four different types of consumption expenditure and three different types of health expenditure are used as outcome variables.

We used regression with different outcome variables as follows.

Model 2: Outcome variable- Adjusted consumption expenditure (adjusted for total health expenditure per capita).

Model 3: Outcome variable-Monthly food expenditure per capita.

Model 4: Outcome variable -monthly non-food expenditure (excludes outpatient and inpatient health expenditure)

Model 5: Outcome variable- Monthly outpatient expenditure per capita

Model 6: Outcome variable: Monthly inpatient expenditure per capita

Model 7: Outcome variable: Monthly total health expenditure per capita

(See Appendix A3 for equations for Model 2 to Model 7).

Each model was run with subsample restrictions for rural and urban areas and caste and expenditure quintiles (see Chapter 4 for results).

3.2.4:Natural Disaster And Household Consumption Expenditure:

The causal nature of the study in social science examines the relationship between variables in observable data. The causal relationships are either exogenous or endogenous. Exogenous causal relationships have causes outside the given specified regression model. Endogenous causal relationships have factors within the model that influence causal relationships. Such causal relationships influenced by endogenous variables affect predictor and outcome variables and may create some bias. In social science, most of the data is observational, which poses a problem in justifying the exogenous variables(Pokropek, 2016).

Standard regression analysis may not hold under several situations, leading to biased estimates. Endogeneity arises when regressors are correlated with the error term (Ullah et al., 2021), which could be because of errors in variables specified in the model, omitted variables or simultaneous causality. Omitted variable bias is a common problem in social science as the important explanatory variable may be omitted from the regression(Bascle, 2008).

Unbiased estimates from observational studies are possible only if there is no relationship between predictor and residual variables. One way to avoid such bias is by adding more variables to specify the model correctly. Otherwise, omitted variable bias is possible (Semykina & Wooldridge, 2010) or self-selection bias(Heckman, 1979). The instrumental variable (IV) facilitates overcoming such bias. As the name suggests, the endogenous aspect of the independent variable can be separated, and this separate part is termed an instrumental variable. This component is related to independent variables but is exogenous; it affects outcome variables via independent variables.

Phillip Wright discovered the IV method in 1928(Stock & Trebbi, 2003)to solve the statistical simultaneous equation problem using the variables in one equation to shift the equation and trace the other. The variable that was shifted was IV. This method also solved the bias from measurement error in the regression model(Angrist & Pischke, 2009; Bui et al., 2014; Warsi, 2019; Maydeu-Olivares et al., 2019; Wright, 2003; Xu et al., 2020).

3.4.3.1: The Choice Between Heckman And IV? (Bascle 2008):

Omitted variable bias is also called self-selection. Heckman uses two equations to address the issue of self-selection. The first step selection equation uses the probit model, wherein the dependent variable is used as a dummy variable. This step helps calculate the inverse mills' ratio, a correction factor. The next equation is the outcome equation computed using OLS and the correction factor, which is significant evidence of self-selection bias.

Choice: The Heckman model is used for omitted variable bias. IV can be used for self-selection and other biases also. In Heckman, in the first stage, the dependent variable must be a binary, categorical or ordered response. IV is more flexible and can handle different functional forms in the first-stage equations. The dependent variable can be continuous or binary.

3.4.3.2:Natural Disaster Model With IV2SLS:

Natural disasters cause direct and indirect damage(Cavallo & Noy, 2009; Hallegatte & Przyluski, 2010; Thomas et al., 2010). These damages impact individuals/ families with different socio-economic backgrounds differently(Israel & Briones, 2013). Households use both formal and informal mechanisms as coping strategies. Without government support, households adapt to perceived climatic changes and often use self-insurance without a formal coping mechanism(Baez et al., 2013; Heltberg et al., 2009). The household employs various adaptation strategies(Baez et al., 2013; Loebach, 2016; Maharjan et al., 2021; Marotzke et al., 2020; McElwee et al., 2017; McLeman & Hunter, 2010). One coping strategy is to sell stocks of interest in this study(Baez et al., 2013; Sawada & Takasaki, 2017). The household witnessing natural disasters shock smoothens consumption, and as a long-term strategy, households look for a permanent source of income (Baez et al., 2013). Households that face repeated weather shocks have the highest negative effect on consumption, which is felt more by poor households with fewer assets(Baez et al., 2013). Some studies find that households as a long-term coping mechanism shift from high risk – high return activity to low risk- low return or from optimal to suboptimal outcomes on investment and employment (Baez et al., 2013; McElwee et al., 2017; Rentschler, 2013). The support system used by the households in the event of natural disasters may also help the households to compensate monetarily for the loss involved. All this may lead to an underestimation of the welfare impact of natural disasters on households (Thomas et al., 2010).

Household assets are endogenous regressors to predict consumption expenditure(Manou et al., 2020; Rosenzweig & Wolpin, 1993). We assume that assets owned by the households are an endogenous variable affected by a natural disaster, among other variables. Assets owned by households are used as a coping mechanism. Households may sell assets during the emergency and build up the assets during normal situations. The second variable that affects the assets owned by the household is confidence in government institutions. Confidence also works similarly (Janada & Teodoru, 2020; Vanlaer et al., 2020). Many formal institution's approach to providing relief and reconstruction creates a sense of safety and security.

In the first stage of the IV estimation, endogenous variable assets owned by the households are regressed on two instruments: natural disaster intensity and confidence intensity and covariates Caste, Conflict intensity, health insurance, household adult education, membership intensity, number of married females in the household, family size, the proportion of children in the household, and public project intensity. The resulting fitted value of assets owned by the household is used in the second stage. Covariates in the regression ensure that instruments are as good as randomly assigned.

We first run the OLS with fixed and random effects (see Equation 1 and Equation 2). Linear OLS with fixed effects was separately executed for two models: consumption expenditure and adjusted consumption expenditure as the dependent variable. Both instruments were found to be insignificant, indicating that they do not directly influence the outcome variable. The Wu-Hausman test was done to test for endogeneity. The Wu-Hausman test chooses between least squares and the instrumental variable approaches(Semykina & Wooldridge, 2010).

Step 1: $Y_{it} = \alpha_o + \alpha_1 W_{it} + \alpha_2 Z_{it} + e_{it}$ (5)

Y_{it}= Variable suspected to be endogenous (in this model, Assets owned by the household)

W_{it} = Covariates

Z_{it}= Instrumental variable.

Equation 5 above is formulated to get the predicted value of assets to perform the Wu-Hausman test. The predicted value of the endogenous variable is used in the next equation, 6.

Step 2: $X_{it} = \alpha_o + \alpha_1 \hat{Y}_{it} + \alpha_2 W_{it}$ + Asset predict $+ e_{it}$ (6)

The t-test value of the asset-predict coefficient is significant, confirming the presence of residuals in endogenous regressor and two-stage least squares in preference to OLS.

Two-stage least square was administered using the *STATA17* user-written command '*IVREGHDFE'*(Correia, 2018). We use fixed effects, standard errors clustered at the village level and absorbed at the household level. The suffix ''absorb' in the command helps activate small non-constant and non-partial options to adjust small sample adjustments for fixed effects (Correia, 2018).

Thus, *IVREGHDFE* is an extended instrumental variable regression with multiple levels of fixed effects. This command drops singleton observations (with only one observation). In regression with fixed effects at multiple levels, singleton observations are very common, which may create bias in the estimates. The standard error provides robust and arbitrary heteroscedasticity and arbitrary intra-group correlation when clustered at the village level. Clustering specifies that the observations are independent across groups but not necessarily independent within the group.

Hansen J Statistics is used to test for over-identification. The null hypothesis (joint) states that the instruments are valid and uncorrelated with the error term, and excluded instruments are correctly excluded from the estimated equation(Schaffer & Stillman, 2016). The LM test is used for under-identification, which tests whether the equation is identified correctly. The excluded instruments need to be correlated with the endogenous variable. Under the null hypothesis, the equation is unidentified. Rejection of the null hypothesis means the model is identified(Baum et al., 2007). We test for instrument identification and verify that instruments (a) are not weak and (b) are valid (Stock & Yogo, 2005). For the validity of instruments, we require that the covariance between the instrument and the error term is zero. A good instrument should be strong and valid (Wooldridge, 2018)(for results, see Chapter 5)

We now discuss the specific equations estimated(for results, see Chapter 5).

Stage 1: IV 2 SLS: Model 1: Outcome variable: Consumption Expenditure.

$$\text{Assets\_predict}_{it} = \alpha_o + \alpha_1 X_{1it} + \alpha_2 X_{2it} + \alpha_3 X_{3it} + \ldots\ldots\ldots.. \alpha_{10} X_{10it} + e_{it} \qquad (7)$$

Asset Predict = Endogenous regressor.

X1 to X8= Covariates

X9= Instrumental variable- Natural disaster Intensity

X10= Instrumental variable- Confidence Intensity

Where e_{it} = stochastic error

Stage 2: IV 2SLS

$$Y_{it} = \gamma_0 + \gamma^* \text{ Assets\_predict}_{it} + \gamma_1{}^* X_{1it} + \gamma_2{}^* X_{2it} + \gamma_3{}^* X_{3it} + \gamma_4{}^* X_{4it} + \gamma_5{}^* X_{5it} + \gamma_6{}^* X_{6it} + \gamma_7{}^* X_{7it} + \gamma_8{}^* X_{8it} + \varepsilon_{it} \qquad (8)$$

Y_{it}= Consumption expenditure

Asset Predict= Asset predicted by the instrumental variable in stage I.

X_1= Conflict Intensity

X_2= Family size

X_3= Health Insurance

X_4= Highest adult education

$X_{5=}$ Membership intensity

X_6= Number of married females

X_7= Proportion of children

$X_{8=}$ Public project Intensity

Where ε_{it} = Stochastic error

In the first stage, the assets are predicted by natural disaster intensity and confidence intensity (see Equation 7). In the second stage, consumption expenditure is expected to be influenced by predicted assets (from stage I) (see Equation 8). Our model includes the following variables as the included exogenous covariates – family size, number of married women in the family, health insurance, the proportion of children in the household, highest adult education completed., and membership of village associations, Public project intensity (the number of public projects in the village), conflict intensity (presence of conflicts in the village).

We used two excluded instruments: Confidence intensity (confidence in government agencies) and natural disaster intensity. To justify the IV method, we need to demonstrate that the IVs do not directly affect the outcome but should influence it indirectly through the endogenous variable or treatment assignment, popularly known as the exclusion restriction. We also test for over-identification of instruments as the number of excluded instruments exceeds the number of endogenous regressors (Baum et al., 2003). The data used is household village-level panel data.

Model 2: Outcome variable: Adjusted consumption expenditure (adjusted for OOPHE) (see appendix A3 for equation). The covariates used are common for both models. These models also study the socioeconomic impact (caste and expenditure quintile) (See Chapter 5 for results).

3.4.3.3: Natural Disaster Model With The Difference In Differences (DID):

For several reasons, the DID model was chosen over the IV analysis in our study for the effect of natural disasters on household consumption. First, it is hard to argue that natural disasters also affect other omitted variables. Second, the weak instrument and over-identification tests do not test the exclusion restriction. Unfortunately, there exists no mechanism to test the exclusion restriction. We have tried to argue intuitively for excluding variables as an instrument. However, one is unsure in most instances about the instrument's validity. We have, therefore, also used the DID model to examine the impact of natural disasters on consumption expenditure and adjusted consumption expenditure.

DID is widely used in the literature to study natural disasters' impact. DID was used for the impact evaluation of the Chennai floods by using data from banks, supermarket sales and night lights among the households living in flood-affected areas and those not (Agarwal et al., 2021). DID was also used for studying the effect of Natural disasters on household expenditure in Indonesia using the Indonesian Family Life Survey between the affected households. The study used three types of monthly household expenditure: total household expenditure, educational expenditure, and food expenditure, along with two proxies: people killed and evacuated to the total population(Sulistyaningrum, 2016). The study of earthquakes in El-Salvador uses treatment intensity (ground shaking) and panel data from the BASIS (El-Salvador) Rural Household survey. Double DID was used to study earthquakes' impact on rural household income and poverty (Baez & Santos, 2008).

The following section provides a description of the methodology and the model used.

3.4.3.3.1: Village Level Data:

The village schedule covered a range of topics. We have used only two variables of interest for this study: the data on natural disasters and the number of public projects undertaken. For various types of disasters between 2006 to 2012, IHDS 2 recorded recall data (from the village head) at the village level(Desai & Vanneman, 2015). We could identify the villages (and, therefore, households Since the disaster information was only collected from rural households and not from urban areas, the scope of our study is limited to rural areas because there is no matching disaster information available for urban respondents. It was evident from the village data that some villages had repeated disasters and were impacted by multiple types of disasters from 2006. For our study, we created a variable Natural Disaster Intensity (NDI) (Israel & Briones, 2013). The number of disaster incidences reported in each village was added across the years to generate the NDI (namely, floods, drought, floods, cyclones, hailstorms, tsunamis, earthquakes, and epidemics).

The village head reports the natural disaster data recorded in IHDS. Many other studies have used data on natural disasters self-reported by households. Researchers have found this acceptable since most of the disasters are geospatially localised. For example, Edwards et al. (2021) used a longitudinal cohort study of children in the Philippines using self-reporting of disasters by households to establish a neighbourhood disaster exposure and community-level measure. However, there have been concerns about the objectivity of self-reported data.

One such concern is that it may be influenced by the economic and health status of the household apart from the issue of moral hazard. For households to consider an event a disaster, it would depend on their exposure to preparedness (ex-ante exposure) and capacity to deal with the aftermath (ex-post capacity). It also depends on the memory and perception of affected households (Karim, 2018). Households that experience labour or asset loss may over-report damages. Contrarily, households and neighbourhoods with good infrastructure are less likely to experience and report shocks (Nguyen et al., 2020). A recent study in the USA observed that less privileged social, economic and demographic groups are more likely to report extreme events (Zanocco et al., 2022). Therefore, subjectivity in reporting the effects of natural disasters is possible, which may create an endogeneity bias. Some studies have tackled the endogeneity problem by mapping household responses with third-party geographical data (Thomas et al., 2010). But, this is possible only if continuous longitudinal data is available at the level of the unit of observation. Since the IHDS survey did not ask any questions on monetary damages caused by natural disasters, the chances of over-reporting natural disasters are less likely.

The village questionnaire also provides information on the presence of public projects in any village. The presence of these programmes is an indicator of two situations. First, villages that are considered poor could be likely to have more public projects. Alternatively, villages with more economically and politically influential residents will corner more public projects. Either way, public projects' presence will influence a village's well-being and resilience (Arouri et al., 2015). IHDS 1 and IHDS 2 have collected information on implementing public programmes in villages (in the last five years preceding the survey). We constructed a variable that captured the extent of public programmes in a village by adding the number of such programmes. The constructed variable is called public project intensity. This variable captures multiple projects that may have benefited the household.

3.4.3.3.2: Household-Level Data:

Conventionally, household consumption expenditure has been used as an indicator of welfare (Offer, 2012). However, a growing literature points out that the component of medical expenditure needs to be adjusted from the aggregate consumption to understand the true level of food and non-food consumption for welfare purposes(Garg & Karan, 2009; Wagstaff & Doorslaer, 2003; Xu, 2005). If a household experiences a health shock that increases health expenditure would adversely affect welfare(Panikkassery, 2020). Households' capacity to pay is an important indicator of household well-being. Capacity to pay is the household's expenditure that remains after making payment for subsistence expenditure(Xu, 2005). In keeping with this literature(Ahmad & Aggarwal, 2017), we have used adjusted consumption expenditure to understand the impact of natural disasters on household well-being.

The adjusted consumption expenditure was derived by subtracting the total health expenditure (OOPHE) from the consumption expenditure.

3.4.3.3.3: Social Categories:

We expect that the impact of natural disasters would not be uniform across the population's different social and economic quintiles. In India, caste is considered an overarching social determinant (Mosse, 2018). We have followed this convention to examine the impact across different caste categories. Following the common administrative framework in India, our analysis has grouped the observations into four categories: general, other backward castes, scheduled caste, and scheduled tribes. IHDS collected information on village conflicts. We used this information to create a variable conflict intensity as an explanatory variable.

3.4.3.3.4: Economic Categories:

We created a variable ‘Poor’ as a dichotomous response variable (with those in the Below Poverty Line (BPL) group taking value one and those in the Above Poverty Line (APL) group taking value zero). As a next step, given the large range in consumption expenditure in the APL group, we divided it into five quintiles. BPL was added to give the sixth quintile (Choudhury et al., 2019; Hooda, 2015; Mehta, 2008). Using the consumption expenditure quintile to study natural disasters aligns with existing literature. For example, Arouri et al. (2015) used expenditure quintiles for Vietnam households, and Edwards et al.(2021) used income quintals to study natural disasters’ impact on Filipino households.

Some studies have used household assets to predict consumption in the study of natural disasters (Arouri et al., 2015; Brown et al., 2018). IHDS provides comparable household assets data across IHDS 1 and IHDS 2. We have used this variable as an explanatory variable.

Other socio-economic household characteristics we have adopted from the literature are the highest adult education in completed years, family size, Number of married females, and proportion of children. These variables are also used elsewhere in the literature for welfare studies (Muttarak & Lutz, 2014; Mynarska et al., 2015; Walugembe et al., 2019).

Among literature on natural disasters and their welfare impact, Caglayan & Astar (2012) have used marital status; Brown et al.(2018) have used the proportion of married females and the proportion of dependency; Arouri et al. (2015) household education and education at country level, is used by(Botzen et al., 2019).

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Households have been found to use both formal (health insurance) and informal mechanisms (self-insurance: running down of assets, reduction in food and education expenditure and labour substitution within the family)(Ajefu, 2017; Onisanwa & Olaniyan, 2019).

For our study, to make information compatible across IHDS 1 and IHDS 2, we created a binary variable health insurance that recorded whether a household had insurance. Households owning insurance is considered an important pre-disaster preparation factor (Botzen et al., 2019).

Human welfare is also known to be influenced by social networks (Calvó-Armengol & Jackson, 2004; Jackson, 2011), sometimes also referred to as social capital (Pena-López et al., 2021) and facilitated the accumulation of assets and faster recovery after disasters. These responses were summed to generate a variable aggregating each household's membership in various organisations.

Trust in public institutions has influenced individual welfare, especially consumption and asset allocation. If an economic agent (household or firm) perceives that the state will offer the security of assets, they are more likely to enhance investments (Janada & Teodoru, 2020; Vanlaer et al., 2020). The IHDS had a single question that captured information on confidence in ten public institutions, from police to schools. We added all these responses for our study to generate a confidence intensity index for each household.

3.4.3.3.5: DID Model:

The DID approach is the preferred model for programme evaluation when a randomised control study is impossible. DID works well when the existing data can be separated between groups that are exposed (or treated) and unexposed (or controlled) to a particular treatment (Wooldridge, 2018). The data for DID is required to be generated from a natural experiment (or quasi-experiment) akin to an exogenous event but needs to fulfil specific criteria (Wing et al., 2018):

a) The outcome did not determine the treatment.
b) Control and treatment groups would be similar if the intervention did not happen (parallel trends).
c) The composition of the groups is stable across waves.
d) There are no spill-over effects of the treatment across groups.

The advantage of the DID approach is that it eliminates two types of biases: (a) permanent differences between the two groups in the post-treatment period and (b) other causes that may influence trend outcomes in the treated group for inter-period comparisons (Callaway &Sant’Anna, 2021). If the treatment significantly impacts target variables, the DID model is expected to capture the additional change attributable to that intervention. In the full sample of observations, we treat natural disasters as a treatment that affects one group of people, not others. Natural disasters replicate a "natural program intervention" and are amenable to using DID (Mu & Chen, 2016).

Conventional DID models use treatment as a binary variable indicating whether a group received the treatment. We improve on this method by using treatment as a continuous variable as the NDI (treatment) in our data takes more than two values (0-18). The advantage of continuous treatment (over binary) is that we can see the differential effect of the intensity even among the treated households. For continuous treatment, we anticipate two effects (corresponding to the dose-response function): a level effect and a slope effect (Callaway & Sant'Anna, 2021). The level effect is like a binary response, while the slope effect captures the incremental change due to the increasing intensity of treatment (in this case, NDI).

The DID regression equation is represented below (Equation 9):

$$Y_{it}= \beta_0+\beta_1*Time_{it}+ \beta_2*Treatment_{it} + \beta_3*Time_{it}*Treatment_{it} + \beta_4*Covariates_{it}+\varepsilon_{it} \quad (9)$$

The intercept term measures the baseline average (β_0). The trend change in the control group is estimated by the slope of the trend line (β_1). The two groups may have differed before the treatment was offered, and β_2 measures this difference between the two groups at the start (pre-treatment). The additional change that the treated group experiences over the control group (after accounting for the trend increase) is measured by β_3. In addition, a vector of other factors (covariates) may affect the outcome variable. The vector of coefficients (β_4) captures their impact. The stochastic error term (ε_i) picks up unaccounted factors influencing the outcome (Y_i).

We use the DID model using panel data to generate estimates with household fixed effects. When used with fixed effects, the model controls for unobserved time-invariant household characteristics (Wooldridge, 2018). The panel data approach has numerous advantages. First, parameter estimates are more efficient, and second, problems of omitted variables and unobserved heterogeneity can be avoided (Hsiao, 2014) and allow us to examine the impacts of natural disasters on welfare while controlling for other factors influencing the outcome. The Average Treatment Effect measures the effect of the treatment on the treated group on the treated (ATET), which is the mean difference in the dependent variable between the controlled group and the treated group. The standard errors are robust and clustered at village level.

Our model includes the following variables as covariates taken from the literature to predict consumption – Caste (Deshpande, 2011; Mosse, 2018; Munshi & Rosenzweig, 2006), family size(Abolhallaje et al., 2013; Orbeta, 2005) and proportion of children(Pal, 2011), Education(Israel & Briones, 2013), number of married females in the household (Blake, 1989; Downey, 1995; Flake & Forste, 2006; Baez & Santos, 2008; Heshmati et al., 2019) presence of health insurance, membership intensity, public project intensity, conflict intensity (Okechukwu, 2017) and confidence intensity(Janada & Teodoru, 2020; Vanlaer et al., 2020).

We have used two models to examine the impact of NDI:(See Chapter 5 for results)

Model1: Outcome variable: Consumption expenditure (See Equation 10)

Model 2: Outcome variable: Adjusted Consumption expenditure (See Appendix A3 for Equations)

The expanded DID equation used in our study is as below (See Equation 10):

$$Y_{it}= \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it} + \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + \varepsilon_{it} \tag{10}$$

where,

Y = Consumption expenditure

X_1= Year

X_2 = Natural Disaster Intensity

X_3 = Year * Natural Disaster Intensity

X_4=Assets

X_5= Caste

X_6= Conflict Intensity

X_7= Health insurance

X_8= Highest adult education in completed years

X_9= Membership Intensity

X_{10}= Number of married females in the household

X_{11}= Number of persons in the household

X_{12}= Proportion of children in the household
X_{13}= Public Project Intensity

X_{14}= Confidence intensity

ε_{it}=The stochastic error term

3.4.4: Health Insurance Model With DID:

Health insurance has been used as a critical input for measuring the impact of health policy in many developing countries in recent years(Thuong et al., 2020). One of the popular methods for studying impact evaluation is DID, which is more popularly used to study the impact of policy intervention in randomised controlled trials and observational studies (Dor & Umapathi, 2014). In its simplest form, DID has two time periods and two groups. The two time periods are used to see a policy change. In the initial period, no group receives any intervention or treatment; in the next period, some receive the treatment, and some are untreated. If no one received treatment over time, the average outcome for all observations follows a parallel path (assumption of parallel trend). Due to exposure to treatment, the treated group is expected to have a different outcome than the controlled group. The average treatment effect on the treated group can be studied by analysing the average change in outcome between the exposed and controlled groups (Callaway & Sant'Anna, 2021).

DID is used traditionally in RCT, but in social sciences, it is also used in observational studies(Gebel & Voßemer, 2014). DID has been used to study the effect of the one-child policy on the sex ratio imbalance in China (Li et al., 2011); high-stakes testing, gender, and school Stress in Europe(Högberg & Horn, 2022); Causal effects of Covid-19 policies (Goodman-Bacon & Marcus, 2020); the impact of re-centralisation on public services

(Malesky et al., 2014)as well as to study the impact of health insurance(Azam, 2018; Selvaraj & Karan, 2012).

We study the causal effect of health insurance on household well-being using DID. Some studies have used DID with health insurance as a treatment to study its impact on various outcome variables. Health insurance reforms in China were studied using DID with the utilisation of inpatient services as an outcome variable(Zhang, 2007). Vietnam, a health insurance scheme for people with low incomes (children below six years) was used as a treatment in DID to study the impact on health service utilisation and the impact on younger children was increased inpatient services(Guindon, 2014). Vietnam used impact analysis with DID using voluntary health insurance and govt health insurance on health care utilisation and OOPHE(Thuong et al., 2020). In Indonesia, the impact of government health insurance was examined using DID on health care utilisation (Erlangga et al., 2019). The impact of publicly sponsored health insurance in Vietnam led to a reduction of OOPE in a DID study (Wagstaff, 2010).In China, Using health insurance with DID exhibited that it improved health outcomes and healthcare utilisation(He & Nolen, 2019). In Columbia, using the DID public health insurance program was evaluated, which helped poor households to increase health care utilisation(Trujillo et al., 2005). China's integrated health insurance schemes were studied using DID for equity and healthcare utilisation, and the results supported the policy that an integrated scheme of health insurance (against fragmented) leads to improvement in utilisation and equity in healthcare (Li et al., 2019). This chapter uses health insurance as an impact variable on the outcome variable consumption expenditure. The next section justifies for type of treatment.

3.4.4.1: Treatment: Continuous And Binary:

Conventional DID models use treatment as a binary variable indicating whether a group received the treatment. We improve this method by using treatment as a continuous variable, as the public-funded health insurance intensity (treatment) takes more than two values. The advantage of continuous treatment (over binary) is that we can see the differential effect of the intensity even among the treated household. For continuous treatment, we anticipate two effects (corresponding to the dose-response function): a level effect and a slope effect (Callaway & Sant'Anna, 2021). The level effect is like a binary response, while the slope effect captures the incremental change due to the increasing intensity of the treatment.

The panel data allowed us to examine the impacts of health insurance on household well-being while controlling for other factors influencing the outcome. We have examined two types of health insurance: a) Publicly Funded Health Insurance (PFHI) and b) Voluntarily purchased health insurance (VPHI). The Average Treatment Effect measures the effect of the treatment on the treated group on the treated (ATET), which is the mean difference between the controlled and treated groups.

We use two treatments. The first type of treatment is a continuous treatment where the control variable is all those households with no health insurance (control variable) and households with either RSBY or government health insurance (treatment; those households with both RSBY and government health insurance (treatment. This continuous treatment variable is Publicly funded health insurance intensity (PFHII). It measures the intensity of the health insurance by measuring the difference in outcome variables among households with no health insurance and those with one or both.

We have used seven models with the following outcome variables to examine the impact of health insurance with continuous treatment (PFHII) (see Chapter 7 for results). See equation 9, presented in the earlier section, for the basic DID regression.

a) **Model 1**: Outcome variable- Monthly consumption expenditure (MCEPC)

b) **Model 2**: Outcome variable-Monthly adjusted consumption expenditure(same as non-health expenditure) (MCEPCHE)

c) **Model 3**: Outcome variable- Monthly food expenditure (MFEPC)

d) **Model 4**: Outcome variable -Monthly non-food expenditure (MNFEPC)

e) **Model 5**: Outcome variable- Household's capacity to pay (HHCTP)

f) **Model 6**: Outcome variable - Monthly inpatient expenditure (MIP)

g) **Model 7**: Outcome variable: Monthly outpatient expenditure (MOP)

All these seven models are examined for those households that incurred health expenditure and catastrophic health expenditures at 10% and 40% thresholds. The analysis is also done for socio-economic categories of caste and consumption expenditure quintile. This impact evaluation of health insurance was done for household-village panel data.

The second type of treatment is the binary treatment of VPHI. The control variable is those not having insurance, and the treatment variable is those with only private insurance.

We have used two different models with the following outcome variables to examine the impact of health insurance with binary treatment (VPHI):

a) Monthly consumption expenditure per capita (MCEPC)

b) Monthly consumption per capita adjusted for health expenditure (MCEPCHE)

The covariates used in all models are the same as given below:

a) Confidence in institutions/ governance intensity

b) Developed Village

c) Family size

d) Highest adult education

e) Household Ownership of Assets

f) Public project intensity

g) Membership (in various organisations) intensity

h) Number of married females in the household

i) Conflict intensity

j) Proportion of children

k) Village Health Infrastructure Index

3.4.4.2: Model 1: Publicly Funded Health Insurance And Continuous Treatment:

3.4.4.2.1: Economic Status Of The Household:

Consumption expenditure MCEPC and consumption expenditure adjusted for health expenditure (non-health expenditure) (MCEPCHE) are used to examine the impact of health insurance on household well-being. Some studies have used this (Ahmad & Aggarwal, 2017; Panikkassery, 2020). Quintiles of MCEPC and MCEPCHE are used to study the impact. The health expenditures that households incur, which are catastrophic, often compel them to compromise their food or non-food expenditures. Poor households' share of food expenditure is much larger, but consumption smoothening for food expenditure is done by non-smoothening of non-food expenditure(Onisanwa & Olaniyan, 2019; Panikkassery, 2020).

Health expenditure impacts household consumption expenditure(Panikkassery, 2020). Health shock households receive due to health expenditure is often responsible for reducing welfare. The most widely used approach for examining the impact of health expenditure on household expenditure is to measure whether the health expenditure is catastrophic. When households spend a certain proportion of their consumption expenditure on health expenditure, it can reach a level where they may be forced to sacrifice their other consumption needs. O'Donnell et al.(2005)used 10% or more of total household expenditure as a threshold level to determine the nature of health expenditure as catastrophic or not. Xu (2005) used 40% or more of a household's expenditure adjusted for subsistence expenditure, which is the household's capacity to pay (HHCTP). The studies that have used these threshold levels at 10% are Kastor & Mohanty (2018), Mondal et al. (2010), Sahoo & Madheswaran(2014), Ghosh (2014), and Panikkassery (2020). Ahmad & Aggarwal (2017) used all thresholds from 5%, 10%, 15%, 20%, 25%, and 30%. Some studies have used total household expenditure as a measure of capacity to pay and used a 10% threshold level (Ahmed et al., 2022). We have used a threshold of 10% or more of non-health expenditure to calculate catastrophic health expenditure, as Wagstaff (2005) suggested. We have used Xu's (2005)methodology for measuring the household's capacity to pay (HHCTP) 40% or more as a threshold to calculate catastrophic expenditure (see Chapter 3 for details).

We have used the non-monetary measure of household assets as provided by IHDS, comparable across both rounds and used elsewhere in the literature(Ahmad & Aggarwal, 2017; Panikkassery, 2020).

3.4.4.2.2: Health Status Of The Household:

When households face health shock, they use different coping mechanisms. These shocks compel households to postpone health treatment/ expenditure (Onisanwa & Olaniyan, 2019). When health shock disturbs household expenditure, it smoothens the consumption expenditure. This smoothening process reveals considerable information about the coping mechanisms used by the households. Household uses both formal (health insurance) and informal mechanisms (self-insurance: running down of assets, reduction in food and education expenditure and labour substitution within the family) (Ajefu, 2017; Onisanwa & Olaniyan, 2019). We considered information about PFHII, which often impacts adjusted consumption expenditure levels(Wagstaff & Pradhan, 2003).

We have used continuous and binary treatment that adjusts estimates for covariates, panel effects, and time effects for average treatment on treated. Further, we have used the plot of group means over the years, drawn using three groups of MCEPCHE of PFHII. We did this since using parallel trends was beyond the scope of continuous treatment and without data on an additional round.

3.4.4.2.3: Village Development:

Developed village: A village was categorised as more developed or less developed. Less developed villages had high OOPHE(Bhattacharjee & Mohanty, 2022).

Human welfare is also known to be influenced by social networks (Calvó-Armengol & Jackson, 2004; Jackson, 2011), sometimes also referred to as social capital (Pena-López et al., 2021) and considered as an independent variable contributing to the health situation of household(Donfouet & Mahieu, 2012) and facilitates the accumulation of assets and faster recovery after any shock. Membership in various formal and informal institutions also affects consumption expenditure(Dehejia et al., 2007; Hassan & Birungi, 2011). Using the responses generated on membership to various organisations and political activities for each household, it captures membership to more than one organisation.

The village health infrastructure index (VHII) is constructed using Principal component analysis (see Chapter 8 for details). Functional PHC showed a greater association with better access to treatment (George et al., 2021).

3.4.4.2.4: Social Categories:

It is expected that the impact of PFHII would not be uniform across the population's different social and economic quintiles. In India, caste is considered an overarching social determinant (Mosse, 2018). We have followed this convention to examine the impact across different caste categories. Some caste groups are socially excluded in India(George et al., 2021). Forward-caste families may suffer from socioeconomic disadvantages due to social class or caste (Desai, 2010).

Conflicts in a village have multiple impacts – apart from the personal loss of lives and properties, it also affects the village community (Ostrom, 1990). Variable conflict intensity is created as an explanatory variable.

Social factors conditioning the household, including the highest adult education in completed years, family size, number of married females, and proportion of children, are also used. These variables are also used elsewhere in the literature for welfare studies (Abolhallaje et al., 2013; Ahmad & Aggarwal, 2017; George et al., 2021; Kastor & Mohanty, 2018; Muttarak & Lutz, 2014; Mynarska et al., 2015; O'Donnell et al., 2005; Pal, 2009; Panikkassery, 2020; Wagstaff & Pradhan,2005; Walugembe, Wamala, & Misinde, 2019; Xu, 2005) among other studies.

Implementing the project at the village level and confidence in the government covers political and bureaucratic intentions. The presence of public programmes is an indicator of two situations. First, villages that are considered poor may be likely to have more public projects. Alternatively, villages with more economically and politically influential residents will corner more public projects. Implementing the public project increased consumption expenditure(Deresse & Calfat, 2021). Either way, public projects' presence will influence a village's well-being and resilience (Arouri et al., 2015). In any village/ district, the average number of schemes already implemented reflects bureaucratic efficiency, Political affiliation of state government with the centre, and corruption, which reflects households' confidence in the government machinery(Nandi et al., 2013). Good governance helps with accountability and transparency(Ijaiya et al., 2011).
Public institutions have influenced individual welfare, especially consumption and asset allocation behaviour. If an economic agent (household or firm) perceives that the state will offer the security of assets, they are more likely to enhance investments (Janada & Teodoru, 2020; Vanlaer et al., 2020). We constructed a variable that captured the extent of public project implementation in the village public project intensity (see earlier sections for details).

We constructed confidence intensity for each household. A study in India used confidence in government hospitals and helped reduce OOPHE (Bhattacharjee & Mohanty, 2022).

3.4.4.2.5: Model 1 Expanded Did Equation:

The expanded DID equation used in our study (see equation 11):

$$Y_i = \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it}+ \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + \varepsilon_{it} \quad (11)$$

Where,

Y = Consumption expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4= Confidence in institutions/ governance intensity

X_5= Developed Village

X_6= Family size

X_7= Highest adult education

X_8= Household Ownership of Assets

X_9= Public projects intensity

X_{10}= Membership Intensity

X_{11}= Number of married females in the household

X_{12}= Conflict intensity

X_{13}= Proportion of children

X_{14}= Village Health Infrastructure Index

ε_i=The stochastic error term

3.4.4.3 Model 2: Voluntary Private Health Insurance And Binary Treatment:

Model 2: We have used the binary treatment here. The treatment is voluntarily purchased health insurance. Voluntarily purchased health insurance:(VPHI) IHDS 2 has information on voluntarily purchased health insurance by the households, which was constructed as a dummy variable. Binary treatment was used in the DID with VPHI and those who did not purchase any insurance. The variable VPHII was constructed only for those who purchased private health insurance. Those who had government insurance and RSBY were excluded from those who did not have any insurance. The covariates used in the model of PFHII were also retained in this model.

3.4.4.3.1: Binary Treatment Model: Expanded Did Equation:

The DID binary treatment model specification is given(See equation 12)

$Y_i= \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it}+ \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + + \varepsilon_{it}$

(12)

where

Y = Consumption expenditure

X_1= Year

X_2 =Voluntarily Purchased health insurance intensity VPHII

X_3 = Year * VPHII

X_4= Confidence in institutions/ governance intensity

X_5= Developed Village

X_6= Family size

X_7= Highest adult education

X_8= Household Ownership of Assets

X_9= Implementation of public projects intensity

X_{10}= Membership(to various organisations) Intensity

X_{11}= Number of married females in the household

X_{12}= Conflict intensity

X_{13}= Proportion of children

X_{14}= Village Health Infrastructure Index

ε_i=The stochastic error term

3.4.4.4: Health Insurance And The Issue Of Endogeneity And Self-Selection:

The health insurance variable has possible issues of endogeneity and self-selection. We provide the following argument in support of this. Since 2005, health insurance was less prevalent, and there was no additional information about the type of health insurance, mostly provided by the government. We assume it was exogenous (Sahoo & Madheshwaran, 2014). State and government-funded health insurance were mandatory; hence, the households had no choice, which rules out the issue of self-selection. Regarding RSBY, the households living below the poverty line and a few other categories were eligible, but the enrolment would happen if households were willing to do so(Bahuguna et al., 2019).

IHDS 2 provided information about private health insurance, government health insurance and household enrolment in RSBY. We have included govt insurance and RSBY. RSBY had a two-step process for beneficiaries. The two-step process involved the identification of eligible beneficiaries and enrolment. Not all eligible beneficiaries had enrolled themselves. Self-selection may not happen, making it exogenous and suitable for observational studies & impact evaluation. Azam (2017) used DID to mitigate the self-selection bias in the impact evaluation of health insurance and used propensity score matching and binary treatment of health insurance. We have used health insurance as a continuous treatment by combining government insurance and RSBY. By doing this, we wanted to examine the impact on households MCEPCHE when households have no insurance, any one type of health insurance and both types of health insurance. The reason that prompted us to do so was that some states had RSBY exclusively, but some states, along with RSBY, had their state-funded health insurance scheme. In Karnataka, RSBY covered secondary sector inpatient treatment, whereas the Yashsaswini scheme covered Tertiary sector treatment and Vajpayee Arogyahsree. There was also ESIS and CGHS, which covered inpatient and outpatient treatment costs. RSBY coverage was limited to inpatient treatment in secondary care (Selvaraj & Karan, 2012). There was an overlap of schemes.

3.4.5: Health Expenditure:

The following section presents the methodology used in calculating catastrophic health expenditure.

3.4.5.1: Catastrophic Health Expenditure:

Health expenditure incurred by households can have catastrophic and impoverishment effects. (Xu, 2004). When households incur expenditures / make payments to access health care, payments not covered by financial protection are termed out-of-pocket health expenditures (OOPHE). OOPHE is a part of the consumption expenditure of households. The consumption expenditure includes food expenditure, and the amount spent on purchasing food is the household's bare minimum expenditure to meet minimum requirements. It includes home-grown produce value but excludes expenditure on alcohol and tobacco. We calculate a household's capacity to pay using the methodology by Xu (2003).

Using the following methodology, we construct the variable POOR using the poverty line given in the IHDS survey.

The poverty line (absolute) defines subsistence spending. Xu (2003) has used a poverty line based on food expenditure to calculate subsistence expenditure.

1. For defining poor (using the poverty line)

$$\mathbf{Poor_h=1 \text{ if } ce_h< sh_h} \qquad (13)$$

$$\mathbf{Poor_h=0 \text{ if } ce_h\geq sh_h} \qquad (14)$$

Where $Poor_h$ = those who are poor (poor before ma),

ce_h = Consumption expenditure of the household

sh_h=Poverty line.

2. We calculate households' capacity to pay (CP). CP equals households' income after adjusting subsistence expenditure (defined by the poverty line). There are households whose food expenditure is lower than the subsistence spending (poverty line in this case). Non-food expenditure is used as non-subsistence spending.

$$\mathbf{cp_h=ce_h-sh_h \quad \text{if } sh_h\leq fe_h} \qquad (15)$$

$$\mathbf{cp_h=ce_h- fe_h \quad \text{if } \quad sh_h >fe_h} \qquad (16)$$

where cp_h= Capacity to pay is the difference between households' total expenditure and the poverty line. In households whose food expenditure is below the poverty line, capacity to pay is calculated as the difference between households' total expenditure and food expenditure.

3. We calculate OOPHE as a share of household capacity to pay:

OOP_h is the difference between total household and medical expenditures (health insurance reimbursement adjusted, if any). The share of OOPHE to capacity to pay is calculated as OOPHE divided by the capacity to pay.

$$\mathbf{OOPHEshare_h = OOP_h / CP_{hi}} \qquad (17)$$

4. We present the methodology for calculating catastrophic health expenditure. It should be noted that every expenditure incurred by the household is not catastrophic. The health expenditure to access health care is catastrophic when it exceeds or is equal to 40 % of households' non-subsistence spending(cp_h). The binary variable 'Oopcat' is created as follows.

$$\mathbf{Oopcat_h = 1 \text{ if } Oopeshare_h \geq 0.4} \qquad (18)$$

$$\mathbf{Oopcat_h = 0 \text{ if } Oopeshare_h < 0.4} \qquad (19)$$

Those households that incur catastrophic expenditures also run the risk of becoming impoverished. Suppose they were not poor before incurring health expenditure but became poor after it and are said to be experiencing the impoverishment effect of health expenditure. The binary variable is calculated as impoverished if household consumption expenditure is greater than the poverty line (before incurring health expenditure) and if household consumption expenditure after out-of-pocket health expenditure is less than the poverty line.

$$\mathbf{Impov_h = 1 \text{ if } ce_h \geq sh_h \text{ And } ce_h - oop_h < sh_h} \qquad (20)$$

$$\mathbf{Impov_h = 0 \text{ if } ce_h \geq sh_h \text{ And } ce_h - oop_h > sh_h} \qquad (21)$$

Catastrophic health expenditure and impoverishment are calculated using household Individual panel data for rural and urban.

3.4.5.2: Alternate Methodology By Wagstaff And Van Doorlsaer(2003):

Wagstaff &Doorslaer (2003) proposed an approach to evaluate health expenditure from an equity angle. The argument is as follows. When households incur payments to avail of the health care facility, this should not be more than a pre-fixed proportion of household income (expenditure), and once the household makes such a payment, this payment should not push the household into poverty. These two concepts are meant to capture the impact of poverty at two levels: intensity and incidence.

Households' payment for accessing health care should not exceed a certain predefined fraction of their income. Let that pre-defined fraction be '$\boldsymbol{k}$' such that $0 \leq \boldsymbol{k} \leq 1$. Any household spending more than '$\boldsymbol{k}$'is termed catastrophic. Households incur expenditures on food and non-food. After making health care payments, households should be left with some income to be spent on other needs, i.e. '**1-$\boldsymbol{k}$'.**

There are two methods of calculating the proportion of health expenditure:

a) The health expenditure ***HE*** can be calculated as a proportion of total income(before making payment for health expenditure) as ***CE*(** Consumption expenditure per capita)(see equation 23)

b) The health expenditure can be calculated as the ability to pay, a deduction of food expenditure and other necessary expenditures made from total household income ***CE***. Let such deductions be ***l(CE).*** We calculate adjusted consumption expenditure (see equation 22) and calculate the proportion of health expenditure as a proportion of adjusted consumption expenditure (see equation 24)

$$AdjCE = CE - l(CE) \qquad (22)$$

Where ***AdjCE***is the household income remaining after making adjustments for food and other necessary expenditure; ***CE*** households consumption expenditure per capita; ***l(CE)*** is food and necessary expenditure.

The definition of ***l(CE)*** is crucial. Food expenditure can be covered based on actual expenditure or fixed allowance regardless of actual expenditure. The issue arises when a fixed allowance is considered and when the income of households is less than the fixed allowance. In that case, ***AdjCE*** can become zero or negative.

$HE/CE=$ (23)

$HE/AdjCE$ (24)

$$HH_{cat}=\frac{1}{N}\sum_{i=1}^{n} P_i = \beta_P \quad (25)$$

'HH_{cat}'is a fraction of households whose health care payment as a proportion of total household income was more than 'K'. This measure gives us the proportion of households that have incurred catastrophic expenditures.

Catastrophic expenditure headcount: Let 'OS_i' be the catastrophic overshoot equal to '$HE_i/CE_i - K$ OR $HE_i/AdjCE_i - K$ if $HE_i/CE_i > K$' and '0' otherwise. Let '$P_i = 1$ if $O_i > 0$'. Equation 25 is obtained. In equation 25, N is the sample size of households, and 'β_P' is themean of 'PI'.

Catastrophic expenditure gap: In measuring poverty, it is pertinent to calculate how much households have become poor(similar to the poverty gap). This gap is called a catastrophic expenditure gap.

$$CEG_{cat}=\frac{1}{N}\sum_{i=1}^{n} OS_i = \beta_{os} \quad (26)$$

In equation 26, 'β_{os}' is the mean of OS_i

$$MG_{cat}= \sum_{i=1}^{n} OS_i / \sum_{i=1}^{n} P_i = \beta_P / \beta_{os} \quad (27)$$

$$\beta_P = \beta_{os} . MG_{cat} \quad (28)$$

Equation 27 gives the overall average catastrophic gap equals a fraction with a positive gap multiplied by a mean positive gap.

To calculate catastrophic health expenditure, we use two threshold levels as given in the literature.

a) Threshold level of 10% of total household expenditure

b) Threshold level of 40% for household ability to pay.

The results from using both these methodologies are given in chapter 6. We have used a household individual merged panel.

3.4.6:Principal Component Analysis (PCA):

Large data sets have a few hundred to thousands of variables. Analysing all those variables may not be feasible. At the same time, it is important to make meaningful interpretations from such large data sets. There are many techniques: descriptive multivariate technique, cluster analysis, factor analysis, multivariate analysis of variance (MANOVA), discriminant analysis, canonical correlation analysis, and multidimensional scaling (Rencher, 2005). Cluster analysis and PCA are the two most popular multivariate techniques used to construct the index (Dohoo et al., 1997). In large surveys, several variables measure many aspects of one large issue. PCA is a statistical technique used to examine the interrelationship among the given variables to identify the underlying structure of those variables(Daffertshofer et al., 2004).PCA helps reduce many variables that are related to each other into unrelated components while preserving the original information in the data (Jolliffe, 2022; Jolliffe, 1987, 1989, 1989, 1990, 1995, 2003; Jolliffe & Cadima, 2016; Karamizadeh et al., 2013).

The earliest work on PCA was provided by Thurstone (1947) by giving five criteria for understanding the simple structure. PCA is a transformation method by linking two vector spaces of different dimensions. It follows the standardised linear combination of uncorrelated original variables (Armeanu & Lache, 2008). PCA is an artificially constructed index that captures the overall coverage of any policy intervention. Often, multiple variables with overlapping outcomes are used to capture the impact of the intervention. PCA constructs an artificial index by using all the relevant and highly correlated variables and converts them into a few basic uncorrelated indicators. These indicators are later summed into the overall index.

This study uses PCA to construct the Village Health Infrastructure Index (VHII) to assess the National Health Rural Mission (NRHM) launched in 2005. The focus of NRHM was to initiate health and health-related infrastructure development in rural areas, and the timing of the IHDS 1 matched with the initiation of NRHM.IHDS 2 conducted seven years after the implementation provided a checkpoint to assess the availability of health infrastructure between 2005 and 2012 and the impact of NRHM. The rationale for using PCA was to capture the changes in many variables by compressing them into fewer variables that measured the health infrastructure between 2005 and 2012.

The new variable is formed to capture the information that may be latent in the original variables and is called the principal component(Bro & Smilde, 2014). PCA reduces dimensionality(Jolliffe, 1987) and is best considered an empirical summary method(Vyas & Kumaranayake, 2006).

PCA technique is used in varied subjects ranging from social science(Hooda, 2015; Jehu-Appiah et al., 2011; Krzyśko et al., 2023) and science(Demšar et al., 2013; Tzeng & Berns, 2005) to medicine(Nandi et al., 2015).PCA is called the 'Hotelling transform or Karhunen-Leove(KL) method'(Kishk et al., 2011). The PCA and factor analysis are multivariate techniques for extracting causal structures based on information redundancy(Reuben & Torsen, 2015).PCA and factor analysis techniques are the same, but there are differences in assumptions and the output generated from the technique. Factor analysis assumes that latent variables exert some causal influence on an observed variable. PCA has no such assumption but is just a method for information redundancy. In factor analysis, the components are correlated to each other. The new components formed in PCA are orthogonal(Paul et al., 2013).

PCA is adopted when the original variables have a high standard deviation and a very high correlation, as it reduces information redundancy. Such variables are eligible for PCA. Thus, PCA is a linear combination of optimally weighted observed variables in the given data set. It is a linear combination because scores on a component area are created by adding scores on the observed variables. The components created by PCA account for the maximum amount of variance in the data set and are optimally weighted.

3.4.6.1: Empirical Applications And Limitations Of PCA:

Some of the applications of PCA are found in the literature(Armeanu & Lache, 2008; Dehury & Mohanty, 2017; Friesen et al., 2016; Goel & Garg, 2018; Hati & Majumder, 2013; Kumar, 2022; Leegwater et al., 2015; Lyngdoh, 2015; Mazziotta & Pareto, 2019; Oyekale, 2017; Redfern & McLean, 2014; Vincent & Sutherland,2013; Vyas & Kumaranayake, 2006). Some unconventional uses of PCA were to construct an index of exposure, vulnerability, and the economy's resilience to epidemics(Noy 2019).

There are some known concerns in using PCA(Abeyasekera,2005; Howe et al., 2008; Lever et al., 2017), and the number of original variables that can be added is based on the researcher's judgement. Flattening the basic information may lead to a myopic reading of reality. Ideally, choosing the set of individual indicators should be linked with a theoretical framework (Mazziotta& Pareto, 2013).

3.4.6.2: Construction Of Index Using PCA In This Study:

We have used variables from individual and village schedules of IHDS to construct PCA indices for this study. These variables reflect the availability of public health infrastructure and other medical infrastructure in rural areas. The data suggest that private health facilities supplement public health facilities in many areas. We created four independent indices measuring the use and availability of public health facilities in the village and nearby villages. The index measures:

a) Advice and treatment obtained from public medical facilities.
b) The availability of public medical facilities available in the village.
c) Accessibility to transportation.
d) Accessibility to a public medical facility nearby.

We use the merged data sets comprising individuals and villages in both IHDS 1 and IHDS 2 rounds. The variables that capture the health facilities in the villages, health infrastructure and the other infrastructure that facilitates the use of health facilities in the villages, towns and districts nearby are recorded in the survey. However, variables are also correlated with each other. Therefore, it is prudent to reduce these variables to fewer variables and capture as many variations as possible in data. Since these variables measure dimensions related to health, intuitively, it would be meaningful to reduce the dimensionality of these variables by constructing an index(Table 103, Chapter 8).

We now present the steps used in the construction of the index. Unless specified otherwise, all the steps mentioned below for PCA are used/compiled from the STATA17 manual on PCA and PCA post-estimation.

The following steps were followed:

Step 1:

The variables that measure related aspects, like health infrastructure, were chosen manually. The common variables from IHDS 1 and IHDS 2 were chosen from individual and village schedules. All these variables were first treated for missing values by replacing the missing value with zero if not assigned a number, which is a common practice. Since the minimum sample size required is 100 or more, IHDS data exceeds this.

Step 2:

Pairwise correlation estimation is done to check whether variables correlate. The chosen variables should be correlated since PCA is a multivariate reduction technique.

Step 3:

It is common for continuous variables to carry more weightage (like variable Distance to the nearest district hospital from the IHDS ranges from 1km to 200 km). PCA technique would attach the distance more weightage than variables with less variation. Some varibale need rescaling(Xiaoli et al., 2010; Yoon, 2012;). Therefore, all variables used in PCA are re-scaled to have equal variance. The Z score standardisation obtains zero mean and one standard deviation. The variables are standardized so that the mean and variance are the same. Standardization prevents bias by not allowing the variables with very high ranges to override the ones with low ranges(Tarquinio et al., 2020). This step is very critical in PCA.

Step 4:

Transformed data**:** If the data have been transformed using normalization, percentiles, or mean-zero standardization (i.e., Z-scores) so that the range and scale of all the continuous variables are the same, then one could use the covariance matrix without any problems. However, these transformations will not remove skewness, and PCA analysis does not involve the removal of skewness.

By default, *STATA* uses a correlation matrix without a subcommand. A correlation matrix will standardise the data, but the mean and standard deviation will not be 0 and 1, respectively. However, it is considered a brutal way of data standardisation. If the index is used in regression, it requires standardisation (Alaba & Chola, 2014; Sauro & Kindlund, 2005).

A covariance matrix (without standardising data) will condition the results to lean towards the variables with higher variance. Thus, the covariance matrix is used when variable scales are the same, and a correlation matrix is used when scales are different for variables. The covariance matrix of standardised data is the correlation matrix of the original dataset. The correlation matrix is invariant to linear changes in units of measurement, and STATA uses it by default. Further, when the *STATA* command of PCA is used with the sub-command '*predict'*, the index results are centred at zero. The variance of each component is equal to the corresponding eigenvalue.

Step 5:

PCA can be constructed when there is sufficient correlation between original variables.

For the PCA command to run, it is necessary to run the Kaiser-Meyer-Olkin Measure of Sampling Adequacy (KMO) and Bartlett's test of sphericity (BTS). The first test (user-written command: “factor test”) gives composite results for determinants of the correlation matrix, BTS(chi-square, degrees of freedom, and P- value). KMO and Bartlett's test must be carried out to determine whether variables can undergo PCA. These tests evaluate the variance proportion among the variables. KMO is a measure of sampling adequacy employed to detect multicollinearity. KMO uses correlations and partial correlations to determine whether variables can be manipulated into components. The observed correlation magnitude is compared to partial correlation coefficients. The logic here is that when the variables have common factors, the value of the partial correlation coefficient will be small compared to the total correlation coefficient. BTS sets the null hypothesis as variables used are not correlated in the correlation matrix, or it is the identity matrix (meant to be rejected)(Xiaoli et al.2010).

BTS compares the correlation matrix from the given sample to the identity. The identity matrix displays a coefficient of 1 along the diagonal, and the rest of the values are zero, implying that the variable is related only to itself and is perfectly orthogonal and, hence, cannot be used in PCA. BTS tests the null hypothesis that variables are orthogonal. If the test suggests that the correlation matrix of variables is significantly different from the identity matrix, then it can be used in PCA. The p-value of BTS should be lower than the chosen significance level for data to be suitable for reducing data dimensionality.

The null hypothesis is that variables are orthogonal, and the alternate hypothesis is that variables are not orthogonal (or the correlation matrix diverges significantly from the identity matrix). BTS is performed before using data reduction techniques like PCA or factor analysis. The BTS and KMO test displays three types of results, and this test needs to be performed strictly before running the PCA analysis.BTS calculates the determinants of the matrix. The matrix is the sum of products and cross-products from which the intercorrelations matrix is derived. The determinant of the matrix is converted to a chi-square statistic and tested for significance. BTS test results also should be significant (Rasheed & Abadi, 2014).

The KMO measure of sampling adequacy is an index for comparing the magnitudes of the observed correlation coefficients to the magnitude of the partial correlation coefficients. A large value of KMO implies that the data is suitable for PCA. The values of KMO can be interpreted as follows: KMO 90 or above means excellent, 80 or above is meritorious, 70 or above is middling, 60 or above is mediocre, 50 or above is miserable, and below 50 is unacceptable (Xiaol et al., 2010).

KMO below 0.50 will not give desirable results (Deyasi et al., 2020). However, the literature indicates that principal component analysis is appropriate when KMO statistics are higher than 0.5 in social sciences (Ma, 2021). Hair et al. (2006) used a KMO value > 0.5); Dziuban & Shirkey (1974) set the cut-off at 0.5 for KMO. Goel & Garg (2018) used a KMO of 0.46, approximated to 0.50; Carillo et al. (2010) used a KMO value 0.645.

PCA method has a few assumptions that need to be fulfilled.The assumption of multivariate normality since PCA generates components independent among the correlated given variables. For the components to be independent and uncorrelated, the assumption of multivariate normality must be fulfilled(Kim & Kim, 2012). Although multivariate normality is one of the assumptions, it is not critical since the PCA technique is not guided by p-value. PCA is a geometrical technique; therefore, the statistical hypothesis may not do much. The PCA was conducted assuming multivariate normality. The application of PCA does not require multivariate normal assumption (Hongtao et al., 2003).

Step 6:

Initial components extraction: Once BTS is done and the assumptions are fulfilled, the PCA commands are run.PCA command, by default, displays initial components equal to the number of variables using the coefficient of the correlation matrix.

The first component will account for the maximum variance in the observed variables and will be correlated with a few variables among the chosen ones processed for PCA. The second component extracted will have two important characteristics: This component will account for the maximum amount of variance not captured by the first component and will be correlated with a few more variables but not with the variables from the first component. The first component and the second component will be orthogonal. The correlation coefficient will be zero between the first and second components. The remaining components will also display Factor loadings with eigenvalues. However, the initial components will show maximum variation. Each new component will account for progressively smaller and smaller amounts of variance, and all the components will be orthogonal. By default, the results display as many components as variables and two types of table results. Typically, two results are displayed when the initial principal component command is run in *STATA*(Allee et al., 2022; Mooi et al., 2018).In PCA, the correlation(covariance) matrix is split into two parts scale part(eigenvalue) and the direction part (eigenvector).

The first table (Tables 107 and 118) displays the number of observations, components, and traced components. The difference between the number of components and components traced is the number of components to be retained after extraction. The results also display information on whether components are rotated or not. The first set of results gives five columns: column 1 gives components, column 2 gives eigenvalues, column 3 gives difference, column 4 is proportion, and column 5 is cumulative.

In column 1, the components are equal to the number of variables selected for the principal component analysis. The corresponding column 2 gives an eigenvalue, indicating the variance in data along the eigenvector or principal component given in column 1. A larger eigenvalue means that the corresponding principal component explains large amounts of the data's variance. Eigenvalues may display positive or negative values, but typically, they display only positive values.

Column 3 gives the difference in subsequent eigenvalues. In column 2, the values in the first and second cells are subtracted from each other to get the value in the first cell in column 3. Column 4 is the proportion of each eigenvalue. This value is derived by dividing the respective eigenvalue by the total number of components. The last column(5) is the cumulative proportion derived by adding column four as cumulative frequencies. The components are unrotated.

The second table displays the results of components and their eigenvector.

The rule of thumb says that any eigenvector having a variable with 0.40 or more value is sufficient to explain the given variance. Friesen et al. (2016) used factor loading as low as 0.30. The table will display all components along with their eigenvectors. The factor loading explains the correlation of variables with the component; therefore, those with high correlation are to be retained. All the variables chosen for constructing PCA will be highly correlated with one or the other component, thus taking care that no data is lost due to low correlation(those with low correlation are dropped (Armeanu & Lache, 2008).

Step 7:

Extraction of significant components: Not all are to be retained from the given components, but one cannot decide which components are to be retained by mere observation. Choosing meaningful components can broadly follow three rules: a). Use the eigenvalue criteria,b). Use the proportion of total variance, c). Use the scree plot test.

1. The eigenvalue: The most commonly used criteria for choosing the number of valid components is when the eigenvalue equals one. Criteria are also known as Kaiser criterion (Kaiser 1960). This rule allows the retention of components with an eigenvalue of more than 1. Each variable used in constructing the concerned PCA contributes one unit of variance to the total variance in the data. Any component with more than one eigenvalue means a single variable accounts for more variance; therefore, all such components must be retained. The purpose of PCA is to reduce the original number of variables but retain meaningful components that would explain the original variance in the data set; components with higher eigenvalues would capture this variance.

This eigenvalue criterion is relatively simple to handle since it does not involve decision-making based on subjectivity. Eigenvalue criteria often retain the accurate number of components (Cliff, 1988).

2. Use the proportion of total variance: There is a thumb rule and common practice to retain those components accounting for 70% of the total variation in the data. 70% is a predefined percentage. Generally, the first few components account for the required total variance. There is no fixed number as to how many components will account for the required total variance. For social science research, achieving 70% to 80% variance may be uncommon, and extracted factors usually explain 50% to 60% variance (Schreiber, 2021).

3. Scree plot test: this graphical technique extracts meaningful components (Holland, 2019). Scree plot orders the eigenvalue from highest to lowest. The ideal pattern for a scree plot representing eigenvalues is a steep curve followed by a bend and a straight line(Kanyongo, 2005). The first component will have the highest variance; subsequently, the remaining eigenvalues account for lesser variance.

Step 8:

We examine the eigenvectors after extracting significant components using the above rules. The components generated comprising eigenvectors are orthogonal to each other. This step involves retaining those variables that are highly correlated or forming clusters on a given component. The last component will give the unexplained variation. Generally, this unexplained variation is very low in value. Once this pattern is identified, the grouping is named suitably.

Step 9:

Variance normality: The LR test of sphericity and independence is used.

The PCA command option in STATA can be administered with the VCE (normal) option. We assume that data are normally distributed, which can be done by estimating the standard errors and related statistics. It specifies how the Variance covariance matrix of the estimators (VCE), and thus the standard errors, is calculated. VCE (none | normal) specifies whether standard errors will be computed for the eigenvalues, the eigenvectors, and the (cumulative) percentage of explained variance. These standard errors are obtained assuming multivariate normality of the data and are valid only for a PCA of a covariance matrix. All extracted(retained) components and the variables retained under each component are tested for multivariate normality at a 95% confidence interval with a right-tail test.

Step 10:

Test of parameters: Postestimation Wald test of simple and composite linear hypotheses about the parameters of the most recently fit model. It provides a useful alternative test that permits a variable list rather than a list of coefficients (allowing the use of standard *STATA* notation, including '-' and '*', which are given the expression interpretation by test).*STATA* command *Testparm* is useful when testing three or more coefficients being equal. All variables used in constructing the concerned PCA are used. To run this test, we need to give the option equal to the number of meaningfully extracted components. This specification helps test the equation's coefficient for the relevant components. Instead of testing that the coefficients are zero, they are tested for being equal (PC are normalised to 1).

The option equal will find out whether all the variables are equal.

Step 11:

After running the PCA command with the necessary options, the scores must be predicted for the retained components. These scores are used in the construction of the index.

Step 12:

Rotation of the components(orthogonal rotation): There are two types of rotations: orthogonal and oblique. We use orthogonal rotation. The components remain uncorrelated in this rotation, but the variances change, and the matrix gets clarity (in Oblique rotation, components are allowed to lose their correlated-ness.). The most popular method is *varimax* (orthogonal: done with Kaiser normalization, which makes all variables equally important in the rotation. The *varimax command rotation* maximises the variance among the squared values of loadings of each component.

All orthogonal and oblique rotations can be done with *Kaiser normalization* (usually) or without it.

Step 13:

Residual covariance matrix: displays the difference between the observed covariance matrix and the fitted matrix using the retained factors. The STATA 'estat residuals' command displays the raw or standardized residuals of the observed correlations concerning the fitted (reproduced) correlation matrix.

How close the retained principal components approximate the correlation matrix can be seen from the fitted (reconstructed) correlation matrix and the residuals, the difference between the observed and fitted correlations.

Step 14:

The squared multiple correlations(SMC)of variables with all other variables: It is a classical method for assessing whether the variables have enough in common to be used in PCA and can also be used as a pre-estimation technique. SMC values need to be high for the inclusion of the variables.

Step 15:

Estimation sample PCA: displays the summary statistics of the variables in the principal component analysis over the estimation sample.

This study reduces the variable's dimensionality to four areas (Table 5). These areas are captured using 10 indices from IHDS 2 and 9 from IHDS 1. PCA generated the index scores for each round. Then, scores were added for all indices and averaged over the indices.

Village Health Infrastructure Index 2012 is the sum of scores of the following indices and averaged over the indices.

a) Major morbidity doctor's advice and treatment

b) Short morbidity first advice and treatment 1

c) Short morbidity second advice and treatment 2

d) Health facility 1

e) Health facility 2

f) Infrastructure facility 1

g) Infrastructure facility 2

h) Health infrastructure facility nearby 1

i) Health infrastructure facility nearby 2

j) Health infrastructure facility nearby 3

Village Health Infrastructure Index 2005 is the sum of scores generated from the following indices and averaged over.

a) Major morbidity doctor's advice and treatment

b) Short morbidity first advice and treatment

c) Short morbidity second advice and treatment

d) Health facility 1

e) Health facility 2

f) Infrastructure facility 1

g) Infrastructure facility 2

h) Health infrastructure facility nearby 1

i) Health infrastructure facility nearby 2

TABLE 5:**VILLAGE HEALTH INFRASTRUCTURE INDEX**

Sr No.	2012	2005
1	Major Morbidity Doctor Advice and Treatment Index 1	Major Morbidity Doctor Advice and Treatment Index.
2	Major Morbidity Doctor Advice and Treatment Index 2	Short Morbidity First Doctor Advice and Treatment Index 2
3	Short Morbidity Doctor Advice and Treatment Index.	Short Morbidity Second Doctor Advice and Treatment Index 1
4	Health Facility Index 1	Health Facility Index 1
5	Health Facility Index 2	Health Facility Index 2
6	Infrastructure Facility Index 1	Infrastructure Facility Index 1
7	Infrastructure Facility Index 2	Infrastructure Facility Index 2
8	Health Infrastructure Facility Nearby Index 1	Health Infrastructure Facility Nearby Index 1
9	Health Infrastructure Facility Nearby Index 2	Health Infrastructure Facility Nearby Index 2
10	Health Infrastructure Facility Nearby Index 3.	

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Step 15:

After averaging, the index generates a unique value for each observation. These were regrouped for ease of interpretation. Thus, these scores were used to draw a histogram to create five categories: Very Low, Low, Average, High and Very High.

This index is mapped with the consumption expenditure quintile. Any improvement in health infrastructure between 2005 and 2012 would be reflected in the index's value. The PCA analysis used the merged Household Individual Village level (wide panel) data. The index generated is also used in the regression analysis as one of the covariates in the impact evaluation of health insurance (see Chapter 7).

3.5: Conclusion:

This chapter laid down the details of the data and methods used in this thesis. The IHDS data is the only longitudinal data available for India over two rounds. This data was combined across different schedules to study the impact of shocks on household well-being. New variables were generated to aid the analysis based on the existing literature. Techniques such as regression technique, instrumental variable using two stages least square, the DID with continuous and binary treatment, construction of index using Principal component analysis, and methodologies for calculating the catastrophic and impoverishment impact of health expenditure were discussed. These are used to generate results for discussion in the following chapters.

In the next chapter, we discuss the impact of disability on household consumption expenditure is examined. Different consumption expenditures are used to understand the changes in household consumption expenditure.

CHAPTER 4:

CONSUMPTION EXPENDITURE AND HOUSEHOLD WELL-BEING: ANALYSIS OF DISABILITY AS AN IDIOSYNCRATIC SHOCK

In the previous chapter, 3, the materials and methods used in this thesis were explained. The IHDS dataset used for this study and the merging of different schedules across IHDS 1 and IHDS 2 is described. A comparative analysis of the large health data sets is presented.

Chapter 4 contains 6 main sections. Section one introduces the chapter, and it comprises seven sub-sections. The next main section is 4.2, materials and methods, followed by sections 4.3 and 4.4 on results. The main findings and discussion are in section 4.5. The chapter is concluded in section 4.6.

4:1:Introduction:

In this chapter, we engage with the first objective. It was to study the impact of the unanticipated idiosyncratic shock on the household's well-being. The idiosyncratic shock caused due to disability is expected to have an adverse impact on consumption.

4.1.1: Background Studies:

According to the United Nations Department of Economic and Social Affairs, of the total world population, 15% are disabled, and, on average, individuals spend roughly about eight years with disabilities (for nations with a life expectancy above or equal to seventy years). Of those poor, around 20% have some disability(UN, 2022).

The socio-economic development of an economy is guided by health. Changes in health or maintaining a given population's health level have policy implications. The relationship between health and economic development is of prime importance, and we add to the empirical literature in this regard. Households in developing economies are at risk of being exposed to various shocks. Shocks faced by households are of two types: the one faced by the given household in isolation, such as chronic illness/death/ disability of head of the household/earning member, damage to a physical asset such as land and livestock calamity. Such shocks are termed idiosyncratic shocks in literature. There are geographically localised shocks, such as climatic shocks or spurted from economic crises or epidemics, which affect clusters of households, entire localities/communities, or sometimes the whole economy. Such shocks are called covariate shocks(Shehu & Sidique, 2015). Shock is any adverse event the household faces that negatively affects household income, decrease in consumption or even loss of productive assets. Shocks are divided into many broad categories, such as climatic, economic, political/social/legal, crime and health(Dercon et al., 2005).

Health shock is among the most critical (Lindeboom et al., 2016). This shock creates temporary or permanent disability (Mitra et al.,2015). The health shock caused by disability works at many levels in affecting consumption expenditure(Ball & Low, 2014). Firstly, it causes health expenditure(Mitra et al., 2017); secondly, earnings get reduced due to days spent on disability (Palmer et al., 2015) and may lead to a decrease in income and eventually affect consumption expenditure(Meyer & Mok, 2019).

4.1.2: Concepts And Definitions:

Health shock has the most adverse effects on human health(Mitra et al., 2011). The measurement of illness is important to understand the concept of health shock. A household survey like NSS and IHDS uses the time duration to distinguish the type of illness. This duration is often a month before the survey or a year before the survey. Short-duration illness is measured as the one that occurred one/ two months before the survey. The period for measuring long-duration illness is generally one year before the survey. There may also be illnesses that may have a longer duration, and one may experience such illnesses for a little over a month. Thus, there are illnesses that individuals and households can easily handle, and there are those that may affect labour productivity and higher health expenditure(Yilma et al., 2021).

4.1. 3: Measurement Of Health Shock:

There are challenges involved in the measurement of health shock. The household surveys use different measurements of health shock. It can be measured as changes in overall health and reported illness. These are based on self-reporting. Death is also considered a health shock(Nguyet & Mangyo, 2010). Health shock is shifting away from the original health status and can be measured in many ways(Mitra et al., 2011).

The literature provides eight health measures as follows:

1. The first measure of health is ‘Self-reported health status; an individual assesses themselves as in excellent, good, fair, or poor health(Nguyet & Mangyo, 2010).

2. Health is measured by determining the limits on the ability to work due to ill health. Post-recovery and its effects on working ability is a health status measurement (Genoni, 2012).

3. Health is measured using Activities of Daily Living (ADL). ADL measures health in terms of an individual's limitations to perform certain functions related to daily activities(Gertler & Gruber, 2002).
4. Whether the illness is acute or chronic? (Bonfrer & Gustafsson-Wright, 2017; Thompson & Conley, 2016).
5. The utilisation of medical care (Doyle, 2005).
6. Clinical assessment of illness (mental illness or alcoholism)(Wade & Collin, 1988).
7. Nutritional status includes weight, height, and body mass index (Wagstaff, 2007).
8. Expected future mortality(Idler & Kasl, 1995; Murray & Lopez, 1997) .

We use disability as a measure of health shock in this chapter. Disability also is a complex phenomenon, and its definition has much scope for ambiguity(Van Oyen et al., 2018). Disability can be defined in many ways, and it varies in terms of nature, severity, and purpose of measurement(Mont, 2007). Disability, like illness, can be measured broadly by first measuring the presence of disability(Mumbardó-Adam et al., 2018)and secondly by measuring the extent to which disability affects individuals' functioning(Fleishman et al., 2002). The medical model identifies disability based on diagnosis with the help of medical procedures. ICD9 -10 codes are used for categorising patients based on disability(McDermott & Turk, 2011). The medical definition of disability is stricter where disability is caused by disease, injury, or other health conditions peculiar to a given individual(Donoghue, 2003; Mitra & Sambamoorthi, 2006). Based on this concept, an individual is considered disabled irrespective of difficulties encountered or not in daily activities(Van Oyen et al., 2018). The underlying construct is that disability requires an individual to undergo medical treatment and rehabilitation post-treatment(Van Oyen et al., 2018). Later, the WHO International Classification of Functioning (ICF), disability, and health defined disability more broadly(Filmer, 2008). Disability includes impairments, activity limitations and participation restrictions and covers three main domains: a) body functioning and structure,b) activities and participation, and c) environmental factors.ICF classification is a broad term that includes aspects like impairment, limitation on activity and restriction on participation (Filmer, 2008; Mitra et al., 2011).

As given in the manual of ICF (2001), impairment is a condition with issues/ limitations with the body's functioning or structure. Limitations on activity involve the difficulty encountered by the individuals in performing certain tasks. Restrictions in participation are issues individuals face in life situations (ICF's 2001) classification model integrates medical and social aspects of health, forming a new Biopsychosocial model. In this model, disability is viewed from a social point of view. Disability also interacts with the social environment, and social change is required for treatment (Burchardt,2004). Broadly, the three measures of disability encompass much wider aspects of disability. Blindness, deafness, mental retardation, stammering, and paralysis(complete or partial) are disabilities very specific to individuals and hence are termed impairments. Individuals also experience functional limitations regarding certain functions associated with the body, such as seeing and walking, hearing, speaking, climbing stairs, and lifting. Individuals also face activity limitations such as going outside the home for work or housework or playing for children (ICF, 2002).

Recent literature has also studied disability by bifurcating into the persistence of disability and severity of the disability(Meyer & Mok, 2019). Persistence measures the existence of a disability, and severity measures the extent to which a disability exists in terms of ordered preference. Typical replies sought on questions measuring the severity of the disability are the ease of difficulty with which a given task is done (Meyer & Mok, 2019). Households with at least one disabled member spend more compared to those households that may not have any disabled members.

The method to measure consumption expenditure is the standard of living approach. This method is adopted as an indirect assessment method to measure the extra consumption expenditure of households with disabled members. This approach of measurement adopts compensating variation. The standard of living method assumes that disability has its own cost. The households that have disabled members will have to allot additional resources to cover disability-related expenses. The households with no disabled members need not incur this additional expenditure. The difference between the consumption expenditure of these two households is the cost of disability. The cost of disability is the cost incurred by the households to maintain the standard of living before the disability occurred (Asuman et al., 2018; Loyalka et al., 2014).

In the standard of living approach, the key indicator is each household's latent standard of living. The basic assumption here is that disabled members must reallocate their resources towards disability care, which otherwise would have been used for enhancing the standard of living. Schulke et al. (2022) used the UK's composite standard of living indicator to determine the disability cost.

This index was calculated using ten variables covering individuals' ownership or deprivation.

The variables used were:

a) Money at the disposal of individuals to have decent décor for home.

b) Participation in hobby or leisure activities of the individual.

c) Staying away for a week in a year with relatives, insurance status of the household.

d)Visit family and friends once a month to share a drink or meal.

e) Amount of money saved in a month(Pound 10).

f) Pair of shoes(minimum 2) including all-weather shoes in perfect shape.

g) Money to replace worn-out furniture and repair electrical items.

h) Finally, money to spend on the individual themselves.

This index was constructed by adding the total score based on weightage.

Apart from standard of living measures, there are other measures for measuring the cost of disability. The standard welfare measure considers the earning capacity of people with disabilities(Baumberg et al., 2015). This approach may underestimate the poverty status of disabled members (Banks et al., 2017; Palmer, 2014).

Alternatively, one can use a quantitative approach using different parameters and econometrically estimate the indirect cost of disability (Koopmanschap & Rutten, 1993). The expenditure diary approach based on the revealed preference method is also used to estimate the cost of disability(Schuelke et al., 2022). Here, consumption expenditure patterns are examined using survey data. There is also a life satisfaction approach(Mollaoğlu et al., 2010). This approach measures an individual’s level of satisfaction concerning their well-being based on an arbitrary quantifiable scale. Although this method allows individuals to compare their actual status with a specified standard of living, the measure is subjective (Schuelke et al., 2022).

4.1.4: Studies On Disabilities Using Household Large-Scale Surveys:

The household surveys that collect health information and other household variables comprise the module on shocks. The module seeks to collect information from households. Households are asked to recollect their experiences of any unexpected event that usually happened a year preceding the survey. The shock module includes questions on health shocks, natural disaster shocks and economic shocks. The cluster of information collected is whether any household member faced illness, death, or disability; floods, storms, livestock epidemic, job loss, price decline, crime and conflict(Yilma et al., 2014).

Many household survey instruments included detailed questions to capture disability; some also had surveys that exclusively covered ADL(Van Oyen et al., 2018). ADL is a better measure for recording individuals' responses based on their ability to carry out some daily activities (Gertler & Gruber, 2002). ADL has been used since 1960 in the literature. In Vietnam, the household large-scale survey (VHLSS) provides data on physical functioning based on difficulties in performing activities of daily living (Mitra et al., 2011). ADLs are very specific and less prone to measurement errors than morbidity measures such as self-reported illness. Indonesian Family Life Survey also collects a module on ADL and other reported health (Lim, 2017). Some household surveys also captured ADL information with five to seven domains (Van Oyen et al., 2018). In a longitudinal study in Indonesia, the ADL index was constructed using seven activities (Carrying a heavy load for a particular distance(20 metres); drawing water from a well; 5 km walk; sweeping the house; kneeling, squatting and bowing; getting up from sitting position from the floor without help; lastly standing without help whilst getting up from a chair). These responses were marked with three options based on the difficulty level or ease experienced.

Individual responses to ADL have been recorded for the construction of the ADL index. Some activities are specified (Simeu & Mitra, 2019). Basic and intermediate ADL indexes were used for an Indonesian Family Life survey study. Carrying water for 20 metres, walking 5 km, drawing water from the well, bending, squatting, and kneeling were used to construct intermediate ADL. Standing up from sitting on the floor or chair without help, sweeping the house, going to the bathroom without help or dressing without help were used for constructing basic ADL(Nguyet & Mangyo, 2010).

We next discuss the different sources of data on disability available in India.

4.1.5: Disability Measurement In India:

The first census in 1872 collected information on disability, discontinued the same in 1931, again collected in 1981 and discontinued in 1991. From 2001 onwards, five types of disabilities were included, extending to 8 in 2011(Reddy & Sree, 2015). The disabilities measured in the 2011 census included disabilities that covered seeing, speech, hearing, movement, mental retardation, mental illness and other multiple disabilities(Mitra & Sambamoorthi, 2006).

The national sample survey started the measurement of disability from the 58th round and used five types of disabilities: mental, visual, speech and locomotor(Jeffery & Singal, 2008). Census and NSS measurements of disability are incomparable(Mitra & Sambamoorthi, 2006).IHDS 1 and 2 have included disability based on ADL and a self-reporting of illness that led to temporary disability. IHDS 1 and IHDS 2 are comparable with each other.

4.1.6: Limitations Of Self-Reporting:

Disability reporting has issues. For example, partial blindness may be reported as complete or mental disability not be reported at all (Filmer, 2008); when the respondent self-reports illness, those who may have lost jobs may overstate the effect of health status. The definition of illness may be subjective across economic backgrounds. Economically affluent households may report illness more than less affluent households. Both the investigator and respondent may misinterpret the reporting of morbidity. Therefore, ADL was used in place of illness (Gertler & Gruber, 2002).

When disability is defined within the given set of parameters, those disabilities or conditions beyond these parameters may go non-recorded and lead to underestimation. On the other hand, when disability is self-reported, the disabilities that are not so severe may be reported (Meyer & Mok, 2019). In most developing economies, households may not be aware of some health conditions, especially chronic ones (Mani et al., 2017). Self-reported measures are also influenced by seasonality, information, and education. Young and retired men's responses about health may also vary between rich and poor (Schultz & Tansel, 1997). The respondent's socio-economic background impacts the self-reporting of health and is responsible for creating bias (Islam & Maitra, 2012).

Health status is also connected to employment. Health status and employment have both positive and negative relationships. It is positive when individuals feel elevated due to social interaction and negative when employed individuals experience work-related stress. Often, if an individual incurs a cost due to the onset of a disability, but there are also gains upon recovery from the disability, it complicates the relationship between health and the labour market (Mani et al., 2018).

4.1.7: Limitations With Measurement Of Health:

This section discusses the issues that may arise when health measures are used to study their impact on economic well-being or welfare. The health surveys or general surveys that collect data on health status have certain limitations. Economic welfare or well-being is also linked with other covariates like age and education. Therefore, some systematic errors or random errors in the measurement of health may arise, causing endogeneity issues. Between health and economic welfare, there are many unobserved heterogeneities. These heterogeneities may vary with time or be time-invariant. Childhood nutrition, vaccination, and hygiene affect an adult's health. These unobserved factors may make it difficult to study the impact of health on economic well-being(Mitra et al., 2016).

Health and economic welfare have two-way causality(Collins & Odrakiewicz,2012). Health may impact economic welfare positively via investment in human capital and vice versa. Thus, challenges arise, such as measurement error in bias, omitted variable bias and the issue of reverse causality not being handled. One option is to use an instrumental variable approach to address the error of random measurement(Genoni, 2012; Islam & Maitra, 2012). Wagstaff (2007) has used lagged specification (health shock in earlier periods affects economic welfare in succeeding periods). Gertler &Gruber (2002) have used first difference or fixed effects to treat systematic measurement error and time-invariant unobserved heterogeneity(Strauss & Thomas, 2022). For employed individuals, the number of days lost in illness or disability revolves around the decisions about the allocation of time. However, wages or other work-related factors also influence this decision and may suffer endogeneity (Mani et al., 2018).

Village consumption could influence household consumption; hence, estimates would be biased and can be resolved using village-fixed and time-fixed effects. Health shocks are endogenous. However, some shocks that affect consumption may also influence health, such as natural disasters. When proceeding with the assumption that health shocks are exogenous, shocks are to be regarded as non-persistent and unpredictable. Fixed-effects estimation validated this assumption (Mbugua et al., 2020).

4.2: Materials And Methods:

The study of the interaction between disability, health expenditure and household well-being gives an accurate picture when longitudinal data is used over cross-sectional data. Longitudinal data provide evidence for disability-led deprivation or households already deprived before the member witnessed disability (Mitra et al., 2011). Household ADL studies capture health shock better over time than at one point (Nguyet & Mangyo, 2010). Work disruption occurs when an individual suffers from short (30 days) or major (365 days) morbidity. From IHDS data, days disabled due to morbidity (short and major) and ADL data are used. The days disabled are divided into different categories based on the duration of illness measured as month and year and based on different types of short and major morbidities.

Variation in household expenditure is captured monthly and annually by constructing different household expenditures such as food and non-food expenditure, consumption expenditure and adjusted consumption expenditure, and consumption expenditure with and without health insurance reimbursements. The difference in consumption expenditure for the households with and without disabilities is tested using a t-test. Days disabled due to morbidity(short and major) are compared with those never disabled for changes in categories of consumption expenditures. The activity of daily living intensity (ADLI) was one of the independent variables. The data was categorised as rural and urban for better analysis(see Chapter 3 for details). The data used is from household individual panel data. The regression is executed using *STATA 17* command *XTREG* with fixed effects and standard errors clustered at villages/ nearest neighbourhood.

4.3: Results:

In this section, we provide results using summary statistics, followed by results of t-test analysis and multiple regression.

4.3.1: Descriptive Statistics:

A higher number of individuals did not suffer from any short morbidity in IHDS 2 compared to IHDS 1(Table 6). More individuals in IHDS 1 reported fever and cough, and diarrhoea was reported more in IHDS 2.

TABLE 6:**DESCRIPTIVE STATISTICS SHORT MORBIDITY**

Variables	**Number of observations**	
Year	**2005**	**2012**
No morbidity	127144	132263
	(84.21)	*(87.6)*
Fever	6686	4101
	(4.43)	*(2.72)*
Cough	14029	10697
	(9.29)	*(7.08)*
Diarrhoea	3129	3927
	(2.07)	*(2.6)*

Note:

1. Total No. of observations: 150988.

2. Percentage in parenthesis.
Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Major morbidity has reduced by 7% among individuals from IHDS 1 to IHDS 2. In IHDS 2, the accident was added to the category of major morbidity and recorded in 0.5% of individuals (Table 7).

Table 7:**Descriptive statistics Major morbidity**

Variables	**Number of observations**	
Year	**2005**	**2012**
No morbidity	142434	131856
	(94.33)	*(87.33)*
Cataract	571	1107
	(0.38)	*(0.73)*
Tuberculosis	378	482
	(0.25)	*(0.32)*
High-BP	1403	3065
	(0.93)	*(2.03)*
Heart Disease	573	983
	(0.38)	*(0.65)*
Diabetes	915	2469
	(0.61)	*(1.64)*
Leprosy	76	79
	(0.05)	*(0.05)*
Cancer	76	106
	(0.05)	*(0.07)*
Asthma	656	1437
	(0.43)	*(0.95)*
Polio	165	153
	(0.11)	*(0.1)*
Paralysis	145	593
	(0.1)	*(0.39)*

Epilepsy	137	280
	(0.09)	*(0.19)*
Mental Illness	216	503
	(0.14)	*(0.33)*
STD-AIDS	71	47
	(0.05)	*(0.03)*
Accident	NA	749
	NA	*(0.5)*
Others	3172	7079
	(2.1)	*(4.69)*

Note: 1. Total No. of observations: 150988.

2. Percentage in parenthesis.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Due to short morbidity, the highest number of days disabled was one week for both IHDS 1 and IHDS 2(Table 8). Compared to IHDS 1, in IHDS 2, more individuals reported disability for one week due to short morbidity. From major morbidity, the disability for one month was highest for both years. In IHDS 2, the number of individuals disabled for one month was almost twice that in IHDS 1(Table 9).

TABLE 8:**Days Disabled(Duration) Due To Short Morbidity**

TABLE 9:**Days Disabled(Duration) Due To Major Morbidity**

	Year			**Year**	
Variables	**2005**	**2012**	**Variables**	**2005**	**2012**
Not disabled	137668	133400	Not disabled	145,365	138,882
	(91.18)	*(88.35)*		*(96.28)*	*(91.98)*
Disabled for 1 week	10039	13121	Disabled for 3 months	4,513	10,197
	(6.65)	*(8.69)*		*(2.99)*	*(6.75)*
Disabled for 2 weeks	2091	2666	Disabled for 6 months	425	854
	(1.38)	*(1.77)*		*(0.28)*	*(0.57)*
Disabled for 3 weeks	803	1225	Disabled for 9 months	106	213
	(0.53)	*(0.81)*		*(0.07)*	*(0.14)*
Disabled for 4 weeks	387	576	Disabled for 12 months	579	842
	(0.26)	*(0.38)*		*(0.38)*	*(0.56)*

Note:

1. Total No. of observations: 150988.

2. Percentage in parenthesis.
Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Two-way distribution of diseases by days disabled due to short morbidity is highest for cough in both years, and the maximum disability reported was for one month, and the minimum was for one week in IHDS 1(Table 10). In IHDS 2, the maximum disability reported from cough was for two weeks, and the minimum was for four weeks. Diarrhoea and fever caused lower disability among short morbidities.

TABLE 10:**Short Morbidity And Days Disabled (2005 And 2012)**

	2005						2012					
Variables	**Not disabled**	**Disabled for 1 week**	**Disabled for 2 weeks**	**Disabled for 3 weeks**	**Disabled for 4 weeks**	**Total**	**Not disabled**	**Disabled for 1 week**	**Disabled for 2 weeks**	**Disabled for 3 weeks**	**Disabled for 4 weeks**	**Total**
No morbidity	116,859	7,823	1,591	581	290	127,144	117,958	10,637	2,173	1,007	488	132,263
	(84.88)	*(77.93)*	*(76.09)*	*(72.35)*	*(74.94)*	*(84.21)*	*(88.42)*	*(81.07)*	*(81.51)*	*(82.20)*	*(84.72)*	*(87.60)*
Fever	5,835	594	157	70	30	6,686	3,457	481	95	53	15	4,101
	(4.24)	*(5.92)*	*(7.51)*	*(8.72)*	*(7.75)*	*(4.43)*	*(2.59)*	*(3.67)*	*(3.56)*	*(4.33)*	*(2.60)*	*(2.72)*
Cough	12,206	1,339	295	127	62	14,029	8,795	1,441	295	114	52	10,697
	(8.87)	*(13.34)*	*(14.11)*	*(15.82)*	*(16.02)*	*(9.29)*	*(6.59)*	*(10.98)*	*(11.07)*	*(9.31)*	*(9.03)*	*(7.08)*
Diarrhoea	2,768	283	48	25	5	3,129	3,190	562	103	51	21	3,927
	(2.01)	*(2.82)*	*(2.30)*	*(3.11)*	*(1.29)*	*(2.07)*	*(2.39)*	*(4.28)*	*(3.86)*	*(4.16)*	*(3.65)*	*(2.60)*
Total	137,668	10,039	2,091	803	387	150,988	133,400	13,121	2,666	1,225	576	150,988

Note: 1. Total No. of observations: 150988.

2. Percentage in parenthesis.
Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

In a two-way table of major morbidity and disability for IHDS 1, the major morbidity days disabled were highest for three months for high blood pressure, followed by 12 months of disability for asthma and cataracts for rural areas (Table 11). For an urban area, for 3 months, disability for high blood pressure was highest, followed by 12 months of disability for high blood pressure and diabetes for 9 months for IHDS 1.

In IHDS 2, for rural, the highest disability was 3 months for high blood pressure, followed by 3 months of disability for asthma and 9 months of disability for tuberculosis and asthma(Table 12). For urban areas, the highest was 3 months of disability caused by diabetes, followed by 3 months of disability for high blood pressure and 12 months of disability for paralysis.

TABLE 11:**Major Morbidity And Days Disabled (Rural And Urban, 2005)**

Morbidity/Disability	Rural						Urban					
	Not disabled	**Disabled for 3 months**	**Disabled for 6 months**	**Disabled for 9 months**	**Disabled for 12 months**	**Total**	**Not disabled**	**Disabled for 3 months**	**Disabled for 6 months**	**Disabled for 9 months**	**Disabled for 12 months**	**Total**
No Morbidity	100263	18	3	2	4	100290	42127	16	1	0	0	42144
	(98.33)	*(0.6)*	*(0.91)*	*(2.41)*	*(1.02)*	*94.8*	*(97.08)*	*(1.07)*	*(1.06)*	*(0)*	*(0)*	*(93.23)*
Cataract	168	200	18	7	38	431	68	61	5	0	6	140
	(0.16)	*(6.64)*	*(5.44)*	*(8.43)*	*(9.69)*	*(0.41)*	*(0.16)*	*(4.06)*	*(5.32)*	*(0)*	*(3.21)*	*(0.31)*
Tuberculosis	96	141	25	8	23	293	36	37	4	1	7	85
	(0.09)	*(4.680*	*(7.55)*	*(9.64)*	*(5.87)*	*(0.28)*	*(0.08)*	*(2.46)*	*(4.26)*	*(4.35)*	*(3.74)*	*(0.19)*
High BP	272	389	13	8	36	718	356	287	8	1	33	685
	(0.27)	*(12.92)*	*(3.93)*	*(9.64)*	*(9.18)*	*(0.68)*	*(0.82)*	*(19.11)*	*(8.51)*	*(4.35)*	*(17.65)*	*(1.52)*
Heart Disease	90	180	24	4	15	313	87	145	13	1	14	260
	(0.09)	*(5.98)*	*(7.25)*	*(4.820)*	*(3.83)*	*(0.3)*	*(0.2)*	*(9.65)*	*13.83*	*4.35*	*7.49*	*0.58*
Diabetes	166	196	17	3	37	419	263	201	8	4	20	496
	(0.16)	*(6.51)*	*(5.14)*	*(3.61)*	*(9.44)*	*(0.4)*	*(0.61)*	*(13.38)*	*(8.51)*	*(17.39)*	*(10.7)*	*(1.1)*
Leprosy	28	12	2	2	6	50	12	12	0	0	2	26
	(0.03)	*(0.4)*	*(0.6)*	*(2.41)*	*(1.53)*	*(0.05)*	*(0.03)*	*(0.8)*	*(0)*	*()*	*(1.07)*	*(0.06)*
Cancer	11	30	5	1	2	49	14	9	2	0	2	27
	(0.01)	*(1)*	*(1.51)*	*(1.2)*	*(0.51)*	*(0.05)*	*(0.03)*	*(0.6)*	*(2.13)*	*(0)*	*(1.07)*	*(0.06)*

Asthma	137	259	26	7	44	473	65	92	9	2	15	183
	(0.13)	*(8.6)*	*(7.85)*	*(8.43)*	*(11.22)*	*(0.45)*	*(0.15)*	*(6.13)*	*(9.57)*	*(8.70)*	*(8.02)*	*(0.4)*
Polio	64	40	2	0	18	124	23	9	0	0	9	41
	(0.06)	*(1.33)*	*(0.6)*	*(0)*	*(4.59)*	*(0.12)*	*(0.05)*	*(0.6)*	*(0)*	*(0)*	*(4.81)*	*(0.09)*
Paralysis	25	37	10	5	24	101	13	17	3	3	8	44
	(0.02)	*(1.23)*	*(3.02)*	*(6.02)*	*(6.12)*	*(0.1)*	*(0.03)*	*(1.13)*	*(3.19)*	*(13.04)*	*(4.28)*	*(0.1)*
Epilepsy	22	60	9	1	5	97	8	25	1	0	6	40
	(0.02)	*(1.99)*	*(2.72)*	*(1.2)*	*(1.28)*	*(0.09)*	*(0.02)*	*(1.66)*	*(1.06)*	*(0)*	*(3.21)*	*(0.09)*
Mental Illness	53	54	7	2	25	141	26	19	5	4	21	75
	(0.05)	*(1.79)*	*(2.11)*	*(2.41)*	*(6.38)*	*(0.13)*	*(0.060*	*(1.26)*	*(5.32)*	*(17.39)*	*(11.23)*	*(0.17)*
STD-AIDS	32	12	1	0	9	54	7	6	0	0	4	17
	(0.03)	*(0.4)*	*(0.3)*	*(0)*	*(2.3)*	*(0.05)*	*(0.02)*	*(0.4)*	*(0)*	*(0)*	*(2.14)*	*(0.04)*
Others	542	1383	169	33	106	2233	291	566	35	7	40	939
	(0.53)	*(45.93)*	*(51.06)*	*(39.76)*	*(27.04)*	*(2.11)*	*(0.67)*	*(37.68)*	*(37.23)*	*(30.43)*	*(21.39)*	*(2.08)*
Total	101969	3011	331	83	392	105786	43396	1502	94	23	187	45202
	(100)	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*

Note: *1. The first row has frequencies, and the second row has column percentages.*

Source: Authors' calculations based on IHDS1 data.

TABLE 12:**Major Morbidity And Days Disabled (Rural And Urban 2012)**

	Rural						Urban					
Morbidity/Disability	**Not disabled**	**Disabled for 3 months**	**Disabled for 6 months**	**Disabled for 9 months**	**Disabled for 12 months**	**Total**	**Not disabled**	**Disabled for 3 months**	**Disabled for 6 months**	**Disabled for 9 months**	**Disabled for 12 months**	**Total**
No Morbidity	89987	13	1	1	5	90007	41845	4	0	0	0	41849
	(95.51)	*(0.19)*	*(0.16)*	*(0.68)*	*(0.85)*	*(88)*	*(93.68)*	*(0.110*	*(0)*	*(0)*	*(0)*	*(85.92)*
Cataract	386	393	28	7	30	844	125	121	6	1	10	263
	(0.410	*(5.86)*	*(4.42)*	*(4.73)*	*(5.13)*	*(0.83)*	*(0.28)*	*(3.46)*	*(2.71)*	*(1.54)*	*(3.89)*	*(0.54)*
Tuberculosis	129	171	35	12	16	363	46	54	11	2	6	119
	(0.14)	*(2.55)*	*(5.53)*	*(8.11)*	*(2.74)*	*(0.35)*	*(0.1)*	*(1.54)*	*(4.98)*	*3.08*	*2.33*	*0.24*
High BP	726	920	21	6	32	1705	722	590	24	5	19	1360
	(0.77)	*(13.73)*	*(3.32)*	*(4.05)*	*(5.47)*	*(1.67)*	*(1.62)*	*(16.88)*	*(10.86)*	*(7.69)*	*(7.39)*	*(2.790*
Heart Disease	134	331	38	9	27	539	157	259	9	3	16	444
	(0.14)	*(4.94)*	*(6)*	*(6.08)*	*(4.62)*	*(0.53)*	*(0.35)*	*(7.41)*	*(4.07)*	*(4.62)*	*(6.23)*	*(0.91)*
Diabetes	483	477	49	8	36	1053	687	663	29	6	31	1416
	(0.51)	*(7.12)*	*(7.74)*	*(5.41)*	*(6.15)*	*(1.03)*	*(1.54)*	*(18.96)*	*(13.12)*	*(9.23)*	*(12.06)*	*(2.91)*
Leprosy	38	12	1	2	5	58	10	8	1	0	2	21
	(0.04)	*(0.18)*	*(0.16)*	*(1.35)*	*(0.85)*	*(0.06)*	*(0.02)*	*(0.23)*	*(0.45)*	*(0)*	*(0.78)*	*(0.04)*
Cancer	11	30	5	3	12	61	12	27	4	0	2	45
	(0.01)	*(0.45)*	*(0.79)*	*(2.03)*	*(2.05)*	*(0.06)*	*(0.03)*	*(0.77)*	*(1.81)*	*(0)*	*(0.78)*	*(0.09)*

Asthma	303	599	49	12	73	1036	151	216	12	6	16	401
	(0.32)	*(8.94)*	*(7.74)*	*(8.11)*	*(12.48)*	*(1.01)*	*(0.34)*	*(6.18)*	*(5.43)*	*(9.23)*	*(6.23)*	*(0.82)*
Polio	59	22	3	0	26	110	30	6	1	0	6	43
	(0.06)	*(0.33)*	*(0.47)*	*(0)*	*(4.44)*	*(0.11)*	*(0.07)*	*(0.17)*	*(0.45)*	*(0)*	*(2.330*	*(0.09)*
Paralysis	128	148	33	6	73	388	64	93	7	4	37	205
	(0.14)	*(2.21)*	*(5.21)*	*(4.05)*	*(12.48)*	*(0.38)*	*(0.14)*	*(2.66)*	*(3.17)*	*(6.15)*	*(14.4)*	*(0.42)*
Epilepsy	53	139	9	1	15	217	15	37	6	2	3	63
	(0.06)	*(2.07)*	*(1.42)*	*(0.68)*	*(2.56)*	*(0.21)*	*(0.03)*	*(1.06)*	*(2.71)*	*(3.08)*	*(1.17)*	*(0.13)*
Mental Illness	134	147	21	3	50	355	55	55	8	2	28	148
	(0.14)	*(2.19)*	*(3.32)*	*(2.03)*	*(8.55)*	*(0.35)*	*(0.12)*	*(1.57)*	*(3.62)*	*(3.08)*	*(10.89)*	*(0.3)*
STD-AIDS	16	12	3	0	2	33	2	11	0	0	1	14
	(0.02)	*(0.18)*	*(0.47)*	*(0)*	*(0.34)*	*(0.03)*	*(0)*	*(0.31)*	*(0)*	*(0)*	*(0.39)*	*(0.03)*
Accidents	46	402	53	11	18	530	22	168	17	4	8	219
	(0.05)	*(6)*	*(8.370*	*(7.43)*	*(3.08)*	*(0.52)*	*(0.05)*	*(4.810*	*(7.69)*	*(6.150*	*(3.11)*	*(0.450*
Others	1582	2885	284	67	165	4983	724	1184	86	30	72	2096
	(1.68)	*(43.05)*	*(44.87)*	*(45.27)*	*(28.21)*	*(4.87)*	*(1.62)*	*(33.87)*	*(38.91)*	*(46.15)*	*(28.02)*	*(4.3)*
Total	94215	6701	633	148	585	102282	44667	3496	221	65	257	48706
	(100)	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*	*(100)*

Note 1)The first row has frequencies, and the second row has column percentages.

Source: Authors' calculations based on IHDS 2 data.

4.3.2: Analysis Of Test Of Significance Between Consumption Expenditure And Morbidity-Specific Disability:

In this section, we provide the results of the t-test. A significance test was conducted to examine the impact of disability on consumption expenditure due to morbidity-specific disability. Separate tests were performed for IHDS 1 and IHDS 2 for short and major morbidity among the subgroups of morbidity and disability. 4 different types of consumption expenditure are considered for analysing the impact of disability: consumption expenditure, adjusted consumption expenditure for health expenditure (with insurance reimbursement and without insurance reimbursements), food expenditure and non-food expenditure. The analysis uses monthly and annual expenditures separately for rural and urban areas.

4.3.2.1: Consumption Expenditure Per Capita And Morbidity-Specific Disability:

This section compares the monthly/ annual consumption expenditure between those who were never disabled from short and major morbidity and those disabled. Short morbidity differentials in consumption expenditure are measured monthly, and annual consumption expenditure is considered for major morbidity.

For short morbidity in rural and urban areas, the per capita consumption expenditure was significantly different for those disabled with fever, cough, and diarrhoea and those who were not disabled (Table 13). The consumption expenditure was higher for those disabled with fever and cough in rural areas. Among the major morbidity, per capita consumption expenditure was significantly different and higher for those with cataracts, high blood pressure, heart disease, diabetes, cancer, asthma, paralysis, and others in rural areas. In urban areas, those disabled with high blood pressure, heart diseases, diabetes, asthma, and others had significantly different and higher consumption expenditures than those not disabled. The differences in consumption expenditure are significant for short morbidity in rural and urban areas. Those disabled with short morbidity of all types had significantly different consumption expenditures for rural and urban areas. Major morbidity disabilities due to cataracts, cancer and paralysis caused significantly different consumption expenditures for rural areas in comparison to urban. Heart disease, diabetes and asthma have caused significantly different expenditures for rural and urban areas.

TABLE 13:**Consumption Expenditure Per Capita and Morbidity-Specific Disability(Rural and Urban, 2005)**

		Rural				Urban			
Morbidity	**Categories**	**Observations**	**Mean**	**t-test**	**p-value**	**Observations**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	93,680	1300.415	**-3.2973**	0.001	41,024	1918.252	**2.6052**	0.0092
	Disabled	12,106	1340.863			4,178	1844.328		
Cough	Never Disabled	96,207	1298.164	**-5.584**	0.0000	41,729	1916.886	**2.3057**	0.0211
	Disabled	9,579	1374.144			3,473	1845.734		
Diarrhoea	Never Disabled	1,02,735	1308.483	**5.1106**	0.0000	44,326	1913.977	**2.2136**	0.0269
	Disabled	3,051	1189.244			876	1782.009		
Cataract	Never Disabled	1,05,185	15640.82	**-5.5619**	0.0000	44,994	22938.15	0.1674	0.8671
	Disabled	601	19108.25			208	22694.23		
Tuberculosis	Never Disabled	1,05,443	15661.18	0.2437	0.8075	45,098	22938.56	0.324	0.7459
	Disabled	343	15460.32			104	22271.5		
High BP	Never Disabled	1,04,763	15576.85	**-18.0961**	0.0000	44,168	22689.24	**-16.4693**	0.0000
	Disabled	1,023	24229.16			1,034	33521.53		
Heart Disease	Never Disabled	1,05,413	15631.33	**-10.4782**	0.0000	44,871	22851.51	**-10.1071**	0.0000
	Disabled	373	23911.18			331	34530.28		
Diabetes	Never Disabled	1,05,316	15605.81	**-17.5017**	0.0000	44,659	22797.21	**-12.8798**	0.0000
	Disabled	470	27920.35			543	34436.26		
Leprosy	Never Disabled	1,05,731	15659.54	-0.9197	0.3577	45,170	22932.18	-1.8469	0.0648
	Disabled	55	17550.2			32	29780.32		
Cancer	Never Disabled	1,05,733	15657.59	**-2.7928**	0.0052	45,171	22937.22	0.0725	0.9422
	Disabled	53	21505.98			31	22664		
Asthma	Never Disabled	1,05,274	15648.64	**-3.635**	0.0003	45,013	22918.09	**-2.9642**	0.003
	Disabled	512	18103.04			189	27448.35		
Polio	Never Disabled	1,05,654	15658.12	-1.4492	0.1473	45,160	22938.97	0.6466	0.5179
	Disabled	132	17581.9			42	20845.92		
Paralysis	Never Disabled	1,05,676	15653.53	**-4.6231**	0.0000	45,155	22938.78	0.5499	0.5824
	Disabled	110	22375.02			47	21256.04		
Epilepsy	Never Disabled	1,05,682	15660.67	0.1009	0.9197	45,159	22941.07	1.3267	0.1846
	Disabled	104	15509.83			43	18696.7		
Mental Illness	Never Disabled	1,05,642	15658.82	-0.9836	0.3253	45,124	22937.93	0.2199	0.826
	Disabled	144	16909.04			78	22415.47		

STD-AIDS	Never Disabled	1,05,728	15659.66	-0.7856	0.4321	45,183	22937.67	0.3179	0.7506
	Disabled	58	17232.35			19	21408.21		
Others	Never Disabled	1,03,553	15578.42	**-11.9381**	0.0000	44,263	22827.44	**-7.634**	0.0000
	Disabled	2,233	19467.78			939	28103.09		

Note 1) Two-tail t-test is used.
Source: Authors' calculations based on IHDS1 data.

4.3.2.2: Adjusted Consumption Expenditure(Without Insurance Reimbursement) Per Capita And Morbidity-Specific Disability:

Adjusted consumption expenditure per capita(adjusted only for health expenditure without insurance reimbursement) was significant for those disabled with short morbidity, i.e., fever, cough and diarrhoea in rural and urban areas(Table 14). In rural areas, those disabled with cataracts, tuberculosis, high blood pressure, heart disease, diabetes, paralysis, epilepsy, and others had significantly different expenditures. But only those disabled with cataracts, high blood pressure, heart disease, diabetes, and others had higher adjusted consumption expenditure. High blood pressure, heart disease, diabetes, asthma and others in urban areas had significantly different and higher adjusted consumption expenditures. Tuberculosis and cataracts that led to different expenditures for rural areas were insignificant for urban areas. Across both areas, those disabled with heart diseases, high blood pressure, and diabetes had higher adjusted consumption expenditures than those not disabled.

TABLE 14:**Adjusted Consumption Expenditure (Without Insurance Reimbursement) And Morbidity-Specific Disability (Rural and Urban, 2005)**

		Rural				**Urban**			
Morbidity	**Categories**	**Obs,**	**Mean**	t-test	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	93,680	1290.294	**6.4142**	0.0000	41,024	1905.781	**6.1334**	0.0000
	Disabled	12,106	1212.195			4,178	1732.899		
Cough	Never Disabled	96,207	1284.253	**2.3683**	0.0179	41,729	1901.924	**5.1464**	0.0000
	Disabled	9,579	1252.26			3,473	1744.15		
Diarrhoea	Never Disabled	1,02,735	1287.706	**9.5077**	0.0000	44,326	1894.839	**4.3886**	0.0000
	Disabled	3,051	1067.554			876	1634.893		
Cataract	Never Disabled	1,05,185	15366.31	**-2.8351**	0.0046	44,994	22684.14	0.9778	0.3282
	Disabled	601	17121.12			208	21268.23		
Tuberculosis	Never Disabled	1,05,443	15382.94	**2.5121**	0.012	45,098	22684.65	1.4926	0.1356
	Disabled	343	13327.24			104	19631.54		
High blood pressure	Never Disabled	1,04,763	15309.97	**-14.4382**	0.0000	44,168	22461.8	**-14.4256**	0.0000
	Disabled	1,023	22167.04			1,034	31896.69		

Heart Disease	Never Disabled	1,05,413	15359.16	**-6.1863**	0.0000	44,871	22616.91	**-7.2166**	0.0000
	Disabled	373	20213.65			331	30907.76		
Diabetes	Never Disabled	1,05,316	15336.39	**-12.8449**	0.0000	44,659	22559.44	**-10.9505**	0.0000
	Disabled	470	24314.58			543	32397.75		
Leprosy	Never Disabled	1,05,731	15376.25	-0.0244	0.9805	45,170	22673.87	-1.4374	0.1506
	Disabled	55	15426.11			32	27970.26		
Cancer	Never Disabled	1,05,733	15377	0.6985	0.4849	45,171	22679.94	0.9044	0.3658
	Disabled	53	13924.94			31	19294.03		
Asthma	Never Disabled	1,05,274	15376.14	-0.0413	0.9671	45,013	22663.72	**-2.1885**	0.0286
	Disabled	512	15403.8			189	25987.6		
Polio	Never Disabled	1,05,654	15376.01	-0.1605	0.8725	45,160	22680.52	0.9681	0.333
	Disabled	132	15587.51			42	19566.31		
Paralysis	Never Disabled	1,05,676	15373.11	**-2.1114**	0.0347	45,155	22681.52	0.0544	0.833
	Disabled	110	18420.86			47	18566.31		
Epilepsy	Never Disabled	1,05,682	15379.24	**2.0298**	0.0424	45,159	22683.19	1.8413	0.0656
	Disabled	104	12366.16			43	16829.71		
Mental Illness	Never Disabled	1,05,642	15377.33	0.6108	0.5413	45,124	22684.84	1.7722	0.0764
	Disabled	144	14606.6			78	18500.11		
STD-AIDS	Never Disabled	1,05,728	15376.13	-0.1306	0.8961	45,183	22678.98	0.6758	0.4992
	Disabled	58	15635.62			19	19447.67		
Others	Never Disabled	1,03,553	15346.89	**-4.3018**	0.0000	44,263	22618.07	**-4.1724**	0.0000
	Disabled	2,233	16739.01			939	25484.62		

Note 1)Two-tail t-test is used.

Source: Authors' calculations based on IHDS 1 data.

4.3.2.3:Food Expenditure Per Capita And Morbidity-Specific Disability:

Food expenditure is an important aspect of household consumption expenditure(Table 15). The food expenditure is significantly different for those disabled with fever, cough, and diarrhoea in rural and urban areas. Only those disabled with fever and cough in a rural area had higher food expenditure than those not disabled. Those disabled with high blood pressure, heart disease, diabetes, leprosy, and others had significantly different consumption expenditures in both rural and urban. Additionally, only those from rural areas disabled with asthma had significantly different and higher food expenditures. Also, those disabled with cataracts, high blood pressure, heart diseases, diabetes, leprosy, and others had higher food expenditures in rural and urban areas.

TABLE 15:**Food Expenditure Per Capita And Morbidity-Specific Disability (Rural and Urban, 2005)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	93,680	600.2699	**-5.7909**	0.0000	41,024	754.8567	**5.0615**	0.0000
	Disabled	12,106	619.5629			4,178	723.8478		
Cough	Never Disabled	96,207	599.3582	**-9.3237**	0.0000	41,729	754.2963	**4.504**	0.0000
	Disabled	9,579	633.8089			3,473	724.2865		
Diarrhoea	Never Disabled	1,02,735	603.2127	**4.0208**	0.0001	44,326	752.5738	**2.3376**	0.0194
	Disabled	3,051	577.7295			876	722.4788		
Cataract	Never Disabled	1,05,185	7225.316	**-4.5912**	0.0000	44,994	9025.635	1.2073	0.2273
	Disabled	601	8002.811			208	8645.699		
Tuberculosis	Never Disabled	1,05,443	7230.241	0.6998	0.484	45,098	9025.23	1.3135	0.189
	Disabled	343	7073.543			104	8441.341		
High BP	Never Disabled	1,04,763	7210.987	**-14.9185**	0.0000	44,168	8980.52	**-13.3336**	0.0000
	Disabled	1,023	9149.458			1,034	10876.33		
Heart Disease	Never Disabled	1,05,413	7223.364	**-8.4143**	0.0000	44,871	9014.245	**-5.2725**	0.0000
	Disabled	373	9029.721			331	10330.98		
Diabetes	Never Disabled	1,05,316	7219.378	**-12.1857**	0.0000	44,659	8998.734	**-10.7234**	0.0000
	Disabled	470	9550.05			543	11092.56		
Leprosy	Never Disabled	1,05,731	7229.083	**-2.2377**	0.0252	45,170	9022.643	**-2.1948**	0.0282
	Disabled	55	8478.613			32	10780.12		
Cancer	Never Disabled	1,05,733	7229.514	-0.7675	0.4428	45,171	9024.402	0.9236	0.3557
	Disabled	53	7666.094			31	8273.016		
Asthma	Never Disabled	1,05,274	7227.02	**-3.0553**	0.0022	45,013	9021.593	-1.662	0.0965
	Disabled	512	7787.388			189	9570.162		
Polio	Never Disabled	1,05,654	7229.142	-1.3132	0.1891	45,160	9024.89	1.5438	0.1226
	Disabled	132	7702.66			42	7945.724		
Paralysis	Never Disabled	1,05,676	7229.528	-0.5	0.617	45,155	9024.985	1.5982	0.11
	Disabled	110	7427.02			47	7968.794		
Epilepsy	Never Disabled	1,05,682	7230.055	0.807	0.4197	45,159	9024.759	1.3267	0.1846
	Disabled	104	6902.277			43	8108.145		
Mental Illness	Never Disabled	1,05,642	7229.68	-0.1128	0.9102	45,124	9024.838	1.0737	0.283
	Disabled	144	7268.64			78	8473.873		
STD-AIDS	Never Disabled	1,05,728	7229.743	0.032	0.9745	45,183	9024.058	0.3911	0.6957
	Disabled	58	7212.331			19	8617.643		
Others	Never Disabled	1,03,553	7217.761	**-6.4061**	0.0000	44,263	9014.338	**-3.0786**	0.0021
	Disabled	2,233	7784.932			939	9474.025		

Note: 1) Two-tail t-test is used.
Source: Authors' Calculations based on IHDS 1 data.

4.3.2.4: Non-Food Expenditure Per Capita And Morbidity-Specific Disability:

Non-food expenditure is also an important component of consumption expenditure since education is included in the non-food expenditure. Short-morbidity disabled had significantly different expenditures than those not disabled across the rural and urban areas (Table 16). For major morbidity, the non-food expenditure was significant for those disabled with high blood pressure, heart disease, diabetes, leprosy, and others. In the rural area, those disabled with cataracts, tuberculosis, and paralysis had significantly different non-food expenditures. Those disabled with cataracts, high blood pressure, heart disease, diabetes, paralysis, and others had high non-food expenditures among major morbidity categories, and among urban those with high blood pressure, heart disease, and others have higher non-food expenditures.

TABLE 16**: Non-Food** E**xpenditure Per Capita And Morbidity-Specific Disability (Rural and Urban, 2005)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	93,680	528.31	**3.5689**	0.0004	41,024	954.5103	**3.7335**	0.0002
	Disabled	12,106	495.4364			4,178	875.3748		
Cough	Never Disabled	96,207	526.4511	**2.0568**	0.0397	41,729	953.5864	**3.6083**	0.0003
	Disabled	9,579	505.4341			3,473	870.4114		
Diarrhoea	Never Disabled	1,02,735	528.3182	**7.4627**	0	44,326	949.7293	**2.9355**	0.0033
	Disabled	3,051	397.5932			876	818.9987		
Cataract	Never Disabled	1,05,185	6287.596	**-2.624**	0.0087	44,994	11373.76	1.4802	0.1388
	Disabled	601	7516.194			208	9762.366		
Tuberculosis	Never Disabled	1,05,443	6298.747	**2.0782**	0.0377	45,098	11370.66	1.2178	0.2233
	Disabled	343	5012.371			104	9497.932		
High BP	Never Disabled	1,04,763	6253.932	**-11.7**	0	44,168	11218.21	**-13.1661**	0
	Disabled	1,023	10456.85			1,034	17694.33		
Heart Disease	Never Disabled	1,05,413	6285.55	**-4.312**	0	44,871	11326.08	**-6.3665**	0
	Disabled	373	8845.275			331	16825.48		
Diabetes	Never Disabled	1,05,316	6274.423	**-8.576**	0	44,659	11282.87	**-10.2875**	0
	Disabled	470	10810.42			543	18232.35		

Leprosy	Never Disabled	1,05,731	6294.838	0.3263	0.7442	45,170	11364.44	-0.9727	0.3307
	Disabled	55	5791.194			32	14058.87		
Cancer	Never Disabled	1,05,733	6294.622	0.0593	0.9527	45,171	11367.26	0.473	0.6362
	Disabled	53	6201.324			31	10036.15		
Asthma	Never Disabled	1,05,274	6294.566	-0.004	0.9969	45,013	11363.62	-0.5708	0.5681
	Disabled	512	6296.547			189	12015.43		
Polio	Never Disabled	1,05,654	6294.746	0.1371	0.8909	45,160	11368.47	0.9426	0.3459
	Disabled	132	6158.069			42	9088.995		
Paralysis	Never Disabled	1,05,676	6289.52	**-4.453**	0	45,155	11370.34	1.6766	0.0936
	Disabled	110	11151.33			47	7537.429		
Epilepsy	Never Disabled	1,05,682	6295.658	0.9804	0.3269	45,159	11370.38	1.7745	0.076
	Disabled	104	5194.822			43	7129.489		
Mental Illness	Never Disabled	1,05,642	6294.899	0.2489	0.8034	45,124	11368.67	0.7572	0.4489
	Disabled	144	6057.344			78	10024.48		
STD-AIDS	Never Disabled	1,05,728	6294.808	0.2815	0.7784	45,183	11367.68	0.8836	0.3769
	Disabled	58	5871.702			19	8191.472		
Others	Never Disabled	1,03,553	6278.852	**-3.043**	0.0023	44,263	11327.14	**-3.6546**	0.0003
	Disabled	2,233	7023.749			939	13214.83		

Note:1) Two-tail t-test is used.

Source: Authors' calculations based on IHDS 1 data.

In 2005, the individuals who were disabled with short morbidity had significantly different consumption expenditures, adjusted consumption expenditures, and food and non-food expenditures in rural and urban areas. Among the major morbidity, those disabled with the three lifestyle diseases, i.e. heart disease, high blood pressure and diabetes, had significantly different expenditures than those not disabled. Additionally, leprosy, asthma, paralysis, and cataract-related disabilities were also responsible for differential consumption expenditure.

In the next section, short morbidity and major morbidity disability and consumption expenditure differentials are discussed for IHDS 2. Morbidity-specific disability is discussed, followed by duration-specific disability.

4.3.2.5: Consumption Expenditure Per Capita And Morbidity-Specific Disability:

Results for consumption expenditure and morbidity-specific disability for rural and urban areas for 2012(Table 17) showed that the consumption expenditure was significant and higher for all types of short morbidity in rural and only for fever in urban. Major morbidity disabilities, cataracts, high blood pressure, heart diseases, diabetes, cancer, asthma, paralysis, accidents, and other disabilities had significant and higher consumption expenditure in rural areas. For urban areas, the consumption expenditure was significantly different for cataracts, high blood pressure, heart disease, diabetes, cancer, asthma, mental illness, and accidents. Among these, except for mental illness, the remaining categories had higher consumption expenditure than those not disabled.

Table 17: **Consumption Expenditure per capita and morbidity-specific disability (Rural and Urban, 2012)**

			Rural				**Urban**		
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	86,893	1768.684	**-4.8604**	0.0000	42,690	2653.369	**2.4643**	0.0137
	Disabled	15,389	1849.724			6,016	2560.241		
Cough	Never Disabled	91,253	1772.912	**-3.8431**	0.0001	44,102	2641.371	-0.1232	0.9019
	Disabled	11,029	1846.777						
Diarrhoea	Never Disabled	1,00,002	1778.356	**-2.8004**	0.0051	47,857	2,644	1.3937	0.1634
	Disabled	2,280	1891.44			849	2511.754		
Cataract	Never Disabled	1,00,755	21311.17	**-6.7411**	0.0000	48,077	31662.1	**-2.3613**	0.0182
	Disabled	1,527	25287.09			629	34782.67		
Tuberculosis	Never Disabled	1,01,788	21370.27	-0.0523	0.9583	48,521	31713.57	1.2124	0.2254
	Disabled	494	21424.21			185	28772.62		
High BP	Never Disabled	99,293	21087.12	**-22.8909**	0.0000	46,043	31149	**15.4584**	0.0000
	Disabled	2,989	30785.22			2,663	41270.48		
Heart Disease	Never Disabled	1,01,481	21273.19	**-15.3316**	0.0000	48,028	31546.36	**-8.8079**	0.0000
	Disabled	801	33702.23			678	42755.64		
Diabetes	Never Disabled	1,00,873	21165.83	**-24.2791**	0.0000	46,990	31244.57	**-16.0979**	0.0000
	Disabled	1,409	36025.11			1,716	44239.3		
Leprosy	Never Disabled	1,02,210	21372.05	0.8041	0.4214	48,679	31700.48	-0.5461	0.585
	Disabled	72	19203.17			27	35162.77		
Cancer	Never Disabled	1,02,206	21356.94	**-6.9683**	0.0000	48,649	31667.91	**-6.754**	0.0000
	Disabled	76	39647.94			57	61132		

Asthma	Never Disabled	1,01,067	21342.4	**-3.5857**	0.0003	48,214	31653.57	**-3.2393**	0.0012
	Disabled	1,215	23710			492	36486.94		
Polio	Never Disabled	1,02,148	21367.04	-1.3472	0.1779	48,652	31699.59	-0.5643	0.5726
	Disabled	134	24031.61			54	34229.83		
Paralysis	Never Disabled	1,01,820	21325.3	**-9.3885**	0.0000	48,424	31689.52	-1.131	0.2581
	Disabled	462	31337.43			282	33913.91		
Epilepsy	Never Disabled	1,02,025	21366.61	-1.0896	0.2759	48,630	31701.71	-0.1157	0.9079
	Disabled	257	22923.7			76	32139.25		
Mental Illness	Never Disabled	1,01,882	21363.22	-1.6301	0.1031	48,535	31722.14	**2.2292**	0.0258
	Disabled	400	23231.71			171	26098.62		
STD-AIDS	Never Disabled	1,02,243	21370.78	0.1832	0.8546	48,687	31702.64	0.0829	0.9339
	Disabled	39	20699.43			19	31076.32		
Accident	Never Disabled	1,01,708	21304.1	**-12.3684**	0.0000	48,460	31645.28	**-5.3734**	0.0000
	Disabled	574	33140.28			246	42952.98		
Others	Never Disabled	97,299	21174.72	**-12.1027**	0.0000	46,610	31446.7	**-8.0859**	0.0000
	Disabled	4,983	25193.8			2,096	37388.41		

Note:1) Two-tail t-test is used.
Source: Authors' Calculations based on IHDS 2 data.

4.3.2.6: Adjusted Consumption Expenditure (Without Insurance Reimbursement)Per Capita And Morbidity-Specific Disability:

The adjusted consumption expenditure for those disabled with short morbidity disability was statistically significant for all categories or short morbidity for rural and urban (Table 18). For major morbidity disabilities, the adjusted consumption expenditure was statistically significant for cataracts, tuberculosis, high blood pressure, heart disease, diabetes, paralysis, accidents, and others in rural areas. But only those disabled with cataracts, high blood pressure, heart disease, diabetes, paralysis, accidents, and others had higher adjusted consumption expenditure. For the urban area, the adjusted consumption expenditure was statistically significant for tuberculosis, high blood pressure, heart diseases, diabetes, mental illness, and others who had significantly different adjusted consumption expenditures than those who were not disabled. Among these, only those with higher blood pressure, heart disease, diabetes and others had higher adjusted consumption expenditure than those not disabled.

Table 18:**Adjusted Consumption Expenditure (without insurance reimbursement) per capita by morbidity-specific disability(Rural and Urban, 2012)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	86,893	1741.221	**5.1872**	0	42,690	2618.248	**6.3027**	0
	Disabled	15,389	1655.635			6,016	2383.178		
Cough	Never Disabled	91,253	1737.109	**4.2738**	0	44,102	2600.942	**2.9574**	0.0031
	Disabled	11,029	1655.824			4,604	2476.855		
Diarrhoea	Never Disabled	1,00,002	1730.207	**2.0911**	0.037	47,857	2594.6	**3.2952**	0.001
	Disabled	2,280	1646.645			849	2285.525		
Cataract	Never Disabled	1,00,755	20716.62	**-2.6978**	0.007	48,077	31057.13	-0.7967	0.4256
	Disabled	1,527	22291.47			629	32096.69		
Tuberculosis	Never Disabled	1,01,788	20750.89	**2.1808**	0.029	48,521	31090.86	**2.2321**	0.0256
	Disabled	494	18524.01			185	25745.36		
HighBP	Never Disabled	99,293	20530.35	**-17.103**	0	46,043	30649.78	**-11.893**	0
	Disabled	2,989	27708.84			2,663	38345.69		
Heart Disease	Never Disabled	1,01,481	20695.45	**-7.1057**	0	48,028	30990.34	**-4.5838**	0
	Disabled	801	26400.95			678	36752.85		
Diabetes	Never Disabled	1,00,873	20585.65	**-18.494**	0	46,990	30704.84	**-13.013**	0
	Disabled	1,409	31799.88			1,716	41085.19		
Leprosy	Never Disabled	1,02,210	20743.85	1.9786	0.048	48,679	31071.19	0.1839	0.8541
	Disabled	72	15462.48			27	29920.46		
Cancer	Never Disabled	1,02,206	20737.93	-1.138	0.255	48,649	31060.56	-1.9827	0.0474
	Disabled	76	23694.55			57	39603.41		
Asthma	Never Disabled	1,01,067	20744.41	0.5516	0.581	48,214	31045.48	-1.685	0.092
	Disabled	1,215	20383.96			492	33527.78		
Polio	Never Disabled	1,02,148	20740.64	0.1992	0.842	48,652	31069.98	-0.1167	0.9071
	Disabled	134	20350.8			54	31586.77		
Paralysis	Never Disabled	1,01,820	20721.72	**-3.8616**	0.004	48,424	31081.92	1.0113	0.3119
	Disabled	462	24798.34			282	29118.22		
Epilepsy	Never Disabled	1,02,025	20741.94	0.5079	0.612	48,630	31076.62	1.0412	0.2978
	Disabled	257	20023.66			76	27190.61		
Mental Illness	Never Disabled	1,01,882	20745.3	1.1643	0.244	48,535	31099.18	**3.2743**	0.0011
	Disabled	400	19424.67			171	22944.82		
STD-AIDS	Never Disabled	1,02,243	20740.92	0.5726	0.567	48,687	31071.7	0.395	0.6928
	Disabled	39	18664.65			19	28124.59		
Accident	Never Disabled	1,01,708	20707.65	**-6.1077**	0	48,460	31053.56	-1.6194	0.1054
	Disabled	574	26494.84			246	34418.93		
Others	Never Disabled	97,299	20695.78	**-2.7683**	0.006	46,610	2,096	**-3.7905**	0.0002
	Disabled	4,983	21606.11			30952.16	33703.47		

Note:1) Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.2.7: Food Expenditure Per Capita And Morbidity-Specific Disability:

The food expenditure was statistically significant for those with short morbidity in rural areas for all categories and fever and cough in urban areas(Table 19). Those disabled with fever, cough and diarrhoea in a rural area had higher food expenditure than those not disabled. It was statistically significant for those disabled by major morbidities like cataracts, tuberculosis, high blood pressure, heart disease, diabetes, cancer, asthma, and paralysis in rural areas. Among those disabled in rural areas with cataracts, high blood pressure, heart disease, diabetes, cancer, asthma, paralysis, accidents, and others had higher food expenditure. It was also significant for those in urban areas disabled with tuberculosis, high blood pressure, heart diseases, diabetes, leprosy, cancer, polio, paralysis, epilepsy, mental illness, and others. Among those with significant food expenditure for major morbidity in urban areas, only those with high blood pressure, heart disease, diabetes, cancer, epilepsy, and others had higher food expenditure than those not disabled.

Table 19**: Food Expenditure per capita and morbidity-specific disability(Rural and Urban, 2012)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	86,893	729.1679	**-5.3782**	0	42,690	910.385	**3.3096**	0.0009
	Disabled	15,389	748.0653			6,016	889.7501		
Cough	Never Disabled	91,253	730.4093	**-3.6676**	0.0002	44,102	909.4285	**2.4022**	0.0163
	Disabled	11,029	745.2648			4,604	892.5835		
Diarrhoea	Never Disabled	1,00,002	731.5694	**-2.3289**	0.0199	47,857	908.0614	0.824	0.41
	Disabled	2,280	751.3886			849	895.1444		
Cataract	Never Disabled	1,00,755	8767.328	**-9.0583**	0	48,077	10893.86	-0.0612	0.9512
	Disabled	1,527	9893.036			629	10907.2		
Tuberculosis	Never Disabled	1,01,788	8786.491	**2.2439**	0.0248	48,521	10897.32	**2.1604**	0.0308
	Disabled	494	8298.52			185	10032.71		
High BP	Never Disabled	99,293	8719.694	**-24.708**	0	46,043	10797.71	**-16.3135**	0
	Disabled	2,989	10924.79			2,663	12559.53		
Heart Disease	Never Disabled	1,01,481	8764.926	**-14.3543**	0	48,028	10868.21	**-8.834**	0
	Disabled	801	11217.61			678	12723.08		
Diabetes	Never Disabled	1,00,873	8750.085	**-19.1426**	0	46,990	10823.24	**-15.0831**	0
	Disabled	1,409	11221.72			1,716	12832.71		

Leprosy	Never Disabled	1,02,210	8784.7	1.4145	0.1572	48,679	10895.3	**2.1811**	0.0292
	Disabled	72	7980.64			27	8614.069		
Cancer	Never Disabled	1,02,206	8783.183	**-2.3136**	0.0207	48,649	10892.26	**-2.1043**	0.0354
	Disabled	76	10063.28			57	12407.52		
Asthma	Never Disabled	1,01,067	8779.316	**-2.9145**	0.0036	48,214	10894.19	0.0634	0.9495
	Disabled	1,215	9184.873			492	10878.59		
Polio	Never Disabled	1,02,148	8784.271	0.2515	0.8014	48,652	10895.96	**2.3464**	0.019
	Disabled	134	8679.443			54	9160.137		
Paralysis	Never Disabled	1,01,820	8779.15	**-4.9083**	0	48,424	10900.78	**3.5902**	0.0003
	Disabled	462	9882.595			282	9735.91		
Epilepsy	Never Disabled	1,02,025	8783.066	-1.4118	0.158	48,630	10892.07	**-2.0158**	0.0438
	Disabled	257	9208.232			76	12149.36		
Mental Illness	Never Disabled	1,01,882	8783.376	-0.8028	0.4221	48,535	10897.56	2.4119	0.0159
	Disabled	400	8977.298			171	9893.698		
STD-AIDS	Never Disabled	1,02,243	8783.959	-0.5932	0.5531	48,687	10894.13	0.2065	0.8364
	Disabled	39	9242.021			19	10636.71		
Accident	Never Disabled	1,01,708	8779.055	**-4.4844**	0	48,460	10890.78	-1.8579	0.0632
	Disabled	574	9684.03			246	11536		
Others	Never Disabled	97,299	8749.332	**-10.2053**	0	46,610	10862.26	**-6.0882**	0
	Disabled	4,983	9463.68			2,096	11600.6		

Note:1) Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.2.8: Non-Food Expenditure Per Capita And Morbidity-Specific Disability:

An analysis of non-food expenditure for those disabled from specific morbidities is provided in the table below (Table 20). The non-food expenditure was significantly different for short morbidities in rural areas for all categories, and in urban areas, it was significant only for diarrhoea. For major morbidities, the non-food expenditure was significant and higher for cataracts, high blood pressure, heart disease, diabetes, cancer, paralysis, accidents, and others in rural areas. It was significantly different for high blood pressure, heart disease, diabetes, asthma, mental illness, and accidents in urban areas. Except for mental illness, all other categories of major morbidities with statistically significant non-food expenditure also had higher non-food expenditure.

Table 20: **Non-Food Expenditure Per Capita And Morbidity Disease-Specific Disability(Rural And Urban, 2012)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	86,893	872.9372	1.8869	0.0592	42,690	1567.93	**4.1684**	0
	Disabled	15,389	848.3598			6,016	1435.338		
Cough	Never Disabled	91,253	871.8573	1.6171	0.1059	44,102	1557.621	1.7943	0.0728
	Disabled	11,029	847.5788			4,604	1493.423		
Diarrhoea	Never Disabled	1,00,002	869.3396	0.1426	0.8866	47,857	1555.164	**2.5908**	0.0096
	Disabled	2,280	864.8423			849	1347.947		
Cataract	Never Disabled	1,00,755	10415.73	**-2.2007**	0.0278	48,077	18602.09	-1.1509	0.2498
	Disabled	1,527	11429.8			629	19882.49		
Tuberculosis	Never Disabled	1,01,788	10436.8	1.523	0.1278	48,521	18628.75	1.3049	0.1919
	Disabled	494	9209.195			185	15964.02		
High blood pressure	Never Disabled	99,293	10267.12	**-16.9125**	0	46,043	18267.79	**-11.6296**	0
	Disabled	2,989	15870.47			2,663	24684.61		
Heart Disease	Never Disabled	1,01,481	10398.56	**-6.5092**	0	48,028	18551.85	**-4.475**	0
	Disabled	801	14524.24			678	23348.87		
Diabetes	Never Disabled	1,00,873	10304.04	**-19.2382**	0	46,990	18322.56	**-12.353**	0
	Disabled	1,409	19510.76			1,716	26726.03		
Leprosy	Never Disabled	1,02,210	10432.88	1.357	0.1748	48,679	18617.22	-0.4778	0.6328
	Disabled	72	7573.716			27	21167.04		
Cancer	Never Disabled	1,02,206	10427.68	**-2.096**	0.0361	48,649	18612.67	-1.3857	0.1658
	Disabled	76	14726.1			57	23703.89		
Asthma	Never Disabled	1,01,067	10429.87	0.1634	0.8702	48,214	18584.72	**-2.6723**	0.0075
	Disabled	1,215	10514.13			492	21941.4		
Polio	Never Disabled	1,02,148	10430.53	-0.1694	0.8655	48,652	18615.16	-0.8284	0.4074
	Disabled	134	10692.17			54	21742.12		
Paralysis	Never Disabled	1,01,820	10412.68	**-4.8344**	0	48,424	18617.36	-0.1326	0.8945
	Disabled	462	14440.96			282	18836.88		
Epilepsy	Never Disabled	1,02,025	10431.2	0.1162	0.9075	48,630	18625.18	1.3201	0.1868
	Disabled	257	10301.52			76	14423.91		

Mental Illness	Never Disabled	1,01,882	10433.17	0.6567	0.5113	48,535	18641.07	**3.0099**	0.0026
	Disabled	400	9845.166			171	12249.45		
STD-AIDS	Never Disabled	1,02,243	10431.75	0.8071	0.4196	48,687	18619.39	0.3083	0.7578
	Disabled	39	8121.562			19	16657.95		
Accident	Never Disabled	1,01,708	10413.95	**-4.0313**	0.0001	48,460	18593.47	**-2.8108**	0.0049
	Disabled	574	13429.34			246	23573.9		
Others	Never Disabled	1,00,115	10414.96	-1.9357	0.0529	47,701	18623.95	0.292	0.7703
	Disabled	2,167	11166.1			1,005	18365.93		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.2.9: Adjusted Consumption Expenditure (With Insurance Reimbursement) Per Capita And Morbidity-Specific Disability:

The adjusted consumption expenditure (without insurance reimbursement)significantly differed for all three categories of short morbidity in rural and urban areas (Table 21). For major morbidity, the adjusted consumption expenditure was significantly different for cataracts, tuberculosis, high blood pressure, heart diseases, diabetes, paralysis, accidents, and others in rural areas. Except for tuberculosis, the other significant categories had higher adjusted consumption expenditure. In urban areas, the categories for which the adjusted consumption expenditure was significantly different were tuberculosis, high blood pressure, heart disease, cancer, and mental illness. Among these, those disabled with high blood pressure, heart disease, cancer, and others had higher adjusted consumption expenditures.

TABLE 21: **Adjusted Consumption Expenditure (insurance reimbursement) per capita and morbidity-specific disability (Rural and Urban, 2012)**

		Rural				Urban			
Morbidity	**Categories**	**Obs**	**Mean**	**t-test**	**p-value**	**Obs**	**Mean**	**t-test**	**p-value**
Fever	Never Disabled	86,893	1740.789	**5.216**	0	42,690	2617.604	**6.347**	0
	Disabled	15,389	1654.745			6,016	2381.035		
Cough	Never Disabled	91,253	1736.672	**4.3062**	0	44,102	2600.291	**3.004**	0.0027
	Disabled	11,029	1654.788			4,604	2474.327		
Diarrhoea	Never Disabled	1,00,002	1729.725	**2.113**	0.0346	47,857	2593.814	**3.3234**	0.0009
	Disabled	2,280	1645.301			849	2282.288		
Cataract	Never Disabled	1,00,755	20711.42	**-2.6043**	0.0092	48,077	31048.33	-0.7289	0.4661
	Disabled	1,527	22231.42			629	31998.8		
Tuberculosis	Never Disabled	1,01,788	20744.87	**2.1817**	0.0291	48,521	31080.91	**2.2331**	0.0255
	Disabled	494	18517.47			185	25736.51		

High BP	Never Disabled	99,293	20525.41	**-17.018**	0	46,043	2,663	**-11.807**	0
	Disabled	2,989	27667.05			30643.15	38278.38		
Heart Disease	Never Disabled	1,01,481	20691.27	**-6.8148**	0	48,028	30982.52	**-4.4652**	0
	Disabled	1,01,481	26162.24			678	36592.41		
Diabetes	Never Disabled	1,00,873	20580.79	**-18.358**	0	46,990	30697.04	**-12.945**	0
	Disabled	1,409	31710.84			1,716	41016.27		
Leprosy	Never Disabled	1,02,210	20737.84	1.9819	0.0475	48,679	31061.27	0.1898	0.8495
	Disabled	72	15448.77			27	29874.17		
Cancer	Never Disabled	1,02,206	20732.11	-1.0358	0.3003	48,649	31051.02	-1.9019	0.0572
	Disabled	76	23422.62			57	39240.54		
Asthma	Never Disabled	1,01,067	20738.73	0.5955	0.5515	48,214	31036.97	-1.5897	0.1119
	Disabled	1,215	20349.66			492	33377.42		
Polio	Never Disabled	1,02,148	20734.81	0.2734	0.7845	48,652	31060.05	-0.1138	0.9094
	Disabled	134	20199.75			54	31563.62		
Paralysis	Never Disabled	1,01,820	20716.04	**-3.7901**	0.0002	48,424	31072.18	1.0299	0.3031
	Disabled	462	24716.4			282	29073.67		
Epilepsy	Never Disabled	1,02,025	20736.41	0.6464	0.518	48,630	31066.66	1.0392	0.2987
	Disabled	257	19822.51			76	27190.61		
Mental Illness	Never Disabled	1,01,882	20739.27	1.1636	0.2446	48,535	31089.2	**3.2726**	0.0011
	Disabled	400	19419.67			171	22944.38		
STD-AIDS	Never Disabled	1,02,243	20734.9	0.571	0.568	48,687	31061.75	0.394	0.6936
	Disabled	39	18664.65			19	28124.59		
Accident	Never Disabled	1,01,708	20702.04	**-6.0322**	0	48,460	31044.97	-1.4911	0.136
	Disabled	574	26416.61			246	34141.63		
Others	Never Disabled	97,299	20692.26	**-2.6132**	0.009	46,610	30945.09	**-3.7005**	0.0002
	Disabled	4,983	21551.41			2,096	33629.42		

Note:1) Two-tail t-test is used.
Source: Authors' calculations based on IHDS 2 data.

4.3.3: Consumption Expenditure And Disability By Duration:

This section deals with the results of disability by duration for different types of monthly consumption expenditure. These tests are carried out separately for IHDS 1 and IHDS 2 for rural and urban areas.

4.3.3.1: Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity:

In Rural areas, the consumption expenditure was significantly different for those disabled for 1 week, 3 weeks, 4 weeks, and higher expenditure. The consumption expenditure was statistically significant for those disabled between 1 week to 4 weeks, 2 weeks to 4 weeks and 3 weeks to 4 weeks in a rural area (Table 22). For urban areas, the consumption expenditure was significantly different for those disabled for 2 weeks and between 1 to 2 weeks.

TABLE 22:**Monthly Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**mean**	**t-test**	**P-value**	**Observations**	**mean**	**t-test**	**P-value**
Not disabled	95,814	1301.071	**-2.0726**	0.0382	41,854	1915.865	0.9575	0.3384
Disabled for 1 week	7,377	1330.814			2,662	1885.687		
Not disabled	95,814	1301.071	-0.4468	0.6551	41,854	1915.865	**2.9291**	0.0036
Disabled for 2 weeks	1,647	1312.138			444	1716.296		
Not disabled	95,814	1301.071	**-2.4115**	0.0162	41,854	1915.865	1.5195	0.1304
Disabled for 3 weeks	623	1405.044			180	1760.709		
Not disabled	95,814	1301.071	**-3.6962**	0.0003	41,854	62	0.2827	0.7783
Disabled for 4 weeks	325	1663.727			1915.865	1849.969		
Disabled for 1 week	7,377	1330.814	0.6664	0.5052	2,662	1885.687	**2.2867**	0.0225
Disabled for 2 weeks	1,647	1312.138			444	1716.296		
Disabled for 1 week	7,377	1330.814	-1.6472	0.0999	2,662	1885.687	1.1772	0.2404
Disabled for 3 weeks	623	1405.044			180	1760.709		
Disabled for 1 week	7,377	1330.814	**-3.3632**	0.0009	2,662	1885.687	0.1521	0.8796
Disabled for 4 weeks	325	1663.727			62	1849.969		
Disabled for 2 weeks	1,647	1312.138	-1.8814	0.0602	444	1716.296	-0.3636	0.7164
Disabled for 3 weeks	623	1405.044			180	1760.709		
Disabled for 2 weeks	1,647	1312.138	**-3.4802**	0.0006	444	1716.296	-0.5512	0.5832
Disabled for 4 weeks	325	1663.727			62	1849.969		
Disabled for 3 weeks	623	1405.044	**-2.4174**	0.016	180	1760.709	-0.3512	0.7263
Disabled for 4 weeks	325	1663.727			62	1849.969		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 1 data.

4.3.3.2: Monthly Adjusted Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity:

In the rural areas, those disabled for one week, two weeks, three weeks, between 1 week to 2 weeks, and 1 week to 3 weeks had significantly different expenditures(Table 23). For urban areas, the adjusted expenditure was significant for those disabled for 1 week, 2 weeks, 3 weeks and 4 weeks, and between 1 week to 2 weeks, 1 week to 3 weeks and 1week to 4 weeks.

TABLE 23:**Adjusted Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	95,814	1289.571	**3.9174**	0.0001	41,854	1902.262	**3.5698**	0.0004
Disabled for 1 week	7,377	1234.651			2,662	1792.118		
Not disabled	95,814	1289.571	**6.8616**	0	41,854	1902.262	**5.5139**	0
Disabled for 2 weeks	1,647	1128.135			444	1537.704		
Not disabled	95,814	1289.571	**5.4959**	0	41,854	1902.262	**4.1831**	0
Disabled for 3 weeks	623	1045.991			180	1501.576		
Not disabled	95,814	1289.571	1.4957	0.1357	41,854	1902.262	**2.6579**	0.01
Disabled for 4 weeks	325	1147.31			62	1320.757		
Disabled for 1 week	7,377	1234.651	**3.9799**	0.0001	2,662	1792.118	**3.5361**	0.0004
Disabled for 2 weeks	1,647	1128.135			444	1537.704		
Disabled for 1 week	7,377	1234.651	**4.0907**	0	2,662	1792.118	**2.9083**	0.004
Disabled for 3 weeks	623	1045.991			180	1501.576		
Disabled for 1 week	7,377	1234.651	0.9101	0.3634	2,662	1792.118	**2.1366**	0.0365
Disabled for 4 weeks	325	1147.31			62	1320.757		
Disabled for 2 weeks	1,647	1128.135	1.6482	0.0996	444	1537.704	0.3121	0.7551
Disabled for 3 weeks	623	1045.991			180	1501.576		
Disabled for 2 weeks	1,647	1128.135	-0.196	0.8447	444	1537.704	0.9505	0.345
Disabled for 4 weeks	325	1147.31			62	1320.757		
Disabled for 3 weeks	623	1045.991	-0.967	0.334	180	1501.576	0.7581	0.4505
Disabled for 4 weeks	325	1147.31			62	1320.757		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 1 data.

4.3.3.3: Monthly Food Expenditure Per Capita And Days Disabled Due To Short Morbidity:

The food expenditure was statistically significant and higher for those disabled for one week. It was also significant for those disabled, between 1 week to 2 weeks for rural areas. For one week, two weeks and three weeks for urban areas; between 1 week to 2 weeks also(Table 24).

TABLE 24:**Food Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	95,814	601.1397	**-3.5768**	0.0003	41,854	753.7788	**2.1204**	0.0341
Disabled for 1 week	7,377	618.6322			2,662	738.0873		
Not disabled	95,814	601.1397	0.4391	0.6607	41,854	753.7788	**3.9547**	0.0001
Disabled for 2 weeks	1,647	597.8016			444	693.1216		
Not disabled	95,814	601.1397	-1.5144	0.1304	41,854	753.7788	**2.0994**	0.0372
Disabled for 3 weeks	623	620.9575			180	701.0098		
Not disabled	95,814	601.1397	-0.8047	0.4216	41,854	753.7788	0.597	0.5527
Disabled for 4 weeks	325	618.5601			62	711.3446		
Disabled for 1 week	7,377	618.6322	**2.3391**	0.0194	2,662	738.0873	**2.6721**	0.0077
Disabled for 2 weeks	1,647	597.8016			444	693.1216		
Disabled for 1 week	7,377	618.6322	-0.1675	0.867	2,662	738.0873	1.4221	0.1565
Disabled for 3 weeks	623	620.9575			180	701.0098		
Disabled for 1 week	7,377	618.6322	0.0033	0.9974	2,662	738.0873	0.3745	0.7093
Disabled for 4 weeks	325	618.5601			62	711.3446		
Disabled for 2 weeks	1,647	597.8016	-1.5381	0.1243	444	693.1216	-0.269	0.7881
Disabled for 3 weeks	623	620.9575			180	701.0098		
Disabled for 2 weeks	1,647	597.8016	-0.9068	0.3651	444	693.1216	-0.2508	0.8028
Disabled for 4 weeks	325	618.5601			62	711.3446		
Disabled for 3 weeks	623	620.9575	0.0949	0.9244	180	701.0098	-0.1372	0.8913
Disabled for 4 weeks	325	618.5601			62	711.3446		

Note: Two-tail t-test is used.

Source: Authors' Calculations based on IHDS 1 data.

4.3.3.4: Monthly Non-Food Expenditure Per Capita And Days Disabled Due To Short Morbidity:

Those in rural areas and disabled for one week, two weeks, three weeks and between 1 to 2 weeks had significantly different expenditures (Table 25.). In urban areas, those disabled for 2 weeks, 3 weeks, between 1 week to 2 weeks, and 1 week to 3 weeks had significantly different non-food expenditures.

TABLE 25: **Non-Food Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	95,814	527.3513	**2.1462**	0.0319	41,854	952.2456	1.6266	0.1039
Disabled for 1 week	7,377	506.5291			2,662	914.3419		
Not disabled	95,814	527.3513	**4.1324**	0	41,854	952.2456	**3.809**	0.0002
Disabled for 2 weeks	1,647	459.3619			444	767.3779		
Not disabled	95,814	527.3513	**2.3144**	0.021	41,854	952.2456	**2.6521**	0.0087
Disabled for 3 weeks	623	463.7481			180	769.0858		
Not disabled	95,814	527.3513	-0.4231	0.6725	41,854	952.2456	1.4458	0.1533
Disabled for 4 weeks	325	553.9739			62	753.6705		
Disabled for 1 week	7,377	506.5291	**2.5388**	0.0112	2,662	914.3419	**2.7697**	0.0058
Disabled for 2 weeks	1,647	459.3619			444	767.3779		
Disabled for 1 week	7,377	506.5291	1.4852	0.1379	2,662	914.3419	**2.0087**	0.0458
Disabled for 3 weeks	623	463.7481			180	769.0858		
Disabled for 1 week	7,377	506.5291	-0.747	0.4556	2,662	914.3419	1.1558	0.252
Disabled for 4 weeks	325	553.9739			62	753.6705		
Disabled for 2 weeks	1,647	459.3619	-0.1383	0.8901	444	767.3779	-0.0204	0.9838
Disabled for 3 weeks	623	463.7481			180	769.0858		
Disabled for 2 weeks	1,647	459.3619	-1.458	0.1457	444	767.3779	0.0943	0.9251
Disabled for 4 weeks	325	553.9739			62	753.6705		
Disabled for 3 weeks	623	463.7481	-1.3167	0.1886	180	769.0858	0.1005	0.9202
Disabled for 4 weeks	325	553.9739			62	753.6705		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 1 data.

In this section, we discuss the changes in Annual consumption expenditure due to disability by duration.

4.3.3.5:Annual Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity:

In rural areas, those disabled for three months, six months, nine months, 12 months and between 3 to 6 months had significantly different annual consumption expenditures compared to those who were not disabled. In urban areas, those disabled for three months, nine months, between 3 to 9 months, 6 to 9 months and between 9 to 12 months had significantly different annual consumption expenditures(Table 26).

TABLE 26: **Annual Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	1,01,969	15493	-11.1171	0	43,396	22739.62	**-6.9962**	0
Disabled for 3 Months	3,011	19885.51			1,502	27811.38		
Not disabled	1,01,969	15493	**-6.6636**	0	43,396	22739.62	-1.736	0.0859
Disabled for 6 Months	331	22086.2			94	27132.88		
Not disabled	1,01,969	15493	**-3.2212**	0.0018	43,396	22739.62	**-2.8311**	0.0097
Disabled for 9 Months	83	21025.69			23	41338.6		
Not disabled	1,01,969	15493	**-5.4475**	0	43,396	22739.62	-1.7933	0.0745
Disabled 12 Months	392	20222.4			187	25224.53		
Disabled for 3 Months	3,011	19885.51	**-2.0696**	0.0391	1,502	27811.38	0.2581	0.7968
Disabled for 6 Months	331	22086.2			94	27132.88		
Disabled for 3 Months	3,011	19885.51	-0.6474	0.519	1,502	27811.38	**-2.0471**	0.0525
Disabled for 9 Months	83	21025.69			23	41338.6		
Disabled for 3 Months	3,011	19885.51	-0.354	0.7234	1,502	27811.38	1.6608	0.0978
Disabled 12 Months	392	20222.4			187	25224.53		
Disabled for 6 Months	331	22086.2	0.5353	0.5933	94	27132.88	-2.0182	0.053
Disabled for 9 Months	83	21025.69			23	41338.6		
Disabled for 6 Months	331	22086.2	1.4177	0.1567	94	27132.88	0.6622	0.5089

Disabled 12 Months	392	20222.4			187	25224.53		
Disabled for 9 Months	83	21025.69	0.4176	0.6769	23	41338.6	**2.4005**	0.0245
Disabled 12 Months	392	20222.4			187	25224.53		

Note: Two-tail t-test is used.
Source: Authors' Calculations based on IHDS 1 data.

4.3.3.6: Annual Adjusted Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity:

The adjusted consumption expenditure was significantly different for those disabled for three months in rural areas. For urban areas, the adjusted consumption expenditure was significantly different for those disabled for three months, nine months, between 3 to 6 months, 3 to 12 months, 6 to 9 months, and 9 to 12 months (Table 27).

TABLE 27: **Annual Adjusted Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	1,01,969	15305.19	**-5.5085**	0	43,396	22574.85	**-4.2675**	0
Disabled for 3 Months	3,011	17367.08			1,502	25550.22		
Not disabled	1,01,969	15305.19	-1.9668	0.05	43,396	22574.85	0.6238	0.5343
Disabled for 6 Months	331	17185.13			94	21528.51		
Not disabled	1,01,969	15305.19	-0.9	0.3707	43,396	22574.85	**-2.2179**	0.0372
Disabled for 9 Months	83	16686.78			23	36964.9		
Not disabled	1,01,969	15305.19	-1.745	0.0818	43,396	22574.85	0.2255	0.8218
Disabled 12 Months	392	16769.91			187	22275.47		
Disabled for 3 Months	3,011	17367.08	0.1776	0.8591	1,502	25550.22	**2.2204**	0.0282
Disabled for 6 Months	331	17185.13			94	21528.51		
Disabled for 3 Months	3,011	17367.08	0.4309	0.6675	1,502	25550.22	-1.7496	0.0938
Disabled for 9 Months	83	16686.78			23	36964.9		
Disabled for 3 Months	3,011	17367.08	0.6515	0.515	1,502	25550.22	**2.1935**	0.029
Disabled 12 Months	392	16769.91			187	22275.47		
Disabled for 6 Months	331	17185.13	0.2758	0.7831	94	21528.51	**-2.3039**	0.0298
Disabled for 9 Months	83	16686.78			23	36964.9		

Disabled for 6 Months	331	17185.13	0.3269	0.7439	94	21528.51	-0.3499	0.7268
Disabled 12 Months	392	16769.91			187	22275.47		
Disabled for 9 Months	83	16686.78	-0.0476	0.9621	23	36964.9	**2.2186**	0.0363
Disabled 12 Months	392	16769.91			187	22275.47		

Note: Two-tail t-test is used.
Source: Authors' calculations based on data IHDS 1 data.

4.3.3.7:Annual Food Expenditure Per Capita And Days Disabled Due To Major Morbidity:

Those in rural areas and disabled for 3 months, 6 months, 9 months, and 12 months, and between 3 and 6 months had significantly different food expenditures (Table 28).

Table 28: **Annual Food Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	1,01,969	7202.096	**-8.7079**	0	43,396	9001.265	**-4.591**	0
Disabled for 3 Months	3,011	7877.918			1,502	9566.058		
Not disabled	1,01,969	7202.096	**-5.2482**	0	43,396	9001.265	-0.5219	0.603
Disabled for 6 Months	331	8590.105			94	9267.254		
Not disabled	1,01,969	7202.096	**-2.9918**	0.0037	43,396	9001.265	-1.6282	0.1177
Disabled for 9 Months	83	9024.284			23	10733.88		
Not disabled	1,01,969	7202.096	**-2.985**	0.003	43,396	9001.265	-1.6282	0.1052
Disabled 12 Months	392	7911.317			187	9586.278		
Disabled for 3 Months	3,011	7877.918	**-2.5896**	0.01	1,502	9566.058	0.5709	0.5693
Disabled for 6 Months	331	8590.105			94	9267.254		
Disabled for 3 Months	3,011	7877.918	-1.8679	0.0652	1,502	9566.058	-1.0906	0.287
Disabled for 9 Months	83	9024.284			23	10733.88		
Disabled for 3 Months	3,011	7877.918	-0.134	0.8935	1,502	9566.058	-0.0534	0.9574
Disabled 12 Months	392	7911.317			187	9586.278		
Disabled for 6 Months	331	8590.105	-0.6541	0.5143	94	9267.254	-1.2434	0.2225
Disabled for 9 Months	83	9024.284			23	10733.88		
Disabled for 6 Months	331	8590.105	1.9118	0.0563	94	9267.254	-0.5122	0.6091

Disabled 12 Months	392	7911.317			187	9586.278		
Disabled for 9 Months	83	9024.284	1.7031	0.0914	23	10733.88	1.0221	0.3157
Disabled 12 Months	392	7911.317			187	9586.278		

Note: Two-tail t-test is used.
Source: Authors' calculations based on IHDS 1 data.

4.3.3.8: Annual Non-Food Expenditure Per Capita And Days Disabled Due To Major Morbidity:

The annual non-food expenditure was significantly different for those disabled for three months, six months, between 3 to 6 months, 3 to 9 months, and 3 to 12 months for rural areas. For the urban area, the non-food expenditure was significantly different for those disabled for three months, between 3 to 6 months and 3 to 12 months (Table 29).

Table 29:**Annual Non-Food Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2005)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	1,01,969	6248.155	**19.0296**	0	43,396	11296.88	**-4.0149**	0.0001
Disabled for 3 Months	3,011	598.061			1,502	13466.11		
Not disabled	1,01,969	6248.155	**-2.6769**	0.0078	43,396	11296.88	1.1104	0.2697
Disabled for 6 Months	331	7819.531			94	10138.27		
Not disabled	1,01,969	6248.155	-0.9863	0.3269	43,396	11296.88	-1.5157	0.1438
Disabled for 9 Months	83	7034.668			23	17478.94		
Not disabled	1,01,969	6248.155	-1.0834	0.2793	43,396	11296.88	0.9521	0.3423
Disabled 12 Months	392	6913.073			187	10486.97		
Disabled for 3 Months	3,011	598.061	**-11.0095**	0	1,502	13466.11	**2.8436**	0.0051
Disabled for 6 Months	331	7819.531			94	10138.27		
Disabled for 3 Months	3,011	598.061	**-7.5772**	0	1,502	13466.11	-0.9756	0.3395
Disabled for 9 Months	83	7034.668			23	17478.94		
Disabled for 3 Months	3,011	598.061	**-9.2877**	0	1,502	13466.11	**2.9724**	0.0032
Disabled 12 Months	392	6913.073			187	10486.97		
Disabled for 6 Months	331	7819.531	0.7936	0.4284	94	10138.27	-1.7441	0.0935
Disabled for 9 Months	83	7034.668			23	17478.94		

Disabled for 6 Months	331	7819.531	1.0692	0.2853	94	10138.27	-0.2598	0.7953
Disabled 12 Months	392	6913.073			187	10486.97		
Disabled for 9 Months	83	7034.668	0.121	0.9038	23	17478.94	1.6787	0.1062
Disabled 12 Months	392	6913.073			187	10486.97		

Note: Two-tail t-test is used.
Source: Authors' calculations based on IHDS 1 data.

The following section discusses results for the year 2012 for different types of consumption expenditure and disabilities.

4.3.3.9: Monthly Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity:

Those disabled for one week, three weeks, four weeks, and between 1 week and 3 weeks, 2weeks to 3 weeks, and 2 weeks to 4 weeks had significantly different consumption expenditures in rural areas. For urban areas, no category had significantly different expenditures(Table 30).

Table 30: **Monthly Consumption Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	89,463	1770.49	**-3.6901**	0.0002	43,937	2645.295	0.0195	0.9845
Disabled for 1 week	9,337	1848.671			3,784	2560.831		
Not disabled	89,463	1770.49	-0.095	0.9244	43,937	2645.295	-1.806	0.0713
Disabled for 2 weeks	2,069	1773.795			597	2690.843		
Not disabled	89,463	1770.49	**-3.702**	0.0002	43,937	2645.295	-0.913	0.3623
Disabled for 3 weeks	947	2001.302			278	3064.107		
Not disabled	89,463	1770.49	**-2.5754**	0.0103	43,937	2645.295	-0.278	0.7818
Disabled for 4 weeks	466	2000.208			110	2726.999		
Disabled for 1 week	9,337	1848.671	1.8845	0.0596	3,784	2560.831	-0.03	0.9761
Disabled for 2 weeks	2,069	1773.795			597	2690.843		
Disabled for 1 week	9,337	1848.671	**-2.34**	0.0195	3,784	2560.831	-0.115	0.9082
Disabled for 3 weeks	947	2001.302			278	3064.107		
Disabled for 1 week	9,337	1848.671	-1.661	0.0973	3,784	2560.831	-0.038	0.9695

Disabled for 4 weeks	466	2000.208			110	2726.999		
Disabled for 2 weeks	2,069	1773.795	**-3.2121**	0.0013	597	2690.843	-0.813	0.4171
Disabled for 3 weeks	947	2001.302			278	3064.107		
Disabled for 2 weeks	2,069	1773.795	**-2.3753**	0.0178	597	2690.843	-0.123	0.9026
Disabled for 4 weeks	466	2000.208			110	2726.999		
Disabled for 3 weeks	947	2001.302	0.0101	0.992	278	3064.107	0.6186	0.5365
Disabled for 4 weeks	466	2000.208			110	2726.999		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.3.10: Monthly Adjusted Consumption Expenditure (Without Insurance Reimbursement) Per Capita And Days Disabled Due To Short Morbidity:

The categories with significantly different expenditures were those disabled for 1 week, 2 weeks, 3 weeks, 4 weeks, and between 1 week to 2 weeks, 1 week to 3 weeks and 1 week to 4 weeks in rural areas. In urban areas, those disabled for one week, two weeks, four weeks, and 1weekto 4 weeks had significantly different expenditures(Table 31).

Table 31: **Monthly Adjusted Consumption Expenditure (Without Insurance Reimbursement) Per Capita And Days Disabled Due To Short Morbidity(Rural and Urban 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	89,463	1739.901	**2.4654**	0.0137	43,937	2608.226	**4.3083**	0
Disabled for 1 week	9,337	1711.837			3,784	2417.367		
Not disabled	89,463	1739.901	**8.0291**	0	43,937	2608.226	**2.108**	0.0354
Disabled for 2 weeks	2,069	1476.314			597	2394.986		
Not disabled	89,463	1739.901	**3.8202**	0.0001	43,937	2608.226	0.2409	0.8098
Disabled for 3 weeks	947	1509.254			278	2496.406		
Not disabled	89,463	1739.901	**4.2959**	0	43,937	2608.226	**2.7455**	0.0071
Disabled for 4 weeks	466	1294.619			110	1828.201		
Disabled for 1 week	9,337	1711.837	**7.0142**	0	3,784	2417.367	0.2054	0.8373
Disabled for 2 weeks	2,069	1476.314			597	2394.986		
Disabled for 1 week	9,337	1711.837	**3.3327**	0	3,784	2417.367	-0.1697	0.8654
Disabled for 3 weeks	947	1509.254			278	2496.406		

Disabled for 1 week	9,337	1711.837	**4.0159**	0.0001	3,784	2417.367	**2.053**	0.0424
Disabled for 4 weeks	466	1294.619			110	1828.201		
Disabled for 2 weeks	2,069	1476.314	-0.4834	0.6289	597	2394.986	-0.2137	0.831
Disabled for 3 weeks	947	1509.254			278	2496.406		
Disabled for 2 weeks	2,069	1476.314	1.6768	0.0941	597	2394.986	1.8827	0.0619
Disabled for 4 weeks	466	1294.619			110	1828.201		
Disabled for 3 weeks	947	1509.254	1.7943	0.0732	278	2496.406	1.2286	0.22
Disabled for 4 weeks	466	1294.619			110	1828.201		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.3.11: Monthly Adjusted Consumption Expenditure (With Insurance Reimbursement) Per Capita And Days Disabled Due To Short Morbidity:

The consumption expenditure was significantly different for those disabled for two weeks, three weeks, four weeks, between 1 week to 3 weeks, and 1 week to 4 weeks in rural areas(Table 32). For urban areas, the consumption expenditure was significantly different for those disabled for one week, two weeks, four weeks, and between 1 and 4 weeks.

Table 32: **Monthly Adjusted Consumption Expenditure (With Insurance Reimbursement) Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	89,463	1740.325	1.3359	0.1816	43,937	2608.866	**4.277**	0
Disabled for 1 week	9,337	1712.531			3,784	2419.285		
Not disabled	89,463	1740.325	**7.9569**	0	43,937	2608.866	**2.038**	0.042
Disabled for 2 weeks	2,069	1478.646			597	2401.66		
Not disabled	89,463	1740.325	**3.7886**	0.0002	43,937	2608.866	0.2413	0.8095
Disabled for 3 weeks	947	1511.123			278	2496.867		
Not disabled	89,463	1740.325	**4.2971**	0	43,937	2608.866	**2.7164**	0.0077
Disabled for 4 weeks	466	1295.206			110	1836.188		
Disabled for 1 week	9,337	1712.531	**6.175**	0	3,784	2419.285	0.161	0.8721

Disabled for 2 weeks	2,069	1478.646			597	2401.66		
Disabled for 1 week	9,337	1712.531	**3.1794**	0.0015	3,784	2419.285	-0.1665	0.8679
Disabled for 3 weeks	947	1511.123			278	2496.867		
Disabled for 1 week	9,337	1712.531	**3.9641**	0.0001	3,784	2419.285	**2.0294**	0.0447
Disabled for 4 weeks	466	1295.206			110	1836.188		
Disabled for 2 weeks	2,069	1478.646	-0.4757	0.6344	597	2401.66	-0.2005	0.8412
Disabled for 3 weeks	947	1511.123			278	2496.867		
Disabled for 2 weeks	2,069	1478.646	1.6936	0.0909	597	2401.66	1.8753	0.0629
Disabled for 4 weeks	466	1295.206			110	1836.188		
Disabled for 3 weeks	947	1511.123	1.805	0.0715	278	2496.867	1.2142	0.2254
Disabled for 4 weeks	466	1295.206			110	1836.188		

Note: Two-tail t-test is used.
Source: Authors' calculations based on IHDS 2 data.

4.3.3.12: Monthly Food Expenditure Per Capita And Days Disabled Due To Short Morbidity:

The food expenditure was significantly different for those disabled for one week, between 1 and 2 weeks for rural areas and one week and four weeks for urban areas (Table 33).

Table 33: Monthly Food Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2012)

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	89,463	729.6709	**-5.4012**	0	43,937	910.3103	**2.902**	0.0037
Disabled for 1 week	9,337	754.7402			3,784	888.3887		
Not disabled	89,463	729.6709	0.7015	0.4831	43,937	910.3103	1.3987	0.1624
Disabled for 2 weeks	2,069	723.4527			597	884.542		
Not disabled	89,463	729.6709	-0.6784	0.4977	43,937	910.3103	1.649	0.1003
Disabled for 3 weeks	947	738.3642			278	863.7129		
Not disabled	89,463	729.6709	-1.1427	0.2537	43,937	910.3103	**2.0883**	0.0391
Disabled for 4 weeks	466	750.9776			110	826.5551		
Disabled for 1 week	9,337	754.7402	**3.1839**	0.0015	3,784	888.3887	0.1955	0.845

Disabled for 2 weeks	2,069	723.4527			597	884.542		
Disabled for 1 week	9,337	754.7402	1.2132	0.2253	3,784	888.3887	0.8483	0.3969
Disabled for 3 weeks	947	738.3642			278	863.7129		
Disabled for 1 week	9,337	754.7402	0.1968	0.8441	3,784	888.3887	1.5193	0.1314
Disabled for 4 weeks	466	750.9776			110	826.5551		
Disabled for 2 weeks	2,069	723.4527	-0.9641	0.3351	597	884.542	0.62	0.5355
Disabled for 3 weeks	947	738.3642			278	863.7129		
Disabled for 2 weeks	2,069	723.4527	-1.3388	0.1811	597	884.542	1.317	0.1898
Disabled for 4 weeks	466	750.9776			110	826.5551		
Disabled for 3 weeks	947	738.3642	-0.5594	0.576	278	863.7129	0.7588	0.4488
Disabled for 4 weeks	466	750.9776			110	826.5551		

Note: Two- tail t-test is used.
Source: Authors' Calculations based on IHDS 2 data.

4.3.3.13: Monthly Non-Food Expenditure Per Capita And Days Disabled Due To Short Morbidity:

For non-food expenditures, those disabled for two weeks and between 1 and 2 weeks had significantly different consumption expenditures for rural areas(Table 34). For the urban area, the expenditure was significantly different for those disabled for one week.

Table 34:Monthly Non-Food Expenditure Per Capita And Days Disabled Due To Short Morbidity (Rural and Urban, 2012)

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	89,463	873.4975	0.4878	0.6257	43,937	1561.962	**3.5916**	0.0003
Disabled for 1 week	9,337	865.0931			3,784	1432.388		
Not disabled	89,463	873.4975	**6.6086**	0	43,937	1561.962	1.2799	0.2011
Disabled for 2 weeks	2,069	730.4174			597	1450.255		
Not disabled	89,463	873.4975	1.1464	0.2519	43,937	1561.962	-0.6069	0.5444
Disabled for 3 weeks	947	823.9253			278	1836.204		
Not disabled	89,463	873.4975	0.421	0.674	43,937	1561.962	0.9253	0.3569
Disabled for 4 weeks	466	843.2729			110	1323.369		

Disabled for 1 week	9,337	865.0931	**5.0331**	0	3,784	1432.388	-0.1917	0.848
Disabled for 2 weeks	2,069	730.4174			597	1450.255		
Disabled for 1 week	9,337	865.0931	0.8947	0.3711	3,784	1432.388	-0.8912	0.3736
Disabled for 3 weeks	947	823.9253			278	1836.204		
Disabled for 1 week	9,337	865.0931	0.2969	0.7667	3,784	1432.388	0.4194	0.6757
Disabled for 4 weeks	466	843.2729			110	1323.369		
Disabled for 2 weeks	2,069	730.4174	-1.9544	0.0508	597	1450.255	-0.839	0.4021
Disabled for 3 weeks	947	823.9253			278	1836.204		
Disabled for 2 weeks	2,069	730.4174	-1.5116	0.1312	597	1450.255	0.4668	0.6414
Disabled for 4 weeks	466	843.2729			110	1323.369		
Disabled for 3 weeks	947	823.9253	-0.2317	0.8169	278	1836.204	0.9861	0.3247
Disabled for 4 weeks	466	843.2729			110	1323.369		

Note: Two-tail t-test is used.
Source: Authors' Calculations based on IHDS 2 data.

This section deals with annual consumption expenditures and disability by duration for 2012.

4.3.3.14: Annual Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity:

The annual consumption expenditure was significantly different for those disabled for 3 months, 6 months, 9 months, and 12 months for a rural area(Table 35). In the urban area, the annual consumption expenditure was significantly different for those disabled for three months and between 3 to 12 months.

Table 35: Annual Consumption Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2012)

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	94,215	20950.79	**-15.78**	0	44,667	31154.7	**-9.9411**	0
Disabled for 3 Months	6,701	25988.81			3,496	38583.8		
Not disabled	94,215	20950.79	**-5.2756**	0	44,667	31154.7	-0.962	0.3371
Disabled for 6 Months	633	26996.25			221	34648.46		
Not disabled	94,215	20950.79	**-2.1621**	0.0322	44,667	31154.7	-1.1405	0.2583

Disabled for 9 Months	148	36273.2			65	36694.65		
Not disabled	94,215	20950.79	**-5.2196**	0	44,667	31154.7	0.9222	0.3573
Disabled 12 Months	585	26210.95			257	29488.64		
Disabled for 3 Months	6,701	25988.81	-0.8501	0.3956	3,496	38583.8	1.0631	0.2888
Disabled for 6 Months	633	26996.25			221	34648.46		
Disabled for 3 Months	6,701	25988.81	-1.4499	0.1492	3,496	38583.8	0.3847	0.7016
Disabled for 9 Months	148	36273.2			65	36694.65		
Disabled for 3 Months	6,701	25988.81	-0.2111	0.8328	3,496	38583.8	**4.68**	0
Disabled 12 Months	585	26210.95			257	29488.64		
Disabled for 6 Months	633	26996.25	-1.2924	0.1982	221	34648.46	-0.3376	0.7362
Disabled for 9 Months	148	36273.2			65	36694.65		
Disabled for 6 Months	633	26996.25	0.5158	0.6061	221	34648.46	1.2738	0.2036
Disabled 12 Months	585	26210.95			257	29488.64		
Disabled for 9 Months	148	36273.2	1.4058	0.1618	65	36694.65	1.3916	0.1678
Disabled 12 Months	585	26210.95			257	29488.64		

Note: Two-tail t-test is used.
Source: Authors' Calculations based on IHDS 2 data.

4.3.3.15: Annual Adjusted Consumption Expenditure (Without Insurance Reimbursement) Per Capita And Days Disabled Due To Major Morbidity:

For the adjusted consumption expenditure (without insurance reimbursement), those disabled for three months, between 3 to 6 months and between 3 to 12 months had significantly different expenditures in rural areas. Those disabled for one month, 12 months, between 3 to 6 months, and 3 to 12 months had significantly different consumption expenditures in urban areas (Table 36).

Table 36: Annual Adjusted Consumption Expenditure (Without Insurance Reimbursement) Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2012)

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	94,215	20620.98	**-5.8421**	0	44,667	150.0416	**-4.966**	0
Disabled for 3 months	6,701	22408.62			3,496	34379.74		
Not disabled	94,215	20620.98	1.3387	0.1811	44,667	150.0416	1.4496	0.1486
Disabled for 6 months	633	19334.99			221	26870.48		

Not disabled	94,215	20620.98	-1.1078	0.2698	44,667	150.0416	0.2657	0.7913
Disabled for 9 months	148	27862.23			65	29663.27		
Not disabled	94,215	20620.98	1.299	0.1945	44,667	150.0416	**4.5577**	0
Disabled for 12 months	585	19483.51			257	24067.76		
Disabled for 3 months	6,701	22408.62	**3.0646**	0.0023	3,496	34379.74	**2.6475**	0.0086
Disabled for 6 months	633	19334.99			221	26870.48		
Disabled for 3 months	6,701	22408.62	-0.8335	0.4059	3,496	34379.74	1.0322	0.3057
Disabled for 9 months	148	27862.23			65	29663.27		
Disabled for 3 months	6,701	22408.62	**3.173**	0.0016	3,496	34379.74	**6.2994**	0
Disabled for 12 months	585	19483.51			257	24067.76		
Disabled for 6 months	633	19334.99	-1.2908	0.1987	221	26870.48	-0.5281	0.5984
Disabled for 9 months	148	27862.23			65	29663.27		
Disabled for 6 months	633	19334.99	-0.1146	0.9088	221	26870.48	0.8968	0.3704
Disabled for 12 months	585	19483.51			257	24067.76		
Disabled for 9 months	148	27862.23	1.2706	0.2058	65	29663.27	1.177	0.2427
Disabled for 12 months	585	19483.51			257	24067.76		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.3.16:Annual Adjusted Consumption Expenditure(With Insurance reimbursement) Per Capita And Days Disabled Due To Major Morbidity:

Table 37 examined adjusted consumption expenditure (with health insurance reimbursement), and those disabled for 3 months, between 3 to 6 months, and between 3 to 12 months had significantly different expenditures in rural areas. Those disabled for 3 months, 12 months, 3 to 6 months, and 3 to 12 months in urban areas had significantly different expenditures.

Table 37: **Annual Adjusted Consumption Expenditure (With Insurance Reimbursement) Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	94,215	20622.66	**-5.9902**	0	44,667	30866.21	**-5.0637**	0
Disabled for 3 months	6,701	22457.16			3,496	34468.83		

Not disabled	94,215	20622.66	1.2473	0.2127	44,667	30866.21	1.3732	0.1711
Disabled for 6 months	633	19422.79			221	27068.86		
Not disabled	94,215	20622.66	-1.1416	0.2555	44,667	30866.21	0.2036	0.8393
Disabled for 9 months	148	28082.16			65	29944.19		
Not disabled	94,215	20622.66	1.2118	0.2261	44,667	30866.21	**4.5474**	0
Disabled for 12 months	585	19558.14			257	24084.96		
Disabled for 3 months	6,701	22457.16	**3.0214**	0.0026	3,496	34468.83	**2.5988**	0.0099
Disabled for 6 months	633	19422.79			221	27068.86		
Disabled for 3 months	6,701	22457.16	-0.86	0.3912	3,496	34468.83	0.9881	0.3266
Disabled for 9 months	148	28082.16			65	29944.19		
Disabled for 3 months	6,701	22457.16	**3.1354**	0.0018	3,496	34468.83	**6.3372**	0
Disabled for 12 months	585	19558.14			257	24084.96		
Disabled for 6 months	633	19422.79	-1.3112	0.1917	221	27068.86	-0.5423	0.5886
Disabled for 9 months	148	28082.16			65	29944.19		
Disabled for 6 months	633	19422.79	-0.1042	0.917	221	27068.86	0.9519	0.3418
Disabled for 12 months	585	19558.14			257	24084.96		
Disabled for 9 months	148	28082.16	1.293	0.198	65	29944.19	1.2302	0.2223
Disabled 12 months	585	19558.14			257	24084.96		

Note: Two-tail t-test is used.

Source: Authors' Calculations based on IHDS 2 data.

4.3.3.17:Annual Food Expenditure Per Capita And Days Disabled Due To Major Morbidity:

The food expenditure was significantly different for those disabled for three months, nine months, 12 months, between 3 to 6 months, 3 to 9 months and 3 to 12 months in rural areas and for three months, 12 months, between 3 to 6 months, 3 to 12 months for urban areas(Table 38).

Table 38: **Annual Food Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	94,215	8715.421	**490.7173**	0	44,667	10841.71	**-32.4573**	0
Disabled for 3 months	6,701	652.128			3,496	11670.14		
Not disabled	94,215	8715.421	-1.7077	0.0882	44,667	10841.71	0.9673	0.3345
Disabled for 6 months	633	9089.433			221	10489.35		
Not disabled	94,215	8715.421	**-2.2838**	0.0238	44,667	10841.71	0.5728	0.5688
Disabled for 9 months	148	10070.94			65	10372.85		
Not disabled	94,215	8715.421	**-2.6729**	0.0077	44,667	10841.71	**3.467**	0.0006
Disabled 12 months	585	9251.995			257	9910.431		
Disabled for 3 months	6,701	652.128	**-38.6079**	0	3,496	11670.14	**3.2492**	0.0013
Disabled for 6 months	633	9089.433			221	10489.35		
Disabled for 3 months	6,701	652.128	**-15.8737**	0	3,496	11670.14	1.5855	0.1178
Disabled for 9 months	148	10070.94			65	10372.85		
Disabled for 3 months	6,701	652.128	**-42.9514**	0	3,496	11670.14	**6.5805**	0
Disabled 12 months	585	9251.995			257	9910.431		
Disabled for 6 months	633	9089.433	-1.5523	0.1223	221	10489.35	0.1301	0.8968
Disabled for 9 months	148	10070.94			65	10372.85		
Disabled for 6 months	633	9089.433	-0.5487	0.5833	221	10489.35	1.2831	0.2002
Disabled for12 months	585	9251.995			257	9910.431		
Disabled for 9 months	148	10070.94	1.3078	0.1926	65	10372.85	0.5372	0.5927
Disabled for 12 months	585	9251.995			257	9910.431		

Note: Two-tail t-test is used.

Source: Authors' calculations based on IHDS 2 data.

4.3.3.18: Annual Non-Food Expenditure Per Capita And Days Disabled Due To Major Morbidity:

The non-food expenditure was significantly different for those disabled for three months, between 3 to 12 months, and for three months, 12 months, to between 3 to 12 months for rural and urban areas, respectively(Table 39).

Table 39: **Annual Non-Food Expenditure Per Capita And Days Disabled Due To Major Morbidity (Rural and Urban, 2012)**

	Rural				Urban			
Categories	**Observations**	**Mean**	**t-test**	**P-value**	**Observations**	**Mean**	**t-test**	**P-value**
Not disabled	94,215	10318.24	**-6.6857**	0	44,667	18423.05	**-5.4829**	0
Disabled for 3 months	6,701	11957.31			3,496	21573.43		
Not disabled	94,215	10318.24	-0.8025	0.4226	44,667	18423.05	0.4753	0.6351
Disabled for 6 months	633	10941.84			221	17225.98		
Not disabled	94,215	10318.24	-1.2129	0.1135	44,667	18423.05	0.0905	0.9281
Disabled for 9 months	148	12530.66			65	18052.28		
Not disabled	94,215	10318.24	0.543	0.5874	44,667	18423.05	**4.9198**	0
Disabled 12 months	585	10001.33			257	13757.37		
Disabled for 3 months	6,701	11957.31	1.2525	0.2108	3,496	21573.43	1.6871	0.0929
Disabled for 6 months	633	10941.84			221	17225.98		
Disabled for 3 months	6,701	11957.31	-0.3118	0.7556	3,496	21573.43	0.8524	0.3971
Disabled for 9 months	148	12530.66			65	18052.28		
Disabled for 3 months	6,701	11957.31	**3.1158**	0.0019	3,496	21573.43	**7.1461**	0
Disabled 12 months	585	10001.33			257	13757.37		
Disabled for 6 months	633	10941.84	-0.802	0.4235	221	17225.98	-0.172	0.8637
Disabled for 9 months	148	12530.66			65	18052.28		
Disabled for 6 months	633	10941.84	0.9712	0.3317	221	17225.98	1.2918	0.1975
Disabled 12 months	585	10001.33			257	13757.37		
Disabled for 9 months	148	12530.66	1.3219	0.1879	65	18052.28	1.0228	0.3099
Disabled 12 months	585	10001.33			257	13757.37		

Note: Two-tail t-test is used.

Source: Authors' Calculations based on IHDS 2 data.

4.4:Results Of Regression Analysis Of Consumption Expenditure:

The following section presents the results of the regression analysis of consumption expenditure.

4.4.1: United Nations And Disability Data:

The United Nations provides data on disability measured as years lived with disability, calculated as the years spent in disability multiplied by the duration spent in disability. (WHO, combined source of 2000, 2012). The data for India is presented below(Table 40). According to WHO, the years lived with disability since 1990 has steadily increased from 8.18 to 9.66 years in 2016.

Table 40:**Years Lived With Disability (YLD) In India.**

Year	Years lived with a disability	Health expenditure per capita, PPP (constant 2011 international $)
1990	8.18	NA
1991	8.24	NA
1992	8.3	NA
1993	8.37	NA
1994	8.45	NA
1995	8.53	60.307
1996	8.56	62.841
1997	8.59	71.15
1998	8.64	75.824
1999	8.7	77.113
2000	8.75	85.211
2001	8.8	94.689
2002	8.86	96.042
2003	8.92	101.456
2004	8.98	108.733
2005	9.03	122.508
2006	9.05	134.735
2007	9.11	148.902
2008	9.14	159.594
2009	9.19	173.42
2010	9.2	186.716
2011	9.3	202.952
2012	9.37	217.184
2013	9.44	240.125
2014	9.53	267.409
2015	9.61	NA
2016	9.66	NA

Source: Statistic Division, UN, 2000.

disability pensions was negligible at 2%, and the households that received remittances from NRI members were overall 8 %; for rural areas, it was 9 %, and for urban, it was 5 %. About 48 % of the households had no toilet facility, with 34 % from rural areas and 78 % from urban. The highest education completed by adults was eight years overall, seven years in rural areas and ten years in urban areas. The percentage of households that owned health insurance was overall 7%; rural was 6%, and 9% was urban. There was a minimum of two organisations to which the households were members.

4.4.3: Regression Results For Different Types Of Consumption Expenditure For Overall, Rural And Urban:

Table 41: **Descriptive Statistics**

	Overall					Rural					Urban				
Variables	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs**	**Mean**	**Std. Dev.**	**Min**	**Max**
Monthly Consumption Expenditure #	301976	1773	1915.62	0	121790	204564	1538	1636.01	0	83934	97412	2264	2323.42	0	121790
Adjusted Consumption Expenditure #	301976	2219	2320.83	0	150238	204564	1932	2010.87	0	150238	97412	2822	2769.26	0	121790
Food Expenditure #	301976	718	401.859	0	9364	204564	666	380.376	0	9364	97412	827	423.344	0	6427
Non-food Expenditure #	301976	870	1517.7	0	120943	204564	694	1260.1	0	74112	97412	1241	1898.23	0	120943
Outpatient Expenditure #	301976	92	275.567	0	16667	204564	91	272.431	0	16667	97412	93	282.037	0	10000
Inpatient Expenditure #	301976	87	553.111	0	83333	204564	82	542.883	0	83333	97412	96	573.878	0	54167
Total Health Expenditure #	301976	179	640.747	0	83371	204564	174	628.935	0	83371	97412	190	664.741	0	54767
Assets owned by the households #	301907	13.538	6.226	0	30	204523	11.625	5.645	0	29	97384	17.556	5.422	0	30
Family size #	301976	6.145	2.991	1	38	204564	6.29	3.102	1	38	97412	5.841	2.718	1	28
Proportion of Children <14 $	301976	0.373	0.792	0	7	204564	0.379	0.789	0	7	97412	0.36	0.8	0	7
Proportion of adults 60+ $	301976	1.69	6.474	0	95	204564	1.771	6.688	0	95	97412	1.52	5.994	0	92
Activity of Daily Living Intensity $	301976	0.143	0.899	0	14	204564	0.146	0.902	0	14	97412	0.137	0.893	0	14
Remittances received by the households #	301976	0.083	0.276	0	1	204564	0.095	0.293	0	1	97412	0.058	0.234	0	1
Disability pension received by the households #	301976	0.002	0.047	0	1	204564	0.002	0.05	0	1	97412	0.002	0.04	0	1
Households without toilets #	301976	0.485	0.5	0	1	204564	0.344	0.475	0	1	97412	0.781	0.414	0	1
Highest completed Education by adults #	301759	8.092	5.002	0	16	204409	7.163	4.92	0	16	97350	10.041	4.596	0	16
Health Insurance #	301066	0.071	0.263	0	2	203948	0.064	0.25	0	2	97118	0.086	0.288	0	2
Membership Intensity #	301976	1.727	1.559	0	13	204564	1.847	1.57	0	13	97412	1.475	1.505	0	12
Days unable to work due to Major morbidity $	301976	0.079	0.38	0	4	204564	0.078	0.38	0	4	97412	0.081	0.378	0	4

***Note**: 1. # Household variables; $ Individual variables.*

2. All Expenditures are expressed as monthly per capita (rounded).

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Table 42: **Regression Results For Different Types Of Consumption Expenditure For Overall, Rural And Urban**

	Overall				Rural				Urban			
Variables	Consumption Expenditure	Adjusted Consumption expenditure	Food expenditure	Non-food expenditure	Consumption Expenditure	Adjusted Consumption expenditure	Food expenditure	Non-food expenditure	Consumption Expenditure	Adjusted Consumption expenditure	Food expenditure	Non-food expenditure
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Activity of Daily Living Intensity(ADLI)$	**15.13****	**-60.10*****	0.388	5.365	7.755	**-56.58*****	1.163	-1.003	**32.18*****	**-64.43*****	-0.606	**19.78****
	(5.888)	*(6.642)*	*(1.048)*	*(4.494)*	*(6.809)*	*(7.384)*	*(1.286)*	*(4.833)*	*(11.14)*	*(13.42)*	*(1.791)*	*(9.422)*
Assets owned by the households#	**105.6*****	**-20.58*****	**22.83*****	**83.52*****	**91.50*****	**-33.31*****	**20.55*****	**72.31*****	**140.3*****	**12.31****	**28.57*****	**111.1*****
	(2.598)	*(3.138)*	*(0.546)*	*(2.195)*	*(2.912)*	*(3.610)*	*(0.643)*	*(2.466)*	*(5.430)*	*(6.241)*	*(1.035)*	*(4.589)*
Days unable to work due to Major morbidity $	**134.1*****	**-65.26*****	-0.560	**23.15****	**110.2*****	**-75.74*****	-0.351	1.287	**188.7*****	-42.33	-0.353	**72.99*****
	(14.38)	*(15.32)*	*(2.437)*	*(10.29)*	*(16.25)*	*(17.05)*	*(3.005)*	*(11.08)*	*(28.67)*	*(31.34)*	*(4.132)*	*(21.87)*
Disability pension received by the households #	6.324	**-296.2*****	-2.042	29.99	73.96	**-217.2***	13.21	72.30	-189.8	**-533.9*****	-49.22	-87.74
	(75.22)	*(94.92)*	*(17.99)*	*(56.73)*	*(91.14)*	*(114.5)*	*(20.79)*	*(66.73)*	*(123.1)*	*(162.7)*	*(35.18)*	*(104.2)*
Family size#	**-133.3*****	**-75.55*****	**-43.93*****	**-80.56*****	**-114.9*****	**-56.46*****	**-39.74*****	**-66.26*****	**-196.2*****	**-139.8*****	**-58.01*****	**-129.8*****
	(5.735)	*(5.547)*	*(1.572)*	*(3.566)*	*(6.347)*	*(5.861)*	*(1.796)*	*(3.526)*	*(11.10)*	*(12.59)*	*(2.579)*	*(9.032)*
Health Insurance #	**309.5*****	0.805	**26.93*****	**279.4*****	**207.3*****	-5.857	**17.33****	**188.7*****	**449.8*****	-9.783	**37.72*****	**406.4*****
	(36.55)	*(45.78)*	*(6.771)*	*(32.28)*	*(37.00)*	*(49.80)*	*(8.368)*	*(32.20)*	*(74.36)*	*(88.96)*	*(11.53)*	*(66.22)*
Highest completed Education by adults #	**19.16*****	**-21.98*****	**3.522*****	**15.17*****	**12.31*****	**-22.20*****	**1.795*****	**9.739*****	**35.14*****	**-22.57*****	**7.653*****	**27.83*****
	(2.695)	*(3.305)*	*(0.570)*	*(2.249)*	*(3.070)*	*(3.802)*	*(0.650)*	*(2.547)*	*(5.510)*	*(6.608)*	*(1.151)*	*(4.667)*

Households without toilets #	**-85.04*** **	**-257.9*** **	-5.844	**-58.81*** **	-33.57	**-257.4*** **	-1.202	-19.85	**-169.1*** **	**-235.2*** **	-9.437	**-118.9*** **
	(24.93)	*(28.45)*	*(4.837)*	*(19.57)*	*(30.12)*	*(34.37)*	*(5.723)*	*(23.17)*	*(42.41)*	*(48.98)*	*(8.939)*	*(35.78)*
Membership Intensity #	**47.25*** **	**179.9*** **	**9.323*** **	**31.87*** **	**50.63*** **	**166.6*** **	**9.196*** **	**37.07*** **	**46.45*** **	**214.7*** **	**10.81*** **	**25.57** **
	(6.533)	*(8.425)*	*(1.256)*	*(5.411)*	*(7.232)*	*(9.354)*	*(1.456)*	*(5.886)*	*(13.61)*	*(17.57)*	*(2.401)*	*(11.62)*
Proportion of children 0-14 $	**-63.39*** **	**-22.98*** **	**-8.641*** **	**-46.68*** **	**-52.80*** **	**-28.56*** **	**-7.129*** **	**-36.83*** **	**-73.98*** **	-6.023	**-9.803*** **	**-57.72*** **
	(5.793)	*(6.585)*	*(1.171)*	*(4.734)*	*(6.282)*	*(7.079)*	*(1.420)*	*(4.838)*	*(11.92)*	*(13.78)*	*(2.049)*	*(10.34)*
Proportion of adults 60+ $	**11.16*** **	**-29.47*** **	**5.216*** **	**3.693*** **	**9.597*** **	**-23.68*** **	**4.762*** **	**2.414* **	**16.00*** **	**-45.05*** **	**6.511*** **	**7.708* **
	(1.745)	*(2.178)*	*(0.300)*	*(1.428)*	*(1.580)*	*(2.025)*	*(0.334)*	*(1.237)*	*(4.853)*	*(5.961)*	*(0.630)*	*(4.108)*
Remittances received by the households #	**199.8*** **	**-76.05* **	**49.70*** **	**125.7*** **	**190.8*** **	-31.52	**48.58*** **	**120.7*** **	**262.0*** **	**-195.4* **	**57.14*** **	**170.7** **
	(33.42)	*(41.75)*	*(6.132)*	*(28.57)*	*(35.10)*	*(44.88)*	*(6.860)*	*(29.81)*	*(83.00)*	*(100.1)*	*(13.27)*	*(71.73)*
Constant	920.5***	3034.5***	625.5***	63.62*	990.0***	2686.4***	636.3***	125.0***	585.3***	3613.2***	566.1***	-220.1**
	(44.90)	*(54.77)*	*(11.19)*	*(35.08)*	*(47.73)*	*(57.86)*	*(12.70)*	*(35.13)*	*(102.2)*	*(122.6)*	*(20.79)*	*(87.62)*
Adj. R2	0.0937	0.0340	0.172	0.0714	0.0968	0.0408	0.166	0.0739	0.102	0.0321	0.198	0.0797
R square	0.0937	0.0341	0.172	0.0714	0.0969	0.0408	0.166	0.0739	0.102	0.0322	0.198	0.0798
F stat	243.1	110.4	351.9	206.6	147.9	86.08	219.5	120.2	112.2	33.76	153.9	93.91
Number of Observations	300817	300817	300817	300817	203772	203772	203772	203772	97045	97045	97045	97045
SE Cluster	34578	34578	34578	34578	23,121	23,121	23,121	23,121	11,457	11,457	11,457	11,457

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01.; 3)# Household variables; $ Individual variables.*

4)SE clustered at Village/Nearest neighbourhood level.; 5)Standard error Adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.; 7)Figures in 'Bold' represent significant regression coefficients

Source: Authors' Calculations based on IHDS 1 and IHDS 2 data.

4.4.2: Descriptive Statistics:

We provide descriptive statistics (Table 41) of the mean, minimum and maximum values of all the variables used in the regression model. The monthly consumption expenditure is Rs 1773; the adjusted consumption expenditure is Rs 2219; the Food expenditure is Rs 718; the Non-food expenditure is Rs 870; the Outpatient Expenditure is Rs 92; the Inpatient expenditure is Rs 87, and the total Health expenditure is Rs 179. In the rural area, the monthly consumption expenditure is Rs 1538; the adjusted consumption expenditure is Rs 1932; Food expenditure is Rs 666; Non-food expenditure is Rs 694; outpatient expenditure is Rs 92; Inpatient expenditure is Rs 82, and total health expenditure is Rs 174. In the urban area, the monthly consumption expenditure is Rs 2264; the adjusted consumption expenditure is Rs 2822; food expenditure is Rs 827; non-food expenditure is Rs 1241; outpatient expenditure is Rs 93, inpatient expenditure is Rs 96, and total health expenditure is Rs 190. The average number of assets owned by the household was 14, in the rural area was 12 and in the urban area was 18. The average family size for rural, urban, and overall was six members. Every household had at least one child and two adults (60 plus) in the household on average. The reported activity of daily living was less than 1 per individual across rural and urban areas. The number of households that received

The results of the regression analysis are presented below. Different types of consumption expenditures are used as outcome variables to examine the impact of various covariates that may affect consumption expenditures (details discussed in chapters 2, 3 and section 4.1). Four different types of consumption expenditures, i.e., Monthly consumption expenditure is adjusted for health expenditure, food expenditure and non-food expenditures, and three types of health expenditures, i.e., total health expenditure, outpatient, and inpatient expenditure, are used. The analysis is presented for socio-economic categories for rural and urban areas.

Table 42 provides combined regression results with sub-sample restrictions of rural and urban areas. Four different dependent variables are used in the analysis, namely in column I, monthly consumption expenditure (dependent variable); in Column II, adjusted consumption expenditure; in column III, food expenditure; in Column IV, non-food expenditure combined results are given (same order is followed for area-specific analysis. Columns V to VIII are regression results for the rural area, and columns IX to XII provide urban-specific regression results. The covariates are ADLI; assets owned by the households; days unable to work due to major morbidity; households that received disability pension; family size; health insurance; highest completed education by the adults; household without toilets; membership intensity; the proportion of children 0-14 and adult 60 plus; remittances received by the households from NRI members.

For combined results, ADLI, Assets owned by the household, days unable to work due to major morbidity, highest completed education, membership intensity, and the proportion of adults and households that received remittances showed positive and significant influence on monthly consumption expenditure. Family size, households without toilets, and the proportion of children 0-14 negatively and significantly impacted consumption expenditure. The households that received disability pensions have a positive coefficient, but it is non-significant. The two covariates focused on disability have positive coefficients. The disability pension has not influenced the expenditure. As mentioned in the literature, assets owned by the household and membership intensity have also shown a positive impact.

For adjusted consumption (adjusted for health expenditure), the ADLI; assets owned by the households; days unable to work due to major morbidity; disability pension; family size; highest completed education; households without toilet; the proportion of children and adults; remittances received have a significant and positive influence on the adjusted consumption expenditure. Health insurance has become non-significant. Membership intensity has helped households to increase the adjusted consumption expenditure, which is nothing but the non-health spending of the household.

When consumption expenditure was not adjusted for health spending, the regression coefficients produced an effect in the opposite direction in comparison to the regression coefficient for adjusted consumption expenditure. The covariates that have produced signs opposite each other in the two models (columns I and II) are ADLI, assets owned by the households, days unable to work due to major morbidity, highest completed education, the proportion of adults and remittances received. Disability pension received by the households is not significant in column I but is significant in column II. Health insurance was significant in column I but not in column II. These findings align with existing literature that has found that those disabled incur additional health expenditures. Most of the covariates in the model contributed towards increasing health expenditure. This argument is because the coefficients that positively impacted consumption expenditure, some of those covariates, especially ADLI and days unable to work due to major morbidity, negatively influence the adjusted consumption expenditure.

The next dependent variable, food expenditure, is positively impacted by assets owned by the household, health insurance, highest completed education, membership intensity; the proportion of adults and household remittances. Family size and proportion of children negatively significantly impacted food expenditure. Assets owned by the households, days unable to work due to major morbidity, health insurance, highest completed education, membership intensity, the proportion of adults and remittances received by the households positively impact the non-food expenditure (health expenditure excluded. The non-significant covariates are ADLI and disability pension. Family size, households without toilets, and the proportion of children negatively and significantly influence non-food expenditure.

The next model (columns V to VIII) is for rural households. Here consumption expenditure is negatively and significantly influenced by family size and the proportion of children. Assets owned by the households, days unable to work due to major morbidity, highest completed education, membership intensity, the proportion of adults and remittances received were statistically significant and positive.

When we check for adjusted consumption in rural areas, ADLI, assets owned by the households, days unable to work due to major morbidity, disability pension, family size, highest completed education, households without toilets, the proportion of children and adults responsible for reducing the adjusted consumption, the membership intensity led to an increase in adjusted consumption. Health insurance and remittances were non-significant.

The food expenditure (column VII) and non-food expenditure (column VIII) were positively and significantly affected by assets owned by the households, health insurance, highest completed education, membership intensity, the proportion of adults and remittances. Family size and proportion of children had the reverse effect on per capita food expenditure.

The urban regression analysis results are presented in columns IX, X, XI and XII for four different types of consumption expenditure. Urban consumption expenditure is influenced positively and significantly by ADLI assets owned by the households, days unable to work, health insurance, highest completed education, membership intensity, and the proportion of aged and household remittances. Family size, a household without a toilet and the proportion of children had negative and significant impacts on monthly consumption expenditure.

ADLI, disability pension, family size, highest completed education, households without a toilet, the proportion of aged and remittances received by the household negatively and significantly impacted the adjusted consumption expenditure. Assets owned by the households ownership and membership intensity influenced adjusted consumption expenditure positively. Health insurance, days unable to work, and the proportion of children were insignificant.

Food expenditure in urban areas is influenced significantly(positively) by assets owned by the households, health insurance, highest completed education and membership intensity. Family size and proportion of children negatively and significantly impact food expenditure.

The urban food and non-food expenditures were affected by similar covariates and coefficients with the same signs; additionally, the non-food expenditure is positively and significantly impacted by ADLI and days unable to work.

Some covariates influence consumption expenditure in the same direction, such as food and non-food expenditures such as asset ownership, health insurance, highest completed education, the proportion of adults and remittances received by the household. The same covariates influence the adjusted consumption expenditure, but the direction of significance is the opposite. Family size, a household without toilets and the proportion of children negatively influence all consumption expenditures for all three categories, ic combined, rural and urban. Membership intensity has helped households to increase all types of consumption expenditure.

These findings are unique because some covariates affect consumption expenditure and adjusted consumption expenditure differently. Are these findings conclusive enough to infer that when the health expenditure component is subtracted from consumption expenditure, the covariates, such as ADLI and days unable to work, negatively impact expenditure? To check this, another set of regression equations was run with fixed effects for three types of health expenditures: outpatient, inpatient, and total.

4.4.4: Regression Results For Different Types Of Health Expenditure:

Table 43: **Regression Results For Different Types Of Health Expenditure**

Variables	Total Health Expenditure	Outpatient Expenditure	Inpatient Expenditure
	I	II	III
Activity of Daily Living Intensity (ADLI)$	**12.15*** **	**2.587***	**9.560*** **
	(3.238)	*(1.466)*	*(2.719)*
Assets owned by the households#	**6.241*** **	**2.031*** **	**4.210*** **
	(0.868)	*(0.491)*	*(0.668)*
Days unable to work due to Major morbidity	**116.4*** **	**26.09*** **	**90.33*** **
	(8.111)	*(3.094)*	*(7.334)*
Disability pension received by the households #	-10.80	-2.698	-8.101
	(33.33)	*(15.11)*	*(28.58)*
Family size#	**-12.85*** **	**-4.448*** **	**-8.400*** **
	(3.051)	*(0.510)*	*(2.992)*
Health Insurance	14.82	0.988	**13.84***
	(9.531)	*(5.571)*	*(7.331)*
Highest completed Education by adults	**2.525*** **	-0.280	**2.804*** **
	(0.961)	*(0.536)*	*(0.747)*
Households without toilet	-12.64	**-15.78*** **	3.142
	(12.45)	*(4.058)*	*(11.61)*
Membership Intensity	-0.840	**2.141** **	-2.981
	(2.463)	*(1.033)*	*(2.187)*
Proportion of children 0-14 $	**-10.14*** **	**-3.058*** **	**-7.087*** **
	(2.520)	*(1.091)*	*(2.225)*
Proportion aged 60+ $	**4.487*** **	**2.648*** **	**1.839*** **
	(0.776)	*(0.376)*	*(0.650)*
Remittances received by the households #	**38.73*** **	**10.39***	**28.34*** **

	(12.18)	*(5.744)*	*(10.20)*
Constant	141.4***	91.33***	50.05***
	(16.71)	*(7.448)*	*(14.48)*
Adj. R2	0.0114	0.00633	0.00787
R square	0.0115	0.00637	0.00791
F stat	32.68	20.69	25.89
Number of Observations	300817	300817	300817
SE cluster	34,578	34,578	34,578

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01*

3)# Household variables; $ Individual variables.

4)SE clustered at Village/Nearest neighbourhood level.

5)Standard error Adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

8)Source: Authors' calculations based on data from IHDS 1 and IHDS 2.

In Table 43, we present results from a model that uses a common set of variables to predict three dependent variables: household health expenditure per capita(Column I), outpatient expenditure(column II), and inpatient expenditure(column III).

We find that ADLI, assets owned by the households, days unable to work, the proportion of aged and remittances received by the households negatively impact all three types of health expenditure. Family size and proportion of children significantly negatively influence all three types of health expenditure. Additionally, the highest education completed by the adults significantly and positively impacts the total health and inpatient expenditure. Membership intensity also seems to increase outpatient expenditure.

4.4.5: Regression Results For Consumption Expenditure By Caste:

Table 44:**Regression Results For Consumption Expenditure By Caste (Rural And Urban)**

	Rural				Urban			
	Caste 1	**Caste 2**	**Caste 3**	**Caste 4**	**Caste 1**	**Caste 2**	**Caste 3**	**Caste 4**
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Activity of Daily Living Intensity(ADLI)$	-19.86	**22.39***	1.828	22.13	28.76	**40.11*****	21.40	29.42
	(22.85)	*(12.51)*	*(10.34)*	*(15.57)*	*(30.69)*	*(15.11)*	*(22.75)*	*(21.84)*
Assets owned by the households#	**121.1*****	**91.30*****	**60.35*****	**95.54*****	**167.5*****	**133.0*****	**96.00*****	**214.8*****
	(8.720)	*(4.712)*	*(5.110)*	*(6.645)*	*(12.50)*	*(9.396)*	*(9.416)*	*(44.49)*
Days unable to work due to Major morbidity $	**78.89***	**146.3*****	**79.72*****	**88.41****	**259.4*****	**149.2*****	**195.7*****	157.7
	(40.87)	*(29.86)*	*(21.15)*	*(35.25)*	*(51.12)*	*(37.74)*	*(46.70)*	*(181.3)*
Disability pension received by the households #	40.31	31.24	17.39	95.21	-299.3	-24.90	-259.1	-742.0
	(271.8)	*(181.8)*	*(107.8)*	*(400.0)*	*(254.3)*	*(161.4)*	*(227.1)*	*(774.6)*
Family size#	**-152.4*****	**-105.8*****	**-95.88*****	**-78.39*****	**-237.4*****	**-163.7*****	**-161.2*****	**-309.8*****
	(10.97)	*(12.11)*	*(7.171)*	*(24.53)*	*(23.05)*	*(14.27)*	*(22.68)*	*(92.99)*
Health Insurance #	**386.1*****	**170.4*****	**164.4*****	41.80	**973.2*****	**245.9****	**534.7*****	-441.6
	(113.5)	(57.50)	(61.11)	(66.91)	(164.9)	(111.4)	(150.7)	(449.9)
Highest completed Education by adults #	8.366	**10.17****	**14.95*****	9.728	**55.99*****	**31.08*****	**27.11*****	27.38
	(9.510)	(4.667)	(4.507)	(6.435)	(12.73)	(9.740)	(9.048)	(27.63)
Households without toilets #	-105.8	-53.07	-14.17	-76.25	**-211.3****	**-224.7*****	-33.95	-503.0
	(68.40)	(59.75)	(42.76)	(54.47)	(85.23)	(73.53)	(77.21)	(349.0)
Membership Intensity #	**82.61*****	**45.00*****	**29.90****	8.741	**46.57***	**64.31*****	11.19	132.0
	(17.88)	(13.51)	(12.59)	(11.85)	(28.03)	(23.98)	(26.34)	(81.81)
Proportion of children 0-14 $	**-86.63*****	**-61.04*****	**-28.30*****	-9.238	**-60.70****	**-79.21*****	**-45.76****	-96.01
	(18.02)	(12.10)	(8.866)	(11.84)	(26.29)	(19.88)	(20.74)	(77.94)
Proportion of adults 60+ $	**11.66****	**9.058*****	**7.156*****	**9.603*****	**28.25****	8.110	**14.37***	4.396
	(5.294)	(2.366)	(2.056)	(3.069)	(13.08)	(5.016)	(8.460)	(9.977)

Remittances received by the households #	**217.1****	**82.22***	**256.6*****	75.31	321.2	**243.3****	249.4	139.4
	(84.98)	(44.64)	(77.51)	(84.57)	(197.5)	(103.7)	(236.4)	(407.5)
Constant	1030.6***	969.3***	1057.0***	676.5***	152.9	516.4***	973.8***	502.4
	(136.5)	(85.57)	(67.41)	(145.0)	(245.2)	(164.6)	(151.5)	(596.4)
Adj. R2	0.0922	0.101	0.118	0.198	0.108	0.0926	0.158	0.186
R square	0.0924	0.101	0.118	0.198	0.108	0.0928	0.158	0.189
F stat	38.36	59.75	43.96	31.82	38.52	35.28	23.68	5.167
Number of Observations	54056	83462	45175	21079	36717	39455	17727	3146
SE cluster	7,440	10,875	5,773	2,888	5,560	5,681	2,509	522

Note:1) Standard errors in parentheses.
2) p<0.1, ** p<0.05, *** p<0.01.*
3)# Household variables; $ Individual variables.
4)Standard errors clustered at Village/Nearest neighbourhood level.
5)Standard error Adjusted for clusters in PSUHH.
6)Fixed-effects (within) regression -Group variable: PERSONID2012.
7)Figures in 'Bold' represent significant regression coefficients.
Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

Table 44 provides regression estimates of four different caste categories for both rural and urban. The ADLI is positive and significant for only caste 2(OBC) in rural and urban areas. The positive and significant coefficients are assets owned by the households, health insurance, highest completed education by adults, membership intensity, the proportion of adults and household remittances. These variables are consistently positive and significant for almost all caste categories, barring a few. Family size, households without toilets and proportion of children had the reverse effect on consumption expenditure. Disability pension was insignificant.

4.4.6: Regression Results For Adjusted Consumption Expenditure By Caste:

Table 45 provides regression estimates by caste for rural and urban for adjusted consumption expenditure. The ADLI negatively and significantly influences expenditure for castes 1, caste 2, caste 3 in rural and urban. Assets owned by the households negatively influence adjusted consumption for rural castes 1, 2, and 3 and a positive coefficient for caste 1 for urban. Days unable to work negatively influence rural castes 1, 2, and caste three and are insignificant for any caste categories in the urban area. Disability pension has a negative coefficient for castes 2 and 4 in urban. Family size has a negative and significant coefficient for rural and urban castes 1, 2 and 3. Health insurance is insignificant. Education negatively influences all caste categories in rural and castes 1 and 2 in urban. Households without toilets negatively influence adjusted consumption expenditure for all caste categories in rural and urban areas. Membership intensity helps to increase the expenditure for all caste categories in rural and urban areas. The proportion of adults negatively and significantly affects all caste categories in rural and castes 1,2 and 3 in urban. Remittances received influence caste 4 negatively in rural areas.

The coefficients of ADLI, assets, days disabled, and health insurance differ for consumption and adjusted consumption expenditure for caste categories. Households with disabled members due to ADLI and those who are disabled due to major morbidity boost consumption expenditure for caste 2 in rural and urban areas. However, ADLI reduces adjusted consumption expenditure for three caste categories 1, 2 and 3, and health insurance becomes non-significant. Understanding the changes in consumption expenditure and adjusted consumption expenditure is pertinent. Households may have to incur more expenditure on health. The adjusted expenditure accounts for household food and other non-food components. A reduction in adjusted consumption would mean lesser expenditure available for these components. The literature supports this; those disabled spend more to maintain their consumption expenditure(Mitra et al., 2017).

Table 45: **Regression Results For Adjusted Consumption Expenditure By Caste For Rural And Urban**

Variables	**Rural**				**Urban**			
	Caste 1	**Caste 2**	**Caste 3**	**Caste 4**	**Caste 1**	**Caste 2**	**Caste 3**	**Caste 4**
	I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**
Activity of Daily Living Intensity (ADLI)$	**-124.8*** **	**-53.53*** **	**-27.08** **	-28.55	**-96.91*** **	**-33.39* **	**-65.61*** **	39.55
	(27.21)	*(11.49)*	*(11.44)*	*(23.73)*	*(34.73)*	*(18.01)*	*(24.31)*	*(32.10)*
Assets owned by the households#	**-36.36*** **	**-30.88*** **	**-38.45*** **	-10.54	**27.46* **	4.642	-14.04	44.31
	(10.74)	*(5.750)*	*(7.025)*	*(7.839)*	*(14.85)*	*(9.829)*	*(11.09)*	*(48.81)*
Days unable to work due to Major morbidity $	**-128.2*** **	**-66.53*** **	**-41.88* **	14.57	8.913	-34.52	-52.98	-171.6
	(49.11)	*(25.30)*	*(22.68)*	*(41.36)*	*(56.33)*	*(44.09)*	*(48.98)*	*(184.2)*
Disability pension received by the households #	-268.9	-249.6	-166.3	-359.9	-352.7	**-442.2* **	-353.2	**-1353.6** **
	(325.3)	*(217.8)*	*(137.4)*	*(495.2)*	*(293.7)*	*(232.5)*	*(236.1)*	*(634.5)*
Family size#	**-75.63*** **	**-48.40*** **	**-36.43*** **	-40.29	**-176.1*** **	**-112.7*** **	**-93.87*** **	-185.8
	(14.85)	*(7.283)*	*(10.14)*	*(32.57)*	*(27.47)*	*(17.64)*	*(22.71)*	*(146.9)*
Health Insurance #	242.5	-96.75	-25.35	-145.6	260.1	-166.9	241.9	-712.8
	(148.8)	*(82.52)*	*(85.81)*	*(88.69)*	*(193.1)*	*(144.4)*	*(170.8)*	*(436.1)*
Highest completed Education by adults #	**-44.46*** **	**-18.47*** **	**-18.37*** **	**-15.58* **	**-24.76* **	**-26.10** **	-3.909	38.01
	(12.57)	*(5.745)*	*(6.328)*	*(8.987)*	*(15.04)*	*(11.22)*	*(11.00)*	*(29.37)*
Households without toilets #	**-290.9*** **	**-325.4*** **	**-242.6*** **	**-118.2* **	-317.9***	**-272.7*** **	**-171.3* **	**-766.0** **

	(79.45)	*(60.03)*	*(63.64)*	*(68.88)*	*(101.5)*	*(82.09)*	*(90.35)*	*(342.3)*
Membership Intensity #	**212.9*****	**169.4*****	**132.3*****	**74.91*****	**307.9*****	**188.8*****	**159.4*****	**349.2*****
	(24.05)	*(16.52)*	*(17.42)*	*(14.47)*	*(40.55)*	*(29.69)*	*(29.53)*	*(110.6)*
Proportion of children 0-14 $	-31.11	**-45.37*****	-7.619	-21.34	34.76	-35.21	23.89	-34.89
	(22.05)	*(11.37)*	*(11.68)*	*(14.32)*	*(30.22)*	*(21.75)*	*(25.25)*	*(89.27)*
Proportion of adults 60+ $	**-40.84*****	**-21.57*****	**-17.88*****	**-8.971****	**-69.38*****	**-37.87*****	**-14.49***	-6.070
	(8.045)	*(2.400)*	*(2.350)*	*(3.721)*	*(15.85)*	*(6.444)*	*(8.554)*	*(11.13)*
Remittances received by the households #	-42.01	-75.92	132.5	**-268.7****	-302.9	-76.06	-37.53	-105.2
	(127.5)	*(54.45)*	*(83.69)*	*(118.6)*	*(223.9)*	*(133.9)*	*(265.0)*	*(514.7)*
Constant	3745.3***	2575.0***	2189.6***	1680.8***	4113.6***	3401.7***	2947.8***	2773.7***
	(176.5)	*(95.97)*	*(102.1)*	*(192.4)*	*(301.7)*	*(192.2)*	*(181.4)*	*(899.7)*
Adj. R2	0.0388	0.0507	0.0611	0.0368	0.0401	0.0301	0.0438	0.0651
R square	0.0390	0.0509	0.0614	0.0374	0.0405	0.0304	0.0444	0.0687
F stat	19.78	39.98	32.09	5.518	13.21	10.44	7.672	2.647
Number of Observations	54056	83462	45175	21079	36717	39455	17727	3146
SE cluster	7,440	10,875	5,773	2,888	5,560	5,681	2,509	522

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01.*

3)# Household variables; $ Individual variables.

4)SE clustered at Village/Nearest neighbourhood level.

5)Standard Error adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

This section presents the regression results for the consumption expenditure quintile and adjusted consumption expenditure quintile for rural and urban areas across five APL and BPL quintile categories.

4.4.7: Regression Results For Rural Consumption Expenditure By Consumption Expenditure Quintile:

Table 46 shows the regression results of the rural consumption expenditure quintile. ADLI has a positive coefficient for APL 3 and APL 4. Assets owned by the household have helped boost the expenditure across all quintiles, and family size has an adverse effect. The days disabled have a positive and significant coefficient for BPL and APL4. Health insurance positively affects BPL and APL5. The highest completed education positively affects BPL, APL 3 and APL4 and increases the consumption expenditure. Membership intensity has a negative and significant coefficient for APL2 and APL 3. The proportion of children positively affects consumption expenditure for BPL and negatively for APL3, APL 4 and APL 5. The proportion of adults has a positive and significant coefficient for BPL, APL2, APL 3 and APL 4. Remittances received affect BPL and APL2 positively.

Table 46:**Regression Results For Rural Consumption Expenditure By Consumption Expenditure Quintile**

	BPL	APL1	APL2	APL3	APL4	APL5
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**
Activity of Daily Living Intensity (ADLI)$	1.727	0.387	0.856	**9.585*** **	**13.82** **	-78.41
	(1.877)	*(1.938)*	*(2.720)*	*(3.568)*	*(5.882)*	*(75.35)*
Assets owned by the households#	**17.20*** **	**7.392*** **	**15.05*** **	**23.42*** **	**44.53*** **	**172.7*** **
	(1.088)	*(1.482)*	*(1.754)*	*(1.826)*	*(3.234)*	*(34.14)*
Days unable to work due to Major morbidity $	**8.677***	2.243	0.497	13.27	**29.51** **	94.51
	(4.442)	*(4.721)*	*(6.836)*	*(8.774)*	*(11.85)*	*(98.13)*
Disability pension received by the households #	26.63	-53.08	36.07	**114.9*** **	**147.1***	-510.8
	(36.02)	*(32.50)*	*(35.82)*	*(40.40)*	*(85.19)*	*(754.1)*
Family size#	**-15.57*** **	**-6.827*** **	**-8.933*** **	**-21.76*** **	**-22.19*** **	**-212.3*** **
	(1.987)	*(1.819)*	*(2.400)*	*(3.362)*	*(4.446)*	*(41.27)*

Health Insurance #	**22.92***	10.64	1.254	30.75	48.97	**738.1****
	(12.26)	*(19.06)*	*(21.21)*	*(28.52)*	*(35.15)*	*(297.3)*
Highest completed Education by adults #	**3.032*****	-1.396	2.507	**4.183****	**8.504*****	32.68
	(1.118)	*(1.352)*	*(1.728)*	*(2.103)*	*(3.299)*	*(32.72)*
Households without toilets #	10.19	-19.47	-9.073	6.622	34.31	47.49
	(10.35)	*(11.86)*	*(15.30)*	*(18.87)*	*(28.45)*	*(282.6)*
Membership Intensity #	0.439	-2.880	**-7.695****	**-10.27****	-5.308	26.56
	(2.304)	*(2.810)*	*(3.770)*	*(4.380)*	*(6.909)*	*(61.33)*
Proportion of children 0-14 $	**8.208*****	-0.942	3.101	**-10.53****	**-18.78****	**-203.2*****
	(1.989)	(2.692)	(4.186)	(5.088)	(7.709)	(66.46)
Proportion of adults 60+ $	**1.670*****	-0.123	**2.666*****	**5.803*****	**7.678*****	12.04
	(0.429)	*(0.445)*	*(0.520)*	*(0.816)*	*(1.078)*	*(11.38)*
Remittances received by the households #	**36.50*****	6.330	**43.87****	39.91	47.01	579.1
	(12.20)	*(12.08)*	*(18.65)*	*(24.60)*	*(39.24)*	*(353.8)*
Constant	568.8***	924.7***	1057.5***	1285.2***	1356.7***	1787.7***
	(15.79)	*(18.65)*	*(22.17)*	*(30.29)*	*(47.93)*	*(606.5)*
Adj. R2	0.179	0.0846	0.243	0.361	0.405	0.0651
R square	0.179	0.0850	0.243	0.362	0.405	0.0655
F stat	42.68	4.763	17.31	38.72	43.87	7.361
Number of Observations	63587	28740	28722	28731	28747	28749
SE cluster	10,454	6,009	6,483	6,508	6,722	6,518

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01.*

3)# Household variables; $ Individual variables.

4)SE clustered at Village/Nearest neighbourhood level.

5)Standard Error adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

4.4.8: Regression Results For Urban Consumption Expenditure By Consumption Expenditure Quintile:

Table 47 presents the results of urban consumption expenditure regression by quintile. The ADLI positively and significantly affects the consumption expenditure for APL 3 and APL 4. Assets owned influenced all quintiles positively. The family size coefficient was negative across all quintiles. APL5 was positively affected by days disabled and negatively influenced by the proportion of children. The last two quintiles, APL 4 and APL 5were positively impacted by health insurance. Education was positive for all quintiles except APL and 2. Membership intensity worked negatively across all quintiles but was significant for APL 2, 3, and 4. The proportion of adults worked favourably on APL 2, APL 3 and APL4 quintiles. Remittances received increased consumption expenditure for APL 2, APL 3 and APL 5 quintiles.

Table 47:**Regression Results For Urban Consumption Expenditure By Consumption Expenditure Quintile**

	BPL	APL1	APL2	APL3	APL4	APL5
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**
Activity of Daily Living Intensity (ADLI)$	-9.409	-0.332	-0.591	**18.14*** **	**34.93** **	140.3
	(5.842)	*(4.029)*	*(4.978)*	*(6.308)*	*(14.18)*	*(122.3)*
Assets owned by the households#	**13.26*** **	**7.877*** **	**31.08*** **	**37.05*** **	**81.94*** **	**383.4*** **
	(2.197)	*(2.528)*	*(3.730)*	*(5.389)*	*(8.383)*	*(61.07)*
Days unable to work due to Major morbidity $	8.574	-1.335	-0.244	31.25	33.14	**674.2** **
	(9.804)	*(11.68)*	*(12.82)*	*(20.11)*	*(27.28)*	*(289.7)*
Disability pension received by the households #	-23.50	122.1	0	-37.76	-454.6	-919.8
	(76.65)	*(81.34)*	*(.)*	*(77.57)*	*(383.1)*	*(1331.7)*
Family size#	**-10.14** **	**-13.53*** **	**-20.71*** **	**-41.70*** **	**-90.23*** **	**-640.0*** **
	(4.507)	*(3.714)*	*(5.730)*	*(10.36)*	*(12.19)*	*(125.7)*
Health Insurance #	-25.16	-2.240	4.354	14.11	**127.9* **	**1124.6*** **
	(39.65)	*(32.60)*	*(57.25)*	*(49.03)*	*(68.41)*	*(389.1)*
Highest completed Education by adults #	**6.665** **	0.364	4.082	**19.87*** **	**26.06*** **	**158.0* **
	(2.980)	*(2.678)*	*(3.358)*	*(5.589)*	*(7.794)*	*(92.99)*
Households without toilets #	-7.922	19.07	11.60	19.89	23.82	-952.9
	(20.22)	*(21.91)*	*(27.29)*	*(51.38)*	*(82.14)*	*(601.6)*
Membership Intensity #	-6.547	-3.256	**-23.34** **	**-21.01** **	**-44.63*** **	130.9
	(7.003)	*(5.638)*	*(9.194)*	*(9.507)*	*(15.85)*	*(106.7)*
Proportion of children 0-14 $	5.853	-6.746	-5.005	-10.59	4.489	**-236.6** **
	(4.698)	*(5.021)*	*(7.146)*	*(10.28)*	*(15.34)*	*(109.3)*

Proportion of adults 60+ $	0.763	1.389	**2.739***	**9.703*****	**16.52*****	29.24
	(1.510)	*(1.021)*	*(1.480)*	*(1.861)*	*(2.361)*	*(30.72)*
Remittances received by the households #	-3.991	19.26	**115.5****	**132.6****	102.7	**1594.7****
	(28.96)	*(24.66)*	*(46.39)*	*(63.11)*	*(72.19)*	*(654.3)*
Constant	652.4***	1136.3***	1122.2***	1336.2***	1257.3***	-1571.3
	(39.56)	(37.09)	(70.74)	(107.3)	(180.2)	(1720.7)
Adj. R2	0.0862	0.101	0.352	0.356	0.388	0.103
R square	0.0868	0.102	0.352	0.356	0.388	0.104
F stat	4.593	3.587	16.29	.	33.19	8.436
Number of Observations	19024	14926	14932	14892	14870	14897
SE cluster	3,214	3,039	3,248	3,374	3,482	3,455

Note 1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01*

3)# Household variables; $ Individual variables.

4)SE clustered at Village/Nearest neighbourhood level.

5)Standard error adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

4.4.9: Regression Results For Rural By Adjusted Consumption Expenditure Quintile:

The next two tables provide regression analysis for adjusted consumption for rural (Table 48) and urban(Table 49).

ADLI negatively affected adjusted consumption expenditure quintile APL 2, APL 3, and APL 5 in rural areas (Table 48). Assets owned by the households helped the BPL quintile but not the APL quintile. Days disabled for major morbidity negatively and significantly impact BPL, APL2, APL 4, and APL 5. Disability pension worked negatively for BPL. The family size coefficient was negative for BPL and positive for all APL quintiles except APL 5. Health insurance was negative for BPL, APL 1- APL 4. Education influenced all quintiles negatively but had no significant impact on BPL. A household without a toilet had negative coefficients for all quintiles but was significant for APL2. Membership intensity positively and significantly affected all quintiles. The proportion of children had a negative influence on BPL but a positive one on APL2. The proportion of adults worked in the negative direction for all quintiles. Household remittances affected all quintiles negatively but were significant for BPL and APL 3.

Table 48: **Regression Results For Rural Adjusted Consumption Expenditure By Adjusted Consumption Expenditure Quintiles**

	BPL	APL1	APL2	APL3	APL4	APL5
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**
Activity of Daily Living Intensity (ADLI)$	-2.780	-2.330	**-8.404*** **	**-13.96** **	-11.58	**-284.6*** **
	(3.403)	*(2.120)*	*(2.926)*	*(5.565)*	*(7.997)*	*(87.02)*
Assets owned by the households#	**3.149***	**-9.498*** **	**-26.37*** **	**-45.43*** **	**-73.24*** **	**-95.97*** **
	(1.706)	*(1.293)*	*(1.662)*	*(2.373)*	*(4.081)*	*(31.80)*
Days unable to work due to Major morbidity $	**-14.98** **	-6.107	**-21.67** **	-4.951	**-44.65*** **	**-204.2***
	(6.589)	*(6.003)*	*(9.195)*	*(13.53)*	*(15.91)*	*(119.6)*
Disability pension received by the households #	**-128.2** **	-0.468	67.35	24.85	-175.1	779.8
	(63.23)	*(34.48)*	*(57.03)*	*(73.14)*	*(133.5)*	*(635.6)*
Family size#	**-8.031*** **	**3.365***	**17.22*** **	**28.43*** **	**55.97*** **	**-55.24**
	(2.400)	*(1.719)*	*(2.487)*	*(3.809)*	*(7.156)*	*(38.19)*
Health Insurance #	**-54.41*** **	**-63.08*** **	**-83.10*** **	**-86.44** **	-24.40	108.7
	(18.21)	*(14.63)*	*(22.26)*	*(36.64)*	*(52.42)*	*(287.2)*
Highest completed Education by adults #	-2.449	**-5.864*** **	**-6.394*** **	**-7.691*** **	**-19.26*** **	**-72.70** **
	(1.941)	*(1.284)*	*(1.911)*	*(2.867)*	*(4.389)*	*(33.77)*
Households without toilets #	-26.55	-3.931	**-39.19** **	-1.214	-54.90	-237.9
	(18.55)	*(12.54)*	*(19.03)*	*(24.83)*	*(41.44)*	*(320.9)*
Membership Intensity #	**16.56*** **	**14.42*** **	**27.90*** **	**36.11*** **	**50.70*** **	**152.2** **
	(4.343)	*(3.325)*	*(4.424)*	*(6.804)*	*(9.059)*	*(68.08)*
Proportion of children 0-14 $	**-10.38*** **	-0.466	**7.178***	8.597	8.190	36.38
	(3.094)	*(2.494)*	*(3.742)*	*(5.485)*	*(9.493)*	*(58.34)*
Proportion of adults 60+ $	**-1.710** **	**-2.571*** **	**-3.829*** **	**-8.276*** **	**-14.15*** **	**-55.14*** **
	(0.795)	*(0.541)*	*(0.667)*	*(1.062)*	*(1.442)*	*(15.11)*
Remittances received by the households #	**-51.99** **	-5.633	-6.235	**-49.35***	-62.65	-62.09
	(21.48)	*(13.98)*	*(21.24)*	*(29.90)*	*(50.41)*	*(418.8)*
Constant	697.2***	1056.5***	1492.7***	2093.9***	3127.8***	7402.3***
	(23.62)	*(16.67)*	*(23.45)*	*(36.10)*	*(71.76)*	*(590.2)*
Adj. R2	0.0582	0.192	0.464	0.475	0.491	0.0264

R square	0.0585	0.193	0.464	0.475	0.491	0.0268
F stat	6.441	23.37	75.78	84.84	99.49	6.084
Number of Observations	37466	33948	33951	33966	33981	33964
SE cluster	7,043	6,547	7,164	7,407	7,646	7,239

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01.*

3)# Household variables; $ Individual variables.

4)Standard error clustered at Village/Nearest neighbourhood level.

5)Standard errors are adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

4.4.10: Regression Results For Urban By Adjusted Consumption Expenditure Quintile:

We now discuss the results of adjusted consumption expenditure in urban areas (Table 49). The quintile-wise regression results of adjusted consumption expenditure showed that ADLI negatively affected APL2, APL 3, and APL4. The assets owned by the households negatively and significantly affected all APL quintiles except APL 5. Days disabled were not significant. Disability pension was negative for BPL, APL1, APL 2, and APL 4. Family size was positive for APL 1 to APL 4 and negative for APL 5. Health insurance was negative for APL 1 and APL 3. The highest completed education was negative for all quintiles and significant for APL1 to APL4. Households without toilets negatively and significantly impacted BPL and APL 2. Membership intensity was positive for all quintiles. The proportion of children influenced BPL negatively, and the proportion of adults negatively influenced all APL quintiles. Household remittance negatively affected only APL 4.

Table 49: **Regression Results For Urban Adjusted Consumption Expenditure By Adjusted Consumption Expenditure Quintile**

	BPL	APL1	APL2	APL3	APL4	APL5
Variables	**I**	**II**	**III**	**IV**	**V**	**VI**
Activity of Daily Living Intensity (ADLI)$	-8.210	-0.00974	**-17.43*****	**-52.72*****	**-34.08****	-177.2
	(5.932)	*(4.377)*	*(5.852)*	*(12.86)*	*(17.32)*	*(114.2)*
Assets owned by the households#	-2.939	**-16.17*****	**-48.25*****	**-69.69*****	**-93.43*****	17.74
	(3.976)	*(2.611)*	*(3.528)*	*(5.673)*	*(10.91)*	*(58.47)*

Days unable to work due to Major morbidity $	-11.82	-8.596	-6.266	-29.66	-59.00	7.076
	(19.63)	*(10.45)*	*(16.32)*	*(22.50)*	*(43.11)*	*(252.0)*
Disability pension received by the households #	**-193.2****	**-96.77***	-243.5	-81.14	**-1450.5*****	654.5
	(84.52)	*(56.69)*	*(199.2)*	*(101.6)*	*(162.6)*	*(1769.9)*
Family size#	5.682	**14.12*****	**25.37*****	**44.72*****	**47.84*****	**-319.5****
	(8.487)	*(4.422)*	*(5.975)*	*(9.779)*	*(17.16)*	*(126.2)*
Health Insurance #	99.08	**-70.24***	-40.75	**-156.1****	-65.88	9.081
	(71.07)	*(36.05)*	*(43.81)*	*(70.04)*	*(95.54)*	*(384.8)*
Highest completed Education by adults #	-3.639	**-14.42*****	**-10.66*****	**-20.61*****	**-36.26*****	-100.6
	(5.964)	*(3.144)*	*(3.947)*	*(6.902)*	*(9.440)*	*(77.17)*
Households without toilets #	**-83.36****	-40.31	**-53.85***	-44.89	-155.6	-714.8
	(39.22)	*(27.03)*	*(31.82)*	*(57.52)*	*(98.12)*	*(634.8)*
Membership Intensity #	**26.19***	**22.08*****	**49.84*****	**58.89*****	**90.42*****	**408.4*****
	(13.71)	*(7.978)*	*(9.110)*	*(16.54)*	*(22.38)*	*(108.5)*
Proportion of children 0-14 $	**-21.53****	-8.865	-11.27	-13.47	-1.699	13.95
	(8.905)	*(5.604)*	*(8.422)*	*(11.33)*	*(17.50)*	*(95.98)*
Proportion of adults 60+ $	-1.700	**-4.782*****	**-9.708*****	**-9.685*****	**-25.65*****	**-108.1*****
	(3.340)	*(1.501)*	*(1.783)*	*(2.246)*	*(3.874)*	*(35.69)*
Remittances received by the households #	-31.04	29.17	41.72	-48.22	**-227.0****	110.3
	(55.12)	*(47.15)*	*(45.33)*	*(92.47)*	*(112.4)*	*(618.7)*
Constant	852.7***	1533.6***	2480.6***	3541.2***	5337.7***	9470.9***
	(90.81)	*(48.06)*	*(67.94)*	*(122.5)*	*(211.8)*	*(1557.3)*
Adj. R2	0.0930	0.241	0.480	0.443	0.331	0.0280
R square	0.0941	0.241	0.480	0.443	0.332	0.0287
F stat	3.192	15.64	47.07	46.68	.	3.509
Number of Observations	10083	16713	16700	16691	16669	16685
SE cluster	7,043	6,547	7,164	7,407	7,646	7,239

Note:1) Standard errors in parentheses.

2) p<0.1, ** p<0.05, *** p<0.01.*

3)# Household variables; $ Individual variables.

4)Standard error clustered at Village/Nearest neighbourhood level.

5)Standard error Adjusted for clusters in PSUHH.

6)Fixed-effects (within) regression -Group variable: PERSONID2012.

7)Figures in 'Bold' represent significant regression coefficients.

Source: Authors' calculations based on IHDS 1 and IHDS 2 data.

4.5: Main Findings And Discussion:

In the following section, we discuss the main findings.

4.5.1: Consumption Expenditure And Adjusted Consumption Expenditure:

For IHDS 1, monthly consumption expenditure, adjusted consumption for health expenditure and food expenditure for short morbidity under all categories led to significantly different expenditures for both rural and urban areas; for major morbidity, high blood pressure, heart disease, diabetes and asthma were common for both rural and urban areas. Additionally, in rural areas, it was cancer and paralysis. For adjusted consumption expenditure, high blood pressure, heart disease, diabetes and others were common categories with significantly different expenditures for rural and urban areas. Further, in rural areas, the adjusted consumption expenditure differentials were also observed for those with cataracts, tuberculosis, paralysis, and epilepsy. The food expenditure differentials showed up for high blood pressure, heart disease, diabetes, leprosy, and others for rural and urban areas. Rural areas also reported expenditure differentials for asthma.

For IHDS 2, the following expenditure differentials were observed: for monthly consumption expenditure, the differences were common across all short morbidity categories for rural areas, but in urban areas, the expenditure differential was only for fever. Expenditure differentials were also observed across rural and urban areas, such as high blood pressure, heart disease, diabetes, cancer, asthma, and accident lead expenditure differentials. The more unique ones were expenditure differentials observed for cataracts, paralysis in rural areas and mental illness in urban areas. The differentials in consumption expenditure adjusted for health were prevalent across all short morbidity categories for rural and urban areas. High blood pressure, heart disease, and diabetes lead to expenditure differentials for rural and urban areas. In rural areas, disabilities caused due to tuberculosis, paralysis and accidents caused expenditure differentials. Mental illness leads to expenditure differentials only in urban areas. Food consumption expenditure differed for all rural short morbidity categories. In urban areas, for short morbidity, only fever and cough caused differentials in food expenditure.

For major morbidity disabilities, the food expenditure differentials were significant for tuberculosis, high blood pressure, heart disease, diabetes, cancer, and paralysis across rural and urban areas. Cataracts and asthma in rural areas and leprosy, polio, epilepsy, and mental illness in urban areas also had expenditure differentials. The non-food expenditure differentials were observed for ailments across short and major morbidity disabilities for rural and urban areas, such as fever, cough, high blood pressure, heart disease, diabetes, and accidents. The non-food expenditure differentials were observed for diarrhoea, asthma, mental illness and accident in urban areas and cataracts, cancer, and paralysis for major morbidity disabilities in rural areas.

Short morbidity expenditure differentials were observed for all categories of short morbidity, suggesting that even short-duration disability also causes expenditure differentials. In IHDS 1 and IHDS 2, the most common major morbidity disabilities for which expenditure differentials were prevalent were heart disease, high blood pressure and diabetes. The non-common morbidities in expenditure differentials were cataracts, tuberculosis, paralysis, epilepsy, asthma, and cancer.

ADLI and days disabled due to major morbidity showed a positive coefficient for monthly consumption expenditure but negative for adjusted consumption expenditure. There is, therefore, a strong case for using consumption expenditure adjusted for health expenditure as a measure of household well-being. A disability may compel households to incur more to take care of health expenditures and maintain a standard of living aligned with those with households without disabled members. The entire debate in the disability literature revolves around the ability of households with disabled members to smoothen consumption, and it was observed that in Indonesia, households were exposed to higher health expenditure(Simeu & Mitra, 2019). Households with disabled members experience a negative impact on non-health consumption(Gertler & Gruber, 2002)(adjusted consumption in this chapter). The components on which the adjusted consumption is distributed are food, education, and non-food expenditure also witnessed a decline(Simeu & Mitra, 2019). Our results match the results in the literature.

Membership in various groups has worked consistently and positively for households. Assets owned by the households have been positive only for consumption expenditure; as far as adjusted consumption expenditure is concerned, the asset coefficient has been negative. The caste and quintile results are almost similar, with few exceptions. The coefficients of ADLI, household assets, days disabled, and health insurance differ for consumption and adjusted consumption expenditure for caste categories. Households with disabled members due to ADLI and those who are disabled due to major morbidity increased consumption expenditure for caste2 in rural and urban areas. However, ADLI reduces the adjusted consumption for three caste categories, making health insurance insignificant.

Understanding the changes in consumption expenditure and adjusted consumption expenditure is pertinent. Households may have to incur more expenditure on health. The adjusted expenditure pays for household food and other non-food components. A reduction in adjusted consumption would mean lesser expenditure available for these components. The literature supports this; those disabled must spend more to maintain their consumption expenditure. The ADLI affects only the bottom two quintiles concerning reduced food expenditures. At the same time, not all subgroups experience significant increases in remittances associated with an increase in the ADLI(Simeu & Mitra, 2019).

Even if there is little evidence in developing countries, the evidence points out that persons with disabilities have lower social and economic status. Households with disabilities have fewer assets(Palmer et al., 2015; World Bank, 2009). Out of 15 countries, in 14 countries, people with disabilities were economically worse off on more than one dimension of economic well-being (dimensions of education, employment, assets owned by the household, consumption expenditure). They also experienced deprivation in multidimensional poverty. Households with disabilities also had lower assets and spent more on health care. Mixed results are for income and household expenditure for disability (Mitra et al., 2011).

4.5.2: Consumption Expenditure Quintiles:

ADLI has a positive coefficient for APL 3 and 4 across rural and urban areas. Assets owned by the household have helped boost the expenditure across all quintiles (rural and urban), and family size works reversely. The days disabled have a positive and significant coefficient for BPL and APL4 for rural, and APL5 was positive for urban. Health insurance positively affects BPL and APL5 for rural and APL4 and APL5 for urban areas. The highest completed education helps BPL, APL3 and APL 4 to increase the consumption expenditure in rural and urban areas and for APL 5 in urban areas.

Membership intensity has a negative and significant coefficient for APL2, APL 3 for rural and urban, and APL4 for urban. The proportion of children positively affects consumption expenditure for BPL and negatively for APL3, APL 4 and APL5 for rural and across all quintiles for urban. The proportion of adults has a positive and significant coefficient for

BPL (rural), APL2, APL3 and APL 4(rural and urban). Remittances received affect BPL (rural), APL2(rural and urban), and APL 3 and APL 5(urban) quintile positively.

One of the dimensions of households' economic well-being is consumption expenditure (Mitra et al., 2011), which needs to be adjusted for health expenditure(in this chapter, we use adjusted consumption expenditure). Without this adjustment, the poverty estimates originating from consumption expenditure tend to underestimate the same (Van Doorslaer et al., 2007).

There is an issue with using consumption expenditure in disability studies. Households with disabilities may have higher expenditures than households otherwise. Also, for those disabled, the distribution of consumption expenditure may be uneven within the household. Using expenditure to compare those disabled and those not may provide accurate results. Assets owned by the household may be more accurate (Mitra et al., 2011).

For adjusted consumption expenditure, APL 2, APL 3 and APL 5 for rural areas and APL 2-APL 4(urban) negatively affected ADLI. Assets owned by the households helped BPL but not APL quintile(APL 1- APL 4 for urban) for rural. Days disabled for major morbidity negatively and significantly impact BPL, APL2, APL4, and APL5 for rural areas and are insignificant for urban quintiles. The chances of households in the lowest wealth quintile were found to be reporting disability more, so also urban households are likely to report disability (Sultana et al., 2017).

Disability pension worked negatively for BPL(rural and urban) and APL1, APL 2 and APL 4 (urban). Family size was negative for BPL, positive for APL1 – APL 4(rural and urban) and negative for APL5(urban). Health insurance negatively influenced BPL, APL1- 3(rural and urban) APL4(Urban). Elsewhere in the literature, those disabled with insurance have lesser chances of incurring catastrophic expenditures (Palmer, 2014).

Education influenced all quintiles negatively but did not significantly impact BPL(rural and urban). A household without a toilet had negative coefficients for all quintiles but was significant for BPL(rural) and APL2(rural and urban). Membership intensity positively and significantly affected all quintiles for rural and urban. The proportion of children had a negative influence on BPL(rural and urban), APL1- APL 5(urban), but positive on APL2(rural). The proportion of adults worked negatively for all quintiles (rural and except BPL urban). Household remittances affected all quintiles negatively but were significant for BPL, APL3(rural) and APL4(urban). A study from Bangladesh reported higher OOPHE for the upper quintile (Sultana et al., 2012).

4.6: Conclusion:

These results help to build a strong case for incorporating morbidity-specific and duration-specific disability components in the disability pension and health insurance. The three lifestyle diseases that cause expenditure differentials are high blood pressure, heart disease and diabetes. Some morbidities are unique to rural areas that cause expenditure differentials, such as epilepsy, paralysis, cataracts, tuberculosis, asthma, and accidents. Mental illness is causing expenditure differentials in urban areas. The productivity loss needs to be compensated differently for rural and urban areas. The reason is that it is mostly manual work with wages paid in rural areas. Loss in daily wages must be compensated, and additional compensation for recovering to the original state of health may also be required. Socio-economic differentials also need to be reflected in the policies related to health intervention. An all-inclusive policy with inclusion and acknowledgement of disabilities is required to attain SDG 3. Building up social capital via membership in various groups seems to be providing a boost to consumption expenditure. Acknowledgement of such an organisation formally may provide boos for attracting more memberships.

The next chapter, chapter 5, deals with natural disasters and their impact on household well-being. It uses two different techniques of assessing the impact on consumption expenditure and adjusted consumption expenditure on the households affected by natural disasters.

CHAPTER 5:

IMPACT OF NATURAL DISASTERS AS COVARIATE SHOCK ON HOUSEHOLD CONSUMPTION EXPENDITURE

The previous chapter examines an idiosyncratic shock: disability and its impact on consumption expenditure. Idiosyncratic shock only affects a given household. Chapter 5 is titled, 'Impact of natural disasters as a covariate shock on household consumption expenditure'. Objective two, 'To investigate the effect of covariate shocks on household consumption expenditure', is exclusively dealt with in this chapter. This chapter is broadly divided into six sections. Two distinct methodologies of impact evaluation are used in this chapter. Section 5.1 starts with an introduction, and the sub-sections deal with background studies, natural disasters in India, and monetary and non-monetary damages from natural disasters in India. Section 5.2 deals with materials and methods. Results follow this. The main findings are given in section 5.4, followed by the conclusion and limitations.

5.1 Introduction:

The 2015 Paris Agreement raised hopes that a globally coordinated action to mitigate climate change is finally in place (Averchenkova & Bass, 2016). There is a strong likelihood that the frequency and intensity of extreme events like floods, droughts, storms, sea-level rise and wildfires will continue to rise, adversely affecting welfare(Klenert et al., 2020). At the same time, world inequality has been rising both within and across nations (UN DESA, 2020), and climate is expected to exacerbate existing vulnerabilities (Eriksen et al., 2021). Disasters have a long-lasting effect on poverty and the overall economic development of those affected (Baez & Santos, 2008) with multi-layered effects, especially on poor households (Benson & Clay, 2004; Cred, U. N. D. R. R, 2020) and reduce their consumption capacity (Soete, 2015). There is growing evidence of the impact of climate-related damages on household well-being across different extreme events (Schmidhuber & Qiao, 2020).

Studies show that developing countries with low per capita income are particularly vulnerable as they host large proportions of the global poor with inadequate social safety nets and infrastructure (Gu, 2019; Yoon, 2012). Vulnerable sections of society are the worst hit, which is truer for developing economies with a dependence on agriculture (Benson & Clay, 2004; Cred, U. N. D. R. R, 2020; Eriksen et al., 2021; Kumar et al., 2004; Yoon, 2012).

Rural populations largely agriculture-dependent will similarly face multi-layered vulnerability, including declining yields, unpredictable rainfall, and agricultural output (Kumar et al., 2004). Hence, it is crucial to understand how adverse events in the recent past have impacted individuals' well-being. India is a geographically, socially, and economically diverse country. Officially, 27 (of the 32 states) states are considered vulnerable to disasters (NDMA, 2019). About 12 % of the landmass is exposed to floods, while droughts threaten 68% of the cultivable land.

5.1.1: Background Studies:

Extreme weather threatens farmers' food security, livelihood and assets (Swaminathan & Rengalakshmi, 2016). Previous studies in India have focused on the loss of human life and household assets due to a super cyclone in Odisha (Chhotray & Few, 2012; Das & Vincent, 2009; Fanchiotti et al., 2020); multiple extreme events like floods, droughts, heatwaves and cyclones in Odisha (Patel et al., 2019), consumption loss due to floods in Gorakhpur in Uttar Pradesh (Patnaik & Narayanan, 2015), loss of assets (Patankar & Patwardhan, 2016) and health impacts (Dholakia et al., 2020) due to floods in Mumbai and long term death rates across all states due to extreme events (Mahapatro et al., 2018; Ray et al., 2021). Some recent studies have focused on climate variability and its impact on inequality (Sedova et al., 2020), social capital (Behlendorf et al., 2020) and mortality in the context of natural disasters (Roy Chowdhury et al., 2021). The existing literature has largely studied extreme events' socio-economic impact and focused on local (or regional) and one-off events. There is growing evidence of the impact of climate-related damages on well-being across different extreme events (Schmidhuber & Qiao, 2020).

5.1.2:Natural Disasters In India:

EMDAT database provides state and district-wise data on natural disasters in India. The monetary value of damages is also provided. This data is given with gaps. The district-wise information provided does not match the district from IHDS 2. The EMDAT classifies natural disasters as given in Table 50. Although many classifications of disasters are listed, only those covered in IHDS 2 are considered. A summary of natural disasters is provided in Table 51 for 2006 to 2012 for all reported natural disasters in IHDS 2. Among all the natural disasters, droughts have a relatively higher mean than other natural disasters.

Table 50**: Types Of Natural Disasters Using EMDAT Classification**

Types	**Natural disasters**
Geophysical	Earthquake, tsunami
Hydrological	Flood
Meteorological	Hailstorm, Cyclone
Climatological	Drought
Biological	Epidemic

Source: Compiled by the author using information from IHDS round 2 based on EMDAT classification.

Table 51: **Distribution Of Natural Disasters By Years**

Variable	Year	Mean
	2006	0.061
	2007	0.081
	2008	0.086
Floods	2009	0.101
	2010	0.103
	2011	0.116
	2012	0.02
	2006	0.125
	2007	0.156
	2008	0.199
Drought	2009	0.238
	2010	0.216
	2011	0.172
	2012	0.058
	2006	0.014
	2007	0.015
	2008	0.012
Earthquake	2009	0.014
	2010	0.02
	2011	0.041
	2012	0.003
	2006	0.044
	2007	0.061
	2008	0.058
Hailstorm	2009	0.072
	2010	0.076
	2011	0.079
	2012	0.008
	2006	0.015
	2007	0.019
	2008	0.03
Epidemic	2009	0.033
	2010	0.018
	2011	0.02
	2012	0.008
	2006	0
	2007	0
	2008	0.001
Tsunami	2009	0.003
	2010	0.001
	2011	0.004
	2012	0
Cyclone	2006	0.019

2007	0.02
2008	0.024
2009	0.04
2010	0.035
2011	0.042
2012	0.006

Note 1) Number of observations 2006-2011= 52722.

2)Number of observations 2012=45336; Min=0 max=1.

Source: Author's calculations based on IHDS 2 data.

Table 52 gives average state-wise disasters as reported. Assam, Jammu Kashmir (now UT) and Himachal Pradesh have reported higher averages of natural disasters. The union territory of Puducherry reported the highest number of natural disasters.

Table 52: **State-Wise Average Of Natural Disasters Between 2006-2012**

States	Observations	Mean	SD	Min	Max
Andhra Pradesh	2610	1.5	2.221	0	8
Arunachal Pradesh	228	0.7	1.934	0	7
Assam	866	3.1	4.12	0	14
Bihar	2170	2.4	3.18	0	14
Chhattisgarh	2026	0.7	1.176	0	4
Goa	220	0.4	0.937	0	3
Gujarat	2126	0.5	1.197	0	6
Haryana	2994	0.9	1.912	0	10
Himachal Pradesh	2326	2.2	3.215	0	15
Jammu & Kashmir	782	2.3	2.801	0	11
Jharkhand	982	1.8	2.267	0	8
Karnataka	4938	0.8	1.694	0	10
Kerala	648	1.3	4.178	0	18
Madhya Pradesh	5028	1.4	2.34	0	12
Maharashtra	4414	0.9	1.59	0	7
Manipur	84	0.5	0.871	0	2
Meghalaya	212	0.8	1.571	0	5
Mizoram	106	2.1	3.134	0	8
Nagaland	136	2.7	5.046	0	15
Odisha	3012	1.5	2.25	0	12
Puducherry	122	4.4	4.737	0	12
Punjab	2354	0.5	0.882	0	4
Rajasthan	3718	1.8	2.392	0	10
Sikkim	48	0.5	0.505	0	1
Tamil Nadu	1696	0.5	0.953	0	4
Tripura	166	0.1	0.327	0	1
Uttar Pradesh	5408	1.4	2.284	0	15
Uttarakhand	574	1.7	2.053	0	6
West Bengal	2580	1.3	2.169	0	8

*Note: *UT of Dadra Nagar Haveli, Daman and Diu dropped due to zero observations.*
Source: Author's calculations based on IHDS 1 and IHDS 2 data.

The geographical issues related to different disasters give an idea about the intensity of the same. Floods and drought were the two most frequently occurring natural disasters. It is often presumed that states that suffer from floods are water surplus and states that do not experience droughts, while states that suffer from droughts are water-scarce and do not see the occurrence of floods. However, most states in India report floods and droughts in the same year repeatedly.

Apart from a few states from the northeast and Union Territories, most were affected by droughts and floods (Table 53). Some states were affected by these disasters during the entire study period. Punjab and Madhya Pradesh reported droughts yearly, and Uttar Pradesh reported floods yearly. These three states account for nearly 42% of India's total food grain production (GOI, 20220).

The northern states of Jammu and Kashmir, Himachal Pradesh, Haryana, Punjab, Uttarakhand, Rajasthan, and Bihar were affected by droughts throughout the study period. Except for Haryana, Rajasthan and Uttar Pradesh were also affected by floods. Droughts are more frequent than floods. Among the northeastern states, Assam was hit by drought and floods; the remaining states had infrequent episodes of drought and floods. The special category states of Jammu and Kashmir, Himachal Pradesh and Uttarakhand have consistently witnessed droughts and a few flood episodes. Assam, also in this category, has regularly witnessed a cycle of droughts and floods.

Odisha, West Bengal, and Bihar reported continuous drought episodes and floods in the east. Jharkhand experienced frequent droughts but infrequent floods(Table 53). Kerala, Andhra Pradesh, and Karnataka experienced continuous drought and floods in the south. Tamil Nadu experienced more floods and a few episodes of drought. The only Union territory that reported floods throughout was Puducherry. In central India, Maharashtra, Madhya Pradesh, and Chhattisgarh witnessed drought cycles and floods. In the west, Gujarat and Rajasthan reported droughts frequently. Goa also reported infrequent episodes of floods.

Table 53: **Major Natural Disasters- Flood And Drought By States**

States	2006	2007	2008	2009	2010	2011	2012
Andhra Pradesh	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Assam	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Floods
Bihar	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	
Chhattisgarh	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Goa		Floods	Floods	Floods		Floods	
Gujarat	Floods	Drought Floods	Drought Floods	Floods	Floods	Drought Floods	Drought
Haryana	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Himachal Pradesh	Drought	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought
Jammu & Kashmir	Drought Floods	Drought	Drought	Drought	Drought	Drought	Drought
Jharkhand	Drought	Drought	Drought	Drought Floods	Drought Floods	Drought Floods	Drought
Karnataka	Drought	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Kerala	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	
Madhya Pradesh	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Maharashtra	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods
Manipur			Drought		Floods		
Meghalaya	Drought Drought	Drought	Drought				
Nagaland		Floods	Floods	Floods	Floods		
Odisha	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought
Puducherry	Floods	Floods	Floods	Floods	Floods	Floods	
Punjab	Drought	Drought	Drought	Drought	Drought Floods	Drought Floods	
Rajasthan	Drought	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	
Tamil Nadu	Drought Floods	Floods	Drought Floods	Drought Floods	Drought Floods	Floods	Drought
Uttar Pradesh	Droughts Floods	Drought Floods	Floods	Floods	Floods	Floods	Drought
Uttarakhand	Drought	Drought	Drought	Drought Floods	Drought Floods	Drought Floods	
West Bengal	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods	Drought Floods

*Note: *UT of Dadra Nagar Haveli, Daman and Diu dropped due to zero observations.*

Source: Authors' calculations based on IHDS1 and IHDS 2 data.

5.1.3: Monetary And Non-Monetary Damages From Natural Disasters For India:

Table 54:**EMDAT On ND From 2006 To 2012 For INDIA: Total Damages/ Damages By Flood And Storms.**

Year	Total number of ND	Total Deaths	Number Injured	Number Affected	Number Homeless	Total Affected	Total Damages, Adjusted ('000 US$)
2006	20	1431	478	32,34,000	41,50,000	73,84,478	45,56,673.00
2007	20	2236	33	3,81,43,000	---	3,81,43,033	4,91,580.00
2008	12	1808	50	1,22,99,018	24,00,000	1,46,99,068	2,13,954.00
2009	18	2208	118	59,92,521	4,000	59,96,639	34,53,163.00
2010	17	1774	717	33,83,635	9,07,000	42,91,352	26,70,485.00
2011	13	1038	250	1,25,04,069	3,25,000	1,28,293	24,48,572.00
2012	10	599	--	---	37,500	43,18,360	2,87,971.00
Total	110	11094	1646	7,55,56,243	78,23,500	7,49,61,223	1,41,22,398.00

Source: Author's calculation based on EMDAT for India from 2006 to 2012.

We have used data on natural disasters provided by EMDAT for India from 2006 to 2012 to understand the extent of damages(Table 54). We have compiled year-wise national disasters and used information on variables such as total death, number of injured, total deaths, number of affected, number of homeless and total damages (adjusted). India was hit by 110 different natural disasters between 2006 to 2010. The highest was in the years 2006 and 2007. The total number of deaths was 11094, the number of injured was 1646, and the number of affected was 7,55,56, 243. Around 78,23,500 people became homeless. The total damages were 1.41.22,398 $ for a total of affected 7,49,61,223 people.

Table 55: **Monetary And Non-Monetary Damages From Floods And Storms In India From 2006 - 2012.**

	Floods			Storm		
Years	$ Monetary damages(adjusted)	Non-monetary Damages (Total affected)	Frequency	$ Monetary damages(adjusted)	Non-monetary Damages (Total affected)	Frequency
2006	45,56,673.00	72,34,178	17	--	1,50,300	2
2007	4,95,180.00	3,81,43,008	16	--	--	1
2008	1,82,490.00	1,39,89,018	8	31,464.00	50	1
2009	30,74,250.00	59,86,008	6	3,78,913.00	9,085	5
2010	26,70,485.00	37,72,408	8	-	5,07,080	7
2011	19,96,081.00	1,20,04,069	7	4,52,491.00	2,50,050	3
2012	2,87,971.00	42,48,360	6	--	70,000	1

Source: Author's calculation based on EMDAT for India from 2006 to 2012

EMDAT provides data for different types of disasters under different categories. Monetary data is used for total damages adjusted. Non-monetary damages are compiled from the number affected, injured, homeless, and those who lost life (Table 55). The highest number of floods was in the years 2006 and 2007. Monetary damages amounted to 45,56,673 $ for 2006, the highest monetary damage. Non-monetary damages were highest for the year 2007 at 3,81,43,008. Some data on storms was missing on EMDAT. The highest monetary damage caused by the storms was in 2011, with $4,52,491. However, non-monetary damages were highest for the year 2010 at 5,07,080.

5.2: Material And Methods:

We use household village panel data from IHDS 1 and IHDS 2. We have used two distinct methodologies, IV2SLS and DID, to examine the impact of natural disasters on household consumption expenditure and adjusted consumption expenditure(see Chapter 3 for details).

5.2.1: Instrumental Variable Model:

An instrumental variable approach using the two stages least square model is used to examine the impact on consumption expenditure and adjusted consumption expenditure of assets owned by the household, which in turn is influenced by the natural disaster intensity and confidence intensity.

The IV model uses two instruments: natural disaster intensity and confidence intensity, one endogenous regressor household ownership of the assets, and nine other independent variables. The data used is panel data of households and villages. The two outcome variables are consumption expenditure and adjusted consumption expenditure. The models are also run for socio-economic categories.

Household ownership of assets is used as an endogenous regressor for predicting consumption expenditure and adjusted consumption expenditure. Household assets are used in times of adversaries, and health insurance also works on similar lines(Sumarto et al., 2007). It is anticipated that assets may not be completely exogenous as a variable. It could be determined by other exogenous shocks like natural disasters in a world where climate change makes disasters unpredictable. Climatic factors greatly impact short-term and long-term assets (Wallemacq & House, 2018). IHDS provides comparable household assets data across both rounds (see Chapter 3 for details). IHDS 2 gives two variables measuring household assets: a) assets owned by the household in IHDS 2 and b) assets owned by the household in IHDS 2(compatible with IHDS 1). We have used the assets from IHDS 1 and are compatible with IHDS 2. The data does not provide a distinction between productive and unproductive assets. Thus, household assets are influenced by

Natural disasters and confidence in institutions/ government. Therefore, these two instruments determine the exogenous component in the endogenous regressor.

EM-DAT database, widely used for measuring monetary losses, also gives data on the total affected (deaths, injured, homeless) along with insured damages for India state-wise and district-wise; we have not used this database. The natural disaster information is used from the village schedule of IHDS 2 (see Chapter 3 for details). We created variable natural disaster intensity (NDI), a continuous variable, by summarising the information from 7 disasters reported in the survey. Since the disaster was repeated, constructing a variable in this manner captures the number of times a specific disaster hit a household during the given period. The data does not cover any information on monetary damages caused by the disaster.

Confidence in institutions/ government is used as one of the instruments. Trust in institutions and government is a multi-dimensional concept developed based on many socio-cultural, economic and environmental factors. Government and society have a crucial role in mitigating the damages and vulnerabilities arising from natural disasters (Kelman et al., 2016). Trust in public institutions influences individual welfare, especially in consumption and asset allocation behaviour. For example, if citizens perceive that the state will offer relief reliably during a crisis, they will have to devote fewer resources to building personal safety nets and deploy the same in productive schemes. Higher levels of confidence in government were associated with higher levels of reported preparedness (DeYoung & Peters, 2016). Confidence in institutions is strongly linked to asset holding (Ellis & Bahiigwa, 2003). Fair and transparent institutions will likely play a critical role in adaptation and resilience-building, especially in calamity-prone areas (Papaioannou, 2009). The poor are most vulnerable to shocks from natural disasters. In Pakistan, during the 2010 floods, relief help from the government as social protection worked to increase the aspirations of the poor (Kosec & Mo, 2017).

In China, post-earthquake, people's faith in the government increased, especially in the government machinery at the grassroots level(You et al., 2020). Public institutions have influenced individual welfare, especially consumption and asset allocation behaviour. If an economic agent (household or firm) perceives that the state will offer the security of assets, they are more likely to enhance investments (Janada & Teodoru, 2020; Vanlaer et al., 2020). Thus, confidence in institutions affects resilience and asset-building post-calamity.

The IHDS had a single question that captured information on ten public institutions ranging from police to schools on confidence. All these responses were summed to generate a confidence intensity for each household.

Human welfare is affected by tangible and lesser tangible factors. Membership in various associations and groups helps build connectivity and a sense of security in the village. The caste associations help the members boost their confidence and sense of belonging, which eventually helps to build resilience against adversaries. Human welfare is also known to be influenced by social networks (Calvó-Armengol & Jackson, 2004; Jackson, 2011), sometimes also referred to as social capital (Pena-López et al., 2021). These facilitate the accumulation of assets and faster recovery after disasters. Membership in various associations and socio-cultural groups has helped households in asset building and consumption. Membership in financial and non-financial groups enhanced human welfare(Haddad & Maluccio, 2003). Accumulating assets is also facilitated by self-help groups(microfinance) and several other similar associations. The Grameen Bank's success with self-help groups (SHG) has influenced development intervention globally (Deininger & Liu, 2009). The presence of SHG has been found to increase overall resilience to crises (Lehmann & Smets, 2020). Social networks impact a household's ability to cope with crises(Bonye & Godfred, 2011). The IHDS data provides information about membership to various social and cultural institutions and organisations. These are summed as membership intensity.

Another important factor that influences well-being and resilience building is the presence of public programmes in a village. The presence of public programmes is an indicator of two situations. First, villages that are considered poor may be likely to have more public projects. Alternatively, villages with more economically and politically influential residents will corner more public projects. Either way, public projects' presence will influence a village's well-being and resilience (Arouri et al., 2015). We use variable public project intensity constructed using the information from IHDS 1 and IHDS 2.

Conflict in the village and among communities has multiple impacts, such as the psychological well-being of individuals(Okechukwu, 2017)and the personal loss of lives and properties (Ostrom, 1990). We have used the variable conflict intensity to measure this impact.

The number of married females, family size and proportion of children(Nguyen et al., 2019) in the household affect consumption expenditure (Blake, 1989; Downey, 1995; Flake & Forste, 2006; Heshmati et al., 2019). Education of the household members also has implications on welfare (Sumarto et al., 2007;Muttarak & Lutz, 2014). The absence of health insurance often impacts adjusted consumption levels (Wagstaff & Pradhan, 2003).

It is expected that the impact of natural disasters would not be uniform across the population's different social and economic cohorts. The impact on consumption is analysed at the disaggregated level of 4 categories of caste and 6 categories of expenditure quintile (Mehta, 2008; Statistical Bulletin 394, 2017; Choudhury et al., 2019; Hooda, 2014; Mehta, 2008). Using the consumption expenditure quintile is in line with existing literature; Arouri et al. (2015) used the expenditure quintile for Vietnam households to study the impact of Natural disasters, and Edwards et al. (2021) used the income quintile to study the impact of natural disasters on the households. Caste is considered an important determinant and social grouping (Deshpande, 2011; Mosse, 2018; Munshi & Rosenzweig, 2006).

5.2.3: Difference In Differences Model:

We also present the model and results from our published study (see Chapter 3 for details). We use NDI as a continuous treatment to examine the impact of NDI on household consumption expenditure and adjusted consumption expenditure. We use monthly consumption expenditure per capita and adjusted consumption expenditure to study the impact of natural disasters on households.

Households use several adaptation strategies to mitigate the impact of any shock from natural disasters on consumption expenditure. Adaptation includes household changes in consumption expenditure patterns from high to low or mitigation to maintain the standard of living before the shocks. The literature points out that Households run down assets, increase labour by employing more members of the households, and reduce expenditure on education and non-food.

Based on Brook's (2003) concept of adaptation, we define adaptation as a mechanism adopted by households that face natural disasters by making some changes in their behaviour that will help them to cope with existing or any stress in future in a better way. These adaptations provide a larger ability for households to deal with natural disasters.

Household assets are used in times of adversaries, and health insurance also works on similar lines(Sumarto et al., 2007). A study in Turkey on household consumption expenditure found that age, income, marital status, and household size significantly impact rural consumption expenditure(Caglayan & Astar, 2012). Our model includes the following variables as covariates – Caste (Deshpande, 2011; Mosse, 2018; Munshi & Rosenzweig, 2006), family size and proportion of children, Education, number of married females in the household (Blake, 1989; Downey, 1995; Flake & Forste, 2006; Baez & Santos, 2008; Heshmati et al., 2019), presence of health insurance, membership intensity, public project intensity, conflict intensity and confidence intensity(see Chapter 3 for details).

5.3:Results:

We present the results of IV 2SLS followed by DID.

5.3.1: Results With IV2SLS:

In this section, we present the regression results for two models: Model 1: Consumption expenditure (dependent variable) (Table 56) and Model 2: Adjusted consumption expenditure (dependent variable) (Table 57). We first run both models for the Hausman specification test followed by the OLS with fixed effects of examining the presence of endogeneity (Table 58 and Table 59).

5.3.1.1: Results of OLS With Fixed And Random Effects For Model 1 Consumption Expenditure:

Table 56: **Results Of OLS With Fixed And Random Effects For Model 1 Consumption Expenditure**

	OLS with FE	**OLS with RE**
I	**II**	**III**
Independent Variables	**Consumption expenditure**	**Consumption expenditure**
Assets owned by the household $	**88.27*** *(3.212)*	**122.4*** *(1.538)*
Confidence Intensity $	3.789 *(2.465)*	**7.193*** *(1.807)*
Conflict Intensity $	**-26.30*** *(8.027)*	**-21.38*** *(5.937)*

Family size $	**-123.2*** (7.107)	**-109.4*** (4.318)
Health Insurance $	**239.1*** *(39.89)*	**202.4*** *(29.38)*
Highest Adult Education $	-0.626 *(3.375)*	0.706 *(1.761)*
Membership Intensity $	**55.96*** *(7.275)*	**55.00*** *(4.753)*
Natural disaster Intensity #	**9.488** *(4.248)*	-2.489 *(3.153)*
Number of married females $	**42.40*** *(23.51)*	-3.634 *(14.20)*
Proportion of children $	**-1014.6*** *(55.69)*	**-888.7*** *(36.46)*
Public Project Intensity #	**-13.63*** *(2.407)*	**-16.22*** *(1.526)*
Constant	1668.0*** (81.81)	1200.2*** (54.68)
R square	0.108	0.1041
F stat/ wald chi	285.8	13693.26
pvalue>F;p value > Chi2	0.000	0.000
Number of observations	52492	52492

Note:1. SE in parenthesis.
2. $ Household data; # Village data .
*3)*** p<0.01, ** p<0.05, * p<0.1*
4)Figures in 'Bold' represent significant regression coefficients.

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Results of the Hausman Specification test for fixed and random effects, model 1, are presented in Table56.

χ^2= 213.79

Prob > chi2 = 0.0000

The null hypothesis is rejected; therefore, we use OLS with fixed effects for further analysis (Table 58)(see Chapter 3 for details).

5.3.1.2: Results Of OLS With Fixed And Random Effects Model 2 Adjusted Consumption Expenditure:

Table 57:**Model No. 2 Adjusted Consumption Expenditure: Results Of OLS With Fixed And Random Effects**

	OLS with FE	OLS with RE
I	II	III
Independent Variables	Adj. Consumption expenditure	Adj. Consumption expenditure
Assets owned by the household $	**84.29*****	**114.2*****
	(2.805)	*(1.346)*
Confidence Intensity $	1.193	**4.639*****
	(2.151)	*(1.578)*
Conflict Intensity $	**-22.10*****	**-17.44*****
	(7.005)	*(5.189)*
Family size $	**-109.8*****	**-93.28*****
	(6.209)	*(3.778)*
Health Insurance $	**237.3*****	**195.2*****
	(35.65)	*(26.30)*
Highest Adult Education $	-0.560	1.939
	(2.949)	*(1.541)*
Membership Intensity $	**56.96*****	**51.45*****
	(6.356)	*(4.158)*
Natural disaster Intensity #	5.667	-3.163
	(3.711)	*(2.758)*
Number of married females $	**43.79****	-10.22
	(20.54)	*(12.42)*
Proportion of children $	**-900.3*****	**-750.1*****
	(48.66)	*(31.89)*
Public Project Intensity #	**-11.55*****	**-17.41*****
	(2.104)	*(1.335)*
_cons	1414.4***	1027.2***
	(71.36)	*(47.76)*
R square	0.114	0.1096
F stat/ wald chi	304.6	14917.18
pvalue>F;p value > Chi2	0.000	0.000
Number of observations	52506	52506

Note:1. SE in parenthesis.

2. $ Household data; # Village data .
*3)*** p<0.01, ** p<0.05, * p<0.1.*
4)Figures in 'Bold' represent significant regression coefficients.

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Hausman specification test results for model 2 adjusted consumption expenditure for fixed and random effects (Table 57):

χ^2= 263.93

Prob > chi2 = 0.0000

The null hypothesis is rejected.

Since the Null hypothesis for both models that used consumption expenditure and adjusted expenditure stands rejected, the next step is to run a regression model with fixed effects for panel data.

5.3.1.3: OLS Regression Results For Consumption And Adjusted Consumption:

The Wu-Hausman endogeneity test was used to examine the presence of endogeneity. The regression model with fixed effects with consumption and adjusted consumption as outcome variables was also executed to observe the coefficient generated by the two instrumental variables, natural disaster intensity and confidence intensity, used as exogenous covariates and household assets. The results are presented below in Tables 58 and 59.

Table 58: **OLS Regression Results For Consumption And Adjusted Consumption Expenditure**

Independent Variables	**Model 1 Consumption expenditure**	**Model 2:Adjusted consumption expenditure**
I	II	III
Assets owned by the household $	**88.27*** **	**84.30*** **
	(3.357)	*(2.988)*
Confidence Intensity $	3.789	1.191
	(2.709)	*(2.529)*
Conflict Intensity $	**-26.30*** **	**-22.10*** **
	(9.339)	*(8.340)*
Family size $	**-123.2*** **	**-109.8*** **
	(6.481)	(5.739)
Health Insurance $	**239.1*** **	**229.6*** **
	(45.62)	*(42.47)*
Highest Adult Education $	-0.626	-0.546
	(3.561)	*(3.123)*

Membership Intensity $	**55.96*** **	**56.87*** **
	(8.513)	*(7.533)*
Natural disaster Intensity #	**9.488** **	5.694
	(4.099)	*(3.728)*
Number of married females $	**42.40***	**43.91** **
	(22.20)	*(19.81)*
Proportion of children $	**-1014.6*** **	**-900.6*** **
	(48.62)	*(43.82)*
Public Project Intensity #	**-13.63*** **	**-11.51*** **
	(2.747)	*(2.300)*
constant	1668.0***	1414.0***
	(86.19)	(79.13)
Adj. R2	0.107	0.114
R square	0.108	0.114
F stat	196.8	224.8
Number of observations	52492	52506

Note:1. SE in parenthesis.

2. $ Household data; # Village data .

*3. *** p<0.01, ** p<0.05, * p<0.1.*

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Of the two instrumental variables from model 1 of consumption expenditure, only one instrument is non-significant (Table 58). For the second model of adjusted consumption expenditure, both the instrumental variables are non-significant; the additional step is to examine whether the instrumental variables used in 2SLS are related to the outcome variable.

5.3.1.4: REGRESSION RESULTS OF WU-HAUSMAN TEST FOR MODELS 1 AND 2:

The Wu-Hausman test was done separately for two different outcome variables. The results of the Wu-Hausman test indicate the presence of endogeneity for both models since the predicted asset is significant (Table 59).

Table 59: **Regression Results Of The Wu-Hausman Test For Models 1 And 2**

Independent Variables	**Asset**	**Consumption expenditure**	**Assets**	**Adjusted Consumption expenditure**
I	**II**	**III**	**IV**	**V**
Family size $	**-0.0536*****	**-121.7*****	**-0.0536*****	**-109.2*****
	(0.0135)	*(6.569)*	*(0.0135)*	*(5.801)*
Proportion of children $	**-1.312*****	**-980.5*****	**-1.312*****	**-883.1*****
	(0.107)	*(50.40)*	*(0.107)*	*(45.12)*
Highest Adult Education $	**0.228*****	-6.571	**0.228*****	-3.582
	(0.00642)	*(4.133)*	*(0.00642)*	*(3.585)*
Number of married females $	**0.595*****	26.84	**0.595*****	**36.06***
	(0.0461)	*(22.27)*	*(0.0461)*	*(20.10)*
Health Insurance $	**1.320*****	**204.2*****	**1.320*****	**212.5*****
	(0.0737)	*(48.51)*	*(0.0737)*	*(45.16)*
Membership Intensity $	0.0218	**55.33*****	0.0218	**56.62*****
	(0.0148)	*(8.537)*	*(0.0148)*	*(7.559)*
Public Project Intensity #	**-0.0240*****	**-13.05*****	**-0.0240*****	**-11.16*****
	(0.00470)	*(2.754)*	*(0.00470)*	*(2.316)*
Conflict Intensity $	-0.0146	**-25.95*****	-0.0146	**-21.88*****
	(0.0155)	*(9.358)*	*(0.0155)*	*(8.352)*
Natural disaster Intensity #	**0.390*****		**0.390*****	
	(0.00760)		*(0.00760)*	
Confidence Intensity $	**0.123*****		**0.123*****	
	(0.00462)		(0.00462)	
Assets owned by the household $		**88.27*****		**84.30*****
		(3.357)		(2.988)
Predicted asset		**26.08*****		**13.25***
		(8.031)		(7.134)
Constant	7.115***	1492.4***	7.115***	1312.0***
	(0.153)	*(106.6)*	*(0.153)*	*(95.92)*
Adj. R2	0.260	0.107	0.260	0.114
R square	0.261	0.108	0.261	0.114
F stat	956.6	216.5	956.6	247.1
Number of observations	52506	52492	52506	52506

Note:1. SE in parenthesis.

2. $ Household data; # Village data .

*3)*** p<0.01, ** p<0.05, * p<0.1.*

4)Figures in 'Bold' represent significant regression coefficients.

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

5.3.1.5: Pairwise Correlations For Consumption Expenditure And Adjustment Consumption Expenditure:

The pairwise correlation was also checked. One of the conditions of IV is that the instrument should be strongly correlated with endogenous regressor. The pairwise correlation indicates that the household assets are correlated with instruments (Tables 60 and 61). Column II gives a correlation coefficient of assets, Confidence intensity and natural disaster intensity with consumption expenditure, and column III gives a correlation coefficient of assets with confidence intensity and natural disaster intensity. Column IV gives a correlation coefficient of confidence intensity with natural disaster intensity. Column VII, column VIII, Column IX and Column X give the correlation coefficient of adjusted consumption expenditure, Assets, confidence intensity and natural disaster intensity with other variables, as mentioned in column VI. We find the correlation of endogenous regressor, i.e., assets (owned by the households), with confidence and natural disaster intensity for both models.

Table 60: **Pairwise Correlations For Consumption Expenditure**

Variables	Consumption expenditure	Assets	Confidence Intensity	Natural disaster Intensity
I	II	III	IV	V
Consumption expenditure	1			
Assets	0.394*	1		
Confidence Intensity	0.061*	**0.090***	1	
Natural disaster Intensity	0.054*	**0.080***	0.246*	1

Table 61: **Pairwise Correlations For Adjusted Consumption Expenditure**

Variables	Adjusted Consumption expenditure	Assets	Confidence Intensity	Natural disaster Intensity
VI	VII	VIII	IX	X
Adjusted Consumption expenditure	1			
Assets	0.416*	1		
Confidence Intensity	0.059*	**0.090***	1	
Natural disaster Intensity	0.053*	**0.080***	0.246*	1

**** p<0.01, ** p<0.05, * p<0.1.*

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

5.3.2: Two-Stage Least Square Regression Results With Instrumental Variables:

5.3.2.1: Descriptive Statistics:

The below section provides descriptive statistics.

Table 62: **Descriptive Statistics**

Variables	Observations	Mean	Std. Dev.	Min	Max
I	II	III	IV	V	VI
Consumption expenditure $	52753	1611.95	1785.326	0	83934.086
Consumption Quintile: BPL$	15156	626.166	176.577	0	1328.623

APL 1	7522	936.95	94.921	690	1113.417
APL 2	7518	1202.628	100.82	1022.68	1414.667
APL3	7519	1520.315	155.137	1249.304	1845.333
APL 4	7519	2044.644	271.642	1575.305	2655.022
APL 5	7519	4342.464	3456.943	2212.414	83934.086
Assets owned by the household $	52758	11.163	5.596	0	29
Adjusted Consumption expenditure $	52770	1422.816	1577.518	0	76813.367
Adjusted Consumption quintile: BPL	18844	616.782	179.337	0	1328.623
APL 1	6786	916.553	83.926	690.487	1066.533
APL 2	6785	1151.865	84.165	998.703	1328.143
APL3	6786	1429.358	128.808	1199.336	1697.714
APL 4	6784	1883.833	231.019	1483.732	2416.667
APL 5	6785	3971.211	3215.808	2048.322	76813.367
Caste $	52770	2.201	0.942	1	4
Confidence Intensity $	52770	17.683	3.995	0	36
Conflict Intensity $	52770	4.935	1.169	0	6
Family size $	52770	5.489	2.867	1	33
Health Insurance $	52561	0.058	0.237	0	2
Highest Adult Education $	52722	6.733	4.936	0	16
Membership Intensity $	52770	1.773	1.522	0	13
Natural disaster Intensity #	52770	1.285	2.289	0	18
Number of married females $	52770	1.333	0.815	0	8
The proportion of children $	52770	0.279	0.221	0	1
Public Project Intensity #	52770	14.387	4.652	0	25

Note:1. $ Household data; # Village data .

2) Values in columns III, V and VI expressed in Rs.

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

The monthly consumption expenditure per capita is Rs 1612, and the adjusted consumption per capita is Rs 1423(Table 62). The average consumption expenditure in the respective quintiles is Rs 626, Rs 937, Rs 1203, Rs 1520, Rs 2015, and Rs 4342, respectively, for those BPL and APL quintiles 1 to 5. The average adjusted consumption expenditure in different quintiles is Rs 617, Rs 917, Rs 1152, Rs 1429, Rs 1883, and Rs 3971, respectively, for those BPL and APL1 to 5. The maximum number of assets owned was 29, and the average asset holdings was 11. The average confidence in institutions score is 18, and the maximum is 36. The average conflict score is 5. The average family size is 5. Only 5 % of the households owned health insurance. Adults in the household had seven years of highest completed education. Households were members of at least 2 organisations, and every household, on average, witnessed at least one disaster between 2006 and 2012. The family composition comprises 27% children; every village had at least 14 projects implemented.

5.3.2.2: Two-Stage Least Square Regression Results For Consumption And Adjusted Consumption Expenditure:

Results of the two-stage least square with IV are presented below.

Table 63: **Two-Stage Least Square Regression Results For Consumption And Adjusted Consumption Expenditure**

Variables	Stage 2	Stage 1	Stage 2	Stage 1
	Consumption	**Asset Predict**	**Adj consumption**	**Asset Predict**
I	**II**	**III**	**IV**	**V**
Natural disaster Intensity #		**0.419*** *(0.00984)*		**0.419*** *(0.00983)*
Confidence Intensity $		**0.101*** *(0.00542)*		**0.101*** *(0.00542)*
Assets owned by the household $	**108.1*** *(8.799)*		**93.99*** *(7.976)*	
Conflict Intensity $	**-27.56*** *(10.58)*	0.00386 *(0.0188)*	**-21.32** *(9.247)*	0.00541 *(0.0188)*
Family size $	**-131.3*** *(7.229)*	-0.0123 *(0.0158)*	**-117.2*** *(6.487)*	-0.0122 *(0.0158)*
Health Insurance $	**223.1*** *(55.02)*	**1.355*** *(0.0856)*	**227.0*** *(49.56)*	**1.355*** *(0.0856)*
Highest Adult Education $	2.880 *(4.504)*	**0.333*** *(0.00614)*	5.742 *(4.102)*	**0.333*** *(0.00614)*
Membership Intensity $	**61.45*** *(9.284)*	**0.157*** *(0.0168)*	**63.21*** *(8.252)*	**0.157*** *(0.0168)*
Number of married females $	26.39 *(23.23)*	**0.538*** *(0.0500)*	**33.38*** *(19.35)*	**0.538*** *(0.0500)*
Proportion of children $	**-972.5*** *(45.77)*	**-0.796*** *(0.109)*	**-829.9*** *(38.41)*	**-0.796*** *(0.109)*
Public Project Intensity #	**-13.19***	**-0.0262***	**-11.21***	**-0.0263***

	(3.357)	*(0.00630)*	*(2.818)*	*(0.00630)*
Fstat	184.7		182.2	
Pvalue	0.000		0.000	
Rsquare	0.124		0.135	
Adj R Square	-0.215		-0.199	
CD Wald F		2084.1		2087.8
StockWright LM stat		197.7		183.3
SandWindMultiF		1424.2		1425.5
KPRKLMS		3228.5		3229.9
FtestExclInstrue		1424.2		1425.5
Anderson-Rubin Wald test		76.36		69.71
Anderson-Rubin Wald testChi		211.8		193.4
HansenJstat	0.00334		0.000228	
HansenJstat Chi P value	0.954		0.988	
Number of Observations	52391	52391	52416	52416
Cluster	22208	22208	22219	22219

Note: 1) $ Household data; # Village Data

2) Robust Std Error clustered at Village level.

3) Number of regressors = 9.

4) Number of endogenous regressors = 1.

5) Number of instruments = 10.

6)Number of excluded instruments = 2.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

Variables are given in column 1, and Stage II and I result for the consumption model are given in columns II and III (Table 63). For the adjusted consumption model, stage 2 and stage 1 results are given in columns IV and V. For the consumption model, the instrumental variable, NDI, and confidence intensity positively and significantly influence assets. The remaining covariates, Health insurance, Highest adult education, membership intensity, and the number of married females, positively and significantly influence household assets. Public project intensity and proportion of children have negative coefficients. In the second stage, assets, health insurance, and membership intensity positively and significantly influence consumption expenditure, and the proportion of children and public project intensity has a negative coefficient.

Some covariates influence asset and consumption expenditure, and some covariates affect either. Health insurance and membership intensity are the covariates that positively and significantly influence assets and consumption. The proportion of children and public project intensity negatively influence assets and consumption expenditure. The highest adult education and the number of married females help increase household assets but have no significant influence on consumption. Conflicts and family size affect consumption negatively but do not influence assets.

5.3.2.3: Two-Stage Least Square Regression Results For Consumption Expenditure By Caste:

The socio-economic categories are used to examine the disaggregated consumption expenditure behaviour analysis. For all caste categories, the instrumental variables natural disaster intensity and confidence intensity positively and significantly influenced household assets(Table 64).

In stage 1, the covariates that influence the assets significantly are Family size and negatively influenced castes 3 and 4; the proportion of children and public projects negatively influences all caste categories. Health insurance and education have a positive and significant influence on all castes. Membership and married females commonly affected castes 1 and 2, and married females affected castes3 positively and significantly.

In stage 2, assets and membership intensity positively and significantly impact consumption across all caste categories. Health insurance has helped to increase consumption expenditure for all the caste categories except caste 4. Family size and proportion of children decrease consumption expenditure. Public projects have influenced only caste 1 and caste 2 negatively. Married females positively impact caste1. Education has no significant influence on consumption expenditure across all categories of caste.

Table 64: **Two-Stage Least Square Regression Results For Consumption Expenditure By Caste**

Caste categories	**Caste 1**		**Caste 2**		**Caste 3**		**Caste 4**	
	Stage 2	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**
Dependent Variable	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
Natural disaster Intensity #		**0.426*** **		**0.422*** **		**0.422*** **		**0.389*** **
		(0.0212)		*(0.0182)*		*(0.0219)*		*(0.0284)*
Confidence Intensity $		**0.0892*** **		**0.121*** **		**0.0929*** **		**0.112*** **
		(0.0120)		*(0.00932)*		*(0.0128)*		*(0.0147)*
Assets owned by the household $	**105.2*** **		**109.9*** **		**78.01*** **		**124.9*** **	
	(20.70)		*(17.62)*		*(12.53)*		*(15.90)*	
Conflict Intensity $	12.82	-0.0158	**-53.54*** **	-0.0480	**-25.01***	0.0338	**-65.89*** **	0.0555
	(26.85)	*(0.0414)*	*(17.40)*	*(0.0323)*	*(15.15)*	*(0.0419)*	*(19.33)*	*(0.0582)*
Family size $	**-196.1*** **	-0.0387	**-110.4*** **	-0.0268	**-101.2*** **	**0.0784** **	**-103.1*** **	**0.0810***
	(20.63)	*(0.0349)*	*(12.05)*	*(0.0267)*	*(9.950)*	*(0.0357)*	*(11.23)*	*(0.0421)*
Health Insurance $	**558.8*** **	**1.135*** **	**197.9** **	**1.352*** **	**165.2** **	**1.409*** **	-82.94	**1.542*** **
	(184.5)	*(0.199)*	*(89.48)*	*(0.138)*	*(70.67)*	*(0.176)*	*(101.8)*	*(0.267)*
Highest Adult Education $	3.530	**0.336*** **	1.761	**0.323*** **	5.777	**0.233*** **	**-12.41***	**0.254*** **
	(11.77)	*(0.0142)*	*(8.084)*	*(0.0100)*	*(5.008)*	*(0.0127)*	*(7.417)*	*(0.0158)*
Membership Intensity $	**91.87*** **	**0.178*** **	**63.74*** **	**0.190*** **	**29.70** **	0.0239	16.06	0.0461
	(26.07)	*(0.0339)*	*(14.53)*	*(0.0293)*	*(13.88)*	*(0.0393)*	*(12.93)*	*(0.0493)*
Number of married females $	**166.8** **	**0.686*** **	-10.41	**0.612*** **	7.607	**0.323*** **	-2.103	0.121
	(64.82)	*(0.106)*	*(45.67)*	*(0.0904)*	*(32.17)*	*(0.108)*	*(32.97)*	*(0.136)*
Proportion of children $	**-1385.7*** **	**-0.857*** **	**-1086.7*** **	**-0.536*** **	**-673.7*** **	**-0.954*** **	**-585.5*** **	**-1.043*** **
	(123.7)	*(0.238)*	*(86.11)*	*(0.181)*	*(72.07)*	*(0.241)*	*(90.01)*	*(0.291)*
PublicProject Intensity #	**-19.20** **	**-0.0457*** **	**-12.80** **	**-0.0302*** **	-3.655	**-0.0509*** **	1.590	**0.0399** **
	(9.655)	*(0.0142)*	*(5.224)*	*(0.0107)*	*(5.240)*	*(0.0142)*	*(5.970)*	*(0.0195)*
Fstat	45.39		69.75		60.94		37.09	
Pvalue	0.000		0.000		0.000		0.000	

Rsquare	0.119		0.117		0.147		0.215	
Adj R Square	-0.332		-0.256		-0.267		-0.136	
CD Wald F		507.3		804.7		450.5		236.8
StockWright LM stat		38.46		57.73		65.39		90.14
SandWindMultiF		304.2		474.2		278.6		164.5
KPRKLMS		759.1		1190.8		701.6		357.0
FtestExclInstrue		304.2		474.2		278.6		164.5
Anderson-Rubin Wald test		12.51		22.08		18.80		28.71
Anderson-Rubin Wald testChi		37.84		62.86		55.89		83.18
HansenJstat	0.279		0.00526		0.104		0.407	
HansenJstat Chi P value	0.598		0.942		0.747		0.523	
Number of Observations	11930	11930	19875	19875	11444	11444	5401	5401
Cluster	5677	5677	9064	9064	4913	4913	2448	2448

Note: 1) $ Household data; # Village Data.

2) Robust Std Error clustered at Village level.

3) Number of regressors = 9.

4) Number of endogenous regressors = 1.

5) Number of instruments = 10.

6)Number of excluded instruments = 2.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

5.3.2.4: Two-Stage Least Square Regression Results For Consumption Expenditure By Quintile:

Table 65: **Two-Stage Least Square Regression Results For Consumption Expenditure By Quintile**

Quintile	**BPL**		**APL 1**		**APL 2**		**APL3**		**APL4**		**APL5**	
	Stage 2	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**
Dependent Variable	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**	**Consumption**	**Asset_predict**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**	**XIII**
Natural disaster Intensity #		**0.272*** *(0.0203)*		**0.428*** *(0.0389)*		**0.478*** *(0.0548)*		**0.427*** *(0.0621)*		**0.558*** *(0.0606)*		**0.469*** *(0.0439)*
Confidence Intensity $		**0.106*** *(0.0110)*		**0.0642*** *(0.0230)*		**0.0794*** *(0.0268)*		**0.0983*** *(0.0244)*		**0.0946*** *(0.0257)*		**0.114*** *(0.0222)*
Assets owned by the household $	**26.57***** *(3.078)*		**22.62***** *(2.930)*		**42.60***** *(4.220)*		**81.44***** *(8.509)*		**98.04***** *(8.232)*		**156.1**** *(71.02)*	
Conflict Intensity $	**-5.003**** *(2.320)*	0.0464 *(0.0434)*	-1.241 *(2.712)*	0.0637 *(0.0782)*	-3.737 *(3.963)*	**0.179**** *(0.0889)*	-3.539 *(7.288)*	0.100 *(0.0930)*	**-18.83**** *(9.243)*	**0.184*** *(0.0957)*	-26.11 *(99.30)*	0.0434 *(0.0719)*
Family size $	**-16.60***** *(2.013)*	**0.107***** *(0.0333)*	**-11.45***** *(2.038)*	**0.286***** *(0.0550)*	**-18.42***** *(3.455)*	**0.247***** *(0.0737)*	**-24.45***** *(6.494)*	**0.200***** *(0.0749)*	**-47.02***** *(8.305)*	**0.268***** *(0.0785)*	**-276.9***** *(75.16)*	-0.0664 *(0.0720)*
Health Insurance $	9.414 *(12.18)*	**1.094***** *(0.193)*	-9.004 *(15.13)*	**1.523***** *(0.367)*	-14.69 *(19.68)*	0.499 *(0.387)*	-40.57 *(37.66)*	0.711 *(0.459)*	-58.06 *(42.74)*	**1.411***** *(0.378)*	**693.6*** *(382.1)*	**1.119***** *(0.262)*
Highest Adult Education $	**-2.239**** *(0.975)*	**0.231***** *(0.0122)*	**-3.887***** *(1.081)*	**0.248***** *(0.0222)*	**-9.140***** *(1.632)*	**0.265***** *(0.0239)*	**-20.69***** *(3.517)*	**0.313***** *(0.0254)*	**-26.02***** *(3.847)*	**0.318***** *(0.0242)*	-31.94 *(39.27)*	**0.375***** *(0.0230)*
Membership Intensity $	**4.422**** *(1.985)*	0.0212 *(0.0383)*	0.120 *(2.286)*	0.0334 *(0.0711)*	-4.315 *(3.208)*	-0.0204 *(0.0729)*	**-16.98***** *(5.455)*	0.102 *(0.0678)*	**-12.85*** *(6.992)*	0.0879 *(0.0729)*	115.9 *(76.07)*	**0.151***** *(0.0552)*
Number of married females $	-6.694	**0.292*****	-1.544	**0.354***	**-21.12****	0.777***	bb	0.340	-10.87	0.321	357.9	**0.866*****

	(5.206)	*(0.0981)*	*(5.981)*	*(0.188)*	*(10.35)*	*(0.205)*	*(17.97)*	*(0.217)*	*(23.52)*	*(0.231)*	*(224.6)*	*(0.211)*
Proportion of children $	**-100.8*****	**-0.397***	**-31.95****	-0.0736	-31.37	0.530	**-88.24****	0.568	-54.08	0.214	**-2191.2*****	-0.576
	(12.61)	*(0.235)*	*(13.08)*	*(0.393)*	*(21.20)*	*(0.437)*	*(38.06)*	*(0.479)*	*(53.55)*	*(0.521)*	*(414.4)*	*(0.489)*
Public Project Intensity #	**-1.607***	-0.00109	-0.387	**-0.0497***	-2.211	-0.0314	0.120	**-0.0683****	-3.659	-0.0346	-68.08*	**-0.0766*****
	(0.830)	*(0.0158)*	*(0.943)*	*(0.0280)*	*(1.434)*	*(0.0312)*	*(2.444)*	*(0.0301)*	*(2.899)*	*(0.0283)*	*(36.37)*	*(0.0238)*
Fstat	51.88		11.98		18.63		17.31		22.88		8.797	
Pvalue	0.000		0.000		0.000		0.000		0.000		0.000	
Rsquare	0.129		-0.100		-0.771		-1.418		-0.498		0.0629	
Adj R Square	-0.329		-0.834		-2.038		-3.086		-1.563		-0.583	
CD Wald F		319.9		134.6		116.4		91.01		127.8		159.7
StockWright LM stat		128.3		108.6		286.5		302.6		277.9		9.505
SandWindMultiF		180.0		75.70		56.39		40.20		67.61		90.61
KPRKLMS		470.7		204.7		159.5		128.6		216.9		234.1
FtestExclInstrue		180.0		75.70		56.39		40.20		67.61		90.61
Anderson-Rubin Wald test		44.69		34.23		113.8		167.0		84.04		2.897
Anderson-Rubin Wald testChi		136.4		114.2		390.8		564.8		287.6		9.795
HansenJstat	25.33		0.693		0.123		0.655		0.0438		0.0187	
HansenJstat Chi P value	0.000000482		0.405		0.726		0.418		0.834		0.891	
Number of Observations	11356	11356	3893	3893	3563	3563	3689	3689	3708	3708	4420	4420
Cluster	6274	6274	2450	2450	2366	2366	2409	2409	2442	2442	2654	2654

Note: 1) $ Household data; # Village Data.

2) Robust Std Error clustered at Village level.

3) Number of regressors = 9.

4) Number of endogenous regressors = 1.

5) Number of instruments = 10.

6)Number of excluded instruments = 2.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations from IHDS 1 and IHDS 2 data.

There are six economic categories, BPL, APL 1 to APL5, based on consumption expenditure quintile(Table 65). In the first stage, both instrumental variables have a positive and significant influence on assets,

Conflict intensity positively influences BPL, APL2, and APL4; family size increases assets for BPL, APL1, APL2, APL3, and APL4 and works in the reverse direction for APL5. Health insurance has worked in favour of assets for BPL, APL1, APL 4, and APL5. Education has worked to build up assets for all quintiles. Married females have helped BPL, APL1, APL 2 and APL 5 quintile for assets. Membership intensity has worked in favour of assets for APL 5. The proportion of children and public project intensity has reduced assets for BPL; additional projects have decreased assets for APL3 and APL5.

In stage II, Assets have positively boosted consumption expenditure in all quintiles. Health insurance has boosted consumption expenditure in APL5 and membership intensity in BPL. Family size has reduced consumption expenditure for all quintiles, education for quintile BPL, APL 1 to APL 4, conflict intensity for BPL and APL4, the proportion of children for BPL, APL1 and APL3, married females for APL2, APL3, and APL5 and public project intensity has significantly and negatively influenced BPL.

This section discusses the impact on adjusted consumption expenditure in a disaggregated manner. The caste-wise and expenditure quintile-wise results are discussed in detail.

5.3.2.5: Two-Stage Least Square Regression Results For Adjusted Consumption Expenditure By Caste:

The results of caste categories are discussed in this section(Table 66). The natural disaster and confidence intensity positively and significantly impact the asset in stage I of 2SLS. Conflict intensity does not impact assets; health insurance and education positively influence all caste categories; family size influences castes 3 and 4; membership affects castes 1 and 2, and married females influence castes 1, caste 2 and caste 3. The proportion of children and project intensity have a negative impact on assets in stage I.

In stage II, the consumption expenditure is positively influenced by the assets for all caste categories. Membership intensity positively influences consumption, health insurance affects consumption positively for caste 1, 2 and 3, and married females influence consumption for caste 1. Conflict, family size, the proportion of children and the public project intensity influence consumption expenditure negatively. Family size and proportion of children have a negative influence on all castes. Conflict intensity reduces consumption expenditure for castes 2, 3, and 4, and project intensity negatively influences castes 1 and 2.

Health insurance and membership intensity are covariates that positively affect assets and consumption expenditure. The proportion of children and public projects negatively influences both assets and consumption.

5.3.2.6: Two-Stage Least Square Regression Results For Adjusted Consumption Expenditure By Quintile:

The results of adjusted consumption expenditures quintiles suggest that the instrumental variables positively impact the asset in stage 1(Table 67). Family size, health insurance, adult education, and married females increase household assets. The proportion of children and public project intensity impact quintiles 3 and 5 and work in the reverse direction. Conflict intensity increased assets for BPL.

In stage II, assets increased consumption expenditure in all quintiles. Conflict intensity, family size, adult education, the proportion of children, and public project intensity have reduced consumption expenditure. Membership intensity and the number of married females have mixed results.

Table 66: **Two-Stage Least Square Regression Results For Adjusted Consumption Expenditure By Caste**

Caste Categories	**Caste 1**		**Caste 2**		**Caste 3**		**Caste4**	
	Stage 2	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**
Dependent Variable	**Adj Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**	**Adj.Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
Natural disaster Intensity #		**0.426*****		**0.422*****		**0.421*****		**0.389*****
		(0.0212)		*(0.0182)*		*(0.0219)*		*(0.0283)*
Confidence Intensity $		**0.0890*****		**0.121*****		**0.0924*****		**0.110*****
		(0.0120)		*(0.00931)*		*(0.0128)*		*(0.0147)*
Assets owned by the household $	**86.42*****		**96.27*****		**69.43*****		**115.8*****	
	(18.97)		*(15.89)*		*(10.83)*		*(15.27)*	
Conflict Intensity $	1.265	-0.0168	**-33.95****	-0.0480	**-20.42***	0.0356	**-62.95*****	0.0514
	(25.12)	*(0.0415)*	*(13.19)*	*(0.0323)*	*(11.49)*	*(0.0418)*	*(18.03)*	*(0.0581)*
Family size $	**-176.7*****	-0.0384	**-99.02*****	-0.0268	**-89.67*****	**0.0780****	**-94.30*****	**0.0808***
	(19.61)	*(0.0349)*	*(10.62)*	*(0.0267)*	*(8.875)*	*(0.0357)*	*(10.33)*	*(0.0421)*
Health Insurance $	**556.3*****	**1.135*****	**195.8****	**1.352*****	**163.0****	**1.414*****	-86.31	**1.543*****
	(176.7)	*(0.199)*	*(77.90)*	*(0.138)*	*(65.46)*	*(0.176)*	*(86.59)*	*(0.267)*
Highest Adult Education $	12.80	**0.336*****	4.404	**0.323*****	5.892	**0.233*****	-10.41	**0.254*****
	(10.98)	*(0.0142)*	*(7.182)*	*(0.0100)*	*(4.238)*	*(0.0127)*	*(6.484)*	*(0.0158)*
Membership Intensity $	**109.2*****	**0.177*****	**62.90*****	**0.190*****	**29.36*****	0.0236	**20.25***	0.0458
	(24.68)	*(0.0339)*	*(12.72)*	*(0.0293)*	*(11.27)*	*(0.0392)*	*(12.25)*	*(0.0493)*
Number of married females $	**145.5****	**0.685*****	8.895	**0.612*****	15.69	**0.324*****	2.897	0.121
	(60.67)	*(0.106)*	*(34.80)*	*(0.0904)*	*(28.16)*	*(0.108)*	*(29.40)*	*(0.136)*
Proportion of children $	**-1224.8*****	**-0.863*****	**-900.3*****	**-0.536*****	**-587.5*****	**-0.954*****	**-552.5*****	**-1.043*****
	(114.7)	*(0.238)*	*(66.50)*	*(0.181)*	*(59.67)*	*(0.241)*	*(83.05)*	*(0.291)*
Public Project Intensity #	**-21.53****	**-0.0458*****	**-10.52****	**-0.0302*****	-3.433	**-0.0509*****	2.718	**0.0400****
	(9.111)	*(0.0142)*	*(4.100)*	*(0.0107)*	*(4.516)*	*(0.0142)*	*(5.510)*	*(0.0195)*
Fstat	39.69		75.43		67.08		35.91	
Pvalue	0.000		0.000		0.000		0.000	
Rsquare	0.113		0.137		0.168		0.221	
Adj R Square	-0.341		-0.228		-0.237		-0.128	

CD Wald F		506.8		805.1		449.7		236.0
StockWright LM stat		31.58		57.11		70.94		85.79
SandWindMultiF		304.0		474.4		278.7		163.6
KPRKLMS		758.6		1191.0		701.9		356.9
FtestExclInstrue		304.0		474.4		278.7		163.6
Anderson-Rubin Wald test		10.18		21.26		19.53		26.90
Anderson-Rubin Wald testChi		30.81		60.52		58.06		77.94
HansenJstat	0.0107		0.00773		0.240		0.535	
HansenJstat Chi P value	0.918		0.930		0.624		0.465	
Number of Observations	11932	11932	19876	19876	11453	11453	5403	5403
Cluster	5678	5678	9064	9064	4917	4917	2449	2449

Note: 1) $ Household data; # Village Data.
2) Robust Std Error clustered at Village level.
3) Number of regressors = 9.
4) Number of endogenous regressors = 1.
5) Number of instruments = 10.
6)Number of excluded instruments = 2.
7)Figures in 'Bold' indicate significant regression coefficients.
Source: Author's Calculations from IHDS 1 and IHDS 2 data.

Table 67: **Two-Stage Least Square Regression Results For Adjusted Consumption Expenditure By Quintile**

quintile	**BPL**		**APL 1**		**APL2**		**APL3**		**APL4**		**APL5**	
	Stage 2	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**	**Stage 2**	**Stage 1**
Dependent Variable	**Adj. Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**	**Adj. Consumption**	**Asset_predict**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**	**XIII**
Natural disaster Intensity #		**0.290*** **		**0.438*** **		**0.478*** **		**0.392*** **		**0.539*** **		**0.478*** **
		(0.0178)		*(0.0419)*		*(0.0534)*		*(0.0604)*		*(0.0549)*		*(0.0478)*
Confidence Intensity $		**0.107*** **		**0.0699*** **		**0.0848*** **		**0.120*** **		**0.118*** **		**0.114*** **
		(0.00965)		*(0.0229)*		*(0.0280)*		*(0.0275)*		*(0.0265)*		*(0.0227)*
Assets owned by the household $	**24.80*** **		**15.35*** **		**35.38*** **		**59.70*** **		**81.38*** **		**120.7* **	
	(2.501)		*(2.557)*		*(3.412)*		*(6.112)*		*(7.467)*		*(68.52)*	
Conflict Intensity $	**-7.140*** **	**0.0607* **	**-5.660** **	-0.00762	-2.794	0.101	-8.470	0.0726	-6.470	0.0513	1.799	0.0375
	(2.016)	*(0.0366)*	*(2.386)*	*(0.0795)*	*(3.368)*	*(0.0889)*	*(5.761)*	*(0.0971)*	*(8.291)*	*(0.0904)*	*(94.58)*	*(0.0782)*
Family size $	**-17.64*** **	**0.125*** **	**-9.926*** **	**0.354*** **	**-15.66*** **	**0.235*** **	**-21.33*** **	**0.228*** **	**-36.27*** **	**0.221** **	**-283.0*** **	-0.0504
	(1.725)	*(0.0292)*	*(2.011)*	*(0.0637)*	*(2.955)*	*(0.0773)*	*(5.268)*	*(0.0788)*	*(7.813)*	*(0.0879)*	*(79.24)*	*(0.0825)*
Health Insurance $	-6.313	**1.238*** **	4.855	**1.055*** **	7.792	0.0733	**-53.20* **	**1.457*** **	12.83	**1.145*** **	**931.1** **	**0.826*** **
	(10.08)	*(0.171)*	*(12.43)*	*(0.375)*	*(16.21)*	*(0.414)*	*(30.30)*	*(0.426)*	*(37.16)*	*(0.399)*	*(388.5)*	*(0.274)*
Highest Adult Education $	**-1.522* **	**0.234*** **	**-1.841** **	**0.212*** **	**-8.601*** **	**0.276*** **	**-13.59*** **	**0.270*** **	**-18.90*** **	**0.325*** **	-6.140	**0.351*** **
	(0.813)	*(0.0107)*	*(0.861)*	*(0.0228)*	*(1.476)*	*(0.0253)*	*(2.427)*	*(0.0249)*	*(3.468)*	*(0.0247)*	*(36.84)*	*(0.0240)*
Membership Intensity $	**4.939*** **	0.0277	-2.196	0.0928	-0.166	-0.000590	**-13.92*** **	0.0912	**-11.57* **	0.0266	**154.0** **	**0.114** **
	(1.653)	*(0.0330)*	*(2.053)*	*(0.0752)*	*(2.739)*	*(0.0754)*	*(4.137)*	*(0.0735)*	*(6.187)*	*(0.0667)*	*(71.91)*	*(0.0553)*

Number of married females $	**-7.972***	**0.301*****	-1.916	0.336	-11.61	**0.632*****	**-28.74****	**0.425***	-28.79	**0.521****	**501.4****	**0.758*****
	(4.546)	*(0.0836)*	*(5.470)*	*(0.205)*	*(8.872)*	*(0.221)*	*(14.39)*	*(0.222)*	*(22.05)*	*(0.241)*	*(226.7)*	*(0.229)*
Proportion of children $	**-109.5*****	-0.308	**-32.18*****	0.259	**-34.07***	0.544	**-82.50*****	0.615	**-131.9*****	0.637	**-1991.2*****	-0.421
	(10.70)	*(0.199)*	*(12.09)*	*(0.412)*	*(18.50)*	*(0.483)*	*(28.48)*	*(0.479)*	*(44.87)*	*(0.500)*	*(416.2)*	*(0.507)*
Public Project Intensity #	-1.079	-0.00486	-0.0518	-0.0419	**-2.204***	-0.00940	1.554	**-0.0841*****	**-5.206***	-0.00911	-35.70	**-0.0712*****
	(0.696)	*(0.0130)*	*(0.881)*	*(0.0306)*	*(1.192)*	*(0.0312)*	*(1.831)*	*(0.0306)*	*(2.666)*	*(0.0301)*	*(28.78)*	*(0.0246)*
Fstat	72.45		9.239		19.25		17.75		22.61		7.875	
Pvalue	0.000		0.000		0.000		0.000		0.000		0.000	
Rsquare	0.168		0.0143		-0.660		-0.929		-0.308		0.0738	
Adj R Square	-0.250		-0.661		-1.840		-2.285		-1.249		-0.592	
CD Wald F		445.5		127.7		111.1		84.64		131.7		156.7
StockWright LM stat		160.4		64.58		231.7		248.9		222.1		6.481
SandWindMultiF		256.7		79.24		58.66		40.03		79.32		78.96
KPRKLMS		658.7		199.2		150.2		115.7		206.3		211.9
FtestExclInstrue		256.7		79.24		58.66		40.03		79.32		78.96
Anderson-Rubin Wald test		54.99		18.89		115.0		124.1		99.41		1.916
Anderson-Rubin Wald testChi		165.3		63.69		393.8		423.1		342.1		6.589
HansenJstat	18.72		0.0917		0.789		1.276		0.294		0.0317	
HansenJstat Chi P value	0.0000152		0.762		0.374		0.259		0.588		0.859	
Number of Observations	14893	14893	3277	3277	3101	3101	3238	3238	3229	3229	3917	3917
Cluster	8014	8014	2124	2124	2089	2089	2129	2129	2134	2134	2313	2313

Note: 1. $ Household data; # Village Data.

2. Robust Std Error clustered at Village level.

3. Number of regressors = 9.; 4. Number of endogenous regressors = 1.

5. Number of instruments = 10.; 6. Number of excluded instruments = 2.

7. Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations from IHDS 1 and IHDS 2 data.

5.3.2.7: Mean Difference Between Consumption And Adjusted Consumption Expenditure And Assets Between Those Who Witnessed The Natural Disaster And Those Who Did Not:

Table 68 has 8 columns: Column I have 5 quintiles of APL and 1 BPL quintile. This column is common for Table 68 and Table 69. Column II provides categories of those exposed to natural disasters and otherwise, and this column is common to Table 68 and Table 69. The mean difference in consumption expenditure for those who witnessed natural disasters and those who did not is given in column IV, and t-test values are given in table V. The mean difference in adjusted consumption expenditure between those who witnessed natural disasters and those who did not is given in column VII, and the t-test values are given in column VIII. Table 69 compares mean differences in household assets with consumption expenditure and adjusted consumption expenditure for those who witnessed natural disasters and those who did not.

The mean difference between the consumption expenditure for those who faced natural disasters and those who did not was statistically significant and lower for the BPL and APL 1 (Table 68). For adjusted consumption expenditure, the mean difference is statistically significant and lower for BPL, APL 1and APL3 quintiles.

The mean asset difference between those who faced natural disasters and those who did not is statistically significant and lower for all quintile categories of consumption and adjusted consumption expenditures (Table 69).

Table 68: **Mean Difference Of Consumption And Adjusted Consumption Expenditure**

Table 69: **Mean Asset Difference For Consumption And Adjusted Consumption Expenditure Quintile**

		Consumption expenditure			**Adjusted consumption expenditure**			**Consumption expenditure**			**Adjusted consumption expenditure**		
quintile	**Natural disasters**	**observations**	**Mean COPC**	**t-test**	**observations**	**Mean Adj COPC**	**t-test**	**observations**	**Mean Assets**	**t-test**	**observations**	**Mean Assets**	**t-test**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**	**XIII**	**IVX**
BPL	No	1,254	688	**5.7206*****	1,642	682	**7.8027*****	1,249	10	**10.1418*****	1,637	10	**11.8398*****
	Yes	3,810	657		5,138	644		3,809	9		5,136	9	
APL1	No	872	982	**7.1848*****	781	950	**5.7385*****	871	11	**6.3766*****	781	11	**5.8*****
	Yes	3,393	954		3,140	929		3,393	10		3,139	10	
APL2	No No	1,071	1258	0.0146	1,040	1195	0.3534	1,071	12	**5.2218*****	1,039	13	**4.4269*****
	Yes	3,193	1258		2,881	1194		3,190	12		2,880	12	
APL3	No	1,233	1616	0.5417	1,143	1509	**2.6581****	1,232	14	**7.6459*****	1,142	14	**6.3243*****
	Yes	3,031	1613		2,778	1499		3,030	13		2,777	13	
APl4	No	1,363	2201	1.2336	1,295	2010	1.5998	1,363	16	**9.0618*****	1,295	16	**8.1733*****
	Yes	2,901	2191		2,626	1998		2,901	14		2,626	15	
APL5	No	1,445	4889	1.4074	1,337	4449	1.4724	1,445	18	**6.2211*****	1,337	19	**5.6461*****
	Yes	2,819	4709		2,584	4271		2,819	17		2,584	18	

**** p<0.01, ** p<0.05, * p<0.1*

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

5.3.3: Difference In Differences Regression Results:

In this section, we present the results of DID regression. We first discuss descriptive statistics, followed by regression results. We have used models with consumption expenditure as the outcome variable.

5.3.3.1: Descriptive Statistics:

To study the mean difference between the treated and non-treated households, we used a t-test (Table 70). The treatment is the households that faced natural disasters and otherwise. Our Null hypothesis was that there is no significant difference between treated and non-treated households concerning the variable of concern. The monthly consumption expenditure, monthly expenditure for BPL, and APL 2, APL 3, APL4, and APL 5 were statistically significant between the treated households and non-treated households. Adjusted monthly consumption expenditure, adjusted monthly expenditure for those BPL, and APL 3, APL 4 and APL 5 were also statistically significant. Assets owned by the households were statistically significant for those treated and those not. Similarly, variables like Confidence intensity, conflict intensity, health insurance, adult education, membership intensity, number of persons in the household, the proportion of children, and public project intensity were statistically significant for treated and not treated households. Only for caste, it was not significant.

Natural disasters negatively affect the treated households' monthly and adjusted consumption expenditure (Table 71). Assets owned by the households, health insurance, membership intensity, and the number of married females positively influence consumption and adjusted consumption. Conflict intensity, the number of persons in the household, the proportion of children, and public project intensity negatively influence monthly and adjusted consumption expenditure.

There is a difference in consumption and adjusted consumption between groups affected by disasters (treated) and those not (controlled). Our results (from the DID regression) confirm that households that face disasters have significantly lower consumption, which is not surprising and is well-known in the literature (Alderman & Paxson, 1994).

Table 70: **Descriptive Statistics Of Treated And Non-Treated Households 2006-2012**

	Treated					Not treated					
	No. Of observations	**Mean**	**Std dev**	**Min**	**Max**	**No. Of observations**	**Mean**	**Std dev**	**Min**	**Max**	**Mean difference**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**
Consumption Expenditure $	22308	1912.97	2131.34	0	68012.66	22350	1383.63	1413.25	0	76813.37	**-529.34*** **
Consumption Expenditure quintile $											
BPL	4227	664.22	167.11	0	1280.47	4265	889.44	654.76	0	10241.78	**225.22 *** **
APL1	3617	962.76	103.11	695.56	1119.25	3621	965.28	669.14	0	9257.4	2.52
APL2	3559	1267.2	88.02	1119.29	1425.2	3559	1231.44	969.82	0	14053.85	**-35.76** **
APL3	3583	1628.51	126.32	1425.21	1866.14	3583	1399.17	1071.39	0	14869.11	**-229.34 *** **
APL4	3621	2217.14	232.93	1866.17	2688.54	3621	1675.12	1437.46	0	22639.31	**-542.02*** **
APL5	3701	4866.62	3912.57	2688.71	68012.66	3701	2208.56	2419.81	0	76813.37	**-2658.06*** **
Adj Consumption Expenditure	22308	1683.07	1925.12	0	68012.66	22350	1298.97	1320.63	0	76813.37	**-384.10 *** **
Adj consumption Expenditure quintile $											
BPL	5661	652.85	171.27	0	1295.62	5699	865.52	618.75	0	10241.78	**212.67 *** **
APL1	2174	888.34	71.45	696.33	992.67	2176	873.43	558.54	0	9032.4	-14.91
APL2	3572	1124.93	78.56	992.73	1265.21	3574	1117.66	826.06	0	13814.96	-7.27
APL3	3610	1440.73	109.66	1265.28	1645.33	3610	1311.9	1001.58	0	14592.72	**-128.83*** **
APL4	3617	1951.36	205.84	1645.39	2365.1	3617	1580.03	1285.63	0	18496.71	**-371.33*** **
APL5	3616	4311.35	3654.99	2365.25	68012.66	3616	2129.53	2334.03	0	76813.37	**-2181.82*** **
Caste $	22308	2.2	0.95	1	4	22350	2.19	0.95	1	4	-0.01
Number of married women	22308	1.26	0.76	0	8	22350	1.3	0.75	0	8	**0.04 *** **
Assets owned by the household $	22297	13.25	6.06	0	31	22350	9.64	5.14	0	29	**-3.61 *** **
Confidence Intensity$	22308	19.16	3.82	0	36	22350	16.18	3.62	0	30	**-2.98*** **
Conflict Intensity$	22308	4.89	1.24	0	6	22350	4.99	1.09	0	6	**0.10 *** **
Health insurance $	22164	0.11	0.31	0	2	22308	0.02	0.13	0	1	**0.06*** **
Household Adult education$	22301	7.12	5.04	0	16	22312	6.22	4.88	0	15	-0.89***
Membership Intensity$	22308	1.65	1.78	0	14	22350	2.2	1.62	0	14	.55***
Number of persons in the household $	22308	5.05	2.5	1	33	22350	5.54	2.66	1	33	.49***
Proportion of children in the household $	22308	0.23	0.22	0	0.86	22350	0.3	0.22	0	1	.07 ***
Public project Intensity#	22308	14.13	4.03	0	24	22350	14.71	5.24	0	25	.58 ***

*Note: * p<0.10, ** p<0.05, *** p<0.010.; Source: Author's calculations based on IHDS 1 and IHDS 2 data.*

5.3.3.2: Difference In Differences Regression Results For Consumption And Adjusted Consumption Expenditure:

Table 71: **Difference In Differences Regression Results**

Variables	Consumption	Adj. Consumption
I	**II**	**III**
Average Treatment Effect on Treated		
Natural disaster Intensity #	**-13.60****	**-9.202***
	(6.003)	*(5.436)*
Controls		
Assets owned by the household $	**74.49*****	**74.58*****
	(4.085)	*(3.660)*
Caste$	23.15	-4.485
	(34.49)	
Confidence Intensity$	-1.995	-3.029
	(3.189)	*(2.998)*
Conflict Intensity$	**-18.51***	**-16.81***
	(10.39)	*(9.654)*
Health insurance $	**206.5*****	**211.0*****
	(49.65)	*(46.54)*
Adult education$	-2.675	-1.944
	(4.026)	*(3.600)*
Membership Intensity$	**66.65*****	**65.36*****
	(9.983)	*(9.070)*
Number of married females $	**86.10*****	**82.16*****
	(25.50)	(23.93)
Family size $	**-155.8*****	**-142.1*****
	(8.402)	*(7.813)*
Proportion of children in the $	**-824.8*****	**-792.5*****
	(59.97)	*(55.19)*
Public project Intensity#	**-11.91*****	**-7.704*****
	(2.961)	*(2.583)*
Year 2012	200.1***	50.64*
	(32.90)	(28.91)
Constant	1781.8***	1620.3***
	(115.7)	(99.27)
SE Cluster Village	22,328	22328
Observations	44419	44419

Note: 1. Robust Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.010 ;2. # Village level data, $ household-level data.*

3. Column II is monthly consumption expenditure at the household level & Column III is adjusted monthly consumption expenditure.

4. Standard errors clustered at the Village level (PSUHH).

5. ATET estimate adjusted for covariates, panel, and time effects

Source: Author's calculation based on IHDS 1 and IHDS 2 data.

Table 72: **Difference In Differences Regression Results For Consumption Expenditure By Caste**

Table 73: **Difference In Differences Regression Results For Consumption Expenditure By Expenditure Quintile**

	Caste 1	**Caste 2**	**Caste 3**	**Caste 4**	**BPL**	**APL 1**	**APL 2**	**APL 3**	**APL 4**	**APL 5**
Dependent Variable	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**	**Consumption**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**
Average Treatment Effect on Treated										
Natural disaster Intensity #	**-27.58***	-13.03	-3.846	-16.00	-2.651	**-12.09****	-7.683	2.755	-10.12	-34.23
	(15.73)	*(11.74)*	*(8.393)*	*(12.31)*	*(5.237)*	*(5.189)*	*(8.254)*	*(7.984)*	*(10.89)*	*(23.62)*
Controls										
Assets owned by the household $	**95.81*****	**73.24*****	**45.26*****	**92.08*****	**16.70*****	**12.61*****	**21.55*****	**25.60*****	**42.82*****	**97.24*****
	(10.84)	*(6.264)*	*(6.297)*	*(10.81)*	*(3.083)*	*(3.492)*	*(4.893)*	*(4.525)*	*(6.475)*	*(18.42)*
Confidence Intensity$	-6.327	-1.516	2.761	**-9.117****	-1.479	**-3.483***	2.716	-0.611	**10.81****	-14.01
	(12.16)	*(4.067)*	*(3.903)*	*(4.480)*	*(2.310)*	*(1.946)*	*(2.899)*	*(3.285)*	*(4.652)*	*(17.96)*
Conflict Intensity$	18.72	-14.61	**-30.28****	**-59.04*****	-0.904	**-10.57***	-8.898	-5.101	23.08	-29.41
	(28.55)	*(11.93)*	*(15.42)*	*(18.90)*	*(6.304)*	*(6.387)*	*(8.933)*	*(10.74)*	*(16.18)*	*(53.93)*
Health insurance $	**405.1****	**216.8*****	**166.7****	-115.9	**89.35****	**81.36*****	**209.1*****	**188.0*****	**186.5*****	**402.7****
	(188.6)	*(68.99)*	*(65.14)*	*(99.82)*	*(36.52)*	*(30.29)*	*(69.95)*	*(70.50)*	*(60.66)*	*(192.4)*
Adult education$	-9.038	-9.704	**9.297***	-3.336	-3.233	-5.743	1.149	1.391	2.618	-7.227
	(11.37)	*(6.235)*	*(5.411)*	*(8.067)*	*(2.715)*	*(4.000)*	*(4.219)*	*(4.095)*	*(4.944)*	*(17.82)*
Membership Intensity$	**118.3*****	**51.97*****	**44.71*****	**25.03***	**29.75*****	**13.32***	**29.99*****	**26.07****	**51.91*****	62.20
	(29.23)	*(15.00)*	*(15.75)*	*(13.92)*	*(5.781)*	*(7.436)*	*(10.61)*	*(11.35)*	*(13.55)*	*(41.25)*
Number of married females $	**236.1*****	60.81	32.77	**88.78****	-22.83	-11.01	**-94.71*****	-0.910	-41.20	**492.9*****
	(83.56)	*(39.63)*	*(36.46)*	*(44.18)*	*(17.08)*	*(18.10)*	*(35.26)*	*(33.10)*	*(50.88)*	*(125.4)*

Family Size $	**-232.3***** *(24.42)*	**-121.2***** *(13.06)*	**-133.3***** *(12.86)*	**-161.2***** *(17.83)*	**-33.58***** *(5.855)*	**-40.77***** *(5.960)*	**-42.37***** *(10.14)*	**-62.99***** *(9.700)*	**-84.72***** *(14.51)*	**-315.4***** *(38.77)*
Proportion of children $	**-1250.3***** *(163.9)*	**-964.6***** *(95.80)*	**-472.2***** *(91.99)*	**-390.7***** *(146.9)*	**-366.5***** *(46.17)*	**-407.4***** *(48.03)*	**-708.6***** *(82.78)*	**-607.4***** *(76.89)*	**-782.4***** *(104.0)*	**-1189.2***** *(282.0)*
Public project Intensity#_	-13.68 *(8.564)*	**-9.879**** *(3.875)*	0.290 *(4.743)*	1.991 *(5.696)*	1.626 *(1.928)*	2.302 *(2.059)*	2.469 *(2.793)*	3.268 *(3.300)*	**9.021**** *(3.637)*	**-33.45***** *(12.74)*
year=2012	244.5** *(95.30)*	176.5*** *(52.17)*	129.7*** *(40.41)*	236.6*** *(58.98)*	-223.3*** *(25.03)*	-7.671 *(25.53)*	-79.68** *(39.61)*	33.97 *(42.09)*	218.5*** *(58.40)*	1849.8*** *(165.6)*
Constant	2001.1*** *(270.7)*	1750.4*** *(135.0)*	1581.8*** *(153.5)*	1561.5*** *(161.2)*	1081.8*** *(76.11)*	1334.0*** *(60.82)*	1502.9*** *(97.13)*	1584.2*** *(104.4)*	1338.8*** *(145.6)*	3007.5*** *(516.1)*
Standard error Clustered at Village	6982	10424	5625	2827	4246	3618	3559	3583	3621	3701
Number of Observations	11465	17826	10143	4985	8424	7203	7087	7131	7209	7365

Note: 1. Robust Standard errors in parentheses.

2) $p<0.10$, ** $p<0.05$, *** $p<0.010$.*

3. # Village level data, $ household-level data.

4. Standard errors clustered at the Village level (PSUHH).

5. ATET estimate adjusted for covariates, panel, and time effects.

Source: Author's calculation based on IHDS 1 and IHDS 2 data.

5.3.3.3: Difference In Differences Regression Results For Consumption Expenditure By Caste And Expenditure Quintile:

The results of DID on socio-economic groups, i.e. caste and expenditure quintile groups, are given below(Tables 72 and 73). This analysis is done for consumption expenditure and adjusted consumption expenditure.

The social groups are by caste Brahmin, OBC, SC, ST, and Others(Table 78), and the economic group were below the poverty line, APL 1 to APL 5(Table 79). Natural disaster intensity has indeed decreased the consumption expenditure for those treated compared to the control group, but this decrease is significant only for caste1(comprised of Brahmins, Forward/general and others).

Assets owned by the household, membership in various organisations, and health insurance push consumption expenditure upward. The number of married females in the household increases consumption expenditure for castes 1 and 4.

The remaining variables have a negative influence on consumption expenditure per capita. Conflicts in the village are responsible for decreasing consumption expenditure for castes 3 and 4. A higher proportion of household children and increasing family size reduce consumption expenditures per capita. Public projects have a significant negative influence on consumption expenditure for caste 2. Confidence in various organisations also negatively influences consumption expenditure caste 2.

The results could be looked upon in two ways. A study using IHDS 2 data in Karnataka and Andhra Pradesh highlighted that Brahmins had more advantages than other castes regarding a better standard of living and socio-political network(Ramachandran & Deshpande, 2021). A study period between 1991 and 2012 found that the asset ownership gap has widened between the general category and SC(Anand & Thampi, 2016). Another study using IHDS 1 in India revealed that the OBC households had the highest spending among all other caste groups in rural areas(Khamis et al., 2012). Losses caused by Natural disasters also incorporate loss of livelihood in the form of land and livestock (Khattri, 2017).

No specific studies have explored the impact of natural disasters on the forwarding caste in India. Hence, we were not able to provide any literature-based evidence. Disaster studies must focus on caste and class for effective disaster management(Ray-Bennett et al., 2019). Larger land ownership or assets also means more wealth exposed to natural disasters(E.

Cavallo et al., 2010). For those households that use assets to mitigate shocks, their productivity may be hampered (Heltberg et al., 2009).

Our study finds that Natural disaster reduces household consumption expenditure, but this decrease is insignificant. When we analysed this for socio-economic groups, we found that Natural Disaster significantly decreases consumption per capita for caste 1. In Indonesia, Households from disaster regions are also found to be cutting down their non-essential expenditure. However, natural disasters did not affect households' total expenditure (Sulistyaningrum, 2016). Those households affected by Bangladesh cyclone Alia had increased food expenditure compared to those not affected(Mottaleb et al., 2013). Thailand witnessed a decline in consumption expenditure due to Natural Disasters because of a reduction in service sector earnings but found an increase in non-durable goods consumption. The Philippines also observed minor changes in consumption expenditure (Tanaka et al., 2021). Floods in Chennai, India, affected consumption for a while but recovered after the disaster. Households were found to be smoothening their consumption using credit cards, bank loans and liquid assets(Agrawal et al., 2020).

Within a given household, the impact of natural disasters will also be felt disproportionately by children and women(Heltberg et al., 2009). As found in our study, the number of married females increased the consumption expenditure. In Malaysia, women made independent decisions about expenditures, especially clothing and personal care. Married women controlled the decisions about day-to-day expenditure(Yusof & Duasa, 2010). In Bangladesh, the wife's assets increased the share of expenditure on children's education and clothing (Quisumbing & De La Brière, 2000).

The effect of Natural disasters on household consumption expenditure across quintiles is given below(Table 75). Natural disasters affected consumption per capita negatively for all quintiles, but they significantly affected only APL1.

Assets helped households across quintiles to increase their monthly consumption per capita. Membership of organisations also significantly boosted consumption expenditure (except APL5).

The households in the higher consumption expenditure bracket may not benefit from the membership. Health insurance has also boosted consumption expenditure. Public projects had a positive and significant influence on APL4 and APL5.

Proportion of children and family size significantly reduced consumption expenditure. Conflicts in the village have negatively influenced the consumption expenditure for APL1. Confidence intensity brought up some curious results. It affected APL1 negatively and APL4 positively. The number of married females has reduced consumption expenditure for the lower quintile but increased for the higher quintile. Public projects in the village also showed mixed results but not significant ones.

In India, rural households mostly dependent on agriculture were vulnerable to consumption shocks due to natural disasters. As such, those households were found to be using different strategies based on the type of shocks, such as government aid was mainly used as a strategy for covariate shock. Besides this, the households used education and labour as coping strategies. Educated households used dissaving, and illiterate used children by withdrawing them from school(Pradhan & Mukherjee, 2016). Our study found that the proportion of children in the household reduced both consumption expenditure and adjusted consumption expenditure. The significance of insurance decreases with the quintile in the higher brackets (Sulistyaningrum, 2016).

Table 74:**Difference In Differences Regression Results For Adjusted Consumption Expenditure By Caste**

Table 75:**Difference In Differences Regression Results For Adjusted Consumption Expenditure By Quintile**

	Caste 1	Caste 2	Caste 3	Caste 4	BPL	APL 1	APL 2	APL 3	APL 4	APL 5
Dependent Variable	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**	**Adj Consumption**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XII**
					Average Treatment Effect on Treated					
Natural disaster Intensity #	-20.03	-8.584	-6.307	-9.962	-3.931	**-14.03*** **	-8.247	-1.558	-1.887	-31.77
	(14.83)	*(10.69)*	*(6.869)*	*(11.77)*	*(4.220)*	*(5.407)*	*(7.288)*	*(8.667)*	*(10.02)*	*(21.50)*
Controls										
Assets owned by the household $	**96.08*** **	**72.93*** **	**50.11*** **	**84.84*** **	**18.37*** **	**18.72*** **	**21.59*** **	**30.72*** **	**50.04*** **	**110.2*** **
	(10.10)	*(5.405)*	*(5.416)*	*(10.44)*	*(2.521)*	*(4.140)*	*(4.286)*	*(4.273)*	*(5.837)*	*(16.79)*
Confidence Intensity$	-10.42	-1.950	2.074	**-8.165** **	-1.937	-3.515	2.383	-0.915	**7.720** **	-11.73
	(11.81)	*(3.631)*	*(3.498)*	*(4.023)*	*(1.826)*	*(2.231)*	*(2.288)*	*(3.384)*	*(3.629)*	*(17.57)*
Conflict Intensity$	13.30	-9.269	-19.67	**-63.97*** **	-1.691	**-14.62** **	-12.55	-9.376	17.74	-23.68
	(26.86)	*(10.54)*	*(11.98)*	*(17.76)*	*(5.018)*	*(6.989)*	*(8.224)*	*(8.184)*	*(14.18)*	*(54.49)*
Health insurance $	**458.1** **	**196.7*** **	**160.2*** **	-110.2	**82.11*** **	**88.41** **	**187.6*** **	**168.5** **	**175.4*** **	**529.4*** **
	(182.2)	*(65.15)*	*(60.89)*	*(94.21)*	*(27.73)*	*(34.32)*	*(59.54)*	*(69.12)*	*(56.20)*	*(184.2)*
Adult education$	-4.891	-4.343	6.556	-0.927	-1.897	-6.820	0.200	-4.694	7.865*	-14.97
	(10.69)	*(5.148)*	*(4.536)*	*(7.398)*	*(2.005)*	*(5.374)*	*(3.620)*	*(4.064)*	*(4.539)*	*(16.74)*
Membership Intensity$	**124.0*** **	**49.00*** **	**45.29*** **	**27.22** **	**23.61*** **	10.32	**34.19*** **	**23.21** **	**45.92*** **	**87.16** **
	(28.02)	*(13.68)*	*(12.69)*	*(13.22)*	*(5.191)*	*(7.462)*	*(8.689)*	*(10.34)*	*(11.38)*	*(38.77)*

Number of married females in the household $	**233.7*** **	44.98	39.26	**92.67** **	**-38.89*** **	-15.59	**-65.65** **	-34.48	-50.87	**586.0*** **
	(80.20)	*(36.52)*	*(32.34)*	*(40.67)*	*(13.62)*	*(21.61)*	*(29.81)*	*(35.96)*	*(47.09)*	*(121.1)*
Family size $	**-220.2*** **	**-107.5*** **	**-120.5*** **	**-148.1*** **	**-31.99*** **	**-27.79*** **	**-49.27*** **	**-46.18*** **	**-96.66*** **	**-337.0*** **
	(23.37)	*(11.88)*	*(11.55)*	*(16.88)*	*(4.606)*	*(6.712)*	*(7.854)*	*(9.251)*	*(13.79)*	*(38.43)*
Proportion of children in the household $	**-1141.5*** **	**-911.8*** **	**-452.4*** **	**-436.2*** **	**-379.7*** **	**-379.8*** **	**-547.2*** **	**-623.2*** **	**-803.2*** **	**-1425.3*** **
	(152.4)	*(87.25)*	*(79.47)*	*(140.3)*	*(36.16)*	*(52.35)*	*(67.86)*	*(68.27)*	*(97.13)*	*(273.7)*
Public project Intensity#	**-14.35** *	-5.034	1.790	4.508	2.201	0.700	**5.329** **	-0.415	1.311	-21.89*
	(8.136)	*(3.326)*	*(4.182)*	*(5.164)*	*(1.546)*	*(2.144)*	*(2.360)*	*(2.599)*	*(3.496)*	*(11.97)*
year=2012	63.50	20.65	27.63	149.7***	-221.0***	-2.536	-97.11***	-61.94	-25.79	1238.4***
	(90.88)	*(45.25)*	*(35.14)*	*(54.70)*	*(20.01)*	*(28.48)*	*(33.38)*	*(43.20)*	*(53.88)*	*(150.9)*
Constant	1854.5***	1472.7***	1322.7***	1456.6***	1067.2***	1179.4***	1324.4***	1529.6***	1395.9***	2554.8***
	(255.9)	*(118.9)*	*(130.8)*	*(145.0)*	*(59.36)*	*(65.73)*	*(71.51)*	*(99.53)*	*(120.1)*	*(524.6)*
Standard error clustered at village level	6982	10424	5625	2827	5680	2175	3572	3610	3617	3616
Observations	11465	17826	10143	4985	11280	4331	7109	7188	7201	7195

Note: :1. Robust Standard errors in parentheses.

** p<0.10, ** p<0.05, *** p<0.010.*

2. # Village level data, $ household-level data.

3. Standard errors clustered at the Village level (PSUHH).

4. ATET estimate adjusted for covariates, panel, and time effects.

Source: Author's calculation based on IHDS 1 and IHDS 2 data.

5.3.3.4: Difference In Differences Regression Results For Adjusted Consumption Expenditure By Caste And Quintiles:

Natural disasters negatively impact adjusted consumption expenditure per capita across all social groups but are insignificant (Tables 74 and 75). However, assets have a significant positive impact on adjusted consumption expenditure.

Confidence and conflict intensity negatively impact caste 4(Table 74). Health insurance has a significant positive impact on all castes except caste 4. Membership intensity has a significant positive impact across all caste groups. The number of married females positively influences consumption expenditure but is significant for castes 1 and 4. Households highest adult education generated mixed results by influencing Caste 3 positively and significantly.

Family size and proportion of children reduce consumption expenditure per capita. Public project intensity has shown mixed results, but caste 1 significantly negatively impacts adjusted consumption per capita.

Across the economic quintile, natural disasters are responsible for reducing adjusted consumption per capita but significantly only for APL(Table 75). Assets owned by households are responsible for increasing consumption expenditure. Caste groups have a negative influence, but it is significant only for caste 4. Confidence and conflict intensity do not give the association/causation a clear direction; however, confidence intensity increases consumption expenditure for APL4, and conflict intensity reduces the same for APL1.

Health insurance increases consumption expenditure across all quintiles. Membership intensity increased consumption expenditure significantly across all quintile groups except APL1.

Household adult education increases consumption expenditure only for APL4. The number of married females significantly negatively impacted the BPL quintile and APL 2 but positively impacted APL 5.

Family size significantly negatively impacted consumption expenditure. Public project intensity exerted a positive influence on APL3 but a negative for APL5.

5.4: Main Findings And Discussion:

The results of IV2SLS provide the basis for understanding consumption expenditure driven by household assets. Some unique results have emerged from this analysis. The instrument's natural disaster intensity and confidence intensity have helped the households increase their assets across all socio-economic categories of both consumption expenditure and adjusted consumption expenditure models. Some covariates that worked towards increasing assets, such as the number of married females, family size and education, have worked in the reverse direction on consumption and adjusted consumption expenditure. Public project intensity and production of children have reduced assets and consumption expenditure. Family size and conflict intensity do not influence assets but work towards reducing consumption expenditure.

Those households hit by natural disasters had significantly different and lower assets than those not. The consumption and adjusted consumption expenditures were significantly different for only the lower quintile of BPL and APL1.

When households are affected by natural disasters, the asset-building exercise is carried out, and confidence in institutions has worked in building the assets. The formal and informal coping mechanisms mentioned in the literature, i.e., health insurance and social capital measured using membership intensity, have worked consistently in stage I for building up assets and mixed results in stage II for consumption expenditure.

For caste 1 (Brahmin and other forward castes) number of married females has helped to increase both assets and consumption expenditure along with assets, health insurance and membership intensity. Caste 4, which scheduled tribe health insurance, has helped to increase assets, but it has not been able to safeguard the consumption expenditure. For BPL, family size, health insurance, education, and married females have increased the assets in stage I. Assets, health insurance, and membership intensity increased consumption expenditure in stage II. family size, education, conflict intensity, the proportion of children, and public project intensity have reduced consumption expenditure in stage II.

For adjusted consumption expenditure by caste, health insurance and education have positively influenced all caste categories; family size influences, the proportion of children and project intensity has a negative impact on assets in stage I on caste 4. In stage II, the consumption expenditure is positively influenced by the assets for all caste categories and membership intensity. Family size and proportion of children have a negative influence on all castes.

For the adjusted consumption expenditure quintile, family size, health insurance, adult education, and married females increase household assets, the proportion of children and public project intensity impact APL 3 and APL negatively and significantly. Conflict intensity increased assets for BPL. In stage II, assets increased consumption expenditure in all quintiles. Conflict intensity, family size, adult education, the proportion of children, and public project intensity have reduced consumption expenditure. Membership intensity and the number of married females have mixed results.

The number of married females and family size is important in determining welfare and influencing expenditure decisions(Biyase & Zwane, 2018; Walugembe & Misinde, 2019). Family size and structure influence expenditure decisions (Blake, 1989; Downey, 1995; Flake & Forste, 2006; Heshmati et al., 2019).

The number of married females in the family positively and significantly impacts assets for all quintiles. Households with a larger number of married women own more assets than others. It is not clear why this should be the case. One possibility is that this could be an outcome of the dowry system that still prevails informally (Roy, 2015), which has increased the assets. The other possibility is that the presence of married women would increase the workforce in the household and allow a greater accumulation of assets. More married women in the household also increased consumption in the BPL and APL5 quintiles. There is a significant and negative impact of the proportion of children on assets and consumption across all quintiles. Social connectedness measured through membership in various associations and socio-cultural groups has positively and significantly impacted assets and consumption. These findings comply with earlier literature on the benefits of social connectedness (Bailey et al., 2018; Putnam, 2001). Implementing public projects in the village is expected to lead to an increase in local welfare. We find mixed evidence of this in our results.

The findings suggest that multiple adaptation strategies would help households that experience natural disasters. At the policy level, insurance would help in both protecting assets as well as consumption. However, insurance coverage in India is relatively low at 6%(IHDS 2). Expedited efforts to provide more comprehensive insurance coverage in areas expected to experience natural disasters would be an effective adaptation strategy. In addition, providing calamity risk insurance would also be a step towards greater resilience (Linnerooth-Bayer & Hochrainer-Stigler, 2011). This option is available in many developed and developing countries (Paleari, 2019).

The DID results suggest that households with assets, health insurance and membership in different organisations help secure their consumption expenditure during Natural Disasters. The household uses the assets to cope with natural disasters(Skoufias, 2003). In our study, we also found that the assets had a positive and significant influence on the consumption expenditure of the households.

Social connectedness measured through membership in various associations and socio-cultural groups has had a positive impact. Social capital in the form of Membership in the youth club, self-help groups for females, associations and networks helped the members (Sanyal & Routray, 2016). In Odisha, for those affected by Cyclone Phailine, Self-help groups helped reconstruct and rebuild assets, but it was not a substitute for emergency food programs(Christian et al., 2019). These findings conform with earlier literature on the benefits of social connectedness(Bailey et al., 2018; Putnam, 2001). Similarly, microfinance (loans, savings, insurance, and other financial services) can act as an important mechanism to fight poverty and help low-income build assets and protect against risk. Micro-finance does not cover the poorest but slightly low (stable) income segment (Heltberg et al., 2009).

Implementing public projects in the village is expected to lead to an increase in local welfare. We find mixed evidence of this in our results. Programs that target households directly for credits and transfers were found to be more effective in rural Vietnam(Arouri et al., 2015).

Our findings suggest that multiple adaptation strategies would help households that experience natural disasters. At the policy level, insurance would help in both protecting assets as well as consumption. Expedited efforts to provide more comprehensive insurance coverage in areas expected to experience natural disasters would be an effective adaptation strategy. In addition, providing disaster risk insurance would also be a step towards greater resilience (Linnerooth-Bayer & Hochrainer-Stigler, 2011). This option is available in many developed and developing countries (Paleari, 2019).

Evidence suggests that education helps people improve their well-being across the population and is an effective adaptation strategy (Muttarak & Lutz, 2014). Household with higher education was found to be resilient to disasters in rural Vietnam(Arouri et al., 2015). The average level of education was one of the important determinants of the coping strategy (Pradhan & Mukherjee, 2016). There is, therefore, a need to ensure access to education, especially for the poor. Confidence in institutions is strongly linked to asset holding (Ellis & Bahiigwa, 2003). Fair and transparent institutions will likely play a critical role in adaptation and resilience-building, especially in disaster-prone areas(Papaioannou, 2009). While emergency consumption relief as an immediate strategy would be an important short-term intervention, building assets as a long-term policy will make them more resilient (Archer et al., 2020).

The areas hit by disasters have increased conflicts(Danilo & Roehlano, 2014). A natural disaster does have a negative impact on the consumption expenditure of minorities (Arouri et al., 2015a; Bui et al., 2014).

5.5: Conclusion:

Households that face natural disasters smoothen consumption via assets, and in turn, these assets are affected by natural disasters and confidence. Evidence suggests that education helps people improve their well-being across the population and is an effective adaptation strategy (Muttarak & Lutz, 2014). There is, therefore, a need to ensure access to education, especially for the poor. Confidence in institutions is strongly linked to asset holding (Ellis & Bahiigwa, 2003). Fair and transparent institutions will likely play a critical role in adaptation and resilience-building, especially in calamity-prone areas (Papaioannou, 2009). While emergency consumption relief as an immediate strategy would be an important short-term intervention, building assets as a long-term policy will make them more resilient (Archer et al., 2020).

Household assets, informal coping mechanisms, and membership intensity, a type of social capital and health insurance, a formal coping mechanism, have worked positively towards building household assets, which in turn have helped households to smoothen consumption expenditure. Without accompanying information on additional factors that could impact consumption, like calamity relief measures, external assistance through remittance or other developmental programmes, the impact of natural disasters cannot be fully comprehended.

5.6: Limitations:

The limitation of this dataset is the use of self-reported natural disasters. We could not map the data from EMDAT to the household level since EMDAT has information for some districts and states. The DID approach makes one critical assumption that the treatment and control groups have parallel trends in the outcome. However, this is untestable in two-period data(Wing et al., 2018). Without accompanying information on additional factors that could impact consumption, like disaster relief measures, external assistance through remittance or other developmental programmes, the impact of natural disasters cannot be fully comprehended.

The next chapter, 6, examines health expenditure as an idiosyncratic shock and its impact on household consumption.

CHAPTER 6:

HEALTH EXPENDITURE ANALYSIS AT THE HOUSEHOLD AND INDIVIDUAL LEVEL

Previous Chapter 5 discusses natural disasters as a covariate shock. Chapter 6 is titled 'Health expenditure analysis at the household and individual level. This chapter deals exclusively with objective 3: To study the impact of health expenditure on household consumption. This chapter is divided into five main sections. Section 1 is the introduction and is subdivided into 3 sub-sections, each dealing with the significance of measuring catastrophic expenditure, sources of health care financing and background studies. The next main section is materials and methods, subdivided into 3 sub-sections. These sub-sections discuss the poverty impact of OOPHE, methodological limitations and refinements, and methods used for calculating health expenditure. The next main section6.3 presents the results. The results section is further divided into 9 sub-sections. Each sub-section presents different results of health expenditure calculated for states, households, and individuals. The last two sections are the discussion and conclusion.

6.1: Introduction:

Households face many shocks that disturb the household's well-being. Health shock is one such shock that works on two levels: first, the days disabled to work and hence loss of income (as discussed in Chapter 4) and second, the expenditure incurred for restoring health to earlier health status. The households incur various health expenditures, some of which are OOPHE on health(Fan et al., 2012; Garg & Karan, 2009; Shahrawat & Rao, 2012). Most households use OOPHE to finance health treatments(Ghosh, 2011; Gupta, 2009; Van Doorslaer et al., 2007).

The need to access health care can cause catastrophic health spending. When the health costs are high but subsidised or paid by the health insurance, they may not be catastrophic. Some households may incur a small amount of health expenditure that can push them below the poverty line(Xu et al., 2003). Shock arising due to health payments is an important source of poverty if they lack social security and private insurance is expensive(He & Zhou, 2022). It is important to understand the households vulnerable to becoming poor due to health payments. The reasons for financial vulnerability could be many, but health expenditure is one among them. Households with higher levels of medical expenditure will have a higher probability of being financially vulnerable(He & Zhou, 2022). Catastrophic expenditure occurs due to access to health care that requires payment at the time of purchase; households may lack adequate financial resources to purchase the health care, and households may not have access to any publicly funded financial security(Xu et al., 2003).

Healthcare expenditures differ from others since they are uneven across households and individuals. Health spending helps individuals restore their original or near to their health status, unlike other expenditures where a household well-being status may get upgraded upon purchase(Wagstaff et al., 2020).

6.1.1: Catastrophic Health Expenditure:

When households receive no financial protection, health payments involve a considerable component of household expenditure, affecting households' well-being. When a household spends a certain amount or more on health expenditures, the amount available for other expenses is compromised. Consequently, the household's well-being is disrupted (Berki, 1986; Gertler & Gruber, 2002). The catastrophic health expenditure also reflects the need for public spending and financial protection to be offered to people by the state(Naga & Lamiraud, 2011).

6.1.2: Sources Of Healthcare Financing:

Households use different coping mechanisms, such as borrowing from friends and relatives, selling assets, or compromising their expenditure on necessary items(Rashad & Sharaf, 2015). This type of financing is referred to as distressed financing. In India, borrowing from friends and relatives is an important source to finance access to health care. These borrowings were higher for women and elderly persons in the household and marginalised groups for illnesses arising from non-communicable diseases(Joe, 2015). In Africa, borrowing and selling assets was a coping mechanism, especially among those households that incurred inpatient expenditure (Leive & Xu, 2008).

6.1.3: Background Studies And Empirical Evidence On Health Expenditure:

A Scoping Review on health expenditure provided global evidence and available literature suggesting the detrimental effects of OOPHE on households in general and poor households in particular (Njagi et al., 2018). OOPHE on health was 5 % of total household expenditure on average. It was more in rural areas and affluent states (Jalali et al., 2021). The highest component of OOPHE was buying medicines(Garg & Karan, 2009). Using the consumption expenditure survey, NSS 61st round, 2004-2005, Shahrawat& Rao (2011) revealed that health expenditure-related poverty affects those below and above the poverty line. Medical expenditure was the highest contributor to OOPHE. The increase in OOPHE is more than the increase in consumption expenditure from 1993-94 to 2011-12(Gupta & Chowdhury, 2015). The major share was hospitalisation for OOPHE, and diagnostics expenditures drive increases in health expenditure(Sinha et al., 2015).

Using the NSS (2017-2018), Swargiary et al.(2021) found that women's access to health care is characterised by financial hardship. Tackling injuries and disabilities was the reason for the highest health expenditure and was catastrophic for many. A comparison of the health expenditure of the elderly and non-elderly showed that the elderly had higher health expenditures and catastrophic for poor households, casual labourers & elderly members (Mohanty et al., 2014). Studies based on the NSS consumption expenditure round, 2011-12, revealed variations among the states regarding catastrophic expenditure on health (Mohanty et al., 2018). These variations had their source in differentials in cost and inequalities associated with access to health care. In two rounds of NSS (2014; 2017-18), a study revealed the differentials in health expenditure among the older population in India(Srivastava et al., 2022). Maternity-related expenditure is also known to be catastrophic in India. These findings were based on the NSS 60th round (2004) (Bonu et al., 2009). The study also observed that using households' capacity to pay approach to measure the extent of the nature of catastrophic expenditure is better than total expenditure). Using the 61st round of NSS, Bonu et al. (2007) used a threshold of 10% for health expenditure exceeding total household expenditure and 40% of households' capacity to pay to describe catastrophic health expenditure. They found that 3.5% of people were moved below the poverty line due to expenditures related to health care. Ladusingh & Pandey (2013) examined the cost incurred on inpatient treatment and compared the cost between those who survived and those who died. The former cost was lower than the latter. Such differentials were considerable for rural areas with longer hospital spells and non-communicable diseases. Those injured in road traffic accidents incurred an OOPHE of 22%, almost 12% falling below the poverty line(Prinja et al., 2019). The NSS 1993-93 and 2004-05 rounds were used to study the incidence and intensity, using the methodology of Wagstaff and Van Doorslaer (2003,)who highlighted that the contribution of expenditure on medicine towards OOPHE was very high and it increased from 13% to about 15% in the said period. The percentage of households that became poor after adjusting for health expenditure was 4%(Ghosh, 2011). NSS data from 2004 and 2014 revealed that the OOPHE incurred for financing health expenditure was 80%, and household savings were primarily used for financing health, followed by borrowing for rural and urban India (Jayakrishnan et al., 2016).

A systematic review in India observed that cancer was associated with an exorbitant cost of treatment, and 62% of individuals faced catastrophic expenditure. The treatment was financed by selling assets, borrowing and savings (Dhankhar et al., 2021). Using the WHO global and ageing data in India, among the 65+ population, OOPHE was more for a) those with disabilities, b) lower income, and c) those with diabetes, heart disease and tuberculosis. The older population incurred 7% catastrophic expenditure (Brinda et al., 2015).

A systematic review of the literature on the countries with all types of incomes, using 38 global studies, revealed that households' economic status and households with elderly and disabled members had evidence of catastrophic health expenditure(Azzani et al., 2019).

In Vietnam, a study on non-communicable diseases revealed that urban households with one member suffering from a non-communicable disease were likely to experience health-related catastrophic expenditure and impoverishment(Kien et al., 2017). In Rural Ethiopia, households with members who suffered from depression faced poverty due to high OOPHE (Hailemichael et al., 2019). Those from the upper quintile of income had a higher share of OOPHE in health in the Philippines. Health expenditure related to impoverishment was prevalent and rising(Ulep & Dela Cruz, 2013). In 14 countries studied in Asia, the reliance on out-of-pocket was very heavy; Nepal, India and Vietnam spent almost ¾ of their total expenditure on health(Van Doorslaer et al., 2007). A systematic literature review of 14 global studies found that morbidity and OOPHE had a higher positive correlation(Sum et al., 2018). Western Balkans (Albania, Kosovo, Serbia, Bosnia, Herzegovina, and Montenegro) suffered from health expenditure-related impoverishment (Mendola et al., 2008). Nigerian households also suffered from catastrophic expenditure (Onoka et al., 2011). In Vietnam, the poorer were pushed to become poorer due to health expenditures, which were more related to non-hospital (Wagstaff & Doorslaer, 2003).

Health expenditure affects all households, but the ones living in conflict regions also have limited access to health care. A study in Columbia regions affected by conflict provided strong evidence for increasing catastrophic expenditure between 2014 and 2018(León-Giraldo et al., 2021). The difference in socioeconomic groups was also visible among rural, middle-aged, and those with physical disabilities and mental and living in areas affected by conflict. Individuals who require a sufficiently long duration of health care, leading to expenditure, also increased the probability of poverty by almost 19%. The likelihood of poverty was higher for single, widowed, or separated with lower education and income levels.

In three Arab countries, Egypt, Jordan, and Palestine, even the more affluent houses face catastrophic health expenditures(Rashad & Sharaf, 2015). A meta-analysis using 47 studies in China revealed that poorer households and households from rural areas had high catastrophic health expenditures(Yuan et al., 2021). In Cambodia, the cause of poverty and poverty-related indebtedness is OOPHE for seeking health care(Van Damme et al., 2004). In 146 country studies, the per capita OOPHE differed from country to country, with $100 in Nepal in a low-income country and $ 1200 in Switzerland in a high-income country(Wagstaff et al., 2020).

There have been multiple studies in India, also. A study using IHDS panel data examined the gender differentials in health(Saikia & Kulkarni, 2016). Panikkassery (2020) used IHDS data and found that non-food expenditure compensates for household health expenditure. Irrespective of state expenditure on health, poor households compromise their expenditure on education and non-food items. The coping mechanisms used by the households included loans to finance health expenditures. Almost 10% of rural and 6% of urban households were impoverished because of out-of-pocket health expenditures (Singh & Pandey, 2013). The out-of-pocket differentials widened due to human health resources such as the availability of health personnel (mainly physicians) and income differentials. Using the same panel dataset, Bhattacharjee & Mohanty (2022) found that confidence in institutions and the information received impacts OOPHE besides location, social status, and education.

6.2: Materials And Methods:

We use data from household and individual schedules from both rounds of IHDS (see Chapter 3 for details). The variable outpatient and inpatient expenditures are from the household schedule. The variables measuring health expenditure components such as doctor fees, medicine costs, transport costs, and insurance reimbursement are from the individual schedule. We have used monthly consumption expenditure and food expenditure from IHDS 1 and IHDS 2.

The OOPHE incurred to access health care is measured in the literature using different indicators like the budget share of OOPHE in the households, Kakwani index, catastrophic expenditure index, concentration index, and impoverishment headcount, among others (Wagstaff et al., 2020).

There are two most used methods to measure the catastrophic and impoverishment impact of health expenditure incurred by households given by Wagstaff and Van Doorlsaer (2003) and Xu (2005).

As suggested by Wagstaff and Van Doorslaer (2003), the measurement method focuses on the ability to pay, the household's share of health expenditure to total expenditure, and the household's share of health expenditure to total consumption expenditure adjusted for food expenditure determines the proportion spent on health expenditure. If this proportion exceeds a certain threshold level, it becomes catastrophic. The impoverishment effect of health payments is measured by Wagstaff & Van Doorlsaer (2003) as the difference between those who were not poor before health payments and became poor after making health payments. The threshold is 10% of total expenditure (see Chapter 3 for details).

As Xu (2005) proposed, exceeding 40% or equal to non-subsistence expenditure becomes catastrophic. The methodology requires calculating the household's subsistence expenditure. The household's capacity to pay is calculated as the difference between total consumption and subsistence expenditures (poverty line). The households that report food expenditure less than the poverty line, households' capacity to pay is calculated as the difference between total consumption expenditure and food expenditure). Household capacity to pay is equal to non-food expenditure. OOPHE on health is calculated as the ratio of health payment(adjusted for insurance reimbursement to household capacity to pay. Those households are said to be incurring catastrophic health expenditure, whose ratio of out-of-pocket health payment to household capacity to pay is 40% or more. We create a dummy variable. This dummy variable will have a binary value of 1 if the household is categorised as catastrophic or 0 if otherwise.

6.2.1: Poverty Impact Of OOPHE:

The number of people who become poor after incurring health expenditure is measured using headcount ratio and intensity before and after payments. The measurement of health expenditure-related poverty and consumption expenditure-related poverty is the same. One addition is that health expenditure is adjusted to study the poverty effect on account of health payments. Before incurring health expenditure, households' consumption expenditure is compared with poverty. Once the household incurs health expenditure, consumption expenditure is adjusted for the same, and the adjusted consumption is compared with the poverty line. It gives the number of people/ households falling below the poverty line due to health expenditure.

The household expenditure to access health care when receiving health care services is OOPHE. It includes consultancy fees paid to the doctor or clinic fees, expenditure incurred to buy medicines, and access to various diagnostic facilities. For any household that receives insurance reimbursement, such reimbursement needs to be adjusted. Households incur health-related non-medical expenditures, such as expenditures on transport, and these have to be excluded from the calculation of OOPHE. Expenditure incurred on alcoholic beverages, tobacco, and food eaten by the restaurant is excluded as a standard methodological practice (Xu, 2005).

In the next stage, OOPHE is calculated, which is also a burden of health payments. It is the proportion of health payments as a share of the capacity to pay. The OOPHE is described as catastrophic only if it exceeds a certain threshold level. This study uses a 10% and 40 % or more threshold. Therefore, if OOPHE exceeds the 10% and 40% threshold, it is considered catastrophic. The headcount of those households with catastrophic health expenditures is the proportion of households that exceed this threshold. This concept of headcount gives the incidence of catastrophe. The households that incur health expenditures may be pushed below the poverty line. Hence, health expenditure-related impoverishment includes those who have become poor after incurring health expenditure, known as the impoverishment effect.

The intensity of poverty is the difference between the poverty line and consumption expenditure before making health payments. After making health payments, it is the difference between the poverty line expenditure and adjusted consumption expenditure. The additional number of people who have fallen below the poverty line because of health expenditure can now be calculated. It is the difference between the number of people below the poverty line before making health payments and those who have fallen below the poverty line after making health payments.

The food expenditure per capita is subtracted from the monthly consumption expenditure(gross) to get net consumption or non-food expenditure. The OOPHE on health is divided by the gross household consumption expenditure to derive the gross OOPHE share. The OOPHE is divided by the net consumption expenditure to derive the share of the net OOPHE. The catastrophic expenditure is a dummy variable for those whose pocket expenditure ratio equals or exceeds 10%. The threshold is subtracted from gross and net OOPHE to get the catastrophic overshoot. When divided by the total population, this overshoot gives an average overshoot.

Similarly, the expenditure that the households fall short of to be above the poverty line (poverty deepening) is also calculated. The overshoot is the shortfall of the threshold and the ratio of health expenditure to total expenditure. The average overshoot is calculated as the overshoot divided by the population. Mean positive overshoot is the ratio of overshoot divided by headcount. Further, the measure of headcount and intensity does not incorporate the adjustment for the poverty line.

The normalised poverty gap is calculated as the gap between the consumption expenditure and the poverty line divided by the poverty line. Also, this gap is standardised with headcount by dividing the headcount by the poverty line(Garg & Karan, 2009). All these expenditure variables are measured as monthly expenditures (Xu, 2005).

We present the results in the next section.

6.3: Results:

The following section discusses the results.

6.3.1: Descriptive Statistics:

Table 76: **Summary Statistics**

Variable	Observations	Mean	Std. Dev.	Min	Max
poverty line round 1	150988	923	128.667	672	1358
Rural poverty line round 2	105786	869	104.763	672	1351
Urban poverty line round 1	45202	1050	82.592	844	1358
Poverty line round 2	150988	933	128.467	695	1398
Rural poverty line round 2	102282	885	110.093	695	1380
Urban Poverty Line Round 2	48706	1035	102.228	849	1398

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

The average poverty line (rural and urban combined) is Rs 923 in IHDS 1 and Rs. 933 in IHDS 2 (Table 76). The average rural poverty line was Rs 869, and the urban poverty line was Rs 1050 in IHDS 1. In IHDS 2, the rural poverty line was Rs 833, and the Urban is Rs 1035 respectively.

6.3.2: Monthly Per Capita Outpatient And Inpatient Expenditure:

Andhra Pradesh has the highest outpatient and inpatient expenditure in rural areas and the highest outpatient expenditure in urban areas (Table 77). Manipur had the highest inpatient expenditure in an urban area. The national rural outpatient and inpatient average is Rs 85 and 58, respectively. The national urban average for an outpatient expenditure is Rs 84, and inpatient is Rs 69.

In IHDS 2, Nagaland had the highest outpatient expenditure, Delhi had the highest inpatient expenditure for rural areas, Mizoram had the highest outpatient expenditure in urban areas, and Pondicherry had the highest urban inpatient expenditure. The national average for outpatient and inpatient rural and urban in IHDS 2 was Rs 97, Rs 105, Rs 101, and Rs 124, respectively.

The outpatient expenditure in IHDS 1 was higher than the inpatient expenditure. In IHDS 2, the inpatient expenditure was higher than the outpatient expenditure.

6.3.3: Total Health Expenditure Monthly Per Capita:

In IHDS 1, in rural areas, Kerala, Andhra Pradesh, Manipur and Tamil Nadu, In union territories, Daman Diu and Pondicherry had higher total health expenditure per capita (Table 78). The states with the highest total health expenditure for urban areas were Manipur, Goa, Andhra Pradesh, Tripura, and West Bengal. In IHDS 2, the states in rural areas with high per capita medical expenditure were Kerala, Goa, Andhra Pradesh, Nagaland, Tamil Nadu, Jammu and Kashmir Karnataka, Uttar Pradesh, Haryana and among the union territories, Delhi, Dadra and Nagar Haveli, Daman, and Diu. Andhra Pradesh, Mizoram, Haryana, Gujarat, Jammu and Kashmir, and the Union Territories of Pondicherry incurred high health expenditures in urban areas in IHDS 2. The national rural and urban average in IHDS 1 was Rs 144 and 154, respectively; in IHDS 2, it was Rs 203 and Rs 226 in rural and urban areas. The state with the highest health expenditure for rural areas in IHDS 1 was Rs 306 in Kerala, and the lowest was Rs 16 for Arunachal Pradesh. In urban areas, the highest expenditure was Manipur, with Rs 854; the lowest was Rs 9 in Mizoram. In IHDS 2, the state/ Union territory with the highest per capita health expenditure in rural areas was Rs 427 Delhi, and the lowest was Meghalaya at Rs 48. In the urban areas, Pondicherry's highest expenditure was Rs 435, and the lowest was Rs 88 in Manipur.

Table 77: **Monthly Per Capita Outpatient And Inpatient Expenditure (Rs)**

2005						2012					
Rural			Urban			Rural			Urban		
States	**Outpatient**	**Inpatient**	**States**	**Outpatient**	**Inpatient**	**States**	**Outpatient**	**Inpatient**	**States**	**Outpatient**	**Inpatient**
Andhra Pradesh	171.79	127.37	Andhra Pradesh	166.87	110.35	Andhra Pradesh	163.72	205.89	Andhra Pradesh	163.62	245.17
Arunachal Pradesh	14.23	2.52	Arunachal Pradesh	6.61	13.87	Arunachal Pradesh	39.03	55.34	Arunachal Pradesh	93.56	144.46
Assam	54.33	36.45	Assam	88.4	59.82	Assam	60.59	57.61	Assam	96.45	84.58
Bihar	107.07	53.46	Bihar	64.55	68.75	Bihar	80.2	95.74	Bihar	68.4	85.62
Chhattisgarh	34.01	18.62	Chandigarh	38.93	0.01	Chhattisgarh	91.51	46.1	Chandigarh	124.1	140.22
Dadra Nagar Haveli	47.4	142.84	Chhattisgarh	99.68	69.78	Dadra Nagar Haveli	78.72	178.99	Chhattisgarh	114.12	65.01
Daman & Diu	142.2	87.04	Delhi	46.26	38.48	Daman & Diu	102.98	143.47	Dadra Nagar Haveli	110.61	106.73
Delhi	14.81	28.44	Goa	201.72	86.53	Delhi	142.81	284.2	Delhi	103.15	174.71
Goa	102.37	66.46	Gujarat	44.55	64.69	Goa	112.69	202.07	Goa	135.39	161.89
Gujarat	72.75	52.45	Haryana	85.09	63.68	Gujarat	61.61	115.56	Gujarat	101	203.29
Haryana	107.53	74.41	Himachal Pradesh	120.14	78.93	Haryana	107.55	125.84	Haryana	140.79	240.67
Himachal Pradesh	113.85	47.05	Jammu & Kashmir	99.41	53.2	Himachal Pradesh	87.24	86	Himachal Pradesh	81.19	91.55
Jammu & Kashmir	142.31	50.49	Jharkhand	56.96	63.42	Jammu & Kashmir	170.05	128.35	Jammu & Kashmir 1255	195.42	105.96
Jharkhand	37.17	18.43	Karnataka	82.83	86.96	Jharkhand	84.81	52.88	Jharkhand	81.21	81.43
Karnataka	80.1	80.26	Kerala	90.24	74.74	Karnataka	109.57	170.89	Karnataka	90.4	188.06
Kerala	152.42	153.84	Madhya Pradesh	86.5	59.6	Kerala	201.46	199.51	Kerala	117.34	145.39
Madhya Pradesh	69.51	44.64	Maharashtra	40.46	43.73	Madhya Pradesh	83.65	57.07	Madhya Pradesh	62.57	58.49
Maharashtra	67.91	68.68	Manipur	136.38	717.7	Maharashtra	83.91	126.74	Maharashtra	64.32	64.68
Manipur	151.25	68.78	Meghalaya	51.78	20.79	Manipur	65.93	79.22	Manipur	71.45	16.08
Meghalaya	51.19	75.72	Mizoram	9.32	0	Meghalaya	38.42	9.4	Meghalaya	62.69	45
Mizoram	50.51	9.36	Nagaland	0	0	Mizoram	113.97	8.78	Mizoram	326.11	23.52
Nagaland	17.33	22.1	Orissa	100.6	68.46	Nagaland	238.58	69.19	Nagaland	56.58	110.86
Orissa	57.07	23.62	Pondicherry	140.74	30.21	Orissa	55.39	27.35	Orissa	105.33	87.82
Pondicherry	130.89	69.19	Punjab	91.26	53.82	Pondicherry	19.24	31.47	Pondicherry	35.95	399.96
Punjab	85.66	82.59	Rajasthan	64.54	67.1	Punjab	99.71	104.18	Punjab	91.15	114.38
Rajasthan	66.72	29.42	Sikkim	24.4	5.47	Rajasthan	86.79	78.26	Rajasthan	66.64	65.02

Sikkim	42.98	5.53	Tamil Nadu	88.74	67.64	Sikkim	173.36	18.61	Sikkim	91.97	29.48
Tamil Nadu	127.06	77.25	Tripura	127.09	89.46	Tamil Nadu	136.14	162.57	Tamil Nadu	120.79	183.23
Tripura	104.62	55.46	Uttar Pradesh	67.97	79.98	Tripura	73.18	120.84	Total	101.91	124.36
Uttar Pradesh	73.89	51.88	Uttaranchal	88.07	70.4	Uttar Pradesh	108.86	119.52	Tripura	98.72	93.95
Uttaranchal	110.93	37.82	West Bengal	144.71	64.1	Uttaranchal	67.24	34.51	Uttar Pradesh	96.73	150.26
West Bengal	80.5	29.95				West Bengal	89.9	45.39	Uttaranchal	93.01	108.49
									West Bengal	140.74	67.47
Total	85.05	58.52	Total	84.28	69.42	Total	97.99	105.49	Total	101.91	124.36

Source: Author's calculations based on IHDS 1 &IHDS 2 data.

Table 78: **Total Health Expenditure Monthly Per Capita (Rs)(2005 & 2012)**

2005				2012			
Rural		Urban		Rural		Urban	
Andhra Pradesh	299.16	Andhra Pradesh	277.22	Andhra Pradesh	369.62	Andhra Pradesh	408.79
Arunachal Pradesh	16.75	Arunachal Pradesh	20.48	Arunachal Pradesh	94.37	Arunachal Pradesh	238.03
Assam	90.78	Assam	148.22	Assam	118.2	Assam	181.03
Bihar	160.54	Bihar	133.3	Bihar	175.94	Bihar	154.02
Chhattisgarh	52.63	Chandigarh	38.94	Chhattisgarh	137.61	Chandigarh	264.32
Dadra Nagar Haveli	190.24	Chhattisgarh	169.46	Dadra Nagar Haveli	257.71	Chhattisgarh	179.13
Daman & Diu	229.24	Delhi	84.73	Daman & Diu	246.45	Dadra Nagar Haveli	217.33
Delhi	43.24	Goa	288.25	Delhi	427	Delhi	277.87
Goa	168.84	Gujarat	109.24	Goa	314.76	Goa	297.28
Gujarat	125.2	Haryana	148.77	Gujarat	177.17	Gujarat	304.29
Haryana	181.94	Himachal Pradesh	199.07	Haryana	233.39	Haryana	381.47
Himachal Pradesh	160.9	Jammu & Kashmir	152.62	Himachal Pradesh	173.24	Himachal Pradesh	172.74
Jammu & Kashmir	192.79	Jharkhand	120.38	Jammu & Kashmir	298.4	Jammu & Kashmir	301.38
Jharkhand	55.6	Karnataka	169.79	Jharkhand	137.69	Jharkhand	162.65
Karnataka	160.36	Kerala	164.98	Karnataka	280.47	Karnataka	278.46
Kerala	306.26	Madhya Pradesh	146.1	Kerala	400.98	Kerala	262.73
Madhya Pradesh	114.15	Maharashtra	84.19	Madhya Pradesh	140.72	Madhya Pradesh	121.07
Maharashtra	136.59	Manipur	854.08	Maharashtra	210.65	Maharashtra	129
Manipur	220.03	Meghalaya	72.58	Manipur	145.14	Manipur	87.53
Meghalaya	126.91	Mizoram	9.32	Meghalaya	47.82	Meghalaya	107.69

Mizoram	59.87	Nagaland	0	Mizoram	122.75	Mizoram	349.63
Nagaland	39.43	Orissa	169.05	Nagaland	307.77	Nagaland	167.44
Orissa	80.68	Pondicherry	170.95	Orissa	82.74	Orissa	193.15
Pondicherry	200.08	Punjab	145.09	Pondicherry	50.71	Pondicherry	435.91
Punjab	168.24	Rajasthan	131.64	Punjab	203.88	Punjab	205.53
Rajasthan	96.14	Sikkim	29.87	Rajasthan	165.05	Rajasthan	131.66
Sikkim	48.51	Tamil Nadu	156.38	Sikkim	191.97	Sikkim	121.45
Tamil Nadu	204.31	Tripura	216.55	Tamil Nadu	298.71	Tamil Nadu	304.02
Tripura	160.08	Uttar Pradesh	147.95	Tripura	194.02	Tripura	192.67
Uttar Pradesh	125.77	Uttaranchal	158.47	Uttar Pradesh	228.37	Uttar Pradesh	246.99
Uttaranchal	148.75	West Bengal	208.81	Uttaranchal	101.76	Uttaranchal	201.5
West Bengal	110.45			West Bengal	135.29	West Bengal	208.21
Total	143.58	Total	153.7	Total	203.48	Total	226.27

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Table 79:**Different Types Of Monthly Health Expenditure Per Capita (Rs), 2005**

	Rural				Urban		
States	**Doctor Fees**	**Medicine cost**	**Travel cost**	**States**	**Doctor Fees**	**Medicine cost**	**Travel cost**
Andhra Pradesh	11.84	28.31	3.43	Andhra Pradesh	11.83	11.38	1.47
Arunachal Pradesh	2.39	0.2	0.04	Arunachal Pradesh	0.94	0	0
Assam	7.48	1.94	1.16	Assam	4.15	10.49	1.39
Bihar	9.51	21.88	1.84	Bihar	6.33	20.02	0.99
Chhattisgarh	13.7	3.06	1.32	Chandigarh	7.82	7.54	1.94
Dadra Nagar Haveli	15.87	21.39	1.75	Chhattisgarh	16.74	7.48	0.46
Daman & Diu	52.36	8.49	2.27	Delhi	4.17	3.06	0.6
Delhi	2	1.08	0.31	Goa	1.28	14.48	0.94
Goa	5.34	19.56	1.89	Gujarat	11.09	9.42	0.93
Gujarat	6.98	10.76	2.34	Haryana	16.96	6.05	1.01
Haryana	16.34	3.21	0.97	Himachal Pradesh	4.77	17.7	1.19
Himachal Pradesh	6.21	16.95	2.51	Jammu & Kashmir	4.4	18	1.98
Jammu & Kashmir	9.88	21.98	2.81	Jharkhand	15.14	5.51	0.45
Jharkhand	7.87	4.27	0.44	Karnataka	20.88	7.8	1.31
Karnataka	18.64	8.57	2.31	Kerala	5.4	13.85	1.73
Kerala	18.27	32.68	5.18	Madhya Pradesh	15.13	7.43	0.99
Madhya Pradesh	12.9	9.37	1.49	Maharashtra	9.97	4.95	0.69
Maharashtra	9.63	7.48	2.38	Manipur	4.8	27.28	0.72
Manipur	4.75	22.54	0.91	Meghalaya	0.72	5.61	3.3
Meghalaya	4.05	20.45	1.63	Mizoram	0	0	0
Mizoram	0	12.45	1.93	Nagaland	0	0	0
Nagaland	3.83	13.39	4.18	Orissa	3.23	19.08	3
Orissa	1.02	10.71	0.8	Pondicherry	7.13	4.67	1.47
Pondicherry	14.32	3.98	2.33	Punjab	10.43	4.13	0.8

Punjab	14.76	7.96	1.97	Rajasthan	5.97	13.58	0.79
Rajasthan	5.43	10.93	1.18	Sikkim	7.93	0.04	0
Sikkim	12.76	0.57	0.27	Tamil Nadu	16.8	2.68	1.43
Tamil Nadu	24.12	5.65	3.93	Tripura	4.65	24.42	3.46
Tripura	24.64	6.26	4.24	Uttar Pradesh	11.69	10.03	1.4
Uttar Pradesh	8.01	8.43	0.93	Uttaranchal	5.03	16.25	0.38
Uttaranchal	12.37	10.15	1.87	West Bengal	10.26	13.1	1.46
West Bengal	9.66	5.28	0.87				
Total	11.1	10.75	1.84	Total	10.41	10	1.21

Source: Author's Calculations based on IHDS 1 and IHDS 2.

Table 80: Different Types Of Monthly Health Expenditure Per Capita

Table 80: Different types of monthly health expenditure per capita (RS), 2012									
	Rural					**Urban**			
States	**Doctor Fees**	**Medicine cost**	**Travel cost**	**Insurance Reimbursement**	**States**	**Doctor Fees**	**Medicine cost**	**Travel cost**	**Insurance Reimbursement**
Andhra Pradesh	394.21	130.78	43.32	30.04	Andhra Pradesh	529.29	204.05	35.96	53.67
Arunachal Prade	192.35	94.13	3.39	0	Arunachal Prade	621.81	112.99	9.8	0
Assam	64.92	63.69	19.93	2.78	Assam	120.8	133.4	31.23	0
Bihar	195.55	125.24	15.67	2.71	Bihar	208.28	119.97	16.91	0.02
Chhattisgarh	138.86	66.07	12.33	3.37	Chandigarh	876.47	121.48	64.58	23.53
Dadra Nagar Ha	343.19	53.14	33.14	0	Chhattisgarh	207.17	184.39	15.14	18.12
Daman & Diu	456.09	37.27	28.36	0	Dadra Nagar Ha	30	286.43	77.89	0
Delhi	324.85	438.39	35.31	0	Delhi	534.14	87.89	21.25	4.89
Goa	290.28	113.63	15.49	10.05	Goa	39.3	148	2.36	0
Gujarat	210.2	34.13	17.26	5.09	Gujarat	438.77	115.27	29.29	12.44
Haryana	290.9	73.48	20.37	0.59	Haryana	426.01	145.31	24.09	22.98
Himachal Prades	199.49	220.31	35.7	15.79	Himachal Prades	218.05	235.92	28.93	41.08
Jammu & Kashn	241.98	195.4	30.76	0	Jammu & Kashn	355.24	318.56	32.24	11.34
Jharkhand	101.88	59.25	11.01	0.14	Jharkhand	183.43	111.31	22.09	1.08
Karnataka	355.92	89.14	30.71	23.04	Karnataka	363.67	96.52	19.69	14.73
Kerala	918.74	189.5	54.95	91.56	Kerala	469.84	115.01	22.2	31.56
Madhya Pradesh	206.65	120.68	19.88	1.45	Madhya Pradesh	173.13	131.39	8.88	2.56
Maharashtra	191.5	66.87	12.08	2.94	Maharashtra	208.74	47.17	6.39	0.84
Manipur	593.42	90.52	10.18	0	Manipur	68.35	102.22	3.29	0
Meghalaya	2.22	15.27	1.17	1.05	Meghalaya	15.67	55.72	1.19	0
Mizoram	0	0	0	0	Mizoram	6.72	5.91	0.81	0
Nagaland	52.5	47.75	4	0	Nagaland	0	0	0	0
Orissa	68.2	55.68	12.7	0.73	Orissa	335.36	83.32	13.16	4.51
Pondicherry	70.81	7.61	20.46	0	Pondicherry	1192.81	0	31.26	0
Punjab	423.34	109.37	22.19	1.01	Punjab	392.91	93.54	14.81	4.46
Rajasthan	159.43	103.5	17.93	1.85	Rajasthan	111.04	95.23	9.93	6.93
Sikkim	37.99	194.48	11.89	0	Sikkim	73.86	117.93	13.48	0
Tamil Nadu	629.45	96.98	42.57	4	Tamil Nadu	359.85	102.6	25.07	12.62
Tripura	107.99	55.73	17.08	0	Tripura	26.88	54.43	8.56	0
Uttar Pradesh	242.64	62.37	15.65	1.65	Uttar Pradesh	336.96	70.2	19.57	7.88
Uttaranchal	100.46	72.81	11.59	0	Uttaranchal	320.79	155.21	20.83	0
West Bengal	113.03	39.49	9.53	0.9	West Bengal	134.52	135.98	7.61	8.2
Total	251.07	92.24	21.16	7.72	Total	303.33	115.16	18.29	11.47

Source: Author's Calculations based on IHDS 1 and IHDS 2 data

6.3.4: Different Types Of Monthly Health Expenditure Per Capita:

Tables 79 and 80 summarise the different monthly per capita health expenditure types. States that paid higher doctor fees in IHDS 1 for rural were Tripura, Tamil Nadu, and Daman. The highest amount paid for medicines in rural areas was by the states of Kerala and Andhra Pradesh, and the lowest was Rs 0.20 in Arunachal Pradesh. Kerala had the highest travel cost of Rs 5, and the lowest was Rs 0.04 for Arunachal Pradesh (Table 79). In urban areas, Karnataka, Tamil Nadu, Chhattisgarh, and Haryana incurred the highest expenditure on doctor fees. The medicine cost was highest for Tripura, Manipur, and Bihar. Meghalaya, Tripura, and Orissa incurred the highest travel costs. The cost of Doctor Fees and that incurred on medicine were almost the same for both rural and urban.

The states that paid the highest doctor fees were Kerala, Tamil Nadu, Manipur, and Punjab (Table 80). Daman and Diu incurred the highest expenditure on doctor fees as a union territory in rural areas. Delhi had the highest cost of medicine and the highest travel cost was in Kerala. In the urban areas, Pondicherry paid high doctor fees of Rs 1193, followed by Arunachal Pradesh and Andhra Pradesh. Chandigarh paid the highest doctor fees as a union territory. The cost of medicine was highest in Jammu and Kashmir, Andhra Pradesh, Himachal Pradesh, and Dadra Nagar and Haveli. The travel cost was highest in Andhra Pradesh, Dadra Nagar, Haveli, and Chandigarh.

The insurance reimbursement received was highest in Kerala, Andhra Pradesh, Karnataka in rural areas, Andhra Pradesh, Himachal Pradesh, and Kerala in urban areas. The national rural average was Rs 251, Rs 92, Rs 21 and 8, respectively, for doctor fees, medicine, travel, and insurance reimbursement. The urban average was Rs 303, Rs 115, Rs 18 and Rs 11 for doctor fees, medicine, travel, and insurance reimbursement. In IHDS 2, doctor fees were higher than the cost of medicine for both rural and urban.

6.3.5: Health Expenditure And OOPHE:

Tables 81 and 82 summarise the percentage of different types of expenditure in OOPHE. The national rural average for doctor fees, medicine, and travel costs was 48.07%,44.92% and 7.01%, respectively (Table 81). The urban average was 47.41%, 45.30% and 7.30% for doctor fees, medicine, and travel costs, respectively, in IHDS 1. In IHDS 2, the percentage changed to 65.02%, 29.43% and 5.56% for rural areas for doctor fees, medicine, and travel costs, respectively. In urban areas, this proportion was 65.67%, 28.83% and 5.50% for doctor fees, medicine, and travel costs, respectively.

The difference in the percentage of health expenditures in OOPHE between rural and urban in IHDS 1 was almost the same (Table 82). In IHDS 2, the rural-urban differentials were also negligible. The highest percentage of OOPHE was doctor fees, followed by medicine costs. OOPHE on travel cost was the least.

Table 81: Proportion of different types of expenditure to OOPHE, 2005

Table 81: Proportion of different types of expenditure to OOPHE, 2005

Rural						Urban					
States	Observations	Doctor fees	Cost of medicine	Cost of travel	Total	States	Observations	Doctor fees	Cost of medicine	Cost of travel	Total
Andhra Pradesh	4379	31.58	60.96	7.46	100	Andhra Pradesh	2088	31.58	60.96	7.46	100
Arunachal Pradesh	401	91.41	7.04	1.55	100	Arunachal Pradesh	102	91.41	7.04	1.55	100
Assam	1681	52.80	37.17	10.03	100	Assam	736	52.80	37.17	10.03	100
Bihar	4351	27.19	67.77	5.04	100	Bihar	1848	27.19	67.77	5.04	100
Chhatishgarh	3767	73.74	20.32	5.93	100	Chandigarh	204	45.23	43.57	11.21	100
Dadra+Nagar Haveli	208	40.69	54.84	4.48	100	Chhatishgarh	942	73.74	20.32	5.93	100
Daman & Diu	218	82.95	13.45	3.60	100	Delhi	1744	53.50	38.71	7.79	100
Delhi	202	53.50	38.71	7.79	100	Goa	268	16.32	77.05	6.64	100
Goa	398	16.32	77.05	6.64	100	Gujarat	2362	40.99	50.05	8.96	100
Gujarat	4342	40.99	50.05	8.96	100	Haryana	734	78.57	16.78	4.66	100
Haryana	6338	78.57	16.78	4.66	100	Himachal Pradesh	962	23.50	67.55	8.95	100
Himachal Pradesh	4206	23.50	67.55	8.95	100	Jammu & Kashmir	1185	25.45	66.44	8.11	100
Jammu & Kashmir	2026	25.45	66.44	8.11	100	Jharkhand	1169	67.07	30.08	2.85	100
Jharkhand	2023	67.07	30.08	2.85	100	Karnataka	2895	64.62	28.34	7.04	100
Karnataka	9912	64.62	28.34	7.04	100	Kerala	2031	31.28	59.68	9.04	100
Kerala	3302	31.28	59.68	9.04	100	Madhya Pradesh	2319	56.29	37.84	5.87	100
Madhya Pradesh	9132	56.29	37.84	5.87	100	Maharashtra	4139	53.41	36.55	10.04	100
Maharashtra	8669	53.41	36.55	10.04	100	Manipur	203	15.64	81.69	2.66	100
Manipur	198	15.64	81.69	2.66	100	Meghalaya	134	14.64	76.11	9.25	100
Meghalaya	409	14.64	76.11	9.25	100	Mizoram	93	0.00	86.57	13.44	100
Mizoram	176	0.00	86.57	13.44	100	Nagaland	1	17.90	62.55	19.55	100
Nagaland	218	17.90	62.55	19.55	100	Orissa	1914	9.96	81.49	8.55	100
Orissa	5993	9.96	81.49	8.55	100	Pondicherry	153	64.18	24.60	11.22	100
Pondicherry	197	64.18	24.60	11.22	100	Punjab	1838	61.33	31.23	7.45	100
Punjab	4833	61.33	31.23	7.45	100	Rajasthan	3344	30.40	63.85	5.75	100
Rajasthan	7216	30.40	63.85	5.75	100	Sikkim	123	95.31	3.24	1.46	100
Sikkim	213	95.31	3.24	1.46	100	Tamil Nadu	3218	75.26	15.10	9.64	100
Tamil Nadu	2752	75.26	15.10	9.64	100	Tripura	152	54.34	34.00	11.66	100
Tripura	357	54.34	34.00	11.66	100	Uttar Pradesh	4341	47.60	46.83	5.58	100
Uttar Pradesh	11527	47.60	46.83	5.58	100	Uttaranchal	497	43.82	50.00	6.18	100
Uttaranchal	1320	43.82	50.00	6.18	100	West Bengal	3463	50.62	43.66	5.72	100
West Bengal	4822	50.62	43.66	5.72	100	Total	45202	47.41	45.30	7.30	100
Total	105786	48.07	44.92	7.01	100						

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Table 82: **Proportion of different types of expenditure to OOPHE, 2012**

Table 82: Proportion of different types of expenditure to OOPHE, 2012											
		Rural						Urban			
States	**Observations**	**Doctor fees**	**Cost of medicine**	**Cost of travel**	**Total**	**States**	**Observations**	**Doctor fees**	**Cost of medicine**	**Cost of travel**	**Total**
Andhra Pradesh	4313	67.10	25.70	7.20	100	Andhra Pradesh	2154	67.10	25.70	7.20	100
Arunachal Pradesh	401	69.53	27.90	2.57	100	Arunachal Pradesh	102	69.53	27.90	2.57	100
Assam	1599	50.70	43.12	6.18	100	Assam	818	50.70	43.12	6.18	100
Bihar	4241	58.16	37.48	4.37	100	Bihar	1958	58.16	37.48	4.37	100
Chhatishgarh	3582	59.80	36.58	3.62	100	Chandigarh	204	82.40	12.07	5.53	100
Dadra+Nagar Haveli	168	61.68	27.17	11.14	100	Chhatishgarh	1127	59.80	36.58	3.62	100
Daman & Diu	218	86.12	8.57	5.32	100	Daman & Diu	40	61.68	27.17	11.14	100
Delhi	48	77.19	19.01	3.80	100	Delhi	1898	77.19	19.01	3.80	100
Goa	398	60.05	35.87	4.08	100	Goa	268	60.05	35.87	4.08	100
Gujarat	4304	73.32	20.16	6.52	100	Gujarat	2400	73.32	20.16	6.52	100
Haryana	6071	73.15	21.53	5.32	100	Haryana	1001	73.15	21.53	5.32	100
Himachal Pradesh	4110	40.56	51.56	7.88	100	Himachal Pradesh	1058	40.56	51.56	7.88	100
Jammu & Kashmir	1956	48.14	45.78	6.08	100	Jammu & Kashmir	1255	48.14	45.78	6.08	100
Jharkhand	1942	57.20	35.91	6.89	100	Jharkhand	1250	57.20	35.91	6.89	100
Karnataka	9741	72.76	20.69	6.54	100	Karnataka	3066	72.76	20.69	6.54	100
Kerala	2378	74.88	18.81	6.31	100	Kerala	2955	74.88	18.81	6.31	100
Madhya Pradesh	9132	61.31	33.69	4.99	100	Madhya Pradesh	2319	61.31	33.69	4.99	100
Maharashtra	8592	70.84	23.71	5.45	100	Maharashtra	4216	70.84	23.71	5.45	100
Manipur	198	75.97	22.49	1.54	100	Manipur	203	75.97	22.49	1.54	100
Meghalaya	409	38.02	54.44	7.54	100	Meghalaya	134	38.02	54.44	7.54	100
Mizoram	176	50.00	44.00	6.00	100	Mizoram	93	50.00	44.00	6.00	100
Nagaland	200	51.06	37.68	11.27	100	Nagaland	19	51.06	37.68	11.27	100
Orissa	5908	59.56	33.52	6.92	100	Orissa	1999	59.56	33.52	6.92	100
Pondicherry	197	94.88	0.72	4.40	100	Pondicherry	153	94.88	0.72	4.40	100
Punjab	4764	77.52	19.16	3.32	100	Punjab	1907	77.52	19.16	3.32	100
Rajasthan	7185	50.70	43.09	6.21	100	Rajasthan	3375	50.70	43.09	6.21	100
Sikkim	56	33.17	60.10	6.74	100	Sikkim	280	33.17	60.10	6.74	100
Tamil Nadu	2751	76.17	17.57	6.26	100	Tamil Nadu	3219	76.17	17.57	6.26	100
Tripura	357	49.02	43.23	7.75	100	Tripura	152	49.02	43.23	7.75	100
Uttar Pradesh	11282	76.88	18.97	4.16	100	Uttar Pradesh	4586	76.88	18.97	4.16	100
Uttaranchal	1124	47.08	47.18	5.75	100	Uttaranchal	693	47.08	47.18	5.75	100
West Bengal	4481	54.46	41.40	4.14	100	West Bengal	3804	54.46	41.40	4.14	100
Total	102282	65.02	29.43	5.56	100	Total	48706	65.67	28.83	5.50	100

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

6.3.6: Catastrophic OOPHE with a Threshold Level of 40% of Household Capacity To Pay And Threshold Level of 10% of Household Non-Food Expenditure.

Tables 83 and 84 summarise catastrophic OOPHE at 40% and 10% threshold levels. Table 88 expresses catastrophic health expenditure with a 40% threshold as households' capacity to pay. Bihar had the highest catastrophic expenditure at 31% in rural areas in IHDS 1, and Tripura was the highest at 18% in urban areas (Table 83). In IHDS 2, Sikkim had the highest catastrophic expenditure in rural areas at 29%, and in urban areas, it was Goa at 15%. The national average for rural areas was 14%, and for urban areas, it was 8% in IHDS 1. In IHDS 2, the rural area's catastrophic expenditure was 13%, and in urban areas, it was 8%, using the methodology given by Xu et al. (2003).

Using a 10% threshold of households' non-food expenditure, in IHDS 1, the states that incurred the highest catastrophic health expenditure were Andhra Pradesh, Bihar at 71% in rural areas and Andhra Pradesh in urban areas at 53%(Table 84). The rural catastrophic expenditure was 51%, and the urban was 38% in 2005. In IHDS 2, Uttar Pradesh and Bihar incurred the highest catastrophic expenditure at 73 and 72% in urban areas, and Goa was the highest at 62%. The national average was 52% in rural and 38% in urban areas.

Table 83: **Catastrophic OOPHE With A Threshold Level Of 40% Of Household Capacity To Pay**

2005				2012			
States	**Rural**	**States**	**Urban**	**States**	**Rural**	**States**	**Urban**
Andhra Pradesh	27	Andhra Pradesh	12	Andhra Pradesh	18	Andhra Pradesh	14
Arunachal Pradesh	6	Arunachal Pradesh	0	Arunachal Pradesh	2	Arunachal Pradesh	2
Assam	18	Assam	10	Assam	7	Assam	3
Bihar	31	Bihar	12	Bihar	22	Bihar	10
Chhattisgarh	13	Chandigarh	2	Chhattisgarh	14	Chandigarh	5
Dadra Nagar Haveli	3	Chhattisgarh	8	Dadra Nagar Haveli	14	Chhattisgarh	8
Daman & Diu	11	Delhi	3	Daman & Diu	5	Dadra Nagar Haveli	0
Delhi	0	Goa	7	Delhi	6	Delhi	5
Goa	2	Gujarat	4	Goa	14	Goa	15
Gujarat	10	Haryana	10	Gujarat	9	Gujarat	8
Haryana	12	Himachal Pradesh	5	Haryana	12	Haryana	8
Himachal Pradesh	12	Jammu & Kashmir	4	Himachal Pradesh	10	Himachal Pradesh	5
Jammu & Kashmir	13	Jharkhand	10	Jammu & Kashmir	11	Jammu & Kashmir	4
Jharkhand	9	Karnataka	8	Jharkhand	16	Jharkhand	8
Karnataka	10	Kerala	13	Karnataka	13	Karnataka	10
Kerala	22	Madhya Pradesh	8	Kerala	13	Kerala	9
Madhya Pradesh	16	Maharashtra	3	Madhya Pradesh	10	Madhya Pradesh	4
Maharashtra	10	Manipur	2	Maharashtra	11	Maharashtra	4
Manipur	17	Meghalaya	0	Manipur	0	Manipur	0

Meghalaya	11	Mizoram	0	Meghalaya	1	Meghalaya	2
Mizoram	4	Nagaland	0	Mizoram	2	Mizoram	4
Nagaland	0	Orissa	10	Nagaland	3	Nagaland	0
Orissa	15	Pondicherry	2	Orissa	9	Orissa	6
Pondicherry	14	Punjab	7	Pondicherry	3	Pondicherry	8
Punjab	6	Rajasthan	10	Punjab	7	Punjab	5
Rajasthan	9	Sikkim	3	Rajasthan	10	Rajasthan	3
Sikkim	1	Tamil Nadu	9	Sikkim	29	Sikkim	3
Tamil Nadu	16	Tripura	18	Tamil Nadu	15	Tamil Nadu	11
Tripura	11	Uttar Pradesh	10	Tripura	10	Tripura	5
Uttar Pradesh	18	Uttaranchal	7	Uttar Pradesh	25	Uttar Pradesh	13
Uttaranchal	19	West Bengal	10	Uttaranchal	10	Uttaranchal	10
West Bengal	16			West Bengal	17	West Bengal	8
Total	14	Total	8	Total	13	Total	8

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

Table 84:**Catastrophic OOPHE With Threshold Level 10% Of Household Non-Food Expenditure**

2005				2012			
States	**Rural**	**States**	**Urban**	**States**	**Rural**	**States**	**Urban**
Andhra Pradesh	71	Andhra Pradesh	53	Andhra Pradesh	65	Andhra Pradesh	52
Arunachal Pradesh	16	Arunachal Pradesh	4	Arunachal Pradesh	24	Arunachal Pradesh	25
Assam	33	Assam	47	Assam	49	Assam	30
Bihar	71	Bihar	51	Bihar	72	Bihar	47
Chhattisgarh	48	Chandigarh	10	Chhattisgarh	48	Chandigarh	27
Dadra Nagar Haveli	13	Chhattisgarh	29	Dadra Nagar Haveli	63	Chhattisgarh	38
Daman & Diu	38	Delhi	29	Daman & Diu	48	Dadra Nagar Haveli	58
Delhi	7	Goa	43	Delhi	31	Delhi	31
Goa	47	Gujarat	25	Goa	68	Goa	62
Gujarat	47	Haryana	35	Gujarat	46	Gujarat	39
Haryana	45	Himachal Pradesh	34	Haryana	49	Haryana	35
Himachal Pradesh	46	Jammu & Kashmir	48	Himachal Pradesh	42	Himachal Pradesh	35
Jammu & Kashmir	56	Jharkhand	37	Jammu & Kashmir	50	Jammu & Kashmir	50
Jharkhand	44	Karnataka	40	Jharkhand	55	Jharkhand	34
Karnataka	46	Kerala	48	Karnataka	45	Karnataka	37
Kerala	64	Madhya Pradesh	46	Kerala	42	Kerala	38
Madhya Pradesh	57	Maharashtra	23	Madhya Pradesh	43	Madhya Pradesh	28
Maharashtra	41	Manipur	27	Maharashtra	51	Maharashtra	27
Manipur	51	Meghalaya	13	Manipur	22	Manipur	14
Meghalaya	44	Mizoram	4	Meghalaya	23	Meghalaya	18
Mizoram	6	Nagaland	0	Mizoram	24	Mizoram	17
Nagaland	10	Orissa	53	Nagaland	40	Nagaland	5
Orissa	57	Pondicherry	31	Orissa	42	Orissa	37
Pondicherry	60	Punjab	34	Pondicherry	13	Pondicherry	19

Punjab	43	Rajasthan	36	Punjab	36	Punjab	29
Rajasthan	45	Sikkim	29	Rajasthan	47	Rajasthan	28
Sikkim	31	Tamil Nadu	37	Sikkim	48	Sikkim	31
Tamil Nadu	49	Tripura	59	Tamil Nadu	61	Tamil Nadu	46
Tripura	54	Uttar Pradesh	40	Tripura	40	Tripura	37
Uttar Pradesh	59	Uttaranchal	36	Uttar Pradesh	73	Uttar Pradesh	54
Uttaranchal	60	West Bengal	38	Uttaranchal	46	Uttaranchal	44
West Bengal	53			West Bengal	64	West Bengal	44
Total	51		38		52		38

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

6.3.7: Household Monthly Consumption Expenditure:

Different types of monthly consumption expenditure per capita: total household consumption expenditure, non-food expenditure and household's capacity to pay (non-subsistence expenditure) are summarised (Table 85). The total household monthly consumption expenditure per capita was Rs 1305, non-food expenditure was Rs 703, and the household's capacity to pay was Rs 745 in rural areas in 2005. In urban areas, the total household monthly consumption expenditure was Rs 1911; the non-food expenditure was Rs 1159, and the capacity to pay was Rs 1215.

In 2012, the total rural household consumption expenditure was Rs 1780, non-food expenditure was Rs 1049, and capacity to pay was Rs 1133. The urban total household consumption expenditure was Rs 2642, non-food expenditure was Rs 1734, and capacity to pay was RS 1849. For both rounds, urban expenditure was higher than rural, and IHDS 2 expenditure was more than IHDS 1.

Table 85: **Household Monthly Consumption Expenditure Per Capita (Rs)**

	2005		2012	
Variables	Rural	Urban	Rural	Urban
Total Household consumption expenditure	1305.031	1911.402	1780.877	2641.866
Household Non-food expenditure	702.566	1159.429	1048.866	1734.03
Household capacity to pay	745.471	1214.877	1133.351	1848.505

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

6.3.8: Health Expenditure And Poverty:

In Table 86, full sample health expenditure and poverty estimates are given. Health expenditure as a proportion of consumption expenditure (OOPHE) is higher for rural than urban in both rounds. The percentage of catastrophic health expenditure for rural areas was 51%. The highest percentage of individuals that incurred catastrophic expenditure in rural IHDS 2 was 11%. The headcount was higher for rural and urban in IHDS 2 than in IHDS 1.

The poverty estimates suggest that the percentage of the population below the poverty line was higher in IHDS 1 and higher for rural. After incurring health expenditure, the poverty percentage increased in IHDS 1 more than in IHDS 2. The net MPG was higher in IHDS 1.

Using Xu et al. (2003) methodology, the proportion of OOPHE to household capacity to pay is higher for rural areas at 17%. The percentage of catastrophic health expenditure was almost the same for rural and urban IHDS 1 and IHDS 2. The percentage of individuals that incurred this expenditure was 2.9%, the highest for rural in IHDS 2. After making health payments, the percentage of impoverished individuals was higher in IHDS 1 and marginally reduced in IHDS 2; rural health expenditure related to impoverishment is still higher.

Table 86: **Health Expenditure And Poverty**

	2005		2012	
Variables	**Rural**	**Urban**	**Rural**	**Urban**
Proportion of health Expenditure to consumption expenditure	8.9	6.8	9.8	7.6
Proportion of health expenditure to consumption expenditure Non-food expenditure	17.8	12.3	17.7	12.7
Catastrophic expenditure threshold 10% (consumption expenditure	28.8	21.6	31.2	23.4
Catastrophic expenditure threshold 10% (Non-food expenditure	51.2	38	51.5	38.4
Headcount 1	5.4	4.3	6.8	5.1
Headcount 2	9.3	7.3	11	8.3
Intensity 1	0.8	0.6	0.1	0.7
Intensity 2	2.2	1.4	2.5	1.6
Mean positive gap 1	14.1	13.1	14.6	13.3

Mean Positive gap 2	22.5	18.7	21.6	18.1
Poor gross	24.4	24.3	21.7	12.9
Poor net	47.7	33.8	27.7	15.9
Gross mean poverty gap	82.21	70.04	39.63	26.57
Net mean poverty gap	122.42	97.15	56.63	36.53
Normalised Gross poverty gap	9.8	6.7	4.6	2.6
Normalised Net poverty gap	14.5	9.3	6.6	3.6
Mean of MPG gross	337.42	288.48	182.69	205.82
Mean of MPG net	256.44	287.06	204.72	230.03
Proportion of OOPHE to CTP	17.4	12.1	17.1	12.3
Out-of-pocket threshold 40%	14.3	8.1	13.4	7.8
Headcount	2.7	1.7	2.9	1.7
Intensity Gap	0.5	0.3	0.5	0.3
Mean positive gap	18.6	16.9	17.5	15.7
Impoverished	7.5	4.9	6.8	3.5

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

6.3.9: State-Wise Intensity And Incidence Of Catastrophic Health Expenditure At Threshold 40 %:

Tables 87 and 88 give state-wise headcount(incidence), overshoot(intensity) and mean positive gap for both rounds using 40% and 10% thresholds. The catastrophic head count was highest for Andhra Pradesh, the overshoot was 1, and the mean-positive gap was highest for Assam in rural areas (Table 93). In the urban areas, the headcount was highest for Tripura, and the mean-positive gap was highest for Manipur in Urban areas in IHDS 1. In IHDS 2, Sikkim had the highest headcount, and Mizoram had a higher mean positive gap in rural areas in IHDS 2. Andhra Pradesh had the highest headcount in 2012 in urban areas, and the mean positive gap was highest for Chhattisgarh and Pondicherry. These were calculations at the 40% threshold.

Table 87:**Intensity And Incidence Of Catastrophic Health Expenditure, Threshold 40 %**

Rural 2005				Urban 2005				Rural 2012				Urban 2012		
States	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**States**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**States**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**
Andhra Pradesh	6	1	19	Andhra Pradesh	3	0	16	Andhra Pradesh	5	1	19	4	1	17
Arunachal Pradesh	1	0	8	Arunachal Pradesh	0	0	.	Arunachal Pradesh	0	0	13	1	0	4
Assam	3	1	25	Assam	2	0	17	Assam	1	0	20	1	0	9
Bihar	5	1	23	Bihar	2	0	20	Bihar	4	1	19	2	0	17
Chhattisgarh	3	0	18	Chandigarh	0	0	4	Chhattisgarh	3	1	18	1	0	22
Dadra Nagar Haveli	1	0	44	Chhattisgarh	2	0	14	Dadra Nagar Have	2	1	22	2	0	14
Daman & Diu	2	0	19	Delhi	0	0	7	Daman & Diu	1	0	19	0	0	.
Delhi	0	0	.	Goa	1	0	13	Delhi	2	0	7	1	0	16
Goa	1	0	9	Gujarat	1	0	18	Goa	3	1	17	3	1	19
Gujarat	2	0	17	Haryana	2	0	11	Gujarat	2	0	17	2	0	17
Haryana	2	0	19	Himachal Pradesh	1	0	13	Haryana	2	0	20	2	0	17
Himachal Pradesh	2	0	17	Jammu & Kashmir	1	0	14	Himachal Pradesh	2	0	17	1	0	11
Jammu & Kashmir	2	0	19	Jharkhand	2	0	17	Jammu & Kashmir 1956	2	0	16	1	0	15
Jharkhand	2	0	20	Karnataka	2	0	15	Jharkhand	3	0	14	1	0	17
Karnataka	2	0	18	Kerala	3	0.01	18	Karnataka	3	1	18	2	0	15
Kerala	5	1	18	Madhya Pradesh	2	0	17	Kerala	3	1	20	2	0	17
Madhya Pradesh	3	0	17	Maharashtra	1	0	12	Madhya Pradesh	2	0	15	1	0	16
Maharashtra	2	0	18	Manipur	0	0	49	Maharashtra	0.03	0	18	1	0	0.16
Manipur	3	0	12	Meghalaya	0	0	.	Manipur	0	0	.	0	0	.
Meghalaya	3	0	12	Mizoram	0	0	.	Meghalaya	0	0	4	1	0	17

Mizoram	1	0	22	Nagaland	0	0	.	Mizoram	1	0	24	1	0	16
Nagaland	0	0	14	Orissa	2	0	17	Nagaland	1	0	20	0	0	.
Orissa	3	1	17	Pondicherry	0	0	24	Orissa	1	0	16	1	0	15
Pondicherry	2	0	17	Punjab	1	0	16	Pondicherry	1	0	18	2	1	36
Punjab	1	0	20	Rajasthan	2	0	16	Punjab	2	0	16	1	0	16
Rajasthan	1	0	18	Sikkim	1	0	1	Rajasthan	2	0	15	1	0	16
Sikkim	0	0	2	Tamil Nadu	2	0	17	Sikkim	8	0	5	0	0	21
Tamil Nadu	4	1	21	Tripura	4	0.01	17	Tamil Nadu	5	1	20	0.03	1	19
Tripura	3	1	19	Uttar Pradesh	1	0	19	Tripura	3	0	12	2	0	8
Uttar Pradesh	3	1	18	Uttaranchal	1	0	34	Uttar Pradesh	5	1	17	2	0	13
Uttaranchal	3	1	17	West Bengal	2	0	18	Uttaranchal	2	0	15	2	0	14
West Bengal	3	1	18	Total	2	0	17	West Bengal	4	1	18	2	0	13
Total	3	1	19					Total	3	1	18	2	0	16

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

Table 88: **Intensity And Incidence Of Catastrophic Health Expenditure, Threshold 10 %**

Rural 2005				Urban 2005				Rural 2012				Urban 2012		
States	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**States**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**States**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**	**Catastrophic payment Headcount**	**Overshoot**	**Mean positive gap**
Andhra Pradesh	16	4	27	Andhra Pradesh	12	2	19	Andhra Pradesh	17	4	12	13	3	21
Arunachal Pradesh	3	1	22	Arunachal Pradesh	1	0	15	Arunachal Pradesh	6	1	10	8	1	11
Assam	6	2	38	Assam	10	2	21	Assam	11	2	15	7	1	14
Bihar	11	4	31	Bihar	8	2	20	Bihar	14	3	24	9	2	19
Chhattisgarh	9	2	21	Chandigarh	3	0	8	Chhattisgarh	10	2	23	6	1	18
Dadra Nagar Haveli	3	1	29	Chhattisgarh	5	1	21	Dadra Nagar Have	10	2	18	8	1	17
Daman & Diu	7	2	27	Delhi	6	1	11	Daman & Diu	10	2	14	13	2	12
Delhi	3	0	6	Goa	9	1	15	Delhi	5	1	15	6	1	16
Goa	10	1	13	Gujarat	5	1	16	Goa	17	3	20	15	3	22
Gujarat	9	2	18	Haryana	6	1	21	Gujarat	10	2	19	9	2	19
Haryana	7	2	23	Himachal Pradesh	7	1	14	Haryana	9	2	21	7	1	20
Himachal Pradesh	9	2	21	Jammu & Kashmir	8	1	15	Himachal Pradesh	10	2	20	9	1	16
Jammu & Kashmir	9	2	21	Jharkhand	7	2	21	Jammu & Kashmir	8	2	20	8	1	15
Jharkhand	7	1	19	Karnataka	8	1	17	Jharkhand	11	2	22	7	1	18
Karnataka	9	2	20	Kerala	9	2	22	Karnataka	10	2	23	8	2	20
Kerala	14	4	25	Madhya Pradesh	8	1	18	Kerala	11	3	24	9	2	20
Madhya Pradesh	10	2	22	Maharashtra	4	1	15	Madhya Pradesh	9	2	20	6	1	16
Maharashtra	8	2	20	Manipur	6	1	15	Maharashtra	11	2	20	6	1	15
Manipur	9	2	24	Meghalaya	2	0	15	Manipur	4	0	11	2	0	8
Meghalaya	9	2	20	Mizoram	1	0	18	Meghalaya	4	0	10	4	1	22
Mizoram	2	1	33	Nagaland	0	0	.	Mizoram	7	1	11	4	0.01	18
Nagaland	2	0	15	Orissa	10	2	18	Nagaland	9	1	14	1	0	15
Orissa	11	2	21	Pondicherry	6	1	12	Orissa	9	2	18	8	1	17
Pondicherry	14	3	22	Punjab	6	1	15	Pondicherry	3	1	15	5	2	37
Punjab	7	1	16	Rajasthan	6	1	20	Punjab	7	1	18	7	1	18
Rajasthan	7	1	18	Sikkim	6	1	12	Rajasthan	9	2	20	5	1	15
Sikkim	7	1	11	Tamil Nadu	9	2	20	Sikkim	11	3	25	6	1	14
Tamil Nadu	12	3	27	Tripura	14	3	22	Tamil Nadu	18	4	21	12	3	20
Tripura	12	2	18	Uttar Pradesh	6	1	21	Tripura	10	2	21	10	2	11
Uttar Pradesh	9	2	24	Uttaranchal	6	1	22	Uttar Pradesh	13	3	25	10	2	20
Uttaranchal	10	3	24	West Bengal	8	2	21	Uttaranchal	9	2	19	9	2	0.18
West Bengal	11	3	23					West Bengal	15	4	22	11	2	17
Total	9	2	22	Total	7	1	19	Total	11	2	22	8	2	18

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

Table 88 uses a 10% threshold for household non-food expenditure. In 2005, the catastrophic headcount in the rural areas was highest for Andhra Pradesh, Assam had the highest mean positive gap, and Kerala, Andhra Pradesh, and Bihar had higher overshoot than other states. Tripura had the highest headcount and the higher mean positive gap in urban areas.

6.4: Main Findings And Discussions:

Some of the features of health expenditure in India, as documented in the literature, are High outpatient expenditure (Johnson & Krishnaswamy,2012), high cost of medicine and diagnostics, Inequalities among rural and urban areas and socioeconomic differentials(Barik & Thorat, 2015). Rural households face a higher probability of catastrophic expenditure (Sahoo & Madheswaran, 2014). Higher regional variation in OOPHE was also observed (Wagstaff & Neelsen, 2020). The households affected due to catastrophic expenditure have reduced access to health insurance(Xu et al., 2003).

Delhi had the highest cost of medicine, and Travel costs were high in Kerala. In the urban areas, Pondicherry paid high doctor fees of Rs 1193, followed by Arunachal Pradesh and Andhra Pradesh. Chandigarh paid the highest doctor fees as a union territory. The cost of medicine was highest in Andhra Pradesh. The travel cost was highest in Andhra Pradesh, Dadra Nagar &Haveli, and Chandigarh. The insurance reimbursement received was highest for Kerala, Andhra Pradesh, and Karnataka in rural areas and Andhra Pradesh, Himachal Pradesh, and Kerala in urban areas.

Bihar, Tripura, Sikkim and Goa Registered the highest catastrophic expenditure under different categories in IHDS 1. In IHDS 2, Bihar, Andhra Pradesh, Uttar Pradesh, and Goa registered higher catastrophic expenditures. In 2005, the rural and urban catastrophic expenditure differentials were negligible. The catastrophic expenditure on health also increased between rounds 1 and 2. In a World Bank study in India in 2002, the OOPHE as a percentage of total health expenditure was 82%(Van Doorslaer et al., 2007). In another study, the -pocket expenditure as a percentage of household consumption expenditure or India was 6%, the catastrophic head count was 25%, and the overshoot was 2.12% in 2004-05(Ghosh, 2011). The incidence of catastrophic expenditure was 13% in 2004 and 13% in 2014, in a study by Mohanty & Dwivedi(2021). Intensity and incidence were higher for rural than urban(Sahoo & Madheswaran, 2014), confirmed by the incidence and intensity calculated above using IHDS panel data.

The health expenditure and calculations using various measurements differ for both rounds of IHDS. The state-wise analysis gives a clear picture of the changes between the two periods. The total health expenditure, expenditure on doctor fees, and medicine have increased in between two time periods.

6.5: Conclusion:

The various measures of health expenditure suggest different ways of impact on household well-being. The increase in such expenditure when households are not financially protected causes hardships. Higher outpatient expenditure, higher rural health expenditure under all categories, and catastrophic and impoverishment effects of health expenditure are evident. With economic development and growth, the catastrophic expenditure may not get eliminated automatically, but consolidated efforts are required to reduce the same. One recommendation from the literature is that the ill effects of health expenditure can be mitigated through health insurance.

In the next chapter,7, the impact of health insurance is discussed using a model that uses the DID approach with continuous treatment.

CHAPTER 7

UNIVERSAL HEALTH COVERAGE AND HEALTH INSURANCE IN INDIA

In the previous Chapter 6, health expenditure is examined and closely linked with health insurance. Chapter 7 is ‘Universal Health Coverage and Health Insurance in India. This chapter exclusively deals with objective 4: To study if Health insurance helped in household consumption smoothing. The role of publicly funded health insurance/ social and private/ voluntary health insurance is examined. This chapter is divided into 5 main sections and several sub-sections. The first section is an introduction, followed by background studies. The materials and methods are in the next section. This section presents the empirical model. Results are presented in section 7.3. This section contains descriptive statistics and DID regression results for continuous and binary treatment. The conclusion follows the discussion in section 7.5 and 7.4.

7.1 Introduction:

According to NITI Ayog (2021), approximately 30% (40 Crore) of individuals have no financial protection for health-related needs. Global evidence on countries sponsoring health expenditure via risk pooling/ sharing mechanisms such as social health insurance has a low share of OOPHE and a higher share if financed from GDP(Wagstaff & Neelsen, 2020). Health financing in India has a large spectrum ranging from revenues based on one hand to sourcing through external funds at the other end (Sahoo & Madheswaran, 2014). India has three types of health insurance schemes tax funded RSBY, mandatory Social health insurance and government insurance schemes and voluntary private health insurance (Bahuguna et al., 2019).

Sustainable development goals (SDG) advocate for providing financial cushioning to mitigate the risk of expenditure on health (Hooda, 2020). SDG Goal Number 3 is about good health and well-being, and one of the specific targets is target 3.8, which aims to achieve universal health coverage (UHC). UHC is about people accessing health care without hardship, including financial hardship like health expenditure.

India has designed systematic strategies for attaining UHC. Two important such strategies were the National Rural Health Mission launched in 2008 (now it is the National Health Mission with the added component of NUHM) for health system strengthening (nhm.gov.in) and Rashtriya Swasth Bima Yojana 2008 (RSBY). In a constant pursuit to achieve SDG 2030, Ayushman Bharat was introduced in 2018 under National Health Policy 2017 in line with universal health coverage. The objective was to provide a health and wellness centre to strengthen existing health infrastructure and Pradhan Mantri Jan Arogya Yojana (PM-JAY) for financial protection. The PMJAY (subsumed RSBY) is the largest in the world. (https://pmjay.gov.in/about/pmjay).

7.1.1: Publicly Funded Health Insurance In India (PFHI):

The PFHI scheme denotes all central and state government schemes(Garg et al., 2020). We used this meaning of PFHI and constructed PFHII(see Chapter 3 for details). India has introduced central PFHI and state PFHI. Besides this, social insurance, ESIS, and CGHS cover outpatient and inpatient treatments.

RSBY was initially for BPL and extended to NREGA workers(Azam, 2018), beedi workers, and street vendors(Palacios et al., 2011). In 2011, it was expanded to seven more unorganised sectors, including rag pickers, rickshaw pullers, taxis, autorickshaw drivers, miners, sanitation workers, and toddy workers (Taneja & Taneja, 2016). Three state governments of AP (Rajiv Aroygyahsree and RSBy in 26 districts), Karnataka and (Kalaignar)Tamil Nadu, implemented through private health insurers. Kerala and Karnataka targeted all vulnerable populations (Garg et al., 2019, 2020; Palacios et al., 2011). The RSBY covered secondary hospitalisation, and the gap for tertiary care was filled by state-funded health insurance(Mukhopadhyay, 2017; Selvaraj & Karan, 2012). Over ten years of RSBY, the NSS survey revealed that the protection received by households through RSBY was much less than a quarter at 12% for urban and 13% for rural populations (NSS, 2017-18).

7.1.2: Growth Health Insurance In India:

As per the IRDA (IRDA Annual Report, 2005), 13 private insurance companies provided services for non-life insurance, and the total growth recorded by them was 15% in 2005; however, there was no information available about the share of health insurance. In 2012, 15 companies were offering non-life insurance, private non-life insurance companies had a growth of 16%, and public non-life insurance had a growth of 20% over the previous year. The total growth was 18%.

In 2022, 21 private insurance companies offered health insurance and recorded a growth of 28% in gross underwritten over the previous year. 5 stand-alone health insurance companies recorded a growth of 28%, and the total private insurance companies' growth was 28%. Four public sector undertakings provided health insurance with 26% growth. Public insurance companies recorded a growth of 26%(IRDA Annual Report, 2022).

Growth in public sector premium was 11%, market share was 45%, private sector growth was 16%, and market share was 30%. For stand-alone health insurers, the growth was 9%, and the market share was 25%. The total growth was 12%(IRDA Annual Report, 2022). In 2013-14, there were 468 types of products offered under health insurance, and in 2021-22, they offered 186 products(more streamlined). In IHDS 1, 1% of the population had health insurance; health expenditure was 1.2% (IRDA Annual Report, 2005).

7.1.3: Background Studies:

The literature has questioned household benefits, specifically regarding protection from OOPHE on health payments. In this line of thought, the empirical evidence has provided divided evidence about health insurance helping households to reduce health expenditure. Health insurance is responsible for increasing household health expenditures as OOPHE, among other factors(Sahoo & Madheswaran, 2014). The households with RSBY benefits witnessed a small decrease in OOPHE on health ((Johnson & Krishnaswamy, 2012). The 71st NSS round on social consumption expenditure observed that a considerable population is yet to be covered by health insurance, and the focus should be on reimbursement (Dwivedi & Pradhan, 2021).

Regional studies were done to evaluate the impact of health insurance. The Arogyashri scheme was launched in Andhra Pradesh in 2007 for beneficiaries from BPL. The scheme's benefits were visible regarding a reduction in inpatient expenditure. The outpatient expenditure was also reduced, but the poverty-reducing effect and catastrophic expenditure were not significant(Fan et al., 2012). Yeshasvini scheme in Karnataka benefited economically more affluent households with reduced OOPHE (Aggarwal, 2010). RSBY was launched in 6 districts of Odisha in 2009. By 2013, of the total BPL families in 30 districts of Odisha, 65% of families were covered. The study observed gendered differentials and suggested strengthening the public health system (Dwivedi & Pradhan, 2017). A study in 3 districts of Chhattisgarh revealed that RSBY leads to a heavy bias towards the private health sector, small nursing homes and complex medical procedures(Dasgupta et al., 2013). Another study in Chattisgarh state using NSS data evaluated PMJAY for examining the changes in access to hospital care and the extent of financial protection received by the households in the event of health expenditure. Publicly funded health insurance did not significantly reduce out-of-pocket and catastrophic health expenditures(Garg et al., 2020). A study in Maharashtra on Rajiv Gandhi Jeevandyee

Yojana focuses on providing tertiary care. The study revealed that among the enrolled families, almost 63% had still incurred OOPHE on health, among which many were BPL families. There was also indirect expenditure involved (Rent & Ghosh, 2015).

A study of beneficiaries in Ahmedabad revealed that beneficiaries were not fully aware of benefits under RSBY(Patel et al., 2013). Substantial regional studies are done(Nandi & Schneider, 2020); Maharashtra (Ghosh, 2014), Delhi (Das & Leino, 2022); Ahmedabad(Patel et al., 2013), Gujarat, Haryana and Uttar Pradesh(Bahuguna et al., 2019)Karnataka (Aggarwal, 2010), Andhra Pradesh (Fan et al., 2012).

There are studies on RSBY using IHDS 1 data that examined the intensity and incidence of catastrophic health expenditure. The study's important findings were that health insurance helped households manage out-of-pocket health expenditures. The probability of catastrophic expenditure and impoverishment is also reduced with health insurance(Sahoo & Madheswaran, 2014). Household and village data from IHDS 2 was used to study the pattern in obtaining an RSBY card. The focus was on the role played by Village Pradhan in facilitating the availability of RSBY cards to households. Those politically connected had better access to RSBY cards (Khan, 2018). Another study used both rounds of IHDS and an HDPI round 1992-93 to study the impact of RSBY(Azam, 2018). Both rounds were used for studying maternal and child health utilisation by comparing public and private health insurance(Gebremedhin et al., 2020). Both rounds of IHDS were also used for examining the extent of coverage and depth of health insurance funded by the government. Government-funded health insurance increased health care utilisation, but OOPHE status remained unchanged(Hooda, 2020). IHDS both rounds were used to study the impact of health insurance on gender differentials in formal education. The study observed that those households that enrolled for RSBY benefited from the enrolment of girls in school in the given household(Ojha, 2022). Using IHDS 1, the study by Barik & Thorat (2015) highlighted the inequities in healthcare access by residence and household socio-economic status. The study further pointed out that caste-based marginalised groups face higher inequities than the rest (Barik & Thorat, 2015). Households were found to be smoothing food expenditures by reducing expenditure on non-food expenditures in the event of medical expenditures and the absence of financial protection(Panikkassery, 2020). Health insurance coverage was a determining factor for catastrophic health expenditure(Ahmad & Aggarwal, 2017).

7.2:Materials And Methods:

Panel data from household and village schedules of IHDS 1 and IHDS 2 is used. We have examined all health insurance schemes prevalent between 2005 and 2012 in India based on the data collected by IHDS.

7.2.1: Methods:

Two main models were executed to examine the impact of health insurance on household well-being.DID with continuous treatment and binary treatment is used. Conventional DID models use treatment as a binary variable indicating whether a group received the treatment. We improve this method by using treatment as a continuous variable, as the health insurance intensity (treatment) takes more than two values. The advantage of continuous treatment (over binary) is that we can see the differential effect of the intensity even among the treated household (see Chapter 3 for details).

Model 1 uses a continuous treatment, where the control variable is all those households with no health insurance, the treatment variable is households with either RSBY or government health insurance, and the treatment variable is those households with both RSBY and government health insurance. This continuous treatment variable is publicly funded health insurance intensity (PFHII). The household monthly consumption expenditure per capita(same as consumption expenditure)(MCEPC), monthly household consumption per capita adjusted for health expenditure(MCEPCHE)(same as adjusted consumption expenditure or household non-health spending), Monthly food expenditure per capita (MFEPC), Monthly non-food expenditure per capita (MNFEPC), households capacity to pay(HHCTP)., and inpatient (MIPEPC) and outpatient expenditure (MOPEPC), are used to examining the impact of health insurance. These expenditures are analysed for households that incurred health and catastrophic health expenditures. The analysis is also done for socio-economic categories of caste and consumption expenditure quintile.

As mentioned in the background literature, plenty of studies have analysed PFHI and social health insurance but rarely research private health insurance. We use private health insurance: Voluntarily purchased health insurance (VPHI) in model 2 with a binary treatment. The control variable is those not having insurance, and the treatment variable is those with only private insurance.

Some of the covariates in studies published earlier that used IHDS data and examined health insurance and health expenditure were types of morbidity and morbidity expenditure from individual modules(Azam, 2018); confidence in government and private hospitals, more developed and less developed villages, Information index(Bhattacharjee & Mohanty, 2022); Khan (2018) used information about members of household having a political connection, members of household participation in public meetings, and village Pradhan characteristics. Debt incurred to cater to medical expenditure was used in the study by Panikkassery (2012). The common covariates used across the studies for health expenditure and health insurance are social groups, adult education, age, age of the head of household, household size, and the share of elderly persons and children. The index is also used as a covariate, like the asset-based wealth index(Pal, 2011) and information index (Bhattacharjee & Mohanty, 2022).

We examined the impact of health insurance (PFHII and VPHI) on different types of household expenditure and for those households that had incurred health expenditure and catastrophic health expenditure at 10% and 40% threshold levels. The household's economic status is measured using assets owned by households. The health status is reflected in inpatient (MIPEPC), outpatient health expenditure (MOPEPC), and Village development comprised of variables developed village, which measures the village development as more developed or less developed and membership to various organisations, VHII. The social outcomes are reflected as conflicts in villages, caste, family size, the proportion of children and the number of married females, highest adult education. Implementing the project at the village level and confidence in the government covers political and bureaucratic intentions. In short, health status affects the household's economic status. The health status of the household, in turn, is affected by the developed village, social outcomes and political and bureaucratic intentions (see Chapter 3 for details).

7.3 Results:

The results of PFHII with continuous treatment are presented first, followed by the results of VPHI with binary treatment.

7.3.1: Descriptive Statistics:

The t-test is used to study the mean difference between the treated and non-treated households(Table 89). The Null hypothesis was that there is no significant difference between treated and non-treated households about the variable of concern, as given in Table 1. There are three groups in Table 1: Group 1 without health insurance as no treatment group or control group, Group 2 with any one type of health insurance or treatment type 1 and Group 3 with two types of health insurance or treatment type 3 with subcategories of household with health expenditure and catastrophic health expenditure. The mean difference in all variables for households with and without health expenditure for the control group is statistically significant.

For the group with treatment type 1, only MCEPCHE and developed village, the mean difference was not statistically significant, and the remaining variable had a statistically significant mean difference. For the group with treatment type 3, village health infrastructure index, implementation of public projects, membership to various organisations, family size, and highest adult education had a statistically insignificant mean difference.

Table 89: **Descriptive Statistics**

Table 89:Descriptive statistics																					
	Households without health insurance							**Households with GFHI or RSBY**							**Households with GFHI & RSBY**						
Variables	**Households without health expenditure**			**Households with health expenditure**				**Households without health expenditure**			**Households with health expenditure**				**Households without health expenditure**			**Households with health expenditure**			
	Observatior	**Mean**	**SD**	**bservatior**	**Mean**	**SD**	**Mean difference**	**bservatior**	**Mean**	**SD**	**bservatior**	**Mean**	**SD**	**Mean differenc e**	**bservatior**	**Mean**	**SD**	**bservatior**	**Mean**	**SD**	**Mean difference**
MCEPC	11,985	1338.01	1695.65	35,737	1653.85	1711.14	**-315.84*** **	691	1840.05	1968.91	2,793	2145.33	2615.51	**-305.28*** **	267	1736.72	2396.2	1,280	1694.06	1755.56	42.66
MCEPCHE	12,002	1336.11	1695.2	35,737	1409.63	1418.23	**-73.52*** **	691	1840.05	1968.91	2,793	1828.62	2456.49	11.43	267	1736.72	2396.2	1,280	1427.68	1581.72	**309.04** **
Developed Village $	12,002	0.17	0.38	35,737	0.22	0.41	**-0.05*** **	691	0.45	0.5	2,793	0.49	0.5	**-0.04** **	267	0.46	0.5	1,280	0.39	0.49	**0.068** **
Village Health Infrastructure Index I#	12,002	0.22	3.03	35,737	-0.01	2.79	**0.23*** **	691	0.3	3.25	2,793	0.3	2.7	0.01	267	0.24	3.57	1,280	0.28	3.44	-0.05
Implementation of public projects #	12,002	14.2	4.92	35,737	14.38	4.62	**-0.18*** **	691	15.22	4.38	2,793	14.9	4.34	**0.32* **	267	14.9	4.12	1,280	14.83	3.75	0.08
Presence of conflicts $	12,002	5.07	1.14	35,737	4.91	1.17	**1.17*** **	691	5.04	1.19	2,793	4.74	1.2	**0.30*** **	267	5.17	1.06	1,280	4.77	1.26	**0.40*** **
Membership to various organisations	12,002	1.82	1.52	35,737	1.85	1.68	**-0.04** **	691	2.26	1.96	2,793	2.62	2.53	**-0.37*** **	267	2.1	1.88	1,280	1.91	1.77	0.19
Proportion of children $	12,002	0.26	0.23	35,737	0.29	0.22	**-0.03*** **	691	0.21	0.21	2,793	0.25	0.22	**-0.04*** **	267	0.22	0.22	1,280	0.29	0.23	**-0.06*** **
Family size $	12,002	5.09	2.57	35,737	5.69	2.98	**-0.59*** **	691	4.63	2.32	2,793	5.03	2.64	**-0.40*** **	267	4.49	2.07	1,280	5.38	2.45	-0.88
Number of married females in the hou	12,002	1.22	0.74	35,737	1.38	0.84	**-0.16*** **	691	1.16	0.7	2,793	1.27	0.76	**-0.11*** **	267	1.13	0.65	1,280	1.31	0.71	**-0.18*** **
Highest adult education $	11,985	6.34	4.92	35,706	6.83	4.91	**-0.49*** **	691	7.85	4.93	2,793	6.9	5.19	**0.95*** **	267	7.08	4.97	1,280	6.58	4.98	0.5
Household Ownership of Assets $	11,996	10.44	5.5	35,735	11.2	5.61	**-0.76*** **	691	13.53	5.7	2,790	12.92	5.26	**0.61** **	266	12.97	5.75	1,280	11.26	10.97	**1.71*** **
Confidence in institutions/ governance	12,002	17.26	4.16	35,737	17.67	3.93	**-0.41*** **	691	18.08	3.85	2,793	18.87	4	**-0.79*** **	267	18.43	3.24	1,280	19	3.47	**-0.56** **

*Note: * p<0.1, ** p<0.05, *** p<0.01*

Source: Author's calculations based on IHDS 1 and IHDS 2

7.3.2: Mean Difference Between MCEPCHE(Control And Treated) Households For Health Expenditure And Catastrophic Health Expenditure:

The mean difference is calculated using a t-test for the mean difference in MCEPCHE for those groups that incurred medical expenses and those that incurred catastrophic expenditures (Table 90). Columns I to III summarise the mean difference for health expenditure and columns IV to VI summarise the mean difference for catastrophic health expenditure. Among those households without health insurance, APL 1 category households, the mean difference was not significant between those that incurred health expenditure and those that did not incur. In treatment type 1, i.e. households with and without health expenditure and those who owned either GFHI or RSBY, the mean difference for the BPL quintile, APL1, APL3, and APL 5 was insignificant. In those households that belonged to the treatment 3 group, no quintile had a significant mean difference between the households that incurred health expenditure and those that did not incur any health expenditure. In those households that incurred catastrophic expenditure and had no health insurance, the mean difference was statistically significant for all quintile groups. In treatment type 1, the mean difference was significant for the BPL quintile, APL2, APL 4 and APL5.

Furthermore, in treatment type 2, the difference was significant only for the APL 5 quintile. For caste groups, the difference was significant for all quintiles in control groups. In treatment type 1, only caste 2 and caste 3 had significant differences; in treatment type 2, none of the caste group's differences were significant—the next category for those households that incurred catastrophic expenditure. In the control group, except for caste 4(scheduled tribe), the mean difference for all groups was significant. In treatment type 1, all caste categories, the mean difference between those who incurred catastrophic expenditure and those who had not, the mean difference was statistically significant. The mean difference was insignificant in treatment type 2, only in caste 4.

The mean difference for MCEPCHE across quintile for a household that incurred health expenditure for the control group is significant for BPL1, APL1, APL2, APL3, and APL 5; for treatment type 1, the mean difference was statistically significant for BPL1 and APL4; for treatment type 2, the mean difference was significant only for BPL 1. The mean difference was statistically significant in the control group only for caste 4; in treatment 2, this difference was significant for caste 1.

Table 90:**Mean Difference Between MCEPCHE Control And Treated Households For Health Expenditure And Catastrophic Health Expenditure For PFHII**

Categories	Control group: HH without insurance	Treatment type 1: HH with GFHI or RSBY	Treatment type 2: HH with GFHI & RSBY	Control group: HH without insurance	Treatment type 1: HH with GFHI or RSBY	Treatment type 2: HH with GFHI & RSBY
	Mean difference between HH without & with health expenditure	**Mean difference between HH without & with health expenditure**	**Mean difference between HH without & with health expenditure**	**Mean difference between households without and with catastrophic health expenditure**	**Mean difference between households without and with catastrophic health expenditure**	**Mean difference between households without and with catastrophic health expenditure**
Column	**I**	**II**	**III**	**IV**	**V**	**VI**
MCEPC quintile						
BPL	**-28.19664*** **	23.4	16.46	**-40.33*** **	**13.94*** **	11.1
APL1	-3.881	-2.95	-17.18	**-14.81*** **	-6.83	-0.37
APL2	**-10.34*** **	**-31.74*** **	-1.15	**-50.66*** **	**-33.57*** **	1.62
APL3	**-16.28*** **	22.47	-9.26	**-72.21*** **	-25.74	-19.87
APL4	**-49.94*** **	**-69.64** **	-70.84	**-112.97*** **	**46.58** **	17.7
APL5	**195.90* **	146.05	128.68	**212.93*** **	**1385.83*** **	**1083.08** **
MCEPCHE quintile						
BPL	**-15.89*** **	**30.33* **	**41.92** **	**-17.93*** **	21.33	**39.94** **
APL1	**-4.84* **	-1.97	-7.05	**-10.68*** **	-5.13	-2.2
APL2	**-11.27*** **	-13.91	3.42	**-38.62*** **	**-17.21** **	-4.82
APL3	**-20.75*** **	3.27	9.77	**63.13*** **	**-32.37*** **	7.49
APL4	-36.932	**-55.80** **	-23.87	**96.56*** **	**-47.47** **	40.34
APL5	**224.56** **	-35.07	269.42	**435.62*** **	**1376.46*** **	**1132.42** **
Caste by MCEPC						
Caste 1	**-319.20*** **	-204.11	470.74	**-185.96*** **	**609.80** **	**1001.80** **
Caste 2	**-253.89*** **	**-363.17** **	-129.77	**230.74*** **	**347.51** **	**378.53** **
Caste 3	**-236.2*** **	**-302.33** **	-50.77	**-204.76*** **	**299.32*** **	**262.66** **
Caste 4	**-296.67*** **	-213.61	67.14	**-290.29*** **	**448.99*** **	146.3

caste by MCEPCHE						
Caste 1	-36.799	123.25	**824.77****	**210.92*****	**999.65*****	**1375.16*****
caste 2	-2.976	-0.27	146.28	**109.17*****	**754.83*****	**671.73*****
Caste 3	-25.911	-25.07	182.91	**81.43*****	**585.43*****	**517.73*****
Caste 4	**-128.56*****	-22.68	216.86	-44.79	**665.01*****	**311.49***

*Note: * p<0.1, ** p<0.05, *** p<0.01.*

Source: Author's calculations based on IHDS 1 and IHDS 2 data.

7.3.3: DID Regression Results For Various Household Expenditures With Health Expenditure And Catastrophic Health Expenditure:

In Tables 91 and 92, regression results of DID for different types of consumption expenditure are presented. The different types of household expenditure used are monthly consumption per capita (MCEPC), monthly consumption expenditure per capita adjusted for health expenditure (MCEPCHE), monthly food expenditure per capita(MFEPC), Monthly non-food expenditure per capita(MNFEPC) and household capacity to pay(HHCTP). In Table 91, the sub-sample restriction is those households that incurred health expenditure. In Table 92, the sub-sample restriction is those households that incurred catastrophic health expenditure at a 10% threshold for consumption expenditure, adjusted consumption expenditure, food expenditure, non-food expenditure and a 40% threshold for household capacity to pay.

The effects of health insurance on various household expenditures controlled for health expenditure are given the different types of household expenditure, consumption expenditure (non-health spending)on non-health, food expenditure non-food expenditure and household capacity to pay. Those households with more than one health insurance have helped households have increased consumption expenditure, non-health expenditure and non-food expenditure and increased household's capacity to pay. For the households that incurred health expenditure, health insurance significantly and positively impacted consumption, non-health, non-food, and household’s capacity to pay. The developed village, household ownership of assets and membership in various organisations helped to influence consumption expenditure, non-health expenditure, non-food expenditure and capacity to pay positively; Family size, implementation of public projects and proportion of children had a significant negative impact. The presence of conflict in the village negatively and significantly impacted household consumption, non-health, and food expenditure. Health insurance had a negative impact on household food expenditure but was statistically insignificant. Those households residing in more developed villages have more assets, and those households’ members of several organisations have helped the households increase their food expenditure. Those households with the highest adult education, larger family size, the public project implemented in villages, conflicts like overall and *jati* conflicts, and a higher proportion of children influenced the household’s food consumption expenditure significantly and negatively.

Confidence in government, the number of married females in the household and the village health infrastructure index exhibited statistically insignificant and mixed signs.

For those households that incurred catastrophic health expenditure, health insurance influenced food expenditure negatively and significantly(Table 92). The developed village, ownership of assets, and membership in various organisations positively and significantly impacted food expenditure. Family size, highest adult education, implementation of public projects, presence of conflicts in the village and proportion of children and village health infrastructure index negatively influenced households' food expenditure. The number of married females in the household and confidence in the government exhibited a statistically insignificant negative impact on food expenditure.

The consumption expenditure for those households that incurred catastrophic expenditure with a 10% threshold level, the highest adult education, assets owned, and membership helped to increase consumption expenditure, the proportion of children, presence of conflicts, implementation of public projects, and family size worked in the reverse direction.

Household non-health expenditure is positively and significantly influenced by developed villages, the highest adult education, ownership of assets, and membership in various organisations. Family size, implementation of public projects, presence of conflicts, and the proportion of children negatively influenced non-health expenditure.

Confidence in government, the number of married females in the household and the village health infrastructure index exhibited statistically insignificant mixed results.

Table 91: **DID Regression Results For Various Household's Expenditures With Health Expenditure**

Table 92: **DID Regression Results For Various Household's Expenditures With Catastrophic Health Expenditure**

Variables	**MCEPC**	**MCEPCHE**	**MFEPC**	**MNFEPC**	**HHCTP**	**MCEPC**	**MCEPCHE**	**MFEPC**	**MNFEPC**	**HHCTP**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**
Average Treatment effect on treated										
PFHII $	**95.21*** **	**89.17*** **	-9.060	**85.42*** **	**99.50*** **	15.75	11.03	**-19.04*** **	19.67	-57.15
	(29.37)	*(26.40)*	*(6.145)*	*(24.77)*	*(28.80)*	*(39.83)*	*(29.40)*	*(7.219)*	*(26.66)*	*(53.59)*
Controls										
Confidence in institutions/ governance $	3.292	1.546	-0.283	2.178	3.895	2.952	2.227	-0.314	2.621	-10.05
	(3.462)	*(3.070)*	*(0.708)*	*(2.866)*	*(3.377)*	*(4.513)*	*(2.724)*	*(1.005)*	*(2.363)*	*(7.388)*
Developed Village $	**142.6*** **	**154.1*** **	**29.50*** **	**143.6*** **	**125.4*** **	57.12	**123.1*** **	**32.63*** **	**108.1*** **	143.6
	(36.77)	*(31.44)*	*(7.581)*	*(29.28)*	*(36.04)*	*(55.41)*	*(32.38)*	*(10.87)*	*(28.19)*	*(109.2)*
Family size $	**-110.0*** **	**-91.97*** **	**-35.19*** **	**-57.68*** **	**-89.07*** **	**-105.1*** **	**-72.17*** **	**-34.23*** **	**-38.59*** **	**-74.29*** **
	(9.613)	*(8.387)*	*(2.477)*	*(7.239)*	*(9.115)*	*(16.23)*	*(7.665)*	*(3.242)*	*(5.968)*	*(21.18)*
Highest adult education $	-5.217	-3.933	**-3.990*** **	-0.0618	-4.230	**14.39** **	**6.960***	**-3.662*** **	**10.31*** **	**23.64** **
	(5.387)	*(4.791)*	*(0.945)*	*(4.551)*	*(5.314)*	*(6.214)*	*(4.172)*	*(1.376)*	*(3.659)*	*(11.61)*
Household Ownership of Assets $	**78.88*** **	**76.56*** **	**14.50*** **	**62.95*** **	**69.15*** **	**67.39*** **	**60.66*** **	**14.91*** **	**46.86*** **	**61.29*** **
	(5.168)	(4.469)	(1.086)	(4.149)	(5.067)	(7.410)	(4.525)	(1.737)	(3.732)	(15.10)
Implementation of public projects #	**-15.83*** **	**-13.82*** **	**-3.138*** **	**-11.89*** **	**-13.81*** **	**-14.32** **	**-12.26*** **	**-3.463*** **	**-10.26*** **	-9.622
	(3.725)	*(3.070)*	*(0.734)*	*(2.880)*	*(3.669)*	*(5.953)*	*(3.304)*	*(0.957)*	*(2.965)*	*(12.78)*
Membership to various organisations $	**73.29*** **	**71.99*** **	**15.41*** **	**57.25*** **	**67.22*** **	**46.34*** **	**50.59*** **	**11.72*** **	**39.17*** **	35.67
	(12.49)	*(10.88)*	*(2.009)*	*(10.24)*	*(12.32)*	*(17.01)*	*(9.108)*	*(2.861)*	*(8.064)*	*(39.95)*

Number of married females in the household $	28.11	27.11	-3.377	32.80	27.30	-59.88	-9.361	-7.117	-1.335	-200.8
	(34.23)	*(29.85)*	*(6.882)*	*(27.62)*	*(33.40)*	*(46.92)*	*(24.39)*	*(9.488)*	*(20.30)*	*(132.7)*
Presence of conflicts $	**-27.06****	**-25.49****	**-15.56*****	-10.98	-20.00	**-47.24****	**-25.17*****	**-16.85*****	-9.753	**-70.07***
	(13.27)	*(11.68)*	*(2.407)*	*(11.13)*	*(13.07)*	*(18.49)*	*(8.544)*	*(3.320)*	*(7.242)*	*(39.39)*
Proportion of children $	**-1085.5*****	**-899.0*****	**-291.7*****	**-606.2*****	**-937.0*****	**-825.2*****	**-592.4*****	**-270.6*****	**-316.5*****	**-1018.0*****
	(67.83)	(57.96)	(15.62)	(53.01)	(66.06)	(94.69)	(54.20)	(22.62)	(43.78)	(207.3)
Village Health Infrastructure Index #	5.483	5.880	-1.765	7.454	6.700	-7.897	-0.798	**-4.924*****	3.329	-8.108
	(6.428)	*(5.529)*	*(1.346)*	*(5.027)*	*(6.324)*	*(10.48)*	*(5.852)*	*(1.560)*	*(5.503)*	*(23.28)*
year=2012	62.29**	32.07	48.39***	33.30	33.75	-21.30	106.7***	52.10***	99.48***	313.3***
	(29.37)	*(25.56)*	*(6.451)*	*(23.49)*	*(28.59)*	*(39.10)*	*(22.81)*	*(9.053)*	*(18.84)*	*(63.45)*
Constant	1814.2***	1438.8***	923.9***	490.7***	1090.5***	2028.5***	1243.5***	897.4***	334.7***	1777.6***
	(127.9)	*(115.4)*	*(23.27)*	*(110.4)*	*(125.7)*	*(161.6)*	*(96.45)*	*(32.54)*	*(85.15)*	*(279.2)*
Degree of freedom	20843	20843	20843	20843	20843	17192	17416	17416	17416	10824
Cluster	20844	20844	20844	20844	20844	17193	17417	17417	17417	10825
Number of observations	39774	39774	39774	39774	39774	25094	25878	25878	25878	14941

Note: 1. Standard errors in parentheses.

*2) * $p<0.1$, ** $p<0.05$, *** $p<0.01$.*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).

6) ATET estimate adjusted for covariates, panel, and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

7.3.4: DID Regression Results For Outpatient And Inpatient Health Expenditure For Health Expenditure And Catastrophic Health Expenditure:

The DID regression for outpatient(MOPEPC) and inpatient expenditure (MIPEPC) suggests that for the households that incurred health expenditure, health insurance had no statistically significant impact on outpatient and inpatient expenditure. Still, outpatient expenditure decreased, and inpatient expenditure increased (Table 93). The confidence in institutions, household ownership of assets, implementation of public projects, membership to various organisations, number of married females in the household, presence of conflicts and village health infrastructure index were insignificant and had mixed signs. Family size and proportion of children negatively and significantly impact outpatient and inpatient health expenditure across both categories. The developed village significantly negatively influenced outpatient expenditure for those who incurred catastrophic expenditures. The highest adult education was negative and significant for outpatient expenditure for those who incurred health expenditure and negative and significant for those who incurred catastrophic inpatient expenditure.

Table 93:**DID Regression Results For Outpatient And Inpatient Expenditure**

	Health expenditure		**Catastrophic health Expenditure**	
Variables	**MOPEPC**	**MIPEPC**	**MOPEPC**	**MIPEPC**
I	**II**	**III**	**IV**	**V**
Average treatment effect on treated				
PFHII $	-0.825	6.869	-7.594	13.74
	(7.019)	*(8.519)*	*(12.13)*	*(16.22)*
Controls				
Confidence in institutions/ governance $	0.0572	1.689	-0.245	2.381
	(0.783)	*(1.102)*	*(1.506)*	*(2.459)*
Developed Village $	-11.46	-1.142	**-28.78***	-44.43
	(8.895)	(14.99)	(16.98)	(33.39)
Family size $	**-7.190*****	**-10.85*****	**-8.250****	**-23.92****
	(1.764)	(3.499)	(3.626)	(11.32)
Highest adult education $	**-2.760***	1.477	-1.011	**6.207***
	(1.504)	*(1.563)*	*(1.873)*	*(3.205)*
Household Ownership of Assets $	0.0138	2.308	0.923	4.452

	(1.427)	*(1.727)*	*(2.876)*	*(4.154)*
Implementation of public projects #	-1.297	-0.706	0.138	-1.117
	(0.940)	*(1.585)*	*(1.487)*	*(3.816)*
Membership to various organisations $	-0.959	2.251	-4.988	4.039
	(2.931)	*(4.403)*	*(6.341)*	*(9.857)*
Number of married females in the household $	-2.283	3.276	-18.76	-15.98
	(5.908)	*(13.63)*	*(12.32)*	*(30.46)*
Presence of conflicts $	-0.277	-1.291	-6.640	-11.46
	(2.904)	*(4.972)*	*(6.312)*	*(11.58)*
Proportion of children $	**-74.39*** **	**-112.1*** **	**-111.8*** **	**-129.2** **
	(17.17)	*(26.02)*	*(33.79)*	*(56.78)*
Village Health Infrastructure Index #	-0.404	0.00651	-2.467	-5.200
	(1.320)	*(2.920)*	*(2.295)*	*(7.369)*
year=2012	5.438	24.78**	-72.34***	-34.29*
	(8.557)	*(9.752)*	*(17.06)*	*(20.10)*
Constant	238.3***	137.2***	384.9***	324.0***
	(30.66)	*(38.19)*	*(52.47)*	*(83.88)*
Degree of freedom	20843	20843	17416	17416
Cluster	20844	20844	17417	17417
Number of observations	39774	39774	25878	25878

Note: 1. Standard errors in parentheses.

*2) * p<0.1, ** p<0.05, *** p<0.01.*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).

6) ATET estimate adjusted for covariates, panel, and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

The breakup of health expenditure into outpatient and inpatient expenditure is very important since health insurance covers only inpatient expenditure, and some outpatient treatments are not covered under this. Hence such a breakup gives an idea about the impact of health insurance on cushioning health expenditure.

7.3.5: DID Regression Results With MCEPC Quintile With Health Expenditure And Catastrophic Health Expenditure:

The regression results of DID with consumption expenditure quintile are summarised in Tables 94 and 95. The impact of health insurance was statistically insignificant for all quintiles except APL4(Table 94). Health insurance had a statistically significant and negative effect on the households that incurred medical expenditure on APL4. For those households that incurred catastrophic health expenditure at the 10% threshold level, the APL3 quintile had a positive and significant effect on health insurance. All other covariates have given mixed results for households with medical and catastrophic expenditures.

For those that incurred health expenditure, confidence in institutions and government had mixed results, with positive and significant influence on the APL3 quintile and negatively significant influence on the APL 4 quintile. Family size influences BPL and APL5 quintiles significantly and negatively. Household ownership of assets positively and significantly impacted BPL, APL1, 4 and APL 5 quintiles. Membership in various organisations helped BPL households increase their MCEPC despite health expenditures. The number of married females significantly positively impacted the MCEPC of the APL5 quintile. Family size negatively and significantly impacted the BPL and APL5 quintiles. Implementation of public projects influenced APL 2 and 5 quintiles negatively and significantly. The proportion of children negatively and significantly impacted BPL, APL1 and APL5 quintiles.

For those households that incurred catastrophic health expenditure, health insurance had a positive and significant impact on APL 3quintile(Table 95). Among the other covariates, confidence intensity negatively and significantly influenced APL4; developed village significantly and positively influenced MCEPC of APL 2 but negatively influenced APL3. BPL quintile was negatively and significantly influenced by family size. Household ownership of assets had a positive and significant influence on BPL and APL 1 households. Implementation of projects had a negatively significant influence on the BPL quintile. Membership in various organisations positively and significantly influenced the BPL quintile. The number of married females had a negative influence on APL 3quintile. The remaining covariates were not significant and had mixed signs.

Table 94: **DID Results With MCEPC Quintile With Health Expenditure**

Table 95: **DID Results With MCEPC Quintile With Catastrophic Health Expenditure**

Variables	**BPL 1**	**APL1**	**APL2**	**APL3**	**APL4**	**APL5**	**BPL 1**	**APL1**	**APL2**	**APL3**	**APL4**	**APL5**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**I**	**II**	**III**	**IV**	**V**	**VII**
					Average Treatment Effect on Treated							
PFHII $	-3.829	8.489	-16.47	2.035	**-45.85****	560.5	-13.26	19.74	-16.55	**46.29****	-50.25	-21.08
	(7.964)	*(10.78)*	*(10.89)*	*(14.58)*	*(23.16)*	*(363.1)*	*(13.39)*	*(14.27)*	*(16.32)*	*(23.59)*	*(33.63)*	*(606.7)*
Controls												
Confidence in institutions/ governance $	-0.808	-0.365	0.240	**3.905****	**-4.671***	-3.140	-1.520	-0.110	1.264	3.918	**-7.791***	13.20
	(1.028)	*(1.194)*	*(1.090)*	*(1.803)*	*(2.514)*	*(33.95)*	*(1.715)*	*(1.650)*	*(1.685)*	*(2.476)*	*(4.086)*	*(46.14)*
Developed Village $	6.203	0.450	18.16	-29.33	34.32	64.14	-0.0392	16.38	**33.04***	**-65.65****	-33.70	188.2
	(11.33)	*(11.43)*	*(11.35)*	*(18.16)*	*(27.59)*	*(352.4)*	*(19.08)*	*(16.71)*	*(17.65)*	*(30.59)*	*(42.94)*	*(447.9)*
Family size $	**-9.209*****	-0.965	2.010	-4.558	0.517	**-376.0*****	**-11.22****	-4.389	0.610	12.33	-0.255	-194.1
	(3.021)	*(2.734)*	*(2.873)*	*(5.231)*	*(8.953)*	*(108.5)*	*(4.702)*	*(3.705)*	*(4.925)*	*(7.697)*	*(13.11)*	*(119.5)*
Highest adult education $	0.965	-0.558	1.077	0.104	-1.418	50.53	3.018	-0.819	1.515	2.977	-5.457	3.131
	(1.587)	*(1.452)*	*(1.297)*	*(2.094)*	*(3.298)*	*(45.49)*	*(2.506)*	*(2.075)*	*(1.996)*	*(3.384)*	*(5.415)*	*(47.56)*
Household Ownership of Assets $	**8.964*****	**5.042*****	-0.232	3.505	**11.66*****	**127.5*****	**11.03*****	**6.942*****	-3.923	2.839	5.768	71.66
	(1.591)	*(1.775)*	*(1.787)*	*(2.188)*	*(4.025)*	*(49.11)*	*(2.527)*	*(2.615)*	*(3.113)*	*(3.906)*	*(6.628)*	*(64.95)*
Implementation of public projects #	-0.660	-1.501	**-1.851***	-1.684	-1.385	**-78.30****	-1.477	**-3.664*****	-2.283	-0.879	-2.758	-64.75
	(1.012)	*(0.986)*	*(1.056)*	*(1.366)*	*(2.246)*	*(35.36)*	*(1.787)*	*(1.361)*	*(1.582)*	*(2.446)*	*(3.567)*	*(48.73)*
Membership to various organisations $	**9.564*****	1.142	3.051	-2.597	12.31	126.8	**9.106***	-0.764	3.937	-7.788	1.646	-88.49
	(3.155)	*(3.349)*	*(3.658)*	*(4.492)*	*(7.718)*	*(101.7)*	*(5.412)*	*(4.602)*	*(6.112)*	*(6.605)*	*(11.10)*	*(116.8)*

Number of married females $	-7.464	-8.995	-14.37	1.064	-13.42	**722.0****	-20.12	5.457	-16.45	**-56.14****	9.847	327.2
	(8.932)	*(8.607)*	*(11.09)*	*(15.48)*	*(26.63)*	*(333.0)*	*(14.46)*	*(12.85)*	*(16.36)*	*(25.02)*	*(40.01)*	*(396.4)*
Presence of conflicts $	-1.243	0.731	-1.281	-2.924	8.381	59.66	7.544	-1.517	-6.327	-4.250	7.809	-30.66
	(3.264)	*(2.988)*	*(3.578)*	*(4.943)*	*(8.425)*	*(106.8)*	*(5.176)*	*(4.497)*	*(6.292)*	*(8.259)*	*(14.32)*	*(163.0)*
Proportion of children $	**-74.80*****	**-66.39*****	-24.44	9.388	-34.18	**-2389.5*****	-34.16	-46.51	-3.429	-46.93	17.87	252.3
	(24.35)	*(24.24)*	*(26.14)*	*(31.89)*	*(54.88)*	*(669.8)*	*(40.49)*	*(33.74)*	*(41.98)*	*(56.33)*	*(79.76)*	*(699.2)*
Village Health Infrastructure Index #	2.062	-0.180	0.721	-2.443	-2.460	21.39	**5.680****	-0.0236	-0.851	-3.208	-0.199	114.6
	(1.643)	*(1.668)*	*(1.882)*	*(2.616)*	*(3.869)*	*(53.23)*	*(2.842)*	*(2.146)*	*(2.854)*	*(5.112)*	*(6.459)*	*(100.8)*
year=2012	48.35***	44.40***	123.6***	195.1***	310.4***	259.7	32.79**	18.69	113.3***	209.1***	366.7***	178.3
	(8.614)	*(9.740)*	*(12.09)*	*(18.23)*	*(29.10)*	*(354.0)*	*(13.90)*	*(14.40)*	*(19.42)*	*(28.03)*	*(51.12)*	*(455.0)*
Constant	659.1***	930.1***	1165.1***	1368.3***	1781.5***	3379.0***	642.4***	959.1***	1222.2***	1359.3***	1945.8***	4274.2***
	(34.58)	*(33.58)*	*(36.56)*	*(53.24)*	*(78.68)*	*(1264.1)*	*(61.97)*	*(42.94)*	*(64.01)*	*(76.43)*	*(116.0)*	*(1449.4)*
Degree of freedom	7155	4814	4950	4982	5175	4966	4468	3654	3604	3676	3728	3480
Cluster	7156	4815	4951	4983	5176	4967	4469	3655	3605	3677	3729	3481
Number of observations	9922	5858	5762	5861	6115	6256	5488	4188	3973	4066	4165	3998

Note: 1. Standard errors in parentheses.

*2) * p<0.1, ** p<0.05, *** p<0.01.*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).

6) ATET estimate adjusted for covariates, panel and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

7.3.6: DID Regression Results With MCEPC Caste Categories With Health Expenditure And Catastrophic Health Expenditure:

The households with health expenditure and health insurance significantly and positively impacted caste 1(Brahmin and forward category) and caste 2(OBC)(Table 96). For the households that incurred catastrophic health expenditure at the 10% threshold level, health insurance negatively impacted caste 4(ST). For castes 1 and 2, developed villages positively and significantly influenced consumption expenditure for castes 1 and 2. Family size and proportion of children negatively impact consumption expenditure for all caste categories. Household ownership of assets positively and significantly influences consumption expenditure in all caste categories. The implementation of public projects had a negative relationship with consumption expenditure for caste 1. Membership in organisations helped all caste categories to increase consumption expenditure except caste 3. The presence of conflicts worked negatively for caste 3. Village health infrastructure had a positive influence on consumption expenditure for caste 4.

For the households that incurred catastrophic expenditure, health insurance negatively influenced consumption expenditure for caste 4 (Table 97). Household assets increased the consumption expenditure for all caste categories, family size, and proportion of children worked against the consumption. Membership in organisations helped castes 2 and 3 increase consumption expenditure; conflicts reduced consumption expenditure for castes 2 and 3. The highest adult education helped caste 3 to increase its consumption expenditure.

Table 96: **DID Results With MCEPC Caste With Health Expenditure**

Table 97: **DID Results With MCEPC Caste With Catastrophic Expenditure**

Variables	**Caste1**	**Caste2**	**Caste3**	**Caste4**	**Caste1**	**Caste2**	**Caste3**	**Caste4**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
Average Treatment Effect on Treated								
PFHII $	**296.9*** **	**80.79** **	45.09	-37.04	15.35	27.94	-18.99	**-226.2** **
	(109.8)	*(40.31)*	*(35.04)*	*(72.48)*	*(115.8)*	*(51.76)*	*(52.47)*	*(107.2)*
Controls								
Confidence in institutions/ governance $	5.232	-1.623	3.178	-1.154	21.55	-8.288	-0.698	14.77
	(9.014)	*(5.729)*	*(5.424)*	*(6.839)*	*(13.17)*	*(7.512)*	*(6.994)*	*(13.38)*
Developed Village $	**185.8***	**186.0*** **	60.57	154.1	81.94	-6.091	66.94	-127.7
	(97.73)	*(61.38)*	*(51.32)*	*(94.41)*	*(127.8)*	*(97.78)*	*(75.72)*	*(171.3)*
Family size $	**-161.8*** **	**-81.78*** **	**-87.74*** **	**-102.2*** **	**-136.7*** **	**-98.83*** **	**-96.62*** **	**-86.09*** **
	(24.34)	*(15.87)*	*(12.55)*	*(20.85)*	*(30.84)*	*(29.24)*	*(20.29)*	*(32.26)*
Highest adult education $	-10.83	-8.142	7.640	-9.923	7.626	14.64	**19.21** **	-1.295
	(15.71)	*(7.690)*	*(5.913)*	*(13.64)*	*(15.93)*	*(11.17)*	*(8.751)*	*(12.45)*
Household Ownership of Assets $	**113.5*** **	**76.02*** **	**55.34*** **	**46.89*** **	**87.94*** **	**73.24*** **	**50.23*** **	**72.48*** **
	(13.26)	*(8.421)*	*(7.825)*	*(10.25)*	*(16.93)*	*(14.36)*	*(12.13)*	*(17.30)*
Implementation of public projects #	**-29.38*** **	-6.500	-0.222	-8.034	**-23.17***	-14.48	3.165	-9.449
	(9.129)	*(5.887)*	*(5.928)*	*(7.435)*	*(11.99)*	*(10.28)*	*(9.952)*	*(11.28)*
Membership to various organisations $	**110.2*** **	**71.89*** **	33.70	**37.52** **	13.12	**99.49*** **	**54.62***	0.157
	(33.71)	*(19.76)*	*(20.58)*	*(17.59)*	*(35.17)*	*(32.20)*	*(33.15)*	*(25.59)*
Number of married females in the household $	144.2	-50.61	0.134	70.00	58.00	-77.65	-75.55	48.92
	(91.72)	*(62.92)*	*(41.64)*	*(63.21)*	*(102.7)*	*(81.83)*	*(66.51)*	*(93.48)*
Presence of conflicts $	14.54	-26.31	**-47.46*** **	13.48	12.86	**-87.07** **	**-58.47***	39.98
	(31.26)	*(18.42)*	*(18.35)*	*(19.33)*	*(41.13)*	*(34.15)*	*(30.01)*	*(32.27)*

Proportion of children $	**-1516.4*** **	**-1188.4*** **	**-678.0*** **	**-815.8*** **	**-1039.3*** **	**-935.9*** **	**-617.9*** **	**-1033.0*** **
	(177.0)	*(127.5)*	*(96.62)*	*(169.0)*	*(229.4)*	*(193.5)*	*(144.9)*	*(278.7)*
Village Health Infrastructure Index #	5.668	-4.229	-8.509	**35.33** **	15.32	-30.35	**-17.67***	-4.409
	(17.18)	*(12.69)*	*(7.457)*	*(15.70)*	*(24.11)*	*(22.81)*	*(10.45)*	*(22.52)*
year=2012	-56.05	82.33*	24.46	169.7***	-262.8**	63.03	10.97	188.3**
	(88.43)	*(47.13)*	*(40.61)*	*(59.22)*	*(104.8)*	*(63.70)*	*(53.66)*	*(87.64)*
Constant	1795.5***	1771.6***	1567.0***	1483.5***	1810.1***	2257.2***	1734.5***	989.5***
	(312.6)	*(187.0)*	*(202.3)*	*(213.6)*	*(373.5)*	*(277.7)*	*(252.3)*	*(341.9)*
Degree of freedom	6228	9266	5136	2334	4766	7552	4212	1760
Cluster	6229	9267	5137	2335	4767	7553	4213	1761
Number of observations	10388	16266	9429	3691	6411	10869	6306	2292

Note: 1. Standard errors in parentheses.
*2) * p<0.1, ** p<0.05, *** p<0.01.*
3) # Village level data, $ household-level data.
4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.
5). Standard errors clustered at the Village level (PSUHH).
6) ATET estimate adjusted for covariates, panel and time effects.
7)Figures in 'Bold' indicate significant regression coefficients.
Source: Author's calculations based on IHDS 1 and IHDS 2 data.

7.3.7: DID Regression Results For The MCEPCHE Quintile With Health Expenditure And Catastrophic Health Expenditure:

The MCEPCHE (non-health expenditure) results for households that incurred health and catastrophic health expenditures are given in Tables 98 and 99. Health insurance significantly and negatively impacted the below-poverty-line quintile, APL 3 and positively impacted APL 4 and APL 5(Table 98). The results were insignificant for the remaining quintile but had a positive sign for APL1 and a negative for APL2.

The non-health expenditure of households living below the poverty line and above the poverty line quintile 3) had decreased despite having health insurance, and for APL 4 and APL 5 quintiles, having any one or both health insurance helped to increase the non-health spending.

For those households living below the poverty line, family size, presence of conflicts in the village, and proportion of children reduced the non-health spending of the households. Household ownership of assets and membership in various organisations helped the household to increase its non-health spending.

The developed village, the highest adult education, and the implementation of projects have positively moved household non-health spending upward, but it is statistically insignificant the number of married females in the household, village health infrastructure, and confidence in government.

For households in the APL3 quintile, family size negatively significantly decreased the non-health expenditure of the households.

For APL 4 and 5 quintiles, Household's asset ownership helped increase the expenditure. Confidence in the government decreased the expenditure. For APL quintile 5, family size, public project implementation, and children's proportion reduced the non-health spending. Membership in various organisations and the number of married females in the household had a statistically positive impact on expenditure.

Among other covariates, confidence in government institutions, family size, implementation of public projects, conflicts in the village, and the proportion of children in the households had negatively affected the consumption expenditure for some quintiles. The covariates exhibited mixed effects on different quintiles, such as the number of married females negatively influencing consumption expenditure for APL2 but positively impacting APL 5. Assets owned by the households and membership to various organisations positively impacted the non-health expenditure of the households. On the other hand, the status of the village, a developed village, village health infrastructure index, and highest adult education did not drive the non-health expenditure.

For those BPL households that incurred catastrophic expenditure with health insurance, the non-health expenditure decreased(Table 99). However, the APL 1 quintile, who are just above BPL, had increased consumption expenditure despite the households incurring catastrophic expenditure. For the remaining quintile, the impact was insignificant. For the BPL quintile, assets and membership to organisations, they had increased the expenditure statistically. Family size, the number of married females, the presence of conflict, and the proportion of children worked in the inverse direction. For the APL 1 quintile, the proportion of children showed a statistically significant negative relationship with expenditure. For APL 4, a developed village, the number of married females and the proportion of children had a negative impact, and the family size was statistically positively significant; for APL 5 highest adult education was negatively significant.

Table 98: **DID Regression Results For MCEPCHE Quintile With Health Expenditure**

Table 99: **DID Regression Results For MCEPCHE Quintile With Catastrophic Health Expenditure**

Variables	**BPL**	**APL1**	**APL2**	**APL3**	**APL4**	**APL5**	**BPL**	**APL1**	**APL2**	**APL3**	**APL4**	**APL5**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**XII**	**XIII**
Average treatment effect on treated												
PFHII $	**-13.39****	11.14	-14.72	**-41.64*****	**37.90***	**678.3***	**-20.49****	**26.11****	-11.60	-19.98	24.26	-38.07
	(6.361)	*(9.885)*	*(9.584)*	*(14.34)*	*(20.97)*	*(367.7)*	*(9.752)*	*(12.18)*	*(12.98)*	*(24.60)*	*(29.28)*	*(441.0)*
Controls												
Confidence in institutions/ governance $	-0.853	0.967	-0.454	0.338	**-7.232*****	-32.39	-1.893	2.114	0.381	-0.947	-1.640	7.872
	(0.833)	*(1.077)*	*(0.989)*	*(1.709)*	*(2.665)*	*(34.48)*	*(1.264)*	*(1.456)*	*(1.398)*	*(3.238)*	*(5.185)*	*(52.43)*
Developed Village $	7.105	-16.01	-5.209	6.182	-15.32	232.4	10.48	18.04	7.713	-19.08	**-80.41***	370.0
	(8.627)	*(11.59)*	*(10.94)*	*(15.19)*	*(27.82)*	*(363.8)*	*(13.17)*	*(18.38)*	*(15.66)*	*(25.67)*	*(48.36)*	*(366.5)*
Family size $	**-11.34*****	-0.153	**-5.778****	**-14.87*****	-3.615	**-395.3*****	**-14.28*****	1.414	-5.523	**-17.54****	**24.11***	-126.3
	(2.460)	*(3.076)*	*(2.598)*	*(4.373)*	*(8.162)*	*(122.7)*	*(3.514)*	*(5.004)*	*(4.218)*	*(7.349)*	*(14.19)*	*(136.8)*
Highest adult education $	0.0281	-1.515	1.220	1.586	1.255	16.10	0.773	-1.137	-1.413	0.171	-1.934	**-91.48***
	(1.069)	*(1.399)*	*(1.510)*	*(2.067)*	*(3.952)*	*(48.37)*	*(1.590)*	*(1.803)*	*(2.102)*	*(3.881)*	*(6.306)*	*(49.33)*
Household Ownership of Assets $	**10.91*****	**4.220****	**4.196*****	-0.699	**9.026****	**173.8*****	**11.36*****	2.888	2.078	-1.700	9.775	72.10
	(1.209)	*(1.769)*	*(1.527)*	*(1.873)*	*(4.411)*	*(52.76)*	*(1.853)*	*(2.874)*	*(2.714)*	*(2.971)*	*(7.057)*	*(64.87)*
Implementation of public projects #	0.0732	-0.398	-0.962	0.551	-3.888	-57.10*	-1.013	1.220	-0.504	-0.584	-7.972	-41.35
	(0.792)	*(1.103)*	*(0.997)*	*(1.252)*	*(2.641)*	*(30.62)*	*(1.178)*	*(1.718)*	*(1.508)*	*(2.159)*	*(4.933)*	*(47.08)*
Membership to various organisations $	**10.68*****	-1.285	**8.282*****	-5.700	4.250	**225.3****	**9.328****	-4.346	**14.53*****	-4.206	7.995	118.1
	(2.500)	*(3.445)*	*(3.109)*	*(4.590)*	*(7.253)*	*(105.8)*	*(3.771)*	*(5.306)*	*(4.710)*	*(7.892)*	*(9.471)*	*(88.30)*

Number of married females in the household $	-8.563	**-16.13***	5.879	21.12	-0.982	**925.9****	-6.381	-17.10	3.858	18.83	**-75.38***	301.3
	(7.492)	*(9.758)*	*(8.941)*	*(13.16)*	*(25.23)*	*(361.2)*	*(11.55)*	*(14.13)*	*(13.91)*	*(21.86)*	*(44.13)*	*(382.5)*
Presence of conflicts $	**-7.393*****	**-5.774***	1.047	-5.049	-3.063	-15.85	**-6.767***	-3.008	3.321	-10.05	1.148	6.424
	(2.592)	*(3.339)*	*(3.386)*	*(4.770)*	*(9.572)*	*(109.9)*	*(3.678)*	*(5.136)*	*(4.991)*	*(9.374)*	*(15.29)*	*(131.6)*
Proportion of children $	**-109.1*****	**-55.48****	-14.72	-7.380	-34.36	**-2697.4*****	**-116.3*****	**-69.73***	-16.12	-2.476	**-215.5****	16.64
	(18.72)	*(25.60)*	*(22.00)*	*(30.43)*	*(55.56)*	*(691.7)*	*(28.07)*	*(39.52)*	*(30.96)*	*(56.95)*	*(83.97)*	*(711.9)*
Village Health Infrastructure Index #	-0.861	-1.868	0.321	-1.455	1.776	38.89	-1.214	-1.839	-4.045	-7.201	4.550	215.0
	(1.325)	*(1.651)*	*(1.774)*	*(2.617)*	*(4.437)*	*(65.00)*	*(2.129)*	*(3.381)*	*(3.163)*	*(4.458)*	*(6.838)*	*(172.6)*
year=2012	44.20***	30.88***	98.31***	151.3***	277.4***	3.696	51.77***	6.995	107.6***	159.3***	290.4***	744.6**
	(6.647)	*(10.52)*	*(10.49)*	*(13.87)*	*(28.18)*	*(372.5)*	*(9.701)*	*(16.09)*	*(16.40)*	*(22.95)*	*(46.27)*	*(356.3)*
Constant	675.4***	927.8***	1072.7***	1416.8***	1807.4***	2742.0**	708.3***	887.2***	1061.7***	1517.7***	1762.5***	2917.2*
	(26.19)	*(33.69)*	*(34.15)*	*(44.89)*	*(103.7)*	*(1312.4)*	*(40.47)*	*(48.08)*	*(49.04)*	*(82.28)*	*(181.1)*	*(1524.2)*
Degrees of freedom	9342	4524	4514	4430	4452	4218	6788	3497	3254	3194	3022	2483
Cluster	9343	4525	4515	4431	4453	4219	6789	3498	3255	3195	3023	2484
Number of observations	13593	5366	5183	5162	5210	5260	8805	3915	3580	3505	3307	2766

Note: 1. Standard errors in parentheses.

*2) * p<0.1, ** p<0.05, *** p<0.01.*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).;6) ATET estimate adjusted for covariates, panel, and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

7.3.8: DID Regression Results For MCEPCHE Caste With Health Expenditure And Catastrophic Health Expenditure:

Health insurance(PFHII) positively and significantly impacts caste 1(Brahmins and other castes) and caste 3(scheduled caste). For caste 2(OBC) and caste 4(ST), the results are statistically irrelevant(Table 100). The non-health expenditure for caste 1 is positively driven by developed villages, ownership of assets, membership in various organisations and family size, implementation of projects, and proportion of children has a negative and significant influence on caste 1.

For caste 3 (SC), ownership of assets and membership in various organisations had a positive influence and family size, presence of conflicts, proportion of children, and village health infrastructure index had a statically negative impact on expenditure. For caste 2 OBC: developed village, assets, and membership to various organisations helped to upscale the expenditure and family size; the proportion of children negatively influenced the expenditure. For caste 4, which is ST, along with another variable, the village health infrastructure index positively influenced non-health expenditure for ST.

The common variables that positively influenced the non-health expenditure for socio-economic categories were ownership of assets, membership in various organisations and developed villages. Family size, the proportion of children, conflict in the village and implementation of public projects negatively influenced non-health expenditure.

For the households with catastrophic health expenditure, caste 4 (ST) (Table 101) impacted non-health expenditure. Ownership of assets increased the expenditure. Family size, the proportion of children, and village health infrastructure negatively impacted non-health expenditure.

Table 100: **DID Regression Results For MCEPCHE Caste With Health Expenditure**

Table 101: **DID Regression Results With MCEPCHE Caste For Catastrophic Health Expenditure**

Variables	**Caste1**	**Caste2**	**Caste3**	**Caste4**	**Caste1**	**Caste2**	**Caste3**	**Caste4**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**
				Average Treatment Effect on Treated				
PFHII $	**309.5***** *(100.6)*	50.49 *(34.96)*	**63.86**** *(30.22)*	-72.61 *(53.73)*	81.59 *(72.45)*	-7.327 *(34.52)*	35.97 *(39.32)*	**-255.2***** *(72.06)*
Controls								
Confidence in institutions/ governance $	-0.504 *(7.997)*	-1.282 *(4.761)*	4.568 *(4.670)*	-2.716 *(5.905)*	1.759 *(8.888)*	-2.733 *(4.389)*	2.563 *(4.485)*	-1.285 *(9.039)*
Developed Village $	**247.9***** *(88.57)*	**192.0***** *(46.00)*	41.76 *(43.32)*	**199.2**** *(83.82)*	**200.3**** *(88.15)*	**99.19**** *(45.99)*	77.49 *(55.26)*	-42.29 *(122.2)*
Family size $	**-143.0***** *(22.51)*	**-64.36***** *(13.23)*	**-74.11***** *(11.09)*	**-85.55***** *(19.63)*	**-101.5***** *(22.63)*	**-58.62***** *(11.63)*	**-75.23***** *(14.89)*	**-64.89***** *(22.94)*
Highest adult education $	-6.016 *(14.72)*	-4.759 *(5.665)*	4.429 *(4.901)*	-1.084 *(11.11)*	6.079 *(11.93)*	3.033 *(7.770)*	**14.65**** *(6.277)*	5.061 *(9.282)*
Household Ownership of Assets $	**109.8***** *(12.13)*	**73.14***** *(6.276)*	**58.28***** *(6.827)*	**40.54***** *(9.298)*	**80.12***** *(12.63)*	**66.41***** *(6.269)*	**52.09***** *(9.585)*	**56.16***** *(12.31)*
Implementation of public projects #	**-29.58***** *(8.309)*	-4.190 *(4.031)*	-1.689 *(5.340)*	-3.683 *(6.600)*	**-27.10***** *(8.147)*	**-12.05***** *(4.256)*	2.423 *(8.598)*	-4.926 *(7.008)*
Membership to various organisations $	**128.2***** *(31.30)*	**54.64***** *(14.97)*	**33.30**** *(16.43)*	**49.21***** *(16.21)*	**69.05***** *(20.40)*	**48.09***** *(12.65)*	**50.90**** *(23.10)*	4.537 *(20.34)*

Number of married females in the household $	113.6	-35.45	2.672	50.28	46.89	-19.61	-53.34	27.99
	(85.79)	*(49.95)*	*(36.39)*	*(56.68)*	*(74.05)*	*(34.09)*	*(48.91)*	*(63.24)*
Presence of conflicts $	3.782	-11.15	**-39.41*****	-11.83	15.58	**-37.22*****	**-41.23****	8.974
	(27.97)	*(12.94)*	*(14.23)*	*(17.77)*	*(22.43)*	*(11.49)*	*(16.65)*	*(23.11)*
Proportion of children $	**-1271.6*****	**-916.1*****	**-573.5*****	**-785.6*****	**-762.6*****	**-541.7*****	**-555.2*****	**-891.1*****
	(159.8)	*(94.62)*	*(82.31)*	*(151.9)*	*(171.5)*	*(82.50)*	*(94.47)*	*(200.5)*
Village Health Infrastructure Index #	7.495	2.975	**-13.35****	**32.53****	16.73	-1.362	**-16.36****	-26.19*
	(16.05)	*(8.736)*	*(5.976)*	*(15.81)*	*(20.16)*	*(7.919)*	*(7.437)*	*(14.64)*
year=2012	-82.16	37.93	16.79	130.3**	4.199	102.5***	86.77**	324.8***
	(79.65)	(37.91)	(35.30)	(50.92)	(64.78)	(33.45)	(35.96)	(57.84)
Constant	1512.9***	1261.4***	1191.6***	1334.1***	1331.6***	1285.0***	1086.9***	986.8***
	(286.6)	*(152.3)*	*(175.0)*	*(180.2)*	*(270.6)*	*(166.2)*	*(160.8)*	*(248.2)*
Degrees of freedom	6228	9266	5136	2334	4766	7552	4212	1760
Cluster	6229	9267	5137	2335	4767	7553	4213	1761
Number of observations	10388	16266	9429	3691	6411	10869	6306	2292

Note: 1. Standard errors in parentheses.

*2) * p<0.1, ** p<0.05, *** p<0.01*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).

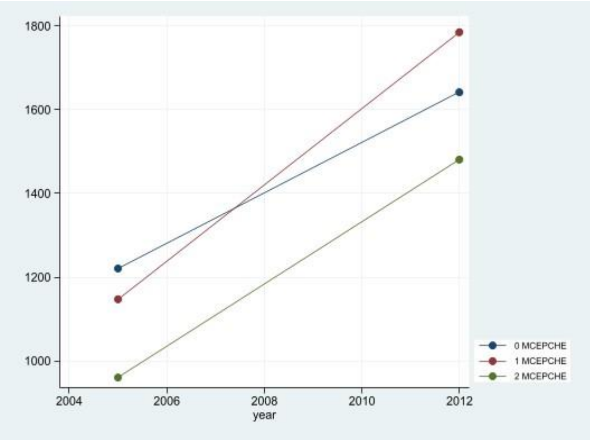
6) ATET estimate adjusted for covariates, panel and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

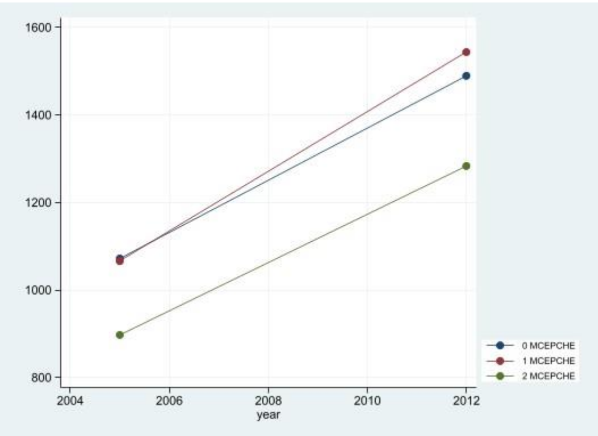
7.3.9: Mean Of MCEPCHE With Health Insurance Intensity For Health Expenditure And Catastrophic Health Expenditure:

Graph 8**: Mean Of MCEPCHE With PFHII For Health Expenditure**



Source: *Author's calculations based on IHDS 1 and IHDS 2 data.*

Graph 9**:Mean Of MCEPCHE With HII For Catastrophic Health Expenditure**



Source: *Author's calculations based on IHDS 1 and IHDS 2 data.*

Graphs 8 and 9 are drawn using means of MCEPCHE for households with health and catastrophic health expenditure separately. There was no information about the different types of health insurance for IHDS 1; the information about health insurance from IHDS 2 is used to trace the average non-health expenditure of the households in IHDS 1 and compare it with IHDS 2. For the household that incurred health expenditure, the mean MCEPCHE without health insurance was Rs 1437; with either GFHI or RSBY, it was Rs

1474, and with GFHI and RSBY, it was Rs 1194. For those households that incurred catastrophic health expenditure without insurance, the mean was Rs 1281; with any one type of health insurance, the average non-health expenditure was Rs 1304, and with both types of health insurance, the mean was Rs 1090. We have three groups where MCEPCHE matches with three groups of HII in the pre-treatment and post-treatment periods. Before receiving the treatment, the households and those who incurred health expenditure had MECPCHE of Rs 1229 for group 1, Rs 1155 for group 2 and Rs 961 for group 3. In IHDS 2, after undergoing treatment with health insurance, the MCEPCHE was Rs 1646 for group 1, Rs 1794 for group 2 and Rs 1428 for group 3. The household from group 1 had a 34% incremental increase in their MCEPCHE, group 2 had 55%, and group 3 had 49%. For the households that incurred catastrophic health expenditure, MCEPCHE for group 1 in 2005 was Rs 1072; for group 2, it was Rs 1066; and for group 3, it was RS 897. In IHDS 2, group 1 had MCEPCHE of Rs 140; group 2 was Rs 1544, and group 3 was Rs 1284. The incremental percentage increase was 39% for group 1, 45% for group 2 and 43% for group 3.

7.3.10: DID Regression Results Of MCEPC, MCEPCHE AND HHCTP With Binary Treatment:

Table 102 gives regression analysis using DID with private health insurance. Since private health insurance has the issue of self-selection, the results are run to check the impact and have no policy implication. The results can’t be compared with those obtained from health insurance intensity with continuous treatment. The results are obtained for consumption expenditure, adjusted consumption expenditure and household capacity to pay. Private health insurance has increased consumption expenditure, adjusted consumption expenditure and household capacity to pay positively and significantly. The developed villages, Household assets, and membership in various organisations have positively influenced households that owned private health insurance. The family size, the proportion of children, and the implementation of projects have negatively affected consumption, adjusted expenditure, and household capacity to pay.

Table 102: **DID Regression Results With Binary Treatment**

Variables	**MCEPC**	**MCEPCHE**	**HHCTP**
I	**II**	**III**	**IV**
	Average treatment effect on treated		
Private Health Insurance $	**578.2*** *(174.1)*	**594.3*** *(150.6)*	**562.4*** *(172.9)*
Controls			
Confidence in institutions/ governance $	3.453 *(3.473)*	1.801 *(3.080)*	3.968 *(3.388)*
Developed Village $	**145.4*** *(36.89)*	**158.8*** *(31.52)*	**127.8*** *(36.15)*
Family size $	**-108.9*** *(9.625)*	**-90.79*** *(8.399)*	**-87.82*** *(9.125)*
Highest adult education $	-5.503 *(5.391)*	-4.368 *(4.798)*	-4.496 *(5.318)*
Household Ownership of Assets $	**77.95*** *(5.159)*	**75.55*** *(4.452)*	**68.22*** *(5.059)*
Implementation of public projects #	**-15.82*** *(3.735)*	**-13.76*** *(3.085)*	**-13.85*** *(3.679)*
Membership to various organisations. $	**72.59*** *(12.49)*	**71.18*** *(10.89)*	**66.72*** *(12.32)*
Number of married females in the household $	28.06 *(34.37)*	26.36 *(29.98)*	26.87 *(33.53)*
Presence of conflicts $	**-30.50** *(13.37)*	**-28.87** *(11.79)*	**-23.49* *(13.17)*
Proportion of children $	**-1101.0*** *(67.82)*	**-915.6*** *(57.94)*	**-953.1*** *(66.07)*
Village Health Infrastructure Index #	4.356 *(6.488)*	4.524 *(5.564)*	5.656 *(6.390)*

year=2012	86.92***	54.70**	59.78**
	(27.74)	*(24.19)*	*(26.98)*
Constant	1830.1***	1454.5***	1108.6***
	(128.7)	*(116.1)*	*(126.5)*
Control	23753	23753	23753
Treatment	786	786	786
Degree of freedom	20806	20806	20806
Cluster	20807	20807	20807
Number of observations	39633	39633	39633

Note: 1. Standard errors in parentheses.

*2) * p<0.1, ** p<0.05, *** p<0.01.*

3) # Village level data, $ household-level data.

4). Panel variable: IDHH2012; Time variable: Year; Cluster Variable: PSUHH.

5). Standard errors clustered at the Village level (PSUHH).

6) ATET estimate adjusted for covariates, panel and time effects.

7)Figures in 'Bold' indicate significant regression coefficients.

Source: Author's Calculations based on IHDS 1 and IHDS 2 data.

7.4: Main Findings And Discussion:

We have studied the health insurance impact on households that incurred health expenditures and catastrophic health expenditures across socio-economic categories. The DID regression results for a household with medical expenditure reveal that those households with any one type of insurance and two insurances increased the consumption expenditure, non-health expenditure of the households, Non-food expenditure and the household capacity to pay. For those households that incurred catastrophic health expenditures, the health insurance did not help to smoothen the food expenditure.

Those households that incurred health expenditure had reduced their food expenditure, but it was not statistically significant for the same households when they faced catastrophic expenditure; their food expenditure decreased. Household's capacity to pay also decreases with catastrophic health expenditure. It is statistically insignificant. Households' non-health and non-food expenditures increased, but it was statistically insignificant.

Households with health expenditure had increased non-health expenditure if they belonged to the developed village, having assets and membership to various organisations. Family size, implementation of projects, and proportion of children worked negatively. Additionally, the presence of conflicts also harmed non-health expenditures.

Those households that face catastrophic expenditure can mitigate the same if they belong to more developed villages, have assets, are members of various organisations and participate in political activities. Households with bigger family sizes project implementation in the village, the presence of conflicts and the proportion of children had an overall negative impact on the non-health expenditure of the household. Additionally, village health infrastructure also had a negative impact. The highest adult education helped households increase their non-health expenditure, non-food expenditure and household capacity to pay but worked negatively for food expenditure.

Since IHDS does not provide any criteria for differentiating between the more developed and less developed villages, the village health infrastructure index includes various health facilities, nearby and transport infrastructure. However, these covariates gave mixed results, and it showed up statistically significant but negative for those households that had incurred catastrophic health expenditure, and as a result, their food expenditure had reduced. Despite the higher cost, there is undue importance to the private health sector in India. Public health care is ignored (Barik & Thorat, 2015) and also because of prejudices against public health care for providing inferior services(Sahoo & Madheswaran, 2014), and this makes a strong case for pumping more resources into the public health sector (Dwivedi & Pradhan, 2017) and not just increasing the number of PHC. However, a well-equipped one is more important (Barik & Desai, 2014); the availability of less well-equipped PHCs constrains access to health care(Johnson & Krishnaswamy, 2012). Functional primary health centres promoted better access to treatment for indigenous communities and widows over health insurance(George et al., 2021). The urban-rural disparity in the availability of health infrastructure(Barik & Thorat, 2015; Singariya, 2013) is also seen in the geographical distribution of private and public health infrastructure.

To study the impact of NRHM, we included two variables: public project implementation in the village and village health infrastructure index. We would have usually expected that the implementation of public projects in the village would have provided a boost to non-health expenditure. Studies have also pointed out the failure of NRHM to provide the required health infrastructure (Sarkar & Mukherjee, 2021). States like Assam, Bihar, Gujarat, Haryana, Jharkhand, Madhya Pradesh, Maharashtra, Punjab, Rajasthan, Tripura, Uttar Pradesh, West Bengal and Delhi had a shortfall of either sub-centre/ primary health centre/ Community health centre between 2005 and 2012(Rural Health Statistics in India 2011). In the Rural health infrastructure index constructed for 2005, the highest percentage of households belong to villages having very low and low health infrastructure. This data and the studies mentioned above exemplify that between rounds 1 and 2, the growth in rural infrastructural facilities was not very impressive. The corruption index was very high during the period; for some states, this could have worked in the opposite direction despite efforts. The political affiliation of the centre and state also matters (Nandi et al., 2013). Similarly, the village health infrastructure index had no significant impact on the expenditure(Prinja et al., 2019).

The presence of conflict in the village, the proportion of children and family size negatively influenced household non-health expenditure. Acceptance of certain government programs by the society also depended on the level of trust, and in South Africa, the violence that occurred post-elections was a deterrent factor towards contribution to social capital (Donfouet & Mahieu, 2012). The families with more members had reduced indirect health expenditure (Pradhan & Prescott, 2002).

Household ownership of assets and membership in various organisations helped households increase their non-health expenditure despite health expenditures. Those households that have no access to a formal mechanism for coping up, like health insurance or borrowing from the credit market, often resort to self-insurance, like the build-up of assets in general and productive assets in particular and use the same as a coping mechanism(Ajefu, 2017; Islam & Maitra, 2012; Leive & Xu, 2008; Onisanwa & Olaniyan, 2019; Sahoo & Madheswaran, 2014; Shahrawat & Rao, 2012; Van Doorslaer et al., 2007).

Confidence in government did not lead to any significant results, and implementing public projects has shown some interesting results of having a statistically negative relation with households' non-health expenditure. Schemes already implemented in the village did not impact RSBY enrolment, but the corruption index had a negative relationship, reflecting a lack of government confidence(Nandi et al., 2013).

The households that incurred inpatient and outpatient expenditures and health insurance did not produce significant results. Inpatient expenditure increased. Some results confirm an increase in hospitalisation, but there is no strong evidence supporting whether the increase in inpatient expenditure was due to a shift in cases from outpatient to inpatient(Fan et al., 2012). RSBY did not provide the required protection against healthcare expenditure (Malhi et al., 2020).

Non-health expenditure quintile also gives some interesting results. The people below the poverty line could not safeguard their non-health expenditures when they incurred health expenditures and when these health expenditures were catastrophic. However, for remaining quintile, like APL 3, which had negative consumption expenditure due to health expenditure, did not show any statistical significance when it incurred catastrophic health expenditure. However, another interesting finding is that in the APL 1 group, which was almost on the margin despite catastrophic health expenditure, the household could increase its non-health spending, which can be attributed to health insurance. APL 2 and APL3 reported a decreased expenditure, but it was statistically insignificant.

Moreover, quintile 5, which had reported a positive coefficient with medical expenditure, now had a negative but insignificant coefficient. The mixed results we have across the quintile could be the sample results (Garg et al., 2019). However, what is interesting to know are some results that specifically affected certain quintiles. As for the BPL quintile and APL quintile 1, the presence of conflicts in the village matters, but confidence in government institutions had no impact.

For BPL households that incurred medical expenditure, ownership of assets and membership in various organisations helped households to boost the expenditure and family size, proportion of children and presence of conflicts worked in the reverse direction. For those who are economically weaker, membership in different organisations like self-help groups would help to smoothen consumption expenditure, and the accumulation of assets also would help; for poor households' the reduction in non-health expenditure was driven by ownership of the assets and membership in various organisations. Since we have not analysed whether households borrowed to pay for health expenditure, the only valid explanation is that those poor households who incurred health expenditure had reduced their non-health expenditure in the presence of health insurance. This reduction could mean that the households cut down their non-health expenditure despite having assets, memberships to organisations and health insurance. Poor households were not able to smoothen their consumption despite health insurance.

Household demographics regarding family size and the number of children are a deterrent factor here. The highest adult education was insignificant except for APL5, which experienced catastrophic health expenditure; it possessed a negative sign. The number of married females also had mixed signs. Additionally, if conflicts in the village are related to *Jati*, that may influence the consumption expenditure since economically weaker sections are vulnerable otherwise.

The absence of further information on the duration taken to complete the project or the benefit the households received poses a limitation for further analysis. APL4, which incurred catastrophic expenditure, the developed village had a negative sign. Health infrastructure was not significant at all.

Since implementation, RSBY warranted that the districts would have some basic facilities in place, but for quintile-wise results, the coefficient sign for developed villages varied and was insignificant. The village health infrastructure index was also not significant.

We got mixed results for some exogenous variables. Such mixed results are also reported elsewhere in the literature(Garg et al., 2019). Households from the BPL category exposed to out-of-pocket health expenditure at hospitalisation reported partial coverage by RSBY (Devadasan et al., 2013).

According to regional studies, RSBY did not help BPL reduce OOPHE or improve healthcare utilisation(Ghosh, 2014). PFHI did not help in providing financial protection(Garg et al., 2019). Caste-wise results show that caste 1 (brahmins/forward caste) and caste 3 scheduled caste had increased non-health spending. Caste 2 (OBC) also had increased non-health expenditure but was not significant. For caste 4 (ST), the catastrophic expenditure incurred and having health insurance reduced the expenditure and having health insurance did not benefit. For other castes, the results were insignificant.

Developed villages helped castes 1,2,3 with medical expenditure and castes 1,2 with catastrophic expenditure to increase their expenditure. The village, but when these households incur catastrophic expenditure, the household expenditure decreases. For scheduled tribe households, only household assets work as self-insurance. Health infrastructure for caste 3 reduced the expenditure, but for caste 4, when the households did not incur catastrophic expenditure, it helped to increase the non-health expenditure. Family size and proportion of children also worked toward reducing the household's non-health expenditure for all caste categories.

Household ownership of assets was significant for all castes. Membership in various organisations also was significant in increasing the expenditure. Conflict in the village affected caste 3 for medical expenditure and castes 2 and 3 for catastrophic expenditure. Households that incurred health expenditure and had any one insurance have benefited. These households had higher incremental increases in their MCEPCHE. Those households that had the lowest MCEPCHE were found to be going for two types of health insurance and also have benefited with an incremental increase of 49% with health expenditure and 43% even with catastrophic health expenditure.

7.5: Conclusion:

Having any one type of Health insurance and both types have helped households increase their non-health spending, but it did not protect the household from catastrophic expenditure. Our results are in addition to the larger literature. Health insurance did not benefit people living below the poverty line and also scheduled tribe population to protect their consumption expenditure against catastrophic health expenditure. Several schemes in the past were of little benefit, but having one all-inclusive scheme may help. Households with insurance had an incremental increase in their MCEPCHE, but this increase was not enough to protect certain households belonging to BPL and ST against catastrophic health expenditure. PMJAY has increased the cover and included outpatient expenditure and travel costs.

PMJAY scheme, which has integrated all existing centre and state-level insurance schemes, needs integration of existing schemes' features. The focus should be on reducing catastrophic expenditure. BPL households and STs may need different policies as compared to the mainstream. Although each household has different socio-economic dynamics having assets acts as self-insurance and membership to various organisations like Mahila Mandal; youth clubs; sports groups or reading rooms; self-help groups; credit or savings groups; religious or social groups or festival society; caste associations; development group or NGO; agricultural, milk or another cooperative. Strengthening public health infrastructure at the village level will also provide an extra boost. Well-equipped public health facilities themselves may act as a perverse incentive.

Limitations: IHDS is the only longitudinal household data from 2005 to 2011-12. The information on health insurance may have an underlying issue of self-reporting, but we have reasonably argued against the same based on our observations and duly supported by literature evidence. Secondly, for 2004-2005 there is no information about the types of health insurance household round carries no information on insurance reimbursement and different types of health-related expenditure.

Next, chapter 8 evaluates health policy and national rural health missions. The index of village health infrastructure is constructed using principal component analysis.

CHAPTER 8:

NATIONAL RURAL HEALTH MISSION POLICY, 2005-2012 AND HEALTH INFRASTRUCTURE IN VILLAGES: AN EVALUATION

Chapter 8 is titled: ‘ National Rural Health Mission 2005-2012 and Health Infrastructure in Villages: An Evaluation’. Objective 5: ‘To assess the extent to which India's Health policy enhances household well-being’ is exclusively dealt with in this chapter. This chapter is divided into 5 main sections and many sub-sections. The chapter starts with the introduction. It gives an insight into the health infrastructure in India. The next section is materials and methods, preceded by results. The results section 8.3 is subdivided into 7 sections. Discussion and conclusion are discussed in sections 8.4 and 8.5, respectively.

8.1:Introduction:

The Bhore committee made the earliest attempt to raise concern for health infrastructure in India(1943). It also acknowledged the efforts to make health accessible to all. The nationwide family planning program(1952) was launched and prioritized, pushing back all other programs from the priority list(Ashtekar, 2008; Goel, 2021). Alma Ata's declaration (1978) rightly stressed the need for all nations to focus on promoting health care at the primary level, which is the grassroots level(Goel, 2021; Hussain, 2011). Some other initiatives for health were a health policy focused on immunization (1982), a universal immunization program strengthened(1992-93), Reproductive and Child Health(RCH) launched (1997), and RCH phase II 2005-2010(Goel, 2021).

UN Alma Ata United National Conference mission health for all 2000 was declared. National Health Policy 2002 outlined the need for a platter of reforms. The health for all of 2000 was replaced by broader, focused millennium development goals(MDG). As a result, the National Rural Health Mission NRHM was carved out to attain MDG (Ashtekar, 2008).

There are many inequities. The most noticeable inequities that led to differences in India were rural-urban disparities and inter and intra-state. Northern and Eastern state’s performance compared to Southern and Western states is unfair. Equity by including the marginalized population is an integral part of GOI. NRHM was one of many such attempts(Prasad et al., 2013). Further, India also has inter and intra-regional differences, and most of the population lives in rural areas. The focus of NRHM was on providing a better quality of healthcare accessible and affordable to rural populations(Dhingra & Dutta, 2011). India's National Health Policy, 2017, a major goal of health and well-being for all. Health care. Primary Health Care is the most important channel for promoting rural health (Muniswamy et al., 2021). The development of infrastructure predetermines the economic growth of a country. India's health infrastructure does not match the growing population's requirements (Agrawal, 2015).

The decline of public health expenditure from 1% of GDP to 0.9% in 1999, curative health services were biased towards the rich, and health expenditure related to poverty provided a rationale for launching NRHM (NRHM 2005-2012, Mission Document). NRHM was launched in 2005 to provide health care to rural areas to fill up the gaps that existed before in health care provisioning, such as making health affordable and available. The goal of NRHM was to be achieved by 2012. For increasing accessibility, the first step is provisioning for well-equipped infrastructure. The three tire structures of primary health centres(PHC), sub-centres(SC) and community health centres(CHC) are the backbones of health infrastructure. The NRHM policy for health infrastructure was to provide for PHC to be available for 24 hours, new SC, and upgradation of the status of PHC and CHC as the first referral unit(Hussain, 2011).

NRHM's mission was to provision health care to rural populations with a focus on 18 states and to increase the public health expenditure to 2%-3% of GDP. NRHM outlined some goals with core and supplementary strategies. One such was strengthening infrastructure that supports public health in rural areas such as sub-centres, primary health centres, and community health centres(NRHM 2005-2012, mission document). The empowered action group was constituted in 2021. 18 states were identified with weak public health indicators and weak infrastructure. There were differentials due to inputs and resources mismatching with the actual needs of the states(Prasad et al., 2013). These states were chosen to receive funds under NRHM. These 18 states were Arunachal Pradesh, Assam, Bihar, Chattisgarh, Himachal Pradesh, Jharkhand, Madhya Pradesh, Nagaland, Orissa, Rajasthan, Sikkim, Tripura, Jammu and Kashmir, Manipur, Mizoram, Meghalaya, Uttaranchal and Uttar Pradesh. (Dhingra, 2011, NRHM mission document). EAG group is subdivided into four categories the High-focus non-North Eastern states(298 districts), High focus North Eastern states (87 districts), non-high focus large states (217 districts) and non-high focus small states and Union territory(21 districts). The district hospitals covered in each group were 292, 72, 183 and 21, respectively. The high-focus Non-Northeast states were Bihar, Chhattisgarh, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh and Uttarakhand; High focus northeastern states are Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura. Small states and Union territories were Andaman, Nicobar, Chandigarh, Dadra Nagar Haveli, Daman and Diu, Delhi, Lakshadweep, and Puducherry. Rest all states grouped as non-high focus large scale(Sarma, 2009) .

8.1.1: Health Infrastructure In India:

India has a three-tier rural health infrastructure. Each tier serves a certain population distinguished based on the geographical location as plain and non-plain areas. Subcentres serve a population of 5000 in plain areas and 3000 in hilly, tribal, and difficult areas. Subcentres are the first referrals for patients. They provide health services for patients suffering from communicable diseases, non-communicable diseases, maternal health and child health. Nutrition and family welfare are covered. Rajasthan, Gujarat, Madhya Pradesh and Chattisgarh witnessed remarkable sub-centre growth (Rural Health Statistics, 2020-21).

The primary health centre serves 30000 population in plains and 20000 in hilly areas. PHC provides curative and preventive health care and is maintained by state governments under a minimum-need programme. Jammu and Kashmir, Karnataka, Rajasthan, Gujarat and Assam witnessed a considerable increase in PHCs, with 25140 functioning PHCs nationally. Community health centres serve as referral centres for primary health centres. From 2005 to 2021, CHCs increased to 5481 (Rural Health Statistics, 2020-21).

Compared to 2005, the increase in sub-centres was 7%; primary and community health centres increased by 9% and 64%, respectively. As per Rural Health Statistics, for 2020-21, there is a shortfall of 24% of Subcentres, 29% of Primary health centres, and 35% of community health centres. At the national level, four villages are covered by sub-centre, 26 by PHC, and 121 by CHC. The population covered as a national average is 5,734 by sub-centre, 35,602 by PHC and 163, 298 by CHC(Rural Health Statistics, 2020-21). Under the NRHM, Rs. 666 billion (US$12.1 billion) was invested in rural areas from April 2005 to March 2012(Prasad et al., 2013).

8.1.2:Background Studies:

Evaluation of NRHM policy is done from the infrastructure perspective in the literature from the supply side perspective(Agrawal, 2015; Ashtekar, 2008; Dhingra & Dutta, 2011; Goel, 2021; Hussain, 2011; Sarma, 2009). Among the surveyed sub-centres, the Indian Public Health Standard criteria were not met in districts of central India, although facilities were present (Narlawar, 2018).

The multidimensional nature of health data makes it difficult to comprehend; hence, dimension reduction is important (Carillo et al., 2018). In an assessment of rural health infrastructure by constructing an index, the patterns of the high, medium, and low availability of health infrastructure in different blocks of the district in the Bulandshahar district of Uttar Pradesh were observed, and disparities in health infrastructure were also found(Kumar et al., 2021). A study of Health infrastructure in Haryana was done using principal component analysis (Goel & Garg, 2018). Using PCA (8 health indicators) health and education index was constructed and reported regional disparities in Uttar Pradesh between 190-91 and 2007-08 (Raman & Kumari, 2012). PCA was used for the construction of an index for measuring social sector disparities for Indian states(Saikia, 2012), for measuring physical health infrastructure for Andhra Pradesh(Lakshmi, 2013), for Uttar Pradesh and Bihar for health infrastructure (Anand, 2014), health infrastructure index for northeastern states(Lyngdoh, 2015). In a study using major states, using a simple average of variables of health infrastructure, an index of health infrastructure was constructed(Varkey et al., 2020) . These studies are concluded using data from Rural health statistics, the world bank, or primary data. No study is concluded using longitudinal panel data.

8.2: Materials And Methods:

The focus of NRHM was to provide public health infrastructure so that it is accessible to rural areas. Several variables in IHDS 1 and 2 measure the availability of such facilities, including human and physical resources, and can be used to measure accessibility and affordability of health care. Ours is the first study that used physical and human resources to construct a village health infrastructure index. NRHM was launched in 2005 and lasted 07 years, 2012, coinciding with the two IHDS rounds 2005-06 and 2011-12. The indices are constructed using wide panels separately for IHDS1 and IHDS 2. Any difference in the index between both rounds can be attributed to the contribution of the NRHM to health facilities.

We have merged the IHDS 1 and IHDS 2 data using household individual and village schedules. We have only retained rural observations matching both rounds. The variables were used mainly from individual and Village schedules. We have used variables that provide information on public health facilities. Table 103 gives a detailed description of the indices constructed and the variables used. Four independent indices were constructed, which measure the availability of medical facilities in the village, Advice and Treatment, Accessibility to transportation, and Accessibility to a medical facility nearby.

Table 103: **Description of Indices**

Index	Purpose of construction	Schedule	Year	Variables used
1. Index of the place of advice and treatment for short and major morbidity	Objective: to determine whether people take treatment with trained professionals for short and major morbidity. It reflects the availability of such professionals in rural areas.	Individual	2012/ 2005	1. Advice is given for first /second treatment for short/ major Morbidity: Govt Doc/Nurse, Govt Doc/Nurse in Pvt, Pvt Doc/Nurse, Chemist, Vaidhya/Hakim, Witchcraft) 2. Place of the first treatment for short /major Morbidity: Home, this village or Town, Another Village, Other Town, District Town, Metro City, Abroad/Others.
2. Index of availability of medical facilities in the village	Objective: to find out the presence of a medical facility in the village	Village	2012	Health Sub centre number; Primary health centre number; Community health centre number; District health centre number; Village health worker number; Government maternity centre number.
		Village	2005	Health sub-centre number, Primary health centre number, Community health centre, District health centre number, Any other govt. A medical facility in the village, a Maternity care centre number, and a communicable disease facility
3. Index of accessibility to infrastructure in the village	Objective: there are villages where medical or advanced facilities are unavailable. The accessibility to infrastructure like pucca road and railway station nearby matters. Availability and accessibility to transport facilities in the village help facilitate access to medical facilities in the nearby villages.	Village	2012	Distance to the nearest town, pucca road, closest bus stop, railway station, (Km)
		Village	2005	Distance to the nearest pucca road, closest bus stop, railway station, town (Km)
4. Index of Access to medical infrastructure nearby.	Objective: in certain villages where basic medical facilities are unavailable, the villagers access the nearby health facilities.	Village	2012	Distance to nearest health sub-centre, govt dispensary, primary health centre, community health centre, district hospital, Health worker distance, Multipurpose health worker distance, Government maternity centre distance.
		Village	2005	Distance to nearest health sub-centre, primary health centre, Communicable disease centre, and closest maternity centre.

***Source**: Author's calculations based on IHDS 1 and IHDS 2 data.*

The variables used in constructing the indices measure various physical and human health infrastructure aspects. The first Index is constructed for the place of advice and treatment for short and major morbidity in the village. The place of advice and treatment has data on the first place and second places of advice and treatment. The various options for place of advice were government doctor/Nurse, government doctor/nurse in private, private doctor/nurse, chemist, vaidya/hakim, witchcraft), and for treatment home, this village or town, another Village, other towns, district town, metro city, abroad/others. The range of options captures the availability of the facility for advice and treatment. The next Index is of health facilities available in the village. Only government facilities were considered for the construction of this Index. The variables that reflect the health facilities available in the villages are the health sub-centre number, primary health centre number, community health centre, District health centre number, and any other government medical facility in the village. There were other variables in exclusively IHDS 2, like distance to Asha worker, trained dai, and other government medical facility numbers. Although they measure health infrastructure facilities, some of these variables had to be dropped since they had no valid component score from IHDS 1, primary health centre, health sub-centre, community health centre, communicable disease facility, and government maternity centre. From IHDS 2, primary health centre, health sub-centre, health worker number, multipurpose health worker, and government maternity number were used.

Those with no facilities in the village would use the nearby health facilities, and an index on nearby health facilities was constructed accordingly. The data had information about distance in kilometres to the nearest sub-centre, primary health centre, community health centre, district health centre, communicable disease centre, and maternity centre. From the IHDS 1 round, the variables used were distance to the nearest Sub-centre, primary health centre, maternity centre, and communicable disease centre. The IHDS 2 round included a sub-centre, primary health centre, community health centre, multipurpose health worker, district hospital, health worker, and maternity centre. The transport network must also be assessed if the villagers need access to nearby health facilities. Accordingly, the Index of infrastructure facilities in the village is constructed by considering the distance to the closest bus stop, pucca road, railway station, nearest town, and district headquarters.

For every index constructed using the PCA command, there are post-estimation steps, such as generating standard errors based on multivariate normality assumption to check whether the factor loadings are equal for each component. Anti-image of the covariance matrix, a negative value generated partialing out all other variables, residual matrix and the sum of squares of all variables (Table 110 to 118)

8.3: Results:

The following section presents the results of the PCA analysis.

8.3.1: Variables With Missing Observations, Treatment for Missing Observations And Standardisation:

Tables 104 and 105 summarise descriptive tables of missing observations, treatment of missing observations and standardization from columns I to XVI for IHDS 1 and IHDS 2, respectively. The variables with missing observations are given in columns II to VI, missing observations replaced with '0' are given in columns VII to XI and standardization of variables is given in columns XII to XVI. The mean value of variables changes if there are missing observations for a given variable (STATA represent such observations with '.'. The variables are standardized since the index constructed is used as one of the covariates in Chapter 7.

Table 104: **Descriptive Statistics of Missing Observations, Treatment For Missing Observations And Standardization (2005)**

	Variables with missing observations					Variables after treating for missing observations					Variables after standardisation				
Variable	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	IVX	XV	XVI
Distance to the nearest town(Km)	97555	13.925	10.827	1	85	99028	13.718	10.877	0	85	99028	0	1	-1.261	6.553
Distance to the pucca road(Kms)	97530	1.573	4.067	0	50	99028	1.549	4.04	0	50	99028	0	1	-0.383	11.993
Distance to the closest bus stop (km)	97658	2.025	3.388	0	40	99028	1.997	3.373	0	40	99028	0	1	-0.592	11.267
Distance to the closest bus stop (km)	91054	22.961	20.839	0	96	99028	21.112	20.936	0	96	99028	0	1	-1.008	3.577
Short morbidity place of first advice	12190	2.659	0.942	1	5	99028	0.327	0.934	0	5	99028	0	1	-0.35	5.003
Short Morbidity place of the first treatment	12186	1.776	0.916	1	4	99028	0.219	0.666	0	4	99028	-0.001	1	-0.329	5.677
Short morbidity place of second advice	1729	2.644	0.838	1	5	99028	0.046	0.364	0	5	99028	-1.137	0.999	-1.264	12.473
Short morbidity place of second advice	1721	2.139	1.048	1	4	99028	0.037	0.312	0	4	99028	0.001	1	-0.119	12.702
Major morbidity place of the first treatment	4484	2.574	1.051	1	4	99028	0.117	0.58	0	4	99028	-0.001	1	-0.202	6.695
Major morbidity place of the second treatment	1088	2.901	1.019	1	4	99028	0.032	0.321	0	4	99028	0	0.999	-0.1	12.361
Major morbidity place of first advice	4488	2.494	0.945	1	5	99028	0.113	0.556	0	5	99028	0	1.001	-0.203	8.79
Major morbidity place of second advice	1092	2.545	0.979	1	5	99028	0.028	0.285	0	5	99028	0	1	-0.098	17.446
Distance to nearest sub-centre (Km)	89081	3.029	5.041	0	80	99028	2.724	4.867	0	80	99028	0	1	-0.56	15.878
Distance to nearest PHC(km)	91376	7.896	7.539	0	62	99028	7.286	7.542	0	62	99028	0	1	-0.966	7.255
Communicable disease centre	97575	45.54	27.928	1	120	99028	44.872	28.258	0	120	99028	0	1	-1.588	2.659
Distance to nearest communicable centre	84989	22.789	19.563	0	95	99028	19.559	19.79	0	95	99028	0	1	-0.988	3.812
Primary health centre	97491	0.146	0.398	0	6	99028	0.143	0.396	0	6	99028	0.001	0.999	-0.361	14.79
Sub centre	97296	0.46	0.729	0	12	99028	0.452	0.725	0	12	99028	0	1	-0.623	15.928
Community health centre	97575	0.02	0.142	0	1	99028	0.02	0.141	0	1	99028	0.001	0.997	-0.142	6.95
Government maternity centre	97575	0.033	0.181	0	2	99028	0.032	0.18	0	2	99028	0.003	0.999	-0.178	10.933
Distance to the closest maternity centre	86597	20.359	17.755	0	95	99028	17.803	17.921	0	95	99028	0	1	-0.993	4.308

***Source**: Author's calculations based on IHDS 1 data.*

Table 105:**Descriptive Statistics With Missing Observations, Treatment For Missing Observations, And Standardization Of Variables, (2012)**

	Variables with missing observations					Variables after treating for missing observations					Variables after standardisation				
Variables	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	IVX	XV	XVI
Distance to nearest sub-centre.	54830	5.183	5.613	0	88	99028	2.87	4.907	0	88	99028	0	1	-0.585	17.349
Distance to the primary health centre	85674	8.124	6.609	0	100	99028	7.029	6.745	0	100	99028	0	1	-1.042	13.784
Distance to the nearest community health centre	95456	14.406	11.753	1	112	99028	13.886	11.847	0	112	99028	0	1	-1.172	8.282
Distance to nearest district hospital	98458	44.251	31.054	1	300	99028	43.997	31.145	0	300	99028	0	1	-1.413	8.22
Distance to the nearest health worker	55797	13.38	65.963	0	888	99028	7.539	49.956	0	888	99028	0	1	-0.151	17.625
Distance to nearest multipurpose health worker	59502	13.694	58.461	0	888	99028	8.228	45.809	0	888	99028	0	1	-0.18	19.205
Distance to Pucca Road	95925	0.586	2.602	0	55	99028	0.567	2.563	0	55	99028	0	1	-0.221	21.238
Distance to the railway station	98315	29.015	34.664	0	400	99028	28.806	34.626	0	400	99028	0	1	-0.832	10.72
Distance to the bus stop	98882	1.922	0.934	1	3	99028	1.919	0.936	0	3	99028	0	1	-2.05	1.155
Short morbidity the first place of advice	15997	2.705	1.067	1	7	99028	0.437	1.084	0	7	99028	0	1	-0.403	6.054
Short Morbidity first place of treatment	16041	2.558	0.952	1	7	99028	0.414	1.017	0	7	99028	0	1	-0.407	6.476
Short morbidity second place of advice	2468	2.559	1.094	1	7	99028	0.064	0.435	0	7	99028	-0.001	0.999	-0.147	15.945
Short morbidity second place of treatment	2480	2.825	1.07	1	7	99028	0.071	0.473	0	7	99028	-0.001	1	-0.15	14.649
Major morbidity first place of advice	10599	2.483	1.022	1	7	99028	0.266	0.837	0	7	99028	0	1	-0.318	8.045
Major Morbidity first place of treatment	10598	3.45	1.175	1	7	99028	0.369	1.134	0	7	99028	0	1	-0.325	5.847
Major morbidity second place for advice	3280	2.602	1.095	1	7	99028	0.086	0.507	0	7	99028	0	0.999	-0.17	13.637
Major morbidity second place of treatment	3285	3.658	1.166	1	7	99028	0.121	0.689	0	7	99028	0.001	1	-0.176	9.984
Primary Health Centre	98626	0.131	0.34	0	2	99028	0.13	0.34	0	2	99028	0.001	0.999	-0.382	5.5
Sub centres	98616	0.481	0.659	0	8	99028	0.479	0.659	0	8	99028	0.001	1	-0.727	11.413
Health workers	95489	0.839	3.053	0	42	99028	0.809	3.002	0	42	99028	0	1	-0.269	13.721
Government maternity centre	98423	0.042	0.205	0	2	99028	0.042	0.204	0	2	99028	0	1.001	-0.206	9.598
Distance to nearest govt, maternity centre	93438	21.312	20.093	1	140	99028	20.109	20.128	0	140	99028	0	1	-0.999	5.956
Multipurpose health worker	95232	0.475	1.592	0	22	99028	0.457	1.564	0	22	99028	0	1	-0.292	13.774
Distance to nearest town	98520	2.526	1.134	1	5	99028	2.513	1.145	0	5	99028	0	1	-2.195	2.172
Distance to nearest district headquarters	98737	4.762	1.599	1	8	99028	4.748	1.617	0	8	99028	0	1	-2.936	2.011

Source: *Author's calculations based on IHDS 2 data.*

8.3.2: Bartlett Test of Sphericity and Kaiser-Meyer-Olkin Measure Of Sampling Adequacy:

We present the results of the Bartlett test of sphericity (BTS) and the Kaiser-Meyer-Olkin (KMO) Measure of Sampling Adequacy (Table 106). Column II gives values of the determinant's matrix, columns III and V give chi-square values and P-values for the BTS test, and column VI gives KMO values. KMO Values are interpreted based on the KMO range given in the table. In column VI, the KMO values are above 0.50 for all indices. Furthermore, the p-values in column V are significant. Hence, the null hypothesis is rejected, the variables used to construct indices for rounds 1 and 2 are correlated, and the sample is adequate.

Table 106: **Results Of Bartlett Test Of Sphericity And Kaiser-Meyer-Olkin Measure Of Sampling Adequacy**

			BTS			
Year	**Variables**	**Determinants of a correlation matrix**	**Chi-square**	**Degrees of freedom**	**P-value**	**KMO**
I	II	III	IV	V	VI	VII
2012	a) Short and major morbidity advice and place of treatment	0.003	5.73E+05	28	0	0.575
	b) Health facility in the village	0.244	1.40E+05	10	0	0.673
	c)Infrastructure facility in the village	0.782	24323.118	10	0	0.594
	d)Health facility nearby	0.47	74682.312	21	0	0.554
2005	e) Short and major morbidity advice and place of treatment	0.004	5.52E+05	28	0	0.569
	f) Health Facility in the village	0.603	50147.056	10	0	0.614
	g) Infrastructure facility in the village	0.811	20804.963	6	0	0.556
	h) Health facility nearby	0.608	49324.893	6	0	0.545

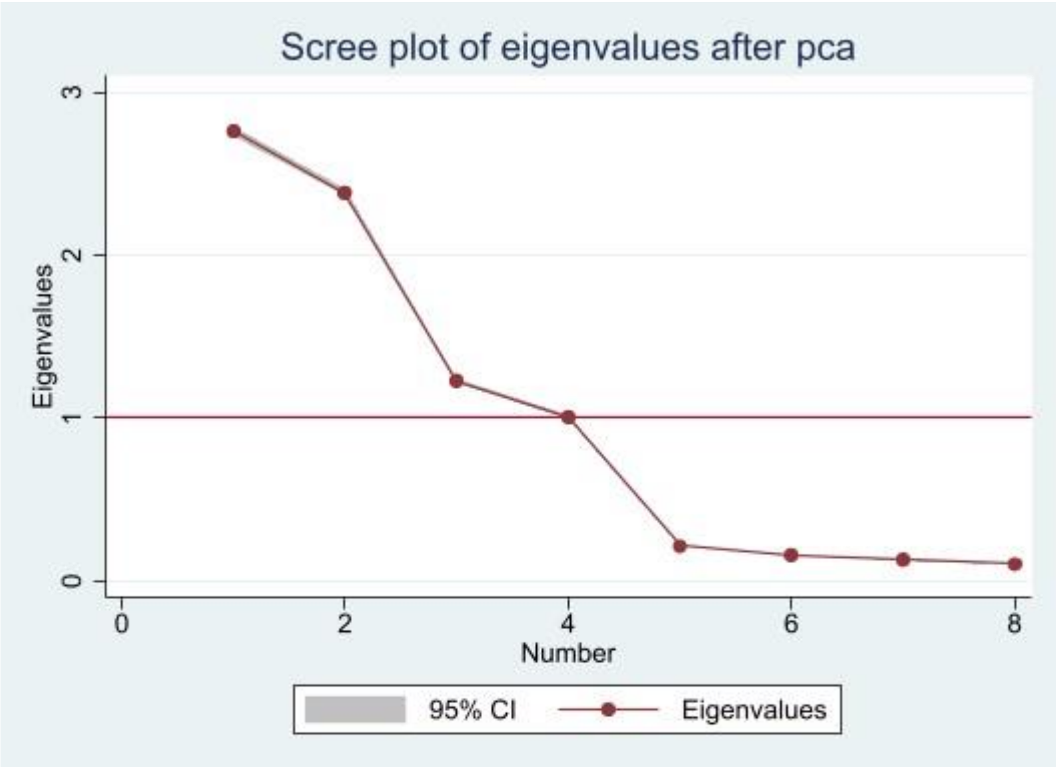
Source: *Author's calculations based on IHDS 1 and IHDS 2 data.*

8.3.3: Step-By-Step Results of Index Construction:

We now present the results of the index constructed using PCA. Since there are 8 indices and each, in turn, is derived using several sub-components (Table 109 and see chapter 3 for details), we present the detailed results of only one index: Short and major morbidity advice and place of treatment for IHDS 1(Table 103). Appendix A.8 of this thesis presents the remaining indices' results.

It is a visual tool for determining meaningful components (see Graph 10). After running the initial PCA, a scree plot is to be drawn. Although visual inspection of the results of PCA gives eigenvalue when drawing a scree plot and with cut-off 1, it becomes easy to identify. The scree plot is drawn based on eigen values and eigen vectors (Tables 107 and 108). Scree plots can be drawn after the eigenvalues and eigenvectors are obtained (using the PCA command in *STATA)*. Graph 10 shows 3 points above the eigenvalue 1(horizontal line parallel to the X-axis). These 3 points are 2 components generated from the PCA of the concerned variables.

Graph 10: **Scree Plot for Short and Major Morbidity Place of Advice and Treatment, 2005**



Source: *Author's calculations based on IHDS 1 data.*

8.3.3.1: Results of the Short And Major Morbidity Index of Construction from IHDS 2005:

The results of the short and major morbidity index of construction are presented in detail in Tables 107 to 109.

PCA results produce two tables: eigenvalues and eigenvectors. In Table 107, we present the results of eigenvalues. Column II gives eigenvalues, and components 1, 2 and 3 have eigenvalues of more than 1; these three components explain 80% variation in data (column V). Component 1 explains a 0.35% variation, component 2 explains a 0.30% variation, and component 3 explains a 0.15% variation. PCA generates maximum components by default. With the help of scree plots with an eigenvalue of more than 1, the required component can be retained, and PCA can be rerun with restricted components by default.

Table 108 is the table of eigenvectors. Table 108 gives factor loadings on components. Choosing variables that explain the component is crucial. PCA command is used with a covariance matrix since the data is standardized. Otherwise, the PCA command, by default, uses a correlation matrix (STATA*17* manual*)*. The variables that are used originally to construct PCA generate values. These values are factor loadings or component loadings. The factor loadings are coefficients of correlation between the variable and the component. The factor loading explains the variation the given variable on that component explains. In Table 108, Major morbidity first place of treatment and second place of treatment, Major morbidity first and second place of advice is heavily loaded on component 1; hence, component 1 explains the Major morbidity place and advice of treatment. Component 1 explains all the major morbidity-related variables. Short morbidity, second place of advice and second place of treatment are heavily loaded on the second component. Hence this explains short morbidity second place of advice and treatment. Short morbidity first advice and first place of treatment is also heavily loaded on component 2, but it is more loaded on component 3; hence, this explains component 3: short morbidity first place and advice of treatment.

Once the cut-offs are generally decided with visual observations (also using scree plot, see Graph 10), the PCA command can be rerun with component and factor loading restrictions; only those required factor loadings remain (Table 109).

8.3.3.2: PCA Post-Estimation Tests:

We present the results of PCA post estimation in Table 110 to Table 118.

Table 110 generates various tables to test whether the eigenvectors and eigenvalues differ significantly from zero. The eigenvalues and eigenvectors are significantly different from zero.

In table 111, The variables chosen are loaded differently on different components. Testsparm is used to check this. The three different components have different loadings.

For each component, the test is carried out separately. The assumption is that coefficients are equal (principal components are normalized to 1). This test performs Wald's test, and for all three components, the null hypothesis is rejected, which means all variables in each component are not equally loaded.

Tables 113 and 114 provide predicted scores for all three components and coefficient correlation for all components generated. PCA generates independent components, and this can be tested by using correlation. When components are independent, they will be correlated to themselves and not with other components, as given in Table 112. Variables are checked for pairwise correlation. All are correlated to each other.

Compared to the original PCA matrix of eigenvalues, the new rotated matrix gives values near one for all those variables that are heavily loaded on the respective factors. E.g. the first component, major morbidity, is heavily loaded on four variables major morbidity, first and second place of advice and first and second place of treatment. In Table 108, the variables have factor loading of 0.461, 0.47, 0.463, and 0.47. When the components are rotated, the values change to 0.497, 0.502, 0.499, and 0.502, respectively. The remaining factors have become closer to 0 in Table 115.

Table 116 is the anti-image of the covariance matrix, and it is the negative of variables obtained by partialling out all other variables. If any of these covariances are very high, it means some variables have no relation with each other; hence, reducing all of them to a low dimension may be meaningless. The variables obtained after anti-image are small.

The residual matrix is obtained as a difference between the observed and fitted covariance values. The residual produced should be small (Table 117); all along the diagonal, residuals are small.

Table 118: The sum of squared correlation is a pre-estimation technique; it gives squared multiple correlations of variables with all other variables, and thus, it helps in separating those variables with a small value. All variables have higher squared multiple correlations and can be reduced to low dimensions.

Table 107:**Principal Components/Covariance**

Component	Eigenvalue	Difference	Proportion	Cumulative
I	II	III	IV	V
Comp1	2.761	0.375	0.345	0.345
Comp2	2.385	1.153	0.298	0.644
Comp3	1.232	0.224	0.154	0.798
Comp4	1.009	0.795	0.126	0.924
Comp5	0.214	0.052	0.027	0.951
Comp6	0.161	0.032	0.02	0.971
Comp7	0.13	0.026	0.016	0.987
Comp8	0.104	.	0.013	1

Note 1) Number of observations = 99,028.

2)Number of components = 8.

3)Trace = 7.995743.

4) Rotation: (unrotated = principal) Rho = 1.0000.

Source: Authors' calculation based on IHDS 1 data.

Table 108:**Principal Components (eigenvectors)**

Variable	**Component1**	**Component2**	**Component3**	**Component4**	**Component5**	**Component6**	**Component7**	**Compooent8**	**Unexplained**
Short morbidity first advice	0.176	0.458	**0.495**	-0.114	-0.643	0.085	0.282	0.032	0
Short morbidity first place of treatment	0.178	0.453	**0.502**	-0.108	0.645	-0.088	-0.273	-0.032	0
Short morbidity second advice	0.187	**0.478**	-0.47	0.115	-0.269	0.075	-0.65	-0.04	0
Short morbidity second place of treatment	0.185	**0.474**	-0.478	0.121	0.273	-0.074	0.644	0.041	0
Major morbidity first place of treatment	**0.461**	-0.186	0.117	0.492	0.092	0.57	0	0.405	0
Major morbidity second place of treatment	**0.47**	-0.176	-0.113	-0.483	0.054	0.403	0.062	-0.576	0
Major morbidity first advice	**0.463**	-0.186	0.114	0.485	-0.101	-0.573	0	-0.405	0
Major morbidity second advice	**0.47**	-0.176	-0.114	-0.486	-0.049	-0.398	-0.059	0.579	0

Source: Authors' calculation based on IHDS 1 data.

Table 109: **Principal Components (eigenvectors) (blanks are abs(loading)<0.4)**

Variable	**Comp1**	**Comp2**	**Comp3**	**unexplained**
Short morbidity first advice			**0.496**	0.113
Short morbidity first place of treatment			**0.502**	0.111

Short morbidity second advice		**0.478**	0.0846
Short morbidity second place of treatment		**0.475**	0.0857
Major morbidity first place of treatment	**0.46**		0.315
Major morbidity second place of treatment	**0.403**		0.298
Major morbidity first advice	**0.463**		0.31
Major morbidity second advice	**0.47**		0.299

Source: Authors' calculations based on IHDS 1 data.

Table 110: **Principal Components/Covariance**

Eigenvalues	**Coefficient**	**Std. err**	**z**	**P>z**	**[95% conf. interval]**	
Comp1	2.761	0.012	222.56	0	2.737	2.785
Comp2	2.385	0.011	222.58	0	2.364	2.406
Comp3	1.232	0.006	222.55	0	1.222	1.243
Component 1						
Short morbidity first advice	0.176	0.01		0	0.156	0.196
Short morbidity first place of treatment	0.178	0.01	17.65	0	0.158	0.197
Short morbidity second advice	0.187	0.011	17.72	0	0.166	0.208
Short morbidity second place of treatment	0.185	0.01	17.62	0	0.164	0.205
Major morbidity first place of treatment	0.46	0.004	105.5	0	0.452	0.469
Major morbidity second place of treatment	0.47	0.004	113.3	0	0.462	0.478
Major morbidity first advice	0.463	0.004	106.1	0	0.455	0.472
Major morbidity second advice	0.47	0.004	112.95	0	0.462	0.478
Component 2						
Short morbidity first advice	0.458	0.005	100.55	0	0.449	0.466
Short morbidity first place of treatment	0.453	0.005	98.54	0	0.444	0.462

Short morbidity second advice	0.478	0.005	102.01	0	0.469	0.487
Short morbidity second place of treatment	0.475	0.005	101.73	0	0.465	0.484
Major morbidity first place of treatment	-0.186	0.01	-18.27	0	-0.206	-0.166
Major morbidity second place of treatment	-0.176	0.01	-16.97	0	-0.197	-0.156
Major morbidity first advice	-0.187	0.01	-18.21	0	-0.207	-0.166
Major morbidity second advice	-0.176	0.01	-17	0	-0.197	-0.156
Component 3						
Short morbidity first advice	0.495	0.003	160.1	0	0.489	0.502
Short morbidity first place of treatment	0.502	0.003	165.85	0	0.496	0.508
Short morbidity second advice	-0.47	0.003	-151.15	0	-0.476	-0.464
Short morbidity second place of treatment	-0.478	0.003	-151.38	0	-0.485	-0.472
Major morbidity first place of treatment	0.118	0.008	14.54	0	0.102	0.133
Major morbidity second place of treatment	-0.113	0.008	-14.17	0	-0.128	-0.097
Major morbidity first advice	0.114	0.008	14.23	0	0.098	0.129
Major morbidity second advice	-0.114	0.008	-14.32	0	-0.13	-0.099

LR test for independence: chi2(28) = 551599.34 Prob > chi2 = 0.0000

LR test for sphericity: chi2(35) = 551603.27 Prob > chi2 = 0.0000

Explained Variance By Components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Component 1	2.761	0.345	0.001	0.345	0.001	0
Component 2	2.385	0.298	0.001	0.644	0.001	0
Component 3	1.232	0.154	0.001	0.798	0.001	0

Component 4	1.009	0.126	0.001	0.924	0	0
Component 5	0.214	0.027	0	0.951	0	0
Component 6	0.161	0.02	0	0.971	0	0
Component 7	0.13	0.016	0	0.987	0	0
Component 8	0.104	0.013	0	1	0	0

SE(Rho) = 0.0006.

SEs assume multivariate normality.

Source: Authors' calculation based on IHDS 1 data.

Table 111:**Results of Testsparm**

(1) - [Comp1]Short morbidity first advice + [Comp1]Short morbidity first place of treatment = 0
(2) - [Comp1]Short morbidity first advice + [Comp1]Short morbidity second advice = 0
(3) - [Comp1]Short morbidity first advice + [Comp1]Short morbidity second place of treatment = 0
(4) - [Comp1]Short morbidity first advice + [Comp1] Major morbidity first advice = 0
(5) - [Comp1]Short morbidity first advice + [Comp1]Major morbidity first place of treatment = 0
(6) - [Comp1]Short morbidity first advice + [Comp1] Major morbidity second advice = 0
(7) - [Comp1]Short morbidity first advice + [Comp1]Major morbidity second place of treatment = 0
chi2(7) = 882.18
Prob > chi2 = 0.0000
(1) - [Comp2]Short morbidity first advice + [Comp2]Short morbidity first place of treatment = 0
(2) - [Comp2]Short morbidity first advice + [Comp2]Short morbidity second advice = 0
(3) - [Comp2]Short morbidity first advice + [Comp2]Short morbidity second place of treatment = 0
(4) - [Comp2]Short morbidity first advice + [Comp2] Major morbidity first advice = 0
(5) - [Comp2]Short morbidity first advice + [Comp2]Major morbidity first place of treatment = 0
(6) - [Comp2]Short morbidity first advice + [Comp2] Major morbidity second advice = 0
(7) - [Comp2]Short morbidity first advice + [Comp2]Major morbidity second place of treatment = 0
chi2(7) =53571.98
Prob > chi2 = 0.0000
(1) - [Comp3]Short morbidity first advice + [Comp3]Short morbidity first place of treatment = 0
(2) - [Comp3]Short morbidity first advice + [Comp3]Short morbidity second advice = 0
(3) - [Comp3]Short morbidity first advice + [Comp3]Short morbidity second place of treatment = 0
(4) - [Comp3]Short morbidity first advice + [Comp3] Major morbidity first advice = 0
(5) - [Comp3]Short morbidity first advice + [Comp3]Major morbidity first place of treatment = 0
(6) - [Comp3]Short morbidity first advice + [Comp3] Major morbidity second advice = 0
(7) - [Comp3]Short morbidity first advice + [Comp3]Major morbidity second place of treatment = 0
chi2(7) = 1.2e+10
Prob > chi2 = 0.0000

Source: Authors' calculation based on IHDS 1 data.

Table 112:**Pairwise Correlations**

Variables	Short morbidity first advice	Short morbidity first place of treatment	Short morbidity second advice	Short morbidity second place of treatment	Major morbidity first place of treatment	Major morbidity second place of treatment	Major morbidity first advice	Major morbidity second advice
Short morbidity first advice	1							
Short morbidity first place of treatment	0.800*	1						
Short morbidity second advice	0.326*	0.290*	1					
Short morbidity second place of treatment	0.287*	0.310*	0.858*	1				
Major morbidity first place of treatment	0.032*	0.047*	0.014*	0.016*	1			
Major morbidity second place of treatment	0.021*	0.024*	0.050*	0.049*	0.434*	1		
Major morbidity first advice	0.039*	0.038*	0.017*	0.017*	0.857*	0.413*	1	
Major morbidity second advice	0.022*	0.021*	0.052*	0.047*	0.405*	0.877*	0.439*	1

Note:1)*** p<0.01, ** p<0.05, * p<0.1.

Source: Authors' calculation based on IHDS 1 data.

Table 113:**Scoring Coefficients:**

Variable	Comp1	Comp2	Comp3
Short morbidity first advice	0.176	0.458	0.495
Short morbidity first place of treatment	0.178	0.453	0.502
Short morbidity second advice	0.187	0.478	-0.47
Short morbidity second place of treatment	0.185	0.474	-0.478
Major morbidity first place of treatment	0.461	-0.186	0.117
Major morbidity second place of treatment	0.47	-0.176	-0.113
Major morbidity first advice	0.463	-0.186	0.114
Major morbidity second advice	0.47	-0.176	-0.114

Note: a) sum of squares(column-loading) = 1.

Source: Author's calculation based on IHDS 1 data.

Table 114: **Matrix of Correlations**

Variables	**Component 1**	**Component 2**	**Component 3**
Component 1	1		
Component 2	0	1	
Component 3	0	0	1

Source: Authors' calculation based on IHDS 1 data.

Table 115: **Rotation: Orthogonal Varimax**

Component	Variance	Difference	Proportion	Cumulative
Component 1	2.712	0.849	0.339	0.339
Component 2	1.863	0.058	0.233	0.572
Component 3	1.805	0	0.226	0.798
		Rotated components		
Variable	Component 1	Component 2	Component 3	Unexplained
Short morbidity first advice	-0.002	0.013	0.697	0.113
Short morbidity first place of treatment	0.001	0.006	0.7	0.112
Short morbidity second advice	0.001	0.696	0.014	0.085
Short morbidity second place of treatment	0	0.699	0.005	0.086
Major morbidity first place of treatment	0.497	-0.086	0.08	0.315
Major morbidity second place of treatment	0.502	0.083	-0.077	0.298
Major morbidity first advice	0.499	-0.083	0.078	0.31
Major morbidity second advice	0.502	0.083	-0.079	0.3
		Component rotation matrix		
Components	Component 1	Component 2	Component 3	
Component 1	0.932	0.263	0.25	
Component 2	-0.363	0.674	0.643	
Component 3	0.001	-0.69	0.724	

Rotation: orthogonal varimax (Kaiser off) Rho = 0.7978.

Source: Authors' calculation based on IHDS 1 data.

Table 116: **Anti-Image Covariance Coefficients -Partialing Out All Other Variables**

Variables	Short morbidity first advice	Short morbidity first place of treatment	Short morbidity second advice	Short morbidity second place of treatment	Major morbidity first place of treatment	Major morbidity second place of treatment	Major morbidity first advice	Major morbidity second advice
Short morbidity first advice	0.3429							
Short morbidity first place of treatment	-0.2701	0.3457						
Short morbidity second advice	-0.0589	0.0375	0.2533					
Short morbidity second place of treatment	0.0397	-0.054	-0.2152	0.2558				
Major morbidity first place of treatment	0.0116	-0.0143	-0.0002	0.0015	0.2513			
Major morbidity second place of treatment	0.0009	-0.0007	0.001	-0.0028	-0.0525	0.2185		
Major morbidity first advice	-0.012	0.0102	0.0014	-0.0011	-0.208	0.035	0.25	
Major morbidity second advice	-0.0005	0.0015	-0.0037	0.0018	0.0373	-0.1863	-0.0533	0.2183

Source: Authors' calculation based on IHDS 1 data.

Table 117**: Residual Covariance Matrix**

Variables	**Short morbidity first advice**	**Short morbidity first place of treatment**	**Short morbidity second advice**	**Short morbidity second place of treatment**	**Major morbidity first place of treatment**	**Major morbidity second place of treatment**	**Major morbidity first advice**	**Major morbidity second advice**
Short morbidity first advice	0.113							
Short morbidity first place of treatment	-0.087	0.112						
Short morbidity second advice	0.001	-0.028	0.085					
Short morbidity second place of treatment	-0.029	0.002	-0.057	0.086				
Major morbidity first place of treatment	-0.06	-0.05	0.057	0.061	0.31517			
Major morbidity second place of treatment	0.054	0.054	-0.057	-0.058	-0.226	0.298		
Major morbidity first advice	-0.051	-0.058	0.057	0.059	0.169	-0.251	0.31	
Major morbidity second advice	0.057	0.05	-0.056	-0.06	-0.254	0.176	-0.224	0.299

Source: Authors' calculation based on IHDS 1 data.

Table 118: **Squared Multiple Correlations of Variables With All Other Variables**

Variable	SMC
Short morbidity first advice	0.657
Short morbidity first place of treatment	0.654
Short morbidity second advice	0.747
Short morbidity second place of treatment	0.744
Major morbidity first place of treatment	0.749
Major morbidity second place of treatment	0.782
Major morbidity first advice	0.75
Major morbidity second advice	0.781

Source: Authors' calculation based on IHDS 1 data.

8.3.4: Combined Summary Table of PCA Index:

The three components extracted from short and major morbidity, place of advice, and treatment generate different scores. The last step is to predict scores. Three components create three indices. Table 119 gives a complete description of the results drawn from the PCA from IHDS 1. Column I to XIV gives indices, variables, KMO, BTS, P-value, eigenvalue, proportion, eigenvector, values of orthogonal rotation, number of observations, mean, SD, min and max value, respectively. The first set of indices is drawn from 8 variables, as in column II. Three components are retained using a scree plot (Refer to appendix A8), which together explain 85% of the data.

The KMO is 0.57, and the BTS test results are also significant, indicating that the data is suitable for the deduction. Pairwise correlation is also carried out, and the results indicate a significant correlation between the variables chosen for PCA (Table 112 and Appendix A8). The first Index is an index of major morbidity places of advice and treatment. This component is visible from column no. VIII, which is heavily loaded on four variables. The next Index is the Index of short morbidity, second place of advice and treatment loaded on two variables. The last Index is the Index of short morbidity, the first place of advice and treatment.

The next set of 5 variables generated two components leading to two indices. These variables were suitable for deduction since pairwise correlations were significant, KMO was 0.61, and the chi-square of BTS was significant. Two components are retained using the scree plots. Together, these two components explain a 60% variation in the data. Three variables are loaded on component 1which is Health infrastructure index 1. The second component is loaded on two variables. These two variables make the health infrastructure index 2. The next set of 4 variables generates two components: KMO 0.55 and BTS chi-square significant. Two variables are loaded on the first component and hence form the Index of Health Infrastructure Facility Nearby Index 1, and the other two variables are loaded on the next component and the Index of Health Infrastructure Facility Nearby Index 2. The last set of 4 variables generates two components and an index of infrastructure facilities 1 and 2. A total of twenty-one variables have generated nine indices from IHDS 1 data.

Table 120 gives a composite description of the Index generated from IHDS II. Twenty-five variables are used to generate ten indices. The pairwise correlations are significant for all sets of variables. The KMO and BTS chi-square test p-value is significant. The first set of eight variables generates three components. Three indices are the Index of major morbidity place of advice and treatment, short morbidity second place for advice and treatment, and short morbidity first place of advice and treatment. The next five variables generate two indices, Index of Health Infrastructure Facility 1 and 2. Seven variables generate three components: Health infrastructure facility nearby 1,2 and 3. The last five variables generate two components: an Index of infrastructure facilities in villages 1 and 2.

Table 119:**Village Health Infrastructure Index,2005**

Index	Variables	KMO	BTS: chi-square	P value	Eigenvalue	Proportion explained	Eigenvector	Orthogonal rotation	Number of observations	Mean	SD	Min	Max
I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV
Major Morbidity Place of Advice and Treatment Index	Major Morbidity First Place of treatment	0.57	5.52E+05	0	2.76	0.35	0.46	0.5	99028	-0.21	1.662	-0.658	23.209
	Major Morbidity Second Place of treatment						0.47	0.5					
	Major Morbidity First Place of advice						0.46	0.5					
	Major Morbidity Second Place of advice						0.47	0.5					
Short morbidity Second place of advice and treatment Index	Short Morbidity Second place of advice				2.39	0.3	0.48	0.7	99028	-0.54	1.544	-9.113	15.98
	Short morbidity Second place of Treatment						0.48	0.7					
Short morbidity First place of advice and treatment Index	Short Morbidity First place of advice				1.23	0.15	0.5	0.7	99028	0.534	1.11	-10.391	7.179
	Short Morbidity First Place of Treatment						0.5	0.7					
Health Infrastructure Facility Index 1	Community Health Centre In the village	0.61	50147.05	0	1.83	0.37	0.4	0.45	99,028	0.004	1.354	-0.524	11.147
	Communicable disease facility in the village						0.56	0.64					
	Government Maternity Centre						0.59	0.59					
Health Infrastructure Facility Index 2	Primary Health centre				1.12	0.22	0.51	0.61	99,028	0	1.058	-4.528	13.15
	Sub-centre						0.76	0.78					
Health Infrastructure Facility Nearby Index 1	Distance to Nearest Maternity Centre	0.55	49324.89	0	1.72	0.43	0.59	0.71	99,028	4.00E-05	1.31	-1.771	9.159
	Distance to Nearest Communicable Disease Facility.						0.59	0.7					

Health Infrastructure Facility Nearby Index 2	Distance to nearest PHC				1.16	0.29	0.56	0.69	99,028	8.00E-05	1.075	-3.837	10.476
	Distance to nearest Sub-centre						0.62	0.72					
Infrastructure Facility in the Village Index 1	Distance to nearest Pucca road	0.56	20804.963	0	1.52	0.38	0.63	0.66	99,028	0	1.231	-1.45	14.819
	Distance to the closest bus stop						0.55	0.75					
Infrastructure Facility in the Village Index 2	Distance to the nearest town				1.01	0.25	0.55	0.68	99,028	1.00E-04	1.006	-5.889	5.049
	Distance to the closest railway station.						0.6	0.71					

Source: Authors' calculation based on IHDS 1 data.

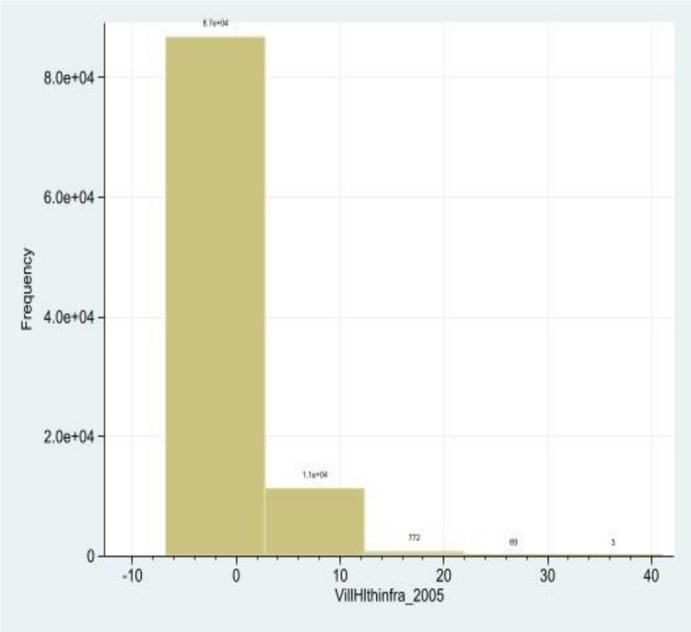
Table 120:**Village Health Infrastructure Index 2012**

Index	Variables	KMO	BTS: chi-square	P value	Eigenvalue	Proportion explained	Eigenvector	Orthogonal rotation	Number of observations	Mean	SD	Min	Max
I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII	XIII	XIV
Major Morbidity Place of Advice and Treatment Index	Major Morbidity First Place of advice	0.58	5.73E+05	0	2.9	0.36	0.43	0.49	99,028	0.00022	1.704	-0.695	16.366
	Major Morbidity Second Place of advice						0.44	0.5					
	Major Morbidity First Place of treatment						0.45	0.51					
	Major Morbidity Second Place of treatment						0.45	0.51					
Short morbidity Second place of advice and treatment Index	Short Morbidity second place of advice				2.32	0.29	0.45	0.7	99,028	-0.00047	1.524	-9.129	15.325
	Short morbidity second place of Treatment						0.45	0.7					
Short Morbidity First place of advice and treatment Index	Short Morbidity First place of advice				1.27	0.16	0.51	0.7	99,028	0.00056	1.126	-8.247	7.434
	Short Morbidity First Place of Treatment						0.47	0.69					
Health Infrastructure Facility Index 1	Health sub-centre	0.67	1.40E+05	0	2.34	0.47	0.5	0.48	99,028	0.00045	1.532	-0.826	20.154
	Health worker						0.56	0.61					
	Multipurpose health worker						0.58	0.62					
Health Infrastructure Facility Index 2	Primary Health centre				1.13	0.23	0.55	0.61	99,028	0.00036	1.065	-6.802	8.764
	Govt. Maternity centre						0.76	0.77					

Health Infrastructure Facility Nearby Index 1	Distance to nearest Primary Health Centre	0.55	74682.31	0	1.71	0.24	0.41	0.46	99,028	-0.0000204	1.308	-2.337	9.785
	Distance to the nearest community health centre						0.45	0.34					
	Distance to nearest district hospital						0.51	0.7					
	Government maternity home						0.41	0.7					
Health Infrastructure Facility Nearby Index 2	Distance to nearest Health worker				1.59	0.23	0.67	0.61	99,028	0.00001	1.261	-4.01	24.846
	Distance to nearest sub-centre						0.66	0.66					
Health Infrastructure Facility Nearby Index 3	Distance to nearest sub-centre				1.03	0.15	0.72	0.78	99,028	-0.00002	1.017	-4.519	13.505
Infrastructure Facility in the Village Index 1	Distance to the nearest town	0.59	24323.12	0	1.58	0.32	0.51	0.55	99,028	0.00006	1.258	-3.278	10.552
	Distance to the nearest district headquarters.						0.54	0.56					
	Distance to the nearest railway station						0.54	0.53					
Infrastructure Facility in the Village Index 2	Distance to Pucca Road				1.32	0.23	0.55	0.62	99,028	0.00003	1.064	-1.801	11.877
	Distance to Bus stop.						0.78	0.76					

Source: Authors' calculation based on IHDS 2 data.

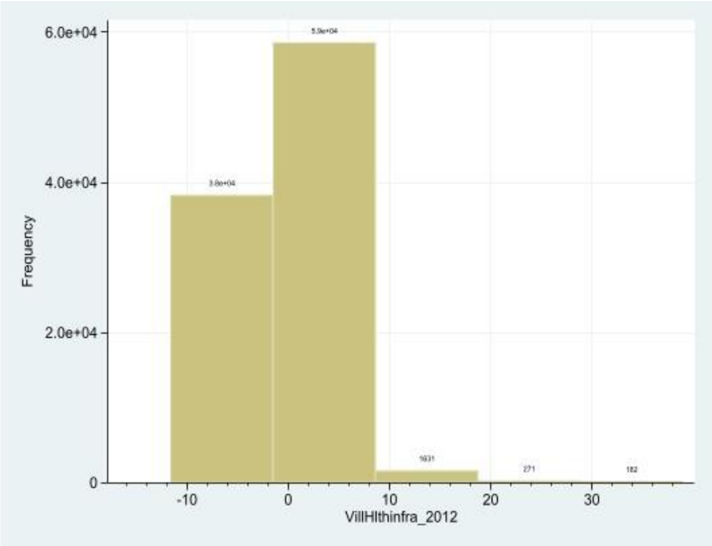
Graph 11**:Histogram for VHII 2005**



Note: (bin=5, start=-6.7876043, width=9.5794668)

Source: Authors' calculation based on IHDS 1 data.

Graph 12: **Histogram for VHII2012**



Note:(bin=5, start=-11.58935, width=10.115636)

Source: Authors' calculation based on IHDS 2data.

Table 121: **Village Health Infrastructure Index (Lower and Upper limit of class)**

Range	2005	2012
Very Low	<2.792	< -1.474
Low	>=2.792 and < 12.371	>=-1.474 and < 8.642
Average	>=12.371 and < 20.327	>=8,642 and < 18.758
High	>=20.327 and < 29.907	>= 18.758 and < 28.873
Very High	>= 29.907	>=28.873

Note: Calculated using the starting range of bin(histogram) and bin width.

Source: *Author's calculations based on IHDS 1 and IHDS 2 data.*

8.3.5: Scores Generated from The Combined Index:

The 9 indices generated from IHDS 1 were added linearly and averaged out. 10 indices generated from IHDS 2 were added linearly and averaged out. The same procedure is repeated for indices generated from IHDS 2. The VHII generated from each round is divided into five categories: very low, low, average, high and very high. The above-given range is generated with the help of a histogram (see Graph 11, Graph 12 and Table 121). These categories indicate availability and access to all types of health infrastructure measured by the VHII. In Table 121, we have presented a lower and upper limit of the categories of VHII.

8.3.6: State Wise Shifts in Village Health Infrastructure Index (2005-2012):

The Index for both rounds of IHDS is compared for states and consumption expenditure quintile (Table 122). We present a two-way table of results of states and VHII. The states are divided into High focus Northeastern states, High focus non-North-eastern states, non-focus small states, and non-focus large states (see Chapter 3 for details). For every category of VHII, the value of the indicator in 2005 and 2012 is given and helps track the states' status changes from 2005 to 2012 for different categories (see columns III to X, Table 122).

For the high focus on North-eastern states between rounds 1 and 2, the distribution of individuals has changed for different ranges of the Index. In Arunachal Pradesh, 98% of individuals had very low access to health infrastructure in IHDS 1, and this distribution changed to 36% in IHDS 2. From IHDS, 1,63% from the category of the very low group have shifted to low, average, very high and high in 2012 and 14% in low, 18% average, and 32% in high availability for health infrastructure. In IHDS 1, the number of individuals with access to health infrastructure was very low and low. In IHDS 2, some individuals had access to the average and high availability of infrastructure.

In IHDS 1, in Assam, 83% of individuals had access to very low infrastructure; in IHDS 2, only 33%had very low infrastructure. 51% of individuals were redistributed in categories of low and average. However, no individuals moved to groups with high and very high infrastructure.

Manipur had 99% of individuals with access to very low infrastructure in IHDS 1, which decreased to 48% in IHDS 2. 52% of individuals received access to low infrastructure in IHDS 2. For Meghalaya, 54% of individuals shifted from very low to low infrastructure from rounds 1 to 2. Another 31% of individuals also shifted to the average availability of infrastructure. In Mizoram, 3% more individuals shifted to very low from low accessibility to health infrastructure, and those with access to low infrastructure reduced from 35% to 32% from IHDS 1 to IHDS 2. In IHDS 1, 0.57% were in the category of average access, but in IHDS 2, there were none. In Nagaland and Sikkim, the major shift was from the very low to low category. In Tripura, 30% of individuals moved from the very low to low infrastructure category. Arunachal Pradesh, Meghalaya and Nagaland shifted from very low to low and to average. Overall, the performance of Northeastern states did not lead to any shifts to a very high category except Arunachal Pradesh to high during the 7 years of NRHM.

Among the high focus non-North-eastern states, Himachal Pradesh and Orissa had new categories of very high in IHDS 2 from none in IHDS 1. Similarly, Madhya Pradesh and Himachal Pradesh also had some shifts to high from none in IHDS 1 to IHDS 2. Rajasthan and Jammu Kashmir were not able to move up to average availability. Chhattisgarh, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, and Uttarakhand were able to shift from very low to low availability of at least 60% population.

The union territories and small states were stuck with very low and low and more percentages of individuals shifting from very low to low categories.

In the non-high focus large states, from IHDS 1 to IHDS 2, only West Bengal had some shifts to high and very high categories. Andhra Pradesh, Haryana, Karnataka, Kerala, and Tamil Nadu had a marginal percentage of individuals in the category of high availability in IHDS 1 but none in IHDS 2. The remaining states had major shifts from low-to-low categories, except for Goa. Goa had the least shift, followed by Tamil Nadu. Andhra Pradesh had the highest shift.

8.3.7: Quintile-Wise Distribution of Rural Health Infrastructure Index:

Tables 123 and 124 give the distribution of individuals with access to a different range of health infrastructure across the consumption expenditure quintile for IHDS 1 and IHDS 2 respectively. In IHDS 1, the percentage of individuals in the BPL group was very high, with access to very low facilities, and in IHDS 2, this decreased. In IHDS 2, BPL, APL1 and APL2 had individuals with access to a very high level of facilities; APL3, APL4, and APl5 also had some shifts from rounds 1 to 2 from very low to low and high.

Table 122: **State-Wise Shifts in Village Health Infrastructure Index (2005, 2012)**

		Very Low		Low		Average		High		Very High		
States	**Observations**	**2005**	**2012**	**2005**	**2012**	**2005**	**2012**	**2005**	**2012**	**2005**	**2012**	**Total**
I	**II**	**III**	**IV**	**V**	**VI**	**VII**	**VIII**	**IX**	**X**	**XI**	**X**	**XI**
HIGH-FOCUS NORTHEASTERN STATES												
Arunachal Pradesh	401	98.25	36.16	1.75	14.21		17.96		31.67			100
Assam	1,365	83.44	32.53	16.56	64.47		3					100
Manipur	198	98.99	47.47	1.01	52.53							100
Meghalaya	409	75.06	20.78	24.69	47.92	0.24	31.3					100
Mizoram	176	64.2	67.05	35.23	32.95	0.57						100
Nagaland	200	96.5	0.5	2.5	80.5	1	19					100
Sikkim	56	91.07	3.57	8.93	96.43							100
Tripura	261	93.1	63.22	6.9	36.78					0.16		100
HIGH-FOCUS NON-NORTHEASTERN STATES												
Bihar	4,241	87.03	44.19	11.53	55.79	1.34	0.02	0.09				100
Chhattisgarh	3,582	87.72	20.74	9.44	78.64	2.76	0.61	0.08				100
Himachal Pradesh	4,110	77.2	35.28	22.36	54.67	0.36	8.08	0.07	1.7		0.27	100
Jammu & Kashmir	1,818	95.6	55.83	3.91	44.17	0.5						100
Jharkhand	1,942	91.52	16.42	8.43	83.24	0.05	0.34					100
Madhya Pradesh	9,132	72.6	24.98	25.99	73.18	1.37	1.77	0.03	0.07			100
Orissa	5,908	88.79	38.59	11.02	59.83	0.17	0.19	0.02			1.39	100
Rajasthan	7,185	93.58	36.74	6.08	63.1	0.33	0.15					100
Uttar Pradesh	11,282	91.88	43.09	7.53	56.01	0.53	0.9	0.05		0.01		100
Uttarakhand	1,124	74.73	16.73	21.71	83.19	3.2	0.09	0.36				100
NON-HIGH-FOCUS SMALL STATES / UT												
Dadra+Nagar Haveli	168	95.83	46.43	3.57	53.57	0.6						100
Daman & Diu	218	92.2	62.39	7.8	37.61							100
Pondicherry	197	96.95	71.07	3.05	28.93							100
Punjab	4,764	94.92	56.8	4.79	43.2	0.29						100
NON-HIGH-FOCUS LARGE STATES												
Andhra Pradesh	4,146	85.21	17.17	14.16	82.56	0.55	0.27	0.07				100
Goa	398	98.74	92.21	1.26	7.79							100
Gujarat	4,144	87.43	36.78	12.23	63.03	0.34	0.19					100
Haryana	6,071	93.53	48.25	4.83	50.5	1.61	1.25	0.03				100
Karnataka	8,825	87.55	46.44	11.94	52.06	0.46	1.51	0.05				100
Kerala	1,057	55.06	9.74	41.06	58.37	3.6	31.88	0.28				100
Maharashtra	8,592	91	37.65	8.53	61.59	0.47	0.76					100
Punjab	4,764	94.92	56.8	4.79	43.2	0.29						
Tamil Nadu	2,577	86.3	64.73	10.67	35.23	1.13	0.04	1.75		0.16		100
West Bengal	4,481	94.02	43.23	5.51	51.62	0.45	2.5	0.02	0.67		1.99	100

Source: *Author's calculations based on IHDS 1 and IHDS 2 data.*

Table 123: **Quintile-Wise Distribution Rural Health Infrastructure Index, 2005**

Quintile	Very Low	Low	Average	High	Very High	No. of Observations	Total
BPL	87.64	11.63	0.69	0.05	0	40788	100
APL1	87.55	11.47	0.85	0.11	0.02	11651	100
APL2	87.33	11.72	0.68	0.27		11651	100
APl3	88.82	10.38	0.75	0.04	0.01	11649	100
APl4	87.93	11.27	0.76	0.03		11641	100
APl5	87.11	11.76	1.06	0.08		11648	100

Source: *Author's calculations based on IHDS 1 data.*

Table 124: **Quintile-Wise Distribution Rural Health Infrastructure Index, 2012**

Quintile	Very Low	Low	Average	High	Very High	No. of Observations	Total
BPL	33.88	63.89	1.65	0.21	0.38	20938	100
APL1	35.45	62.86	1.33	0.06	0.31	15620	100
APL2	37.62	60.51	1.55	0.2	0.13	15616	100
APl3	40.08	57.82	1.65	0.38	0.08	15623	100
APl4	42.68	55.13	1.8	0.29	0.1	15614	100
APl5	44.18	53.33	1.91	0.53	0.04	15617	100

Source: *Author's calculations based on IHDS 2 data.*

Table 125: **Surplus/Shortage Of SC, PHC And CHC, 2011**

State/ UT	SC	PHC	CHC
Andhra Pradesh	**-630**	**-331**	**-207**
Arunachal Pradesh	-27	49	36
Assam	**-1237**	**-15**	**-130**
Bihar	**-8837**	**-1220**	**-700**
Chhattisgarh	172	-35	-46
Goa	65	1	1
Gujarat	**-660**	**-157**	**-15**
Haryana	**-798**	**-107**	**-30**
Himachal Pradesh	798	243	24
Jammu & Kashmir	-88	72	2
Jharkhand	**-2085**	**-634**	**-53**
Karnataka	939	1006	-146
Kerala	1050	223	78
Madhya Pradesh	**-3445**	**-821**	**-161**
Maharashtra	**-2830**	**-380**	**-182**
Manipur	-72	3	-3
Meghalaya	-353	-5	1
Mizoram	197	31	3
Nagaland	-61	58	4
Odisha	-1448	-80	50
Punjab	**-513**	**-131**	**-15**
Rajasthan	113	-334	-86
Sikkim	42	8	-2
Tamil Nadu	1190	-45	73

Tripura	**-41**	**-27**	**-15**
Uttarakhand	325	1	-4
Uttar Pradesh	**-10516**	**-1480**	**-778**
West Bengal	**-2680**	**-1239**	**-189**
Andaman & Nicobar Islands	62	11	2
Chandigarh	12	0	2
Dadra & Nagar Haveli	-4	-2	-1
Daman & Diu	14	1	2
Delhi	-42	-5	-3
Lakshadweep	10	4	3
Puducherry	-25	11	0
India	**-30143**	5326	2766

Source: Compiled from Rural Health Statistics, 2013-14.

8.3.8: Surplus/Shortage of SC, PHC And CHC:

Table 125 provides details of the shortfall and surplus in SC, PHC and CHC in 2011, as given in Rural Health Statistics 2013-14. The states with the deficit are with a minus sign and otherwise. The states that had a deficit in all 3 categories are highlighted. India had a shortfall of 30000 odd SCs, but PHC and CHC were in surplus. Andhra Pradesh, Assam, Bihar, Gujarat, Haryana, Jharkhand, Madhya Pradesh, Maharashtra, Punjab, Tripura, Uttar Pradesh, and West Bengal had a deficit of SC, PHC, and CHC. Uttar Pradesh had the highest SC, PHC and CHC deficit in 2011.

8.4: Main Findings and Discussion:

Choosing variables and fulfilling pre-estimation and post-estimation steps is crucial in PCA. PCA helps reduce the data to meaningful interpretations, but the choice of variables is still subjective. The construction of the rural health infrastructure index using PCA facilitates the incorporation of large amounts of data compressed into smaller dimensions that are easy to comprehend. Variables used broadly measured the availability of health infrastructure in the village in rounds 1 and 2. Variables like the place of advice and treatment, availability of physical infrastructure in the village, distance to nearby facilities and availability of transport are measured. All these variables were compressed to form indices for both years and averaged into two indices for IHDS 1 and IHDS 2; the index is used in the health insurance impact analysis in Chapter 7.

State-wise analysis reveals that although shifts took place from the very low to a low category, shifts to high and very high were small. Among Non- North Eastern states, only Himachal Pradesh, Orissa, and West Bengal among non-focus groups experienced shifts to a very high category. However, the percentage of individuals experiencing such shifts was very small. Most shifts were from very low to low and to average. The most noticeable inequities that led to differences in India were rural-urban disparities and inter and intra-state. Northern and Eastern states' performance differs from Southern and Western states(Prasad et al., 2013). A mid-term review of NRHM revealed that by 2008, the states lacking pre-NRHM did not show any remarkable changes. The challenge was the human resource requirement(Sarma, 2009). Some recent regional studies found deficiencies in physical public health infrastructure, especially in sub-centres in Andhra Pradesh(Sriram, 2019). Some well-performing states under NRHM were Chhattisgarh, Rajasthan, Orissa, and Karnataka for Subcentres, Uttar Pradesh, Bihar, Maharashtra and Andhra Pradesh for primary health centres and Tamil Nadu for the community health centres. Bihar, Andhra Pradesh, Assam, and Rajasthan remain other relevant variables constant (Singariya, 2013). Rural health infrastructure in North Eastern states is not very impressive(Lyngdoh, 2015). There were disparities in health infrastructure noticed in Uttar Pradesh and Bihar(Anand, 2014). The state-level data study's findings confirmed the existence of a positive correlation between the health infrastructure index and gross state domestic product (Varkey et al., 2020).

The quintile shifts from 2005 to 2012 provide evidence of the impact of NRHM on individuals. The decline in population in BPL from 2005 to 2012 for very low facilities showcases marginal improvement in healthcare facilities. In IHDS 2, the fact that some individuals had access to very high facilities from BPL, APL1 and APL2 and shifts from rounds 1 to 2 from very low to low and high provides evidence for improved health infrastructure.

8.5: Conclusion

India has intra and inter-regional differences, and it hosts most of its population lives in rural areas (Dhingra & Dutta, 2011). Therefore, extending health infrastructural facilities is crucial to these areas. The objective of NRHM was to provide better-quality health facilities to rural areas. The NRHM lacked completion of many targets by 2012, as revealed by studies undertaken then. NRHM's mission is to redistribute resources with a fair share of public health (Hussain, 2011). Private sector contribution was significant at 70%, and its role was overarching in NRHM. In Indian health care, the focus was lessor on PHCs (PHCs are important for rural health is neglected, urban sector, private players are gaining importance (Ashtekar, 2008). Some recent studies also pointed out that the focus of NRHM's mission was to increase healthcare expenditure, but from 2000 to 2011, it declined from 1.3% of GDP to 1.2%. Besides, a few issues in the health sector remain challenging, such as inadequate and inferior infrastructure, poor public service delivery, and lack of access to the poor due to private health sector dominance(Agrawal, 2015). Although the healthcare sector has expanded physically, the quality is still questionable despite health standards introduced in public health (Goel, 2021). Although the statewide analysis does not provide robust evidence towards improvement in health infrastructure in villages, individuals have access to high and very high health infrastructure facilities.

We have examined the impact evaluation of NRHM using the unconventional method of constructing the VHII index. We have looked at shifts in consumption expenditure quintiles from both rounds separately for the panel data. Some positive shifts are observed across quintiles, indicating towards availability of health infrastructure for BPL and APL1 quintiles.

Based on Rural Health statistics 2018, a study observes that rural infrastructure is falling short in terms of the requirements of the people (Sarkar & Mukherjee, 2021). The findings from IHDS rounds 1 and 2 by constructing rural health infrastructure revealed that the individuals with access to very high health infrastructure were negligible. The rural health statistics for 2020-21 revealed that the shortfall in subcentres, PHC and CHC is above 20%. The efforts for building up infrastructure and increasing public health expenditure are crucial.

The last chapter of the thesis, chapter 9, is the conclusion.

CHAPTER 9:

CONCLUSION

The previous chapter 8, discussed about village health infrastructure. Chapter 9 is the Conclusion. It is divided into 5 main sections. The section is an introduction; section 2 contains the main findings and policy implications. In section 9.4, we discuss the conclusion, followed by the future scope of research.

9.1 Introduction:

Health is human capital, and its contribution to economic development is documented in the literature. Economic development and health have a causal relationship. This causal relationship is examined in the literature using indicators such as life expectancy, infant mortality, and body mass index. The reverse causality of the impact of health on economic development is also examined using labour productivity, days unable to work due to illness.(Ajayi & Akinbobola, 2021; Galor & Tsiddon, 1997; Grosse & Harkavy, 1980; Guisan & Aguayo, 2007; Nutbeam & Muscat, 2021; Strittmatter & Sunde, 2013; Suhrcke et al., 2006).

Achieving SDG is very crucial for India. Essentially, the health policies of the last 1.5 decades reflect India's intention to do so. The provisioning of publicly funded financial protection to households and strengthening of health infrastructure is outlined in the health policy. The achieved targets and milestones are also documented and available in the public domain. The concerns raised are about health infrastructure, health expenditure, health-related poverty, and quality of health care(Accountability Initiative, Centre for Policy Research, 2012; Economic Survey, 2021; Rural Health Statistics, GOI, 2015; 2020; Hooda, 2014, 2015, 2017a, 201b, 2020; Hussain,2011; NHA, 2021). All these concerns have binding on the economic well-being of the household.

Shock has an impact on the economic well-being of the household. Shock the household faces in the form of illness or disability generates two types of costs. One is the cost in the form of lost productivity due to ill health, which affects income earned; the other is when the expenditure incurred for treatment is an OOPHE on health, which is the direct effect of shock (Simeu & Mitra, 2019). Eventually, to meet these costs, households resort to self-insurance coping mechanisms. The households use many informal coping mechanisms(Gertler & Gruber, 2002). Despite using coping mechanisms, households may not be able to get to the level of full insurance, which may lead to a reduced standard of living (Meyer & Mok, 2018) and may trigger poverty(Nguyet & Mangyo, 2010).

Households that face shocks also smoothen consumption by diversifying economic activities, especially activities that may be exposed to seasonal income shocks. Productive assets may not have a role to play in consumption smoothing (Nguyen et al., 2019). Households respond to shocks in many ways, but assets are the household's most important coping mechanism.

Similarly, selling productive assets or incurring less investment in accumulating assets may lead to a future income decrease(Berloffa & Modena, 2013). When households experience shocks leading to a loss in income, and if this loss gets translated into drastic decisions about asset investment, there may be some consequences of such shocks in the long run, even if the shock was temporary. Households are often found to maintain the asset level even at the cost of consumption. The impact of idiosyncratic shocks on households is minimal, and the mitigation strategies that households use more often serve as insurance(Ajefu, 2017). Households can insure against those illness shocks that are recurrent and small over large and rare(Gertler & Gruber, 2002). When the shock is idiosyncratic, like health shock, households borrow and sell assets. However, those that face covariate shocks, such as natural disasters, lead to a reduction in consumption and dissaving (Yilma et al., 2014).

In this study, an attempt is made to examine the relationship between economic development and health in India. This relationship is examined using micro-level household data. Many studies are done on policy intervention and household shocks using cross-sectional data. This study has used longitudinal data from nationally representative data using IHDS 1and 2 for households, individuals, and villages. In this study, we have analysed three types of shocks(idiosyncratic and covariate shocks) that upset household well-being and two health-related policies are evaluated health insurance and the National Rural Health mission. The first known study used disability, health expenditure and natural disasters to examine the impact on household well-being using consumption expenditure and adjusted consumption expenditure. This study fills the gap in studying multiple shocks to household well-being and the policy implications of two national-level health policies from the same source data.

The specific objectives of our study were:

1. To examine the impact of unanticipated idiosyncratic shocks on household well-being.
2. To investigate the effect of covariate shocks on household consumption expenditure.
3. To study the impact of health expenditure on household consumption expenditure.
4. To study if Health insurance helped in household consumption smoothing.

5. To assess how India's Health policy enhances household well-being.

The **Research questions** with which this thesis proceeded were:

1. How much do unanticipated shocks impact adjusted consumption expenditure?
2. What has been the role of public and private insurance financing on the health expenditure of households?
3. Whether a health policy like NRHM achieve its targets at the household level?

The IHDS data is the only longitudinal data available for India from 2004-05 to 2011-12. Researchers widely use IHDS data for analysing various aspects using households and individual schedules. Handling large data sets is an experience. The panel and cross-sectional data analysis have their importance. Analysing patterns in data assists in meaningful conclusions. This data is combined in different ways to generate results for examining the impact of shocks on household well-being. Many new variables were created. Techniques such as multiple regression technique, Instrumental variable using two stages least square, the DID with continuous and binary treatment, construction of index using Principal component analysis, and world Bank methodologies for calculating the catastrophic and impoverishment impact of health expenditure are used. The latest version of *STATA 17* is used to process the data.

As mentioned in chapters 1 and 2 of this thesis, the shocks that a household receives affect consumption expenditure. The effect is different in the short run and the long run.
Truer for those households that reside in developing economies. Shocks are sudden and unpredictable, like illness. When households face shocks, it affects consumption, leading to a loss in welfare(Gertler & Gruber, 2002). Literature proves that shocks eventually affect human capital(Heltberg et al., 2015). The source of the shocks is often traced back to macro and micro disturbances. Macro disturbance could be due to disturbances related to the economy and politics.
Moreover, micro-ones are more focused on the household, such as illness. Without financial protection, the shocks translate from affecting income to consumption expenditure. Each Household's ability to smoothen consumption differs (Ajefu, 2017). Shocks may be temporary or permanent. Those that are permanent are often traced to chronic illness and disability. The more permanent shocks affect consumption(Sultana et al., 2012), and economic well-being is affected once consumption is affected. The shocks

related to disability invite two types of costs. The cost that affects productivity and hence lost income and cost in the form of expenditure incurred for restoring ill health affects consumption expenditure. Without financial protection, the expenditure on illness becomes out-of-pocket (Gertler & Gruber, 2002). Such shocks affect earning capacity, and expenditure is the direct effect of shock(Simeu & Mitra, 2019). Households use different coping mechanisms for handling the shocks depending on the nature of the shocks. Idiosyncratic shocks, such as health shocks, make households borrow or sell assets, and those facing covariate shocks, such as natural disasters, affect consumption (Yilma et al., 2014). These coping mechanisms may not be full-fledged because they may not provide full insurance, reducing living standards (Mayer &Mok, 2018).

9.2: Main Findings:

Chapter 4 is titled 'Consumption expenditure and household well-being: analysis of disability as an idiosyncratic shock'. The first objective, which examines the impact of unanticipated idiosyncratic shocks on household well-being, is dealt with in this chapter.

This chapter deals with two types of household disabilities, the duration and Disease-specific disability, Activity of Daily Living (ADL). The disability is measured as the number of days disabled. A duration of thirty days measures the disability caused due to short morbidity. The time for calculating the major morbidity is three hundred and sixty-five days. The disease-specific disability is measured using three short morbidities and fourteen major morbidities. The activity of Daily Living is calculated using six disabilities as given in the IHDS survey by constructing a variable Activity of daily living intensity (ADLI).

The disability is measured using the variable the days disabled (unable to work) due to Short and major morbidity based on the number of days disabled. The second measure is the Activity of Daily Living Intensity (ADLI) constructed using ADL. The impact of disability is analysed using two different methods of analysis. The duration of disability and specific diseases analyses the days disabled due to short and major morbidity. The consumption expenditure, a proxy for household well-being measurement, examines the changes caused by disability. In addition, consumption expenditure adjusted for health expenditure (non-health expenditure) is examined and categorised as monthly and annual consumption/ adjusted consumption expenditure.

Additionally, monthly and annual food and non-food expenditures are used to examine the changes for those disabled. Test of significance is used by constructing different hypotheses to determine the effect of disabilities on household consumption expenditure. The analysis is done for both rural and urban areas. The significance test is done for different types of short and major morbidities and days disabled due to short and major morbidities.

ADL intensity is used as one of the independent variables to examine the changes in consumption and adjusted consumption expenditure through regression. The other independent variables are assets owned by the households, days unable to work due to major morbidity, disability pension received, family size, health insurance, education, households without a toilet, households' membership to various organisations/ institutions, the proportion of children in the age group 0-14 and proportion of children 60+, remittances received by the households and analysed using regression with fixed effects for panel data. The regression model is run for seven different types of household expenditure: 4 different types of consumption expenditure, i.e., consumption expenditure, adjusted consumption expenditure, food expenditure and non-food expenditure, and three different types of health expenditure: Total health expenditure, Inpatient expenditure, and Outpatient expenditure. These analyses are carried out separately for socio-economic disaggregation at the household level for rural and urban.

The results of the test of significance were that short morbidity expenditure differentials were observed for all categories of short morbidity for both rural and urban areas. Short morbidity expenditure differentials were observed for both rural and urban categories of short morbidity, suggesting that even short-duration disability also causes expenditure differentials. Evidence was also found for consumption smoothing against disability(Onisanwa & Olaniyan, 2019)through community sharing of resources(Shehu & Sidique, 2015) and crop inventory (Townsend, 1995), safeguarding non-health consumption in the short run (Simeu & Mitra, 2019).

In IHDS 1 and IHDS 2, the most common major morbidity categories for which expenditure differentials were prevalent were heart disease, high blood pressure and diabetes. The non-common morbidities in expenditure differentials were cataracts, tuberculosis, paralysis, epilepsy, asthma, and cancer. The most common duration of illness by expenditure differentials was one week and three months in IHDS 1 and IHDS 2. Those households with major morbidity shocks must receive subsidies, and their welfare may improve if supplemented by disability insurance. A worker from the informal sector had substantial indirect health expenditure and loss of income from disability(Lim, 2017). Furthermore, cash transfers helped to increase food consumption(Tiwari, 2019). The onset of disability increases the probability of transitions in and out of the job market (Mani et al., 2018).

The regression results for monthly and adjusted consumption expenditure had opposite signs for many predictor variables; another regression with different health expenditures was executed. The regression results of health expenditure show a significant positive impact of ADLI, and days unable to work due to major morbidity are significant. Understanding the changes in consumption expenditure and adjusted consumption expenditure is pertinent. Households may have to incur more expenditure on health. The adjusted expenditure pays for the households' food and other non-food components. A reduction in adjusted consumption would mean lesser expenditure available for these components. The literature supports this; those disabled must spend more to maintain their consumption expenditure. Literature provides evidence that households with disabilities incur higher health expenditures, a higher share of OOPHE and the frequency of hospitalisation(Azzani et al., 2019; Hong et al., 2022; Mekonen et al., 2018; Palmer et al., 2015; Simeu & Mitra, 2019; Sultana et al., 2017).

ADLI and days disabled due to major morbidity showed a positive coefficient for monthly consumption expenditure but negative for adjusted consumption expenditure indicating that the possible differentials could be because of the adjustment for health expenditure and makes a strong case for using consumption expenditure adjusted for health expenditure as a measure of household well-being. The disability may compel households to incur more to take care of health expenditures and maintain a standard of living aligned with those with no disabled members. Family size, a household without toilets, the number of married females, and the proportion of children have worked towards reducing consumption expenditure. Family size positively correlates with exposure to shocks; rural households reported more shocks, reducing food and non-food expenditure (Isoto et al., 2017).

What has worked consistently and favourably for households is the membership of various groups. Assets have helped only for consumption expenditure; as far as adjusted consumption expenditure is concerned, the asset coefficient has turned negative. The caste and quintile results are almost similar, with few exceptions. Households, when faced with disability, use different coping mechanisms such as labour substitution, remittances from relatives, borrowings and using assets and savings(Genoni, 2012; Islam & Maitra, 2012; Mitra et al., 2016; Nguyen et al., 2011; Sauerborn et al., 1996; Wagstaff & Pradhan, 2005; Yilma et al., 2014) Households use the available resources to smoothen consumption by selling assets, migrating to non-affected areas, or selling livestock. The Source of permanent income, such as loss of productive assets, would significantly impact consumption (Townsend, 1995). Social networks help smooth consumption (Mbugua et al., 2020).

Chapter 5, titled 'Impact of Natural disasters as covariate shock on Household Consumption Expenditure'. This chapter deals with the second objective: To investigate the effect of covariate shocks on household consumption expenditure. The second shock analysed is a natural disaster. Natural disasters impact household well-being. Climatic changes impact household well-being, and some changes may permanently affect economic development(Baez & Santos, 2008; Schmidhuber & Qiao, 2020). Studies show that developing countries with low per capita income are particularly vulnerable due to poverty. The number of poor in these countries is increasing because of inadequate social safety nets, infrastructure and dependence on agriculture(Benson & Clay, 2004; Cred, U. N. D. R. R, 2020; Eriksen et al., 2021; Kumar et al., 2004; Yoon, 2012). A natural disaster is an unanticipated covariate shock. Households use different formal and informal coping mechanisms to tackle the same. One of the informal coping mechanisms is self-insurance used by households to build up. These assets are used to meet unplanned and un-anticipatory expenditures. The risk of shock from illnesses and damages caused by a natural disaster is a precautionary motive for asset demand (Skidmore, 2001). Natural disaster intensity and confidence in government institutions are exogenous instruments that influence the endogenous regressor, i.e., household assets. Other covariates include family size, the proportion of children, the number of married females, membership intensity, health insurance, and conflict intensity used in IV2SLS.

The results of IV2SLS have provided the basis for understanding consumption expenditure driven by household assets. Some exceptional results have emerged from this analysis. The instruments natural disaster intensity and confidence intensity have helped the households increase their assets across all socio-economic categories of both the models of consumption expenditure and adjusted consumption expenditure models. Some covariates that worked towards increasing assets, such as the number of married females, family size and education, have worked in the reverse direction on consumption and adjusted consumption expenditure. Public project intensity and proportion of children have reduced assets and consumption expenditure. Family size and conflict intensity do not influence assets but work towards reducing consumption expenditure. Those households that were hit by natural disasters had significantly different assets than those that were not hit. The consumption expenditure and adjusted consumption expenditure were significantly different for only the lower quintile of BPL and APL1. When households are affected by natural disasters, the asset-building exercise is carried out, and confidence that institutions have worked in building the assets. The coping mechanisms mentioned in the literature: formal and informal,i.e., health insurance and social capital measured using membership intensity, have worked consistently in stage I for building up assets and mixed results in stage II for consumption expenditure.

The effects on socio-economic categories are also not surprising. Scheduled tribes have safeguarded their assets through health insurance but not consumption expenditure. For the BPL quintile, in stage I, health insurance increased the asset; in stage II Assets, health insurance and membership intensity increased consumption expenditure. Health insurance and education have positively influenced all caste categories for adjusted consumption expenditure by caste. In stage II, the adjusted consumption expenditure is positively influenced by the assets for all caste categories—membership intensity. Family size and proportion of children have a negative influence on all castes. For adjusted consumption expenditure quintile, Family size, health insurance, adult education, and married females increase household assets. In stage II, assets increased consumption expenditure in all quintiles.

The number of married females and family size is important in determining its welfare and influencing expenditure decisions(Biyase & Zwane, 2018; Walugembe, Wamala, Misinde, et al., 2019) And family size and structure influence expenditure decisions (Blake, 1989; Downey, 1995; Flake & Forste, 2006; Heshmati et al., 2019). Social connectedness measured through membership in various associations and sociocultural groups has positively and significantly impacted assets and consumption, complying with earlier literature on the benefits of social connectedness (Bailey et al., 2018; Putnam, 2001). The implementation of public projects in the village is expected to lead to an increase in local welfare. We find mixed evidence of this in our results. The findings suggest that multiple adaptation strategies would help households that experience natural disasters. At the policy level, insurance would help in both protecting assets as well as consumption. However, insurance coverage in India is relatively low (6%, as per IHDS 2). Expedited efforts to provide more comprehensive insurance coverage in areas expected to experience natural disasters would be an effective adaptation strategy. In addition, providing disaster risk insurance would also be a step towards greater resilience (Linnerooth-Bayer & Hochrainer-Stigler, 2015). This option is already available in many developed and developing countries (Paleari, 2019). Households that face natural disasters smoothen consumption via assets, and in turn, these assets are affected by natural disasters and confidence. Evidence suggests that education helps people improve their well-being across the population and be an effective adaptation strategy (Muttarak & Lutz, 2014). There is, therefore, a need to ensure access to education, especially for the poor. Confidence in institutions is strongly linked to asset holding (Ellis & Bahiigwa, 2003). Fair and transparent institutions are likely to play a critical role in adaptation and resilience-building, especially in disaster-prone areas (Papaioannou, 2009). While emergency consumption relief as an immediate strategy would be an important short-term intervention, building assets as a long-term policy will make them more resilient(Archer et al., 2020b).

Household assets, informal coping mechanisms, membership intensity, types of social capital and health insurance; a formal coping mechanism has worked positively towards building household assets, which in turn have helped households to smoothen consumption expenditure. Without accompanying information on additional factors that could impact consumption, like disaster relief measures, external assistance by way of remittance or other developmental programmes, the impact of natural disasters cannot be fully comprehended.

Chapter 6 deals with health expenditure as an idiosyncratic shock, titled 'Health expenditure analysis at household and individual level'. The third objective that studies health expenditure's impact on household consumption is dealt with in this chapter. The health expenditure is analysed for the household rounds and individual rounds separately. Total health and inpatient and outpatient expenditures are used from the household rounds. Health expenditure on short and major morbidity from individual rounds is further disaggregated as doctor fees, consultancy, and medicine and travel-related expenditures. A descriptive analysis of different types of health expenditure for rural and urban is done.

The shock of health expenditure is examined using world bank methodologies for catastrophic health expenditure and impoverishment. Health expenditure has an impact on household well-being. As documented in the literature, some of India's health expenditure features are.

1. High outpatient expenditure(Johnson & Krishnaswamy, 2012).

2. High cost of medicine and diagnostics.

3. Inequalities among rural and urban areas and socioeconomic differentials(Barik & Thorat, 2015).

4. Rural households face a higher probability of catastrophic expenditure(Sahoo & Madheswaran, 2014).

5. Higher regional variation in out-of-pocket expenditure (Wagstaff & Neelsen, 2020).

The households affected due to catastrophic expenditure have reduced access to health insurance (Xu et al., 2003).

Literature provides growing evidence regarding the detrimental effects of health spending from own pocket on households, especially poor households(Jalali et al., 2021). The results of different measures of health expenditure are in affirmation with these studies.

The findings of this study are that Delhi had the highest cost of medicine, and travel costs were high in Kerala. In the urban areas, Pondicherry paid high doctor fees of Rs 1193, followed by Arunachal Pradesh and Andhra Pradesh. Chandigarh paid the highest doctor fees as a union territory. The cost of medicine was highest in Andhra Pradesh. The travel cost was highest in Andhra Pradesh, Dadra Nagar, Haveli, and Chandigarh. The insurance reimbursement received was highest for Kerala, Andhra Pradesh, and Karnataka in rural areas and Andhra Pradesh, Himachal Pradesh, and Kerala in urban areas.

Bihar, Tripura, Sikkim and Goa Registered the highest catastrophic expenditure under different categories in IHDS 1. In IHDS 2, Bihar, Andhra Pradesh, Uttar Pradesh, and Goa registered higher catastrophic expenditures. In IHDS 1, the rural and urban catastrophic expenditure differentials were negligible. The catastrophic expenditure on health also increased between rounds 1 and 2. In a world bank study in India in 2002, the OOPHE as a percentage of total health expenditure was 82% (Van Doorslaer et al., 2007).In another study, the OOPHE as a percentage of household consumption expenditure for India was 6%, the catastrophic head count was 25%, and the overshoot was 2% in 2004-05(Ghosh, 2011). The Incidence of catastrophic expenditure was 13% in 2004 and 13 % in 2014, as calculated by a study(Mohanty & Dwivedi, 2021). Intensity and Incidence were higher for rural than urban(Sahoo & Madheswaran, 2014), and this is confirmed by the incidence and intensity calculated above using IHDS panel data.

The health expenditure and calculations using various measurements differ for both rounds of IHDS. The state-wise analysis gives a clear picture of the changes between the two periods. The total health expenditure, expenditure on doctor fees, and medicine have increased in between two time periods. The results of OOPHE and poverty-related estimates differ across the methodologies and the thresholds in this panel data and a cross-sectional study elsewhere in the literature(Kimnai, 2015). These findings are also in confirmation of the findings stated above.

The health expenditure and various concepts calculated that express different facets of health expenditure are very important measures of household well-being. As mentioned in the literature above, the increase in such expenditure and when households are not financially protected cause hardships. Higher outpatient expenditure, higher rural health expenditure under all categories, and catastrophic and impoverishment effects of health expenditure are observable. With economic development and growth, the catastrophic expenditure may not get eliminated automatically, but consolidated efforts are required to reduce the same. The most recommended mechanism is through health insurance(Xu et al., 2003). The ill effects of health expenditure can be mitigated through health insurance.

Chapter 7 evaluates 'Universal health coverage and health insurance in India '. The fourth objective, which examines the role of health insurance in household consumption smoothing, is dealt with in this chapter. The IHDS data provides information on publicly funded health insurance RSBY and other government-funded insurance. There is also information on private health insurance. Impact evaluation of health insurance is done using DID. Publicly funded health insurance comprising RSBY and other government-funded insurance creates a continuous treatment. Privately pre-paid health insurance by households and employers makes binary treatment. Household data merged with individual data is used for the impact evaluation of health insurance with two different types of treatment. This analysis is done separately for rural and urban using socioeconomic categories.

Healthcare expenditure differs from other expenditures since its uneven across households and individuals. It helps individuals restore their original or near-to-original health status, unlike other expenditures where household well-being status may be upgraded upon purchase(Wagstaff & Neelsen, 2020). Health expenditure comprises the direct and indirect costs of expenditure on medicine and diagnostics, doctor fees and consultation and indirect costs such as transportation and accommodation. Health insurance covers mostly inpatient expenditure, but outpatient is not covered.

Without financial protection, households' expenditure to access health care is high, disrupting household well-being(Berki, 1986; Gertler & Gruber, 2002). The literature provides ample evidence that health expenditure is catastrophic with global impoverishment effects (Azzani et al., 2019; Bonu et al., 2007). Households use different coping mechanisms, such as borrowing from friends and relatives, selling assets, or compromising their expenditure on necessary items(Joe, 2015; Leive & Xu, 2008; Rashad & Sharaf, 2015).

Therefore, the provision of financial protection against health expenditure that is catastrophic and may have impoverishment effects is vital. Global evidence is available in the literature for reducing OOPHE when health expenditure is sponsored via risk pooling/ social health insurance(Wagstaff et al., 2020). Sustainable development goals (SDG) advocate for providing financial cushioning to mitigate the risk of expenditure on health(Hooda, 2020). SDG Goal Number 3 is about good health and well-being. Its focus is to ensure healthy lives and promote well-being for all. (UN). One of the specific targets is target 3.8, which aims to achieve universal health coverage (UHC). UHC is about people accessing health care without hardship, including financial hardship like health expenditure.

The impact of government health insurance was examined using differences in differences. The health insurance intensity variable is engineered as a continuous variable. The treatment of health insurance used is continuous. The impact of health insurance is examined on consumption expenditure, consumption expenditure adjusted for health expenditure, nonfood expenditure, food expenditure and household capacity to pay.

Households that owned any one type of health insurance or both and those who incurred medical expenditure had increased adjusted consumption expenditure, household capacity to pay, and food and non-food expenditure.

The DID regression results for households with medical expenditure reveal that those with any insurance and two insurances increased the non-health expenditure of the households, Non-food expenditure and household capacity to pay. For those households that incurred catastrophic health expenditures, the health insurance did not help to smoothen the food expenditure: food expenditure and household capacity to pay decreased in those with catastrophic health expenditures.

Households with health expenditure had increased non-health expenditure if they belonged to the developed village and had assets and membership in various organisations. The households that face catastrophic expenditure can mitigate the same if they belong to more developed villages and have assets and membership in various organisations. Additionally, the village health infrastructure index(for more details, chapter 8), which included various health facilities in the village and nearby transport infrastructure, was used as an independent variable. However, these covariates gave mixed results and showed up statistically significant but negative for those households that had incurred catastrophic health expenditure, and, as a result, their food expenditure had reduced.

Despite the higher cost, there is undue importance to the private health sector in India. Public health care is ignored (Barik & Thorat, 2015) and also because of prejudices against public health care for providing inferior services(Sahoo & Madheswaran, 2014), and this makes a strong case for pumping more resources into the public health sector (Dwivedi & Pradhan, 2017) and not just increasing the number of PHC. However, a well-equipped one is more important(Barik & Desai, 2014); the availability of less well-equipped PHCs constrains access to health care (Johnson & Krishnaswamy, 2012). Functional primary health centres promoted better access to treatment for indigenous communities and widows over health insurance(George et al., 2021). There is an urban-rural disparity in the availability of health infrastructure(Barik & Thorat, 2015; Singariya, 2013). This disparity is also seen in the geographical distribution of private and public health infrastructure. In this study, only public health infrastructure is used. Studies have also pointed out the failure of NRHM to provide the required health infrastructure(Sarkar & Mukherjee, 2021).

The results of this study confirm that household ownership of assets and membership in various organisations helped households increase their non-health expenditure despite health expenditures. Those households with no access to a formal mechanism for coping, like health insurance or borrowing from the credit market, often resort to self-insurance, like the build-up of assets in general and productive assets in particular and use the same coping mechanism((Ajefu, 2017; Islam & Maitra, 2012; Leive & Xu, 2008; Onisanwa & Olaniyan, 2019; Sahoo & Madheswaran, 2014; Shahrawat & Rao, 2012; Van Doorslaer et al., 2007).

The consumption expenditure quintile also gives some interesting results. The people below the poverty line could not safeguard their non-health expenditures when they incurred health expenditures and when the health expenditure was catastrophic despite health insurance. Nevertheless, another interesting finding is that the households increased their non-health spending in the APL 1 group(almost on the margin and closer to BPL) despite catastrophic health expenditure. Perhaps this can be attributed to health insurance. For BPL households that incurred medical expenditure, ownership of assets and membership in various organisations helped to boost the expenditure.

Literature states that BPL households with health expenditures partially could cover their health expenses through RSBY at the time of hospitalisation(Devadasan et al., 2013). RSBY did not provide the necessary support to BPL in reducing OOPHE(Ghosh, 2014). Publicly funded health insurance did not help to provide financial protection(Garg et al., 2019). Scheduled tribe households incurred catastrophic expenditures despite ownership of health insurance. Those households that were Brahmins and another forward caste, Other backward classes, and scheduled castes residing in developed villages had increased consumption expenditure despite incurring health expenditure. For scheduled tribe households, only household assets work as self-insurance. Village Health infrastructure for caste 3 reduced the expenditure, but for caste 4, when the households did not incur catastrophic expenditure, it helped to increase the non-health expenditure.

Households that incurred health expenditure and had any one insurance have benefited. These households had a higher incremental increase in their adjusted consumption expenditure. Those households with the lowest adjusted expenditure were found to be opting for two types of health insurance and also benefited from an incremental increase in household expenditure of 49% with health expenditure and 43% even with catastrophic health expenditure.

Having health insurance or both types has helped households increase their non-health spending, but it does not protect them from catastrophic expenditures. Health insurance did not benefit people living below the poverty line and scheduled tribe population for protecting their consumption expenditure against catastrophic health expenditure. Many health insurance schemes in the past were of little benefit, but having one all-inclusive scheme may help. Households with insurance had an incremental increase in their adjusted consumption expenditure, but this increase was not enough to protect a certain group of households belonging to BPL and ST against catastrophic health expenditure.

PMJAY scheme, which has integrated all existing centre and state-level insurance schemes, needs integration of features of existing schemes. PMJAY has increased the cover and included outpatient expenditure and travel costs. The focus should be on reducing catastrophic expenditure. BPL households and STs may need different policies as compared to the mainstream. However, each Household has different socio-economic dynamics, having assets acts as self-insurance and membership in various organisations like Mahila Mandal; youth clubs; sports groups or reading rooms; self-help groups; credit or savings groups; religious or social groups or festival societies; caste associations; development group or NGO; agricultural, milk or another cooperative. Strengthening public health infrastructure at the village level will also provide an extra boost. Well-equipped public health facility itself may provide a boost to utilisation.

Chapter 8 is 'National Rural Health Mission Policy and Health Infrastructure: An Evaluation' and covers the last objective, which assesses how India's Health policy has enhanced household well-being. The VHII is constructed using Principal Component Analysis (PCA). The decline of public health expenditure from 1.3% of GDP to 0.9% in 1999, curative health services were biased towards the rich, and health expenditure related to poverty provided a rationale for launching NRHM (NRHM, GOI, 2012-13, 2012) (NRHM 2005-2012, mission document). The objective was to provide health care to rural areas to fill the existing gaps in health care provisioning, such as making health affordable and available. The goal of NRHM was to be achieved by 2012. For increasing accessibility, the first step is provisioning for well-equipped infrastructure. The three tire structures of primary health centres (PHC), sub-centres(SC) and community health centres(CHC) are the backbones of health infrastructure. The NRHM policy for health infrastructure was to provide for PHC to be available for 24 hours, new SC, and upgradation of the status of PHC and CHC as the first referral unit(Hussain, 2011).

NRHM's mission was to provision health care to rural populations with a focus on the Empowered Action Group (EAG) of 18 states and to increase the public health expenditure to 2-3% of GDP. NRHM outlined some goals with core and supplementary strategies. One such was strengthening infrastructure that supports public health in rural areas, such as sub-centres, primary health centres, and community health centres (NRHM 2005-2012, mission document). The empowered action group was constituted in 2001. Eighteen states were identified with weak public health indicators and weak infrastructure. There were differentials due to inputs and resources mismatching with the actual needs of the states (Prasad et al., 2013). These states were chosen to receive funds under NRHM. These 18 states were Arunachal Pradesh, Assam, Bihar, Chattisgarh, Himachal Pradesh, Jharkhand, Madhya Pradesh, Nagaland, Orissa, Rajasthan, Sikkim, Tripura, Jammu and Kashmir, Manipur, Mizoram, Meghalaya, Uttaranchal and Uttar Pradesh(Dhingra & Dutta, 2011; NRHM mission document). EAG group is subdivided into four categories: High focus non-North-Eastern states (298 districts), High focus North-Eastern states (87 districts), non-high focus large states (217 districts), and non-high focus small states and Union territory (21 districts). The district hospitals covered in each group were 292, 72, 183 and 21, respectively. The high focus Non-North-Eastern states were Bihar, Chhattisgarh, Himachal Pradesh, Jammu and Kashmir, Jharkhand, Madhya Pradesh, Orissa, Rajasthan, Uttar Pradesh, and Uttarakhand; High focus north-eastern states are Arunachal Pradesh, Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura. Small states and Union territories were Andaman, Nicobar, Chandigarh, Dadra Nagar Haveli, Daman and Diu, Delhi, Lakshadweep, and Puducherry. Rest all states grouped as non-high focus large states (Sarma, 2009).

Different variables that measure the availability of health infrastructure at the village level are used for constructing the index. Data merged for households and individuals at the village level separately for both rounds are used for the same. The constructed index has five categories that measure different levels of infrastructure development. Descriptive statistics of index values using States and expenditure quintiles are given.

The construction of the Village Health Infrastructure Index (VHII)using PCA facilitates the incorporation of a large amount of data compressed into smaller dimensions that are easy to comprehend. Variables used broadly measured the availability of health infrastructure in the village in rounds 1 and 2. The variables include the location of advice and treatment, availability of physical infrastructure in the village and distance to nearby facilities. The availability of transport was also measured. All these variables were compressed to form indices for both years and averaged into two for rounds 1 and 2. The VHII has five ranges: very low, low, average, high and very high. VHII is used in the analysis of health insurance impact evaluation in chapter 7 as one of the independent variables. Choosing variables and fulfilling pre-estimation and post-estimation steps is crucial in PCA.

The results of this study reveal that state-wise analysis reveals that although shifts took place from the very low to the low category of VHII, shifts to high and very high availability were small. Among Non- North-eastern states, only Himachal Pradesh, Orissa, and West Bengal among the non-focus group experienced shifts to a very high category. However, the percentage of individuals experiencing such shifts was very small. Most shifts were from very low to low and to average VHII.

The literature studies reveal that the most noticeable inequities in India that led to differences in health infrastructure were rural-urban disparities, inter and intra-state(Prasad et al., 2013), Human resource deficit(Sarma, 2009) and deficiencies in sub-centres(Sriram, 2019). Some well-performing states under NRHM were Chhattisgarh, Rajasthan, Orissa and Karnataka for Subcentres; Uttar Pradesh, Bihar, Maharashtra and Andhra Pradesh for primary health centres; and Tamil Nadu for the community health centre between IHDS 1 and IHDS 2. However, Bihar, Andhra Pradesh, Assam and Rajasthan maintained the status quo(Singariya, 2013). Also, a positive correlation was found between the health infrastructure index and gross state domestic product (Varkey et al., 2020).

With most of India's population living in rural areas(Dhingra & Dutta, 2011), the health infrastructure availability and accessibility are paramount, but NRHM lacked completion of many targets by 2012, as revealed by studies undertaken then(Hussain, 2011).

The findings from IHDS 1 and IHDS 2 by constructing village health infrastructure index revealed that the individuals with access to very high health infrastructure were negligible. The rural health statistics for 2020-21 revealed that the shortfall in subcentres, PHC and CHC is above 20%. Based on Rural Health statistics 2018, a study observes that rural infrastructure is falling short in terms of the requirements of the people (Sarkar & Mukherjee, 2021).

9.3: Policy Implications:

Economic conditions were linked to access to medical care, and those households with harsh economic backgrounds were also found to have low levels of health, and this, in turn, served as a pathway for the economic adversaries faced by the household (Lee et al.,2020). Rural households risk medical poverty when members have chronic diseases (Wang et al., 2022; Ma et al., 2022). Financial protection against OOPHE is required for poorer households with disabled members (Yilmaz et al., 2009). Effective health policies can de-escalate this vicious circle between disability and poverty(Eide & Ingstad, 2011). A negative correlation between disability and standard of living was found in a developed country (Schuelke et al., 2022). These results help to build a strong case for incorporating morbidity-specific and duration-specific disability components in the disability pension and health insurance. The three lifestyle diseases that have shown common patterns are high blood pressure, heart disease and diabetes. Some morbidities are unique to rural areas that cause expenditure differentials, such as epilepsy, paralysis, cataracts, tuberculosis, asthma and accidents. Mental illness is causing expenditure differentials in urban areas. The productivity lost needs to be compensated differently for rural and urban areas. The reason is that it is mostly manual work with wages paid in rural areas. Loss in daily wages must be compensated, and additional compensation for recovering to the original state of health may also be required. Socio-economic differentials also need to be reflected in the policies related to health intervention.

Despite coordinated efforts toward providing health for all, the disabled population remains vulnerable, and SDG does not explicitly mention SDG (Guets & Behera, 2022). An all-inclusive policy with inclusion and acknowledgement of disabilities is required. Building up social capital via membership in various groups seems to be providing a boost to consumption expenditure. Acknowledgement of such an organisation formally may provide boos for attracting more memberships.

The household consumption expenditure and household consumption expenditure adjusted for medical expenditure are examined for shocks that households experience. The household members who faced disability for one week to one year have differential expenditures. Those who faced disability for a short duration also had consumption differentials, which may be a starting point for providing compensation via cash transfers or incorporated in health insurance for days disabled due to illness. Those disabled on ADL had reduced adjusted consumption expenditure (non-health spending) and higher medical expenditure. The disability may compel households to incur more to care for health expenditures and maintain a standard of living aligned with those with no disabled members. Designing existing health insurance to incorporate disability insurance or a separate one may be strategic.

For households with disabled members, membership in various organisations has worked consistently in favour of increasing adjusted consumption expenditure. Ownership of assets influences non-health spending negatively; as suggested in the literature, consumption smoothing is not happening via assets. Those households with at least one member suffering from High blood pressure, heart disease and diabetes across rural and urban areas have significantly different consumption expenditures. Some morbidities are unique to rural areas that cause expenditure differentials, such as epilepsy, paralysis, cataracts, tuberculosis, asthma and accidents. Mental illness is causing expenditure differentials in urban areas. The productivity lost needs to be compensated differently for rural and urban areas. The reason is that it is mostly manual work with wages paid in rural areas. Loss in daily wages must be compensated, and additional compensation for recovering to the original state of health may also be required. Socio-economic differentials also need to be reflected in the policies related to health intervention. Building up social capital via membership in various groups seems to be providing a boost to consumption expenditure. Acknowledgement of such an organisation formally may provide boos for attracting more memberships.

Those households facing natural disasters have increased assets, increasing consumption expenditure and adjusted consumption expenditure. The number of married females, family size and highest adult education have helped households increase their assets. Health insurance and membership intensity have consistently worked towards increasing household assets. These assets have helped households with consumption smoothing when hit by natural disasters. Strong institutions have helped households to build up assets. Disaster insurance may provide a solution that specifically works towards safeguarding household assets.

For BPL households, health insurance has provided a boost in increasing assets and assets, and membership and health insurance have increased consumption expenditure. Scheduled tribes also have safeguarded their assets via health insurance, but consumption is affected. When households face natural disasters, multiple adaptation strategies may work since membership intensity and health insurance helped households, but public project implementation has not. While emergency consumption relief as an immediate strategy would be an important short-term intervention, building assets as a long-term policy will make them more resilient (Archer et al., 2020).

There are regional variations in health expenditure and different costs associated with access to health care. Higher outpatient expenditure, higher rural health expenditure under all categories, and catastrophic and impoverishment effects of health expenditure are observable. There is impoverishment due to health payments, and more for rural than urban; 6.8% and 3.5% were pushed below the poverty line in 2012 from rural and urban areas, respectively, when a 40% threshold for catastrophic expenditure as the household capacity to pay was used. Moreover, 27.7% of rural and 12.9% of urban were impoverished due to catastrophic health payments at a 10% threshold of non-food expenditure. Household consumption expenditure can be protected through health insurance. The evidence in this regard is provided in the impact evaluation of health insurance on household consumption expenditure in this study. Households that incurred health expenditures and had health insurance could increase their non-food expenditures and capacity to pay. Households with catastrophic health expenditures were not able to smoothen food expenditures. Ownership of assets and membership in an organisation helped households increase their adjusted consumption expenditure in the presence of medical expenditure and health insurance.

BPL households could not safeguard their adjusted consumption even with health insurance. However, interesting households in the APL 1 quintile, which are also on the margin, were able to increase their adjusted consumption expenditure in the presence of health insurance. What helped BPL households is the ownership of assets and membership in various organisations that boosted its consumption expenditure. Scheduled tribes with catastrophic expenditures could not safeguard the adjusted consumption expenditure even with health insurance. Households that incurred health expenditures and had any one insurance have benefited. These households had a higher incremental increase in their adjusted consumption expenditure. Those households with the lowest adjusted expenditure were found to be opting for two types of health insurance and benefited with an incremental increase in household expenditure of 49% with health expenditure and 43% even with catastrophic health expenditure.

Examining consumption expenditure without making adjustments for health expenditure may provide misleading results. All results generated in this thesis provide evidence for this. Similarly, analysed separately and used as a covariate in examining different results has made a strong case favouring health insurance for safeguarding consumption expenditure. Using longitudinal data has also helped to observe the changing patterns in consumption expenditure of the same households in two periods.

Policy recommendations: To boost consumption expenditure ownership of assets, membership in various organisations called social capital and health insurance has helped households increase their household consumption consistently. These are coping mechanisms, as mentioned in the literature. The households mitigate the shocks to consumption through informal and formal mechanisms. This thesis strongly recommends insurance safeguarding assets during natural disasters and disability health insurance with a special clause for compensation for lost income/ expenditure during the disability period. Increasing health insurance coverage to households other than the target households may also help. Formal recognition of social capital, such as various groups and organisations and their involvement in policy decisions, may also be productive.

This research has policy bearing. The two existing government policies, i.e., publicly funded health insurance and national health rural mission are evaluated to study the impact of the same. These policies are also directly related to the well-being of the households. NRHM, now NHM, needs more coordinated efforts to increase the availability of health infrastructure since a very negligible percentage of the population has access to high levels of health infrastructure.

Health insurance provides financial protection against OOPHE to access health care as a formal coping strategy. The provisioning of health infrastructure gives a boost to public health infrastructure. The utilisation of public health infrastructure reduces the health expenditure of the household.

9.4: Conclusion:

This thesis tried to examine the impact of economic development on health in India by examining the consumption expenditure of households. In this thesis, household consumption expenditure, consumption expenditure adjusted for health expenditure (non-health spending), food expenditure and non-food expenditure are examined for changes due to shocks caused by the disability of a member, natural disasters, and health expenditure. These changes are observed spatially, regionally, and socio-economically. Different types of health expenditure variables are investigated, such as inpatient expenditure, outpatient expenditure, short morbidity expenditure, major morbidity expenditure, and OOPHE. The IHDS data is the first longitudinal data at household and individual levels. This data is merged into different panels, such as household individuals and individual household villages. The data is analysed using descriptive statistics and regression with fixed effects, an instrumental variable approach using the two-stage least square method, DID with continuous treatment. The World Bank measurements of Incidence and intensity of OOPHE on health and poverty effect; Village health infrastructure index is constructed using principal component analysis.

Some of the independent variables used in measuring the causal relationships are family size, the number of married females, the highest completed education by the adults, households without a toilet, the proportion of adults 60+, households that received a disability pension, remittances, households living in more and less developed villages, health insurance, health insurance intensity, membership intensity, conflict intensity, public project intensity, natural disaster intensity.

Some of the critical results that are generated from this study with policy implications are:

The household consumption expenditure and household consumption expenditure adjusted for medical expenditure are examined for shocks that households experience. The household members who faced disability for one week to 1 year have differential expenditures. Those who faced disability for a short duration had consumption differentials as well. Providing compensations via cash transfers or incorporated in health insurance for days disabled due to illness may be necessary. Those disabled on ADLI had reduced adjusted consumption expenditure (non-health spending) and higher medical expenditure. The disability may compel households to incur more to care for health expenditures and maintain a standard of living aligned with those with no disabled members. Designing existing health insurance to incorporate disability insurance or a separate one may be strategic.

For households with disabled members, membership in various organisations has worked consistently in favour of increasing adjusted consumption expenditure. Ownership of assets influences non-health spending negatively; as suggested in the literature, consumption smoothing is not happening via assets. Those households with at least one member suffering from High blood pressure, heart disease and diabetes across rural and urban areas have significantly different consumption expenditures. Some morbidities are unique to rural areas that cause expenditure differentials, such as epilepsy, paralysis, cataract, tuberculosis, asthma and accidents. Mental illness is causing expenditure differentials in urban areas. The productivity lost needs to be compensated differently for rural and urban areas. The reason is that it is primarily manual work with wages paid in rural areas. Loss in daily wages must be compensated, and additional compensation for recovering back to the original state of health may also be required. Socioeconomic differentials also need to be reflected in the policies related to health intervention. Building up social capital via membership in various groups seems to be providing a boost to consumption expenditure. Acknowledgement of such an organisation formally may work positively towards attracting more memberships.

Those households facing natural disasters have increased assets, which, in turn, increases the consumption expenditure and adjusted consumption expenditure. The number of married females, family size and highest adult education have helped households to increase their assets. Health insurance and membership intensity have consistently worked towards growing household assets. These assets have helped households with consumption smoothing when hit by a natural disaster. Strong institutions have allowed households to build up assets. Disaster insurance may provide a solution that safeguards assets owned by the families.

For BPL households, health insurance has provided a boost in increasing assets, and membership and health insurance have increased consumption expenditure. Scheduled tribes also have safeguarded their assets via health insurance, but consumption is affected. When households face natural disasters, multiple adaptation strategies may work since membership intensity and health insurance helped households, but public project implementation has not. While emergency consumption relief as an immediate strategy would be a critical short-term intervention, building assets as a long-term policy will make them more resilient (Archer et al., 2020; Petrova, 2021).

There are regional variations in health expenditure and different costs associated with access to health care. Higher outpatient expenditure, higher rural health expenditure under all categories, and catastrophic and impoverishment effects of health expenditure are observable. There is impoverishment due to health payments, and more for rural than urban, 7% and 4% were pushed below the poverty line in 2012 from rural and urban areas, respectively, when the 40% threshold for catastrophic expenditure as the household capacity to pay was used. Furthermore, 28% of rural and 12% of urban areas were impoverished due to catastrophic health payments at the 10% threshold of non-food expenditure. Household consumption expenditure can be protected through health insurance. The evidence in this regard is provided in the impact evaluation of health insurance on household consumption expenditure in this study. Households that incurred health expenditures and had health insurance could increase their non-health, non-food expenditure and capacity to pay. Households with catastrophic health expenditures were not able to smoothen food expenditures. Ownership of assets and membership in organisations helped households to increase their adjusted consumption expenditure in the presence of medical expenditure and health insurance.

BPL households could not safeguard their adjusted consumption even with health insurance. However, households in the APL1 quintile, which is also on the margin, were able to increase their adjusted consumption expenditure in the presence of health insurance. What helped BPL households was the ownership of assets and membership in various organisations that boosted their consumption expenditure. Scheduled tribes with catastrophic expenditures could not safeguard the adjusted consumption expenditure even with health insurance. Households that incurred health expenditures and had one type of health insurance benefit. These households had a higher incremental increase in their adjusted consumption expenditure. Those households with the lowest adjusted expenditure were found to be opting for two types of health insurance and benefited with an incremental increase in household expenditure of 49% with health expenditure and 43% even with catastrophic health expenditure.

NRHM, now NHM, needs more coordinated efforts to increase the availability of health infrastructure since a very negligible percentage of the population has access to high levels of health infrastructure.

Examining consumption expenditure without adjusting for health expenditure may provide misleading results. All results generated in this thesis provide evidence for this. Similarly, analysed separately and used as covariates in examining different results, it has made a strong case in favour of health insurance for safeguarding consumption expenditure. Using longitudinal data has also helped to observe the changing patterns in consumption expenditure of the same households in two time periods.

9.5: **Limitations:**

In this study we have used panel data from IHDS. We faced certain methodological limitations. To begin with since the data is for only two-time periods, we could not test the parallel trends assumption under DID for the methodology used in Chapter 5 and 7 in the absence of 3rd period. However, we made modest attempt using groups in chapter 7 to with trends. Our instruments used in IVSLS as argued earlier are purely intuitive based on existing literature. As such we were provided very reasonable argument in favour of the instruments.

The variables natural calamity intensity, Health insurance intensity, Health expenditure, and days disabled due to morbidity are self-reported. The self-selection bias could not be tested using the Heckman selection model since this model converts the dependent variable as binary, and in this thesis, the dependent variable used in different models is continuous or ordered categorical.

We have used non-conventional approach for analysing NRHM impact by constructing index of village health infrastructure with the presumption that any impact of NRHM will be visible on the physical growth of health infrastructure as such. And we used consumption expenditure quintiles to track this growth in rural areas.

9.6: Future Scope for Research:

Future work may focus on a more detailed investigation of health poverty using socio-economic disaggregation. Health expenditure and household economic well-being associated with accidental injury and mental illness need to be examined. The impact of PMJAY could be studied using the third round of IHDS (in the data collection stage) once it is available in the public domain. The new data will provide longitudinal data for three rounds. Health poverty could be examined as a separate topic based on existing data. Several schemes for poverty alleviation and social support (the data available in the IHDS) could be examined for impact evaluation from a policy perspective. Membership in various organisations can be specifically studied while dealing with household-level idiosyncratic and covariate shocks. A panel study of the monetary value of household assets may provide a different perspective in understanding household economic well-being.

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APPENDIX

Appendix A3

A3.1: Model 2

$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$

Y_{it} = Outcome variable: Adjusted consumption expenditure per capita

$\beta_{1} \ldots \beta_{12} =$ Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A.3.2: Model 3: Monthly food expenditure per capita

$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$

Y_{it} = Outcome variable: Monthly food expenditure per capita

$\beta_{1} \ldots \beta_{12} =$ Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A.3.3: Model 4: Monthly non food expenditure per capita

$$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$$

Y_{it} = Outcome variable: Monthly non food expenditure per capita

$\beta_{1 \ldots} \beta_{12} =$ Respective coefficients of the predictor variable.

$X_1 .. X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A.3.4: Model 5: Monthly outpatient expenditure per capita

$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$

Y_{it} = Outcome variable: Monthly outpatient expenditure per capita

$\beta_{1} \ldots \beta_{12}$ = Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A.3.4: Model 6: Monthly inpatient expenditure per capita

$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$

Y_{it} = Outcome variable: Monthly inpatient expenditure per capita

$\beta_{1} \ldots \beta_{12}$ = Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A.3.5: Model 7: Monthly Total Health expenditure per capita

$Y_{it} = \alpha_i + \beta_1 X_{1it} + \beta_2 X_{2it} + \beta_3 X_{3it} + \beta_4 X_{4it} + \beta_5 X_{5it} + \beta_6 X_{6it} + \beta_7 X_{7it} + \beta_8 X_{8it} + \beta_9 X_{9it} + \beta_{10} X_{10it} + \beta_{11} X_{11it} + \beta_{12} X_{12it} + \varepsilon_{it}$

Y_{it} = Outcome variable: Monthly Total Health expenditure per capita

$\beta_1 \ldots \beta_{12}$ = Respective coefficients of the predictor variable.

$X_1 \ldots X_{12}$ = Predictor variables

X_1 = Activity of Daily Living Intensity (ADLI)

X_2 = Assets owned by the households

X_3 = Days disabled due to Major morbidity

X_4 = Disability pension received by the households

X_5 = Family size

X_6 = Health Insurance

X_7 = Highest completed Education by adults in years

X_8 = Households without toilet

X_9 = Membership Intensity

X_{10} = Proportion of children 0-14

X_{11} = Proportion of adults 60+

X_{12} = Remittances received by the households

ε_{it} = Stochastic Error

A5.1: Model 2

Stage 1: IV 2 SLS :

$Assets\_predict_{it} = \alpha_o + \alpha_1 X_{1it} + \alpha_2 X_{2it} + \alpha_3 X_{3it} + \ldots\ldots\ldots. \alpha_{10} X_{10it} + e_{it}$

Asset Predict = Endogenous regressor.

X1 to X8= Covariates

X9= Instrumental variable- NDI

X10= Instrumental variable- Confidence intensity

Where e_{it} = stochastic error

Stage 2: IV 2SLS

$Y_{it} = \gamma_0 + \gamma * Assets\_predict_{it} + \gamma_1 * X_{1it} + \gamma_2 * X_{2it} + \gamma_3 * X_{3it} + \gamma_4 * X_{4it} + \gamma_5 * X_{5it} + \gamma_6 * X_{6it} + \gamma_7 * X_{7it} + \gamma_8 * X_{8it} + \varepsilon_{it}$

Y_{it}= Adjusted Consumption expenditure

Asset Predict= Asset predicts by the instrumental variable in stage I.

X_1= Conflict Intensity

X_2= Family size

X_3= Health Insurance

X_4= Highest adult education

X_5= membership intensity

X_6= Number of married females

X_7 = Proportion of children

X_8= Public project Intensity

Where ε_{it} = stochastic error

A5.2 :Modle 2: Adjusted cosnumptionepxenditure with DID

$Y_{it}= \beta_0+\beta_1*Time_{it}+ \beta_2*Treatment_{it} + \beta_3*Time_{it}*Treatment_{it} + \beta_4*Covariates_{it}+\varepsilon_{it}$

The expanded DID equation used in our study is as below (equation 10):

$Y_{it}= \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it} + \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} +\varepsilon_{it}$

where,

Y = Consumption expenditure

X_1= Year

X_2 = Natural Disaster Intensity

X_3 = Year * Natural Disaster Intensity

X_4=Assets

X_5= Caste

X_6= Conflict Intensity

X_7= Health insurance

X_8= Highest adult education in completed years

X_9= Membership Intensity

X_{10}= Number of married females in the household

X_{11}= Number of persons in the household

X_{12}= Proportion of children in the HH
X_{13}= Public project Intensity

X_{14}= Confidence intensity

ε_{it}=The stochastic error term

A5.3

The expanded DID equation used in our study:

$Y_i = \beta_0 + \beta_1 * X_{1it} + \beta_2 * \beta X_{2it} + \beta_3 * X_{3it} + \beta_4 * X_{4it} + \beta_5 * X_{5it} + \beta_6 * X_{6it} + \beta_7 * X_{7it} + \beta_8 * X_{8it} + \beta_9 * X_{9it} + \beta_{10} * X_{10it} + \beta_{11} * X_{11it} + \beta_{12} * X_{12it} + \beta_{13} * X_{13it} + \beta_{14} * X_{14it} + \varepsilon_{it}$

where

Y = Monthly adjusted consumption expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

A7.1

The expanded DID equation used in our study:

$Y_i= \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it}+ \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + \varepsilon_{it}$

where

Y = Monthly food expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

A7.2

The expanded DID equation used in our study:

$$Y_i= \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it}+ \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + \varepsilon_{it}$$

where

Y = Monthly non-food expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

A7.3:

The expanded DID equation used in our study:

$Y_i = \beta_0 + \beta_1 * X_{1it} + \beta_2 * \beta X_{2it} + \beta_3 * X_{3it} + \beta_4 * X_{4it} + \beta_5 * X_{5it} + \beta_6 * X_{6it} + \beta_7 * X_{7it} + \beta_8 * X_{8it} + \beta_9 * X_{9it} + \beta_{10} * X_{10it} + \beta_{11} * X_{11it} + \beta_{12} * X_{12it} + \beta_{13} * X_{13it} + \beta_{14} * X_{14it} + \varepsilon_{it}$

where

Y = Household's capacity to pay

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

A3.12 Monthly inpatient expenditure

The expanded DID equation used in our study:

$Y_i = \beta_0+\beta_1*X_{1it}+ \beta_2* \beta X_{2it} + \beta_3*X_{3it} + \beta_4*X_{4it} + \beta_5* X_{5it} + \beta_6*X_{6it} + \beta_7* X_{7it} + \beta_8*X_{8it} + \beta_9*X_{9it} + \beta_{10}* X_{10it} + \beta_{11}* X_{11it} + \beta_{12}*X_{12it} + \beta_{13}* X_{13it} + \beta_{14}* X_{14it} + \varepsilon_{it}$

where

Y = Monthly inpatient expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

A7.4

The expanded DID equation used in our study :

$Y_i = \beta_0 + \beta_1 * X_{1it} + \beta_2 * \beta X_{2it} + \beta_3 * X_{3it} + \beta_4 * X_{4it} + \beta_5 * X_{5it} + \beta_6 * X_{6it} + \beta_7 * X_{7it} + \beta_8 * X_{8it} + \beta_9 * X_{9it} + \beta_{10} * X_{10it} + \beta_{11} * X_{11it} + \beta_{12} * X_{12it} + \beta_{13} * X_{13it} + \beta_{14} * X_{14it} + \varepsilon_{it}$

where

Y = Monthly outpatient expenditure

X_1= Year

X_2 =Publicly funded health insurance intensity PFHII

X_3 = Year * PFHII

X_4=Confidence in institutions/ governance intensity CGI

X_5= Developed Village DV

X_6= Family size FS

X_7= Highest adult education HAE

X_8= Household Ownership of Assets HOA

X_9= Implementation of public projects intensity PPI

X_{10}= Membership to various organisations Intensity MI

X_{11}= Number of married females in the household NMFH

X_{12}= Presence of conflicts intensity CNI

X_{13}= Proportion of children PCH

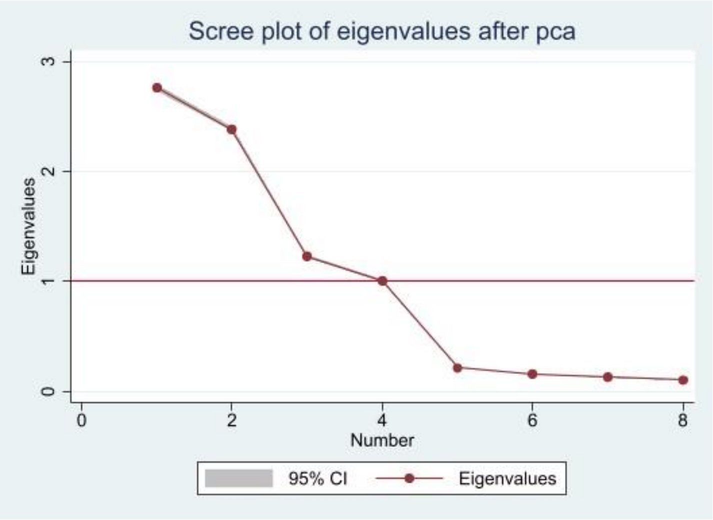
X_{14}= Village Health Infrastructure Index VHII

ε_i=The stochastic error term

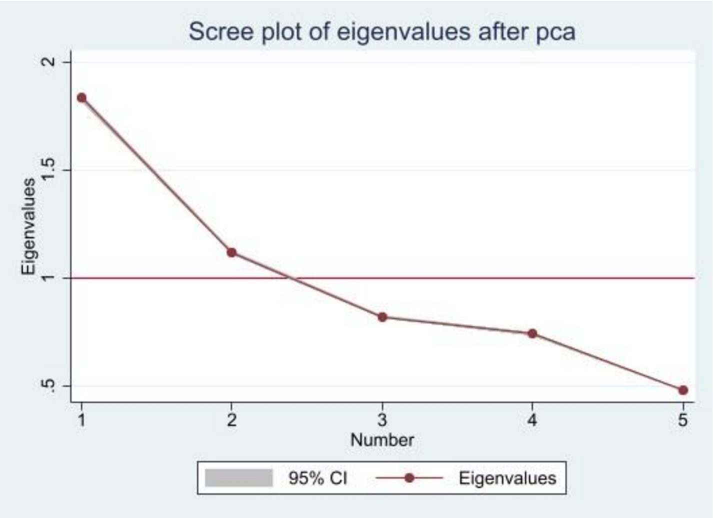
A8:

A8.1: Scree plots

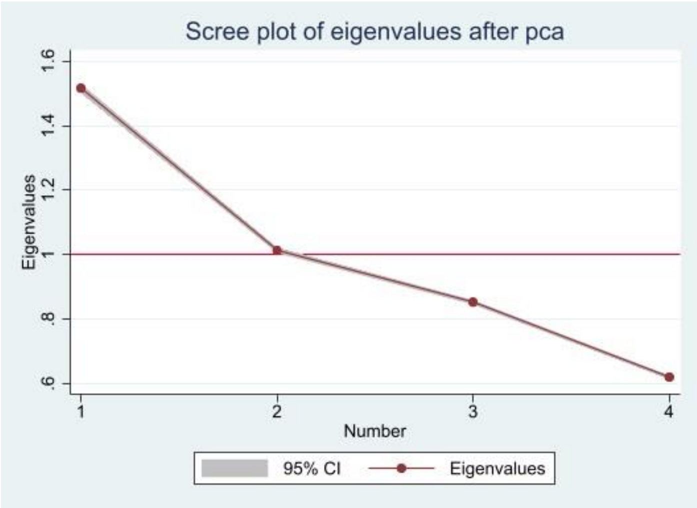
1. Scree plot short and major morbidity doctor advice and treatment 2005



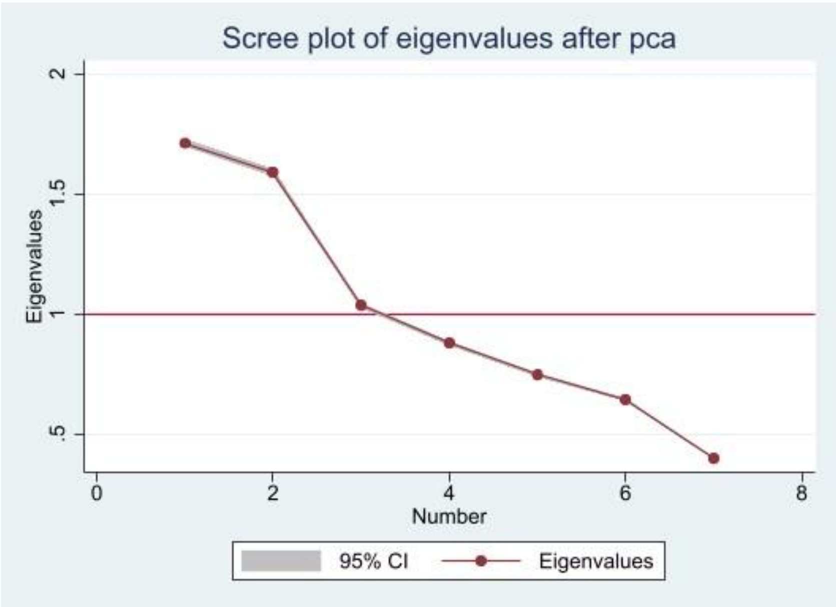
2. Scree plot for health facilities in the village 2005



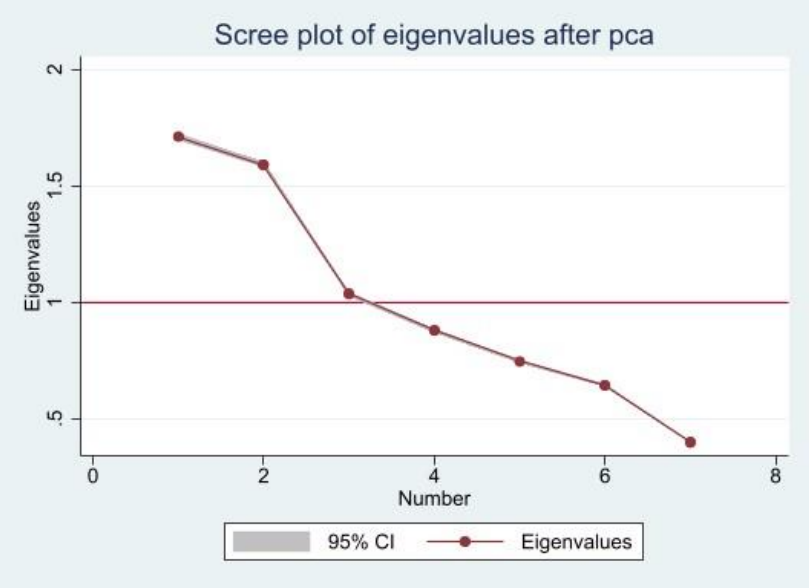
3. Scree plot for infrastructure facility in the village 2005



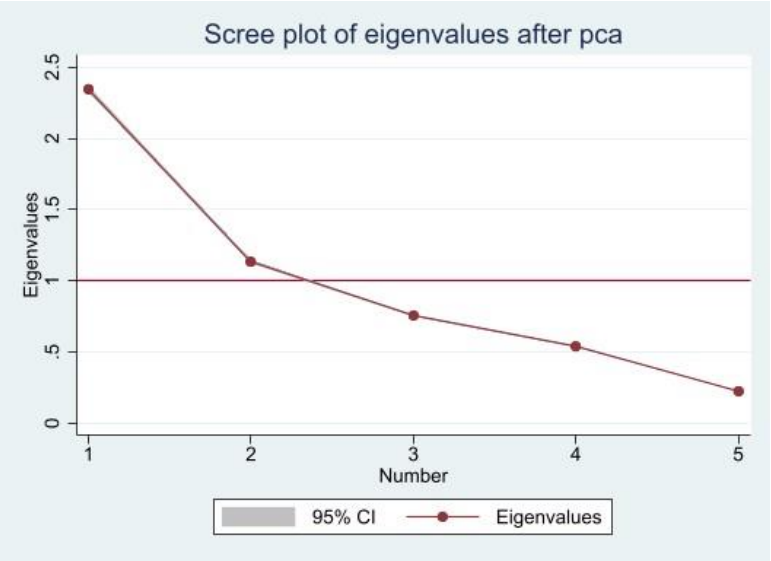
4. Scree plot for health facilities nearby 2005



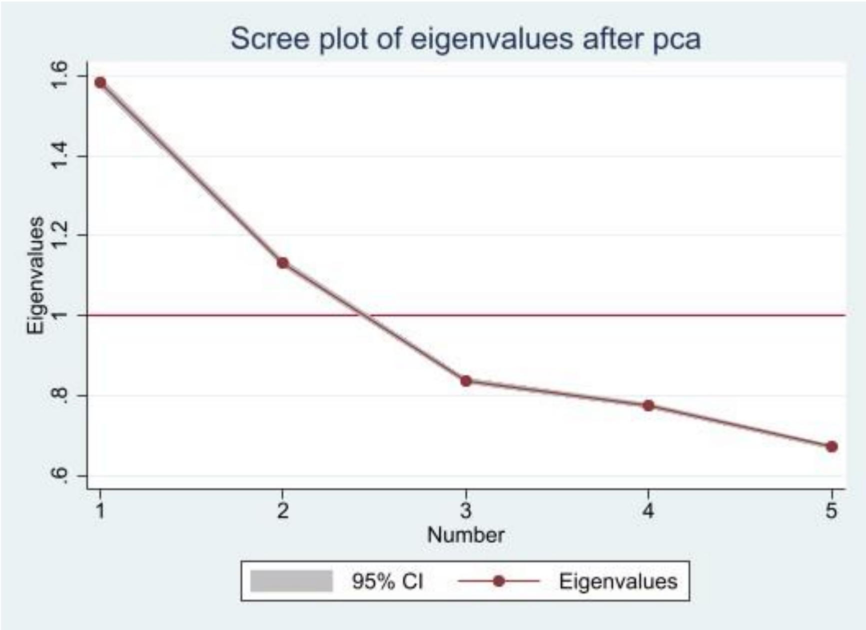
5. Scree plot for short and major morbidity doctor's advice and treatment 2012



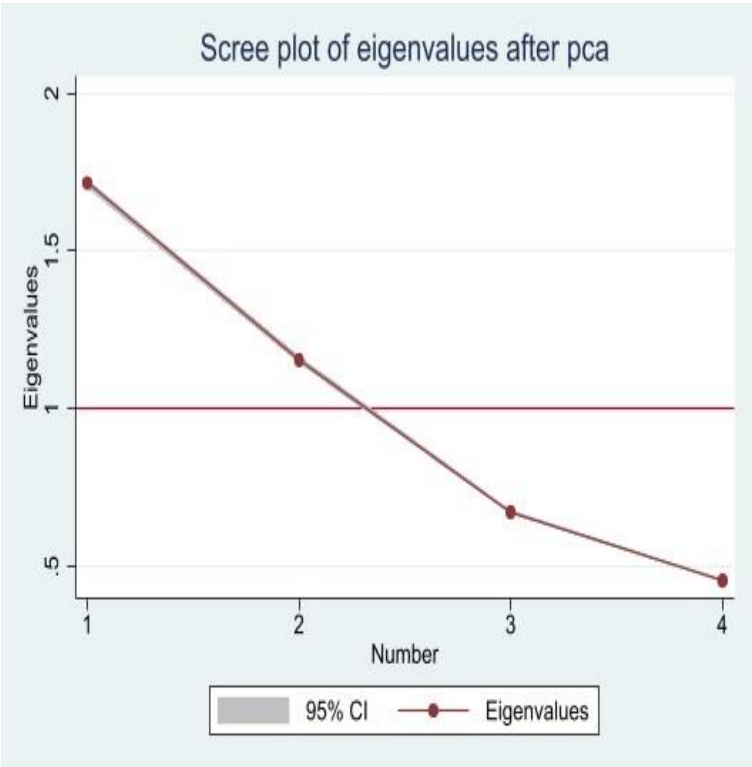
6. Scree plot for health facilities in the village 2012



7. Scree plot for infrastructure facilities in the village 2012



8/ Scree plot for health facilities in the nearby village 2012



A8.2: PCA Estimation and post-estimation results for Health facilities in the village 2005

Table A8.2.a: Initial extraction of components

Principal components/covariance		Number of obs = 99,028		
Number of comp. = 5		Trace = 4.993702		
Rotation: (unrotated = principal)		Rho = 1.0000		
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.833	0.715	0.367	0.367
Comp2	1.118	0.298	0.224	0.591
Comp3	0.82	0.079	0.164	0.755
Comp4	0.742	0.262	0.149	0.904
Comp5	0.48	.	0.096	1

Table A8.2.b: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Z_Vill_primary_Hlthcntr_2005	0.375	0.511	-0.254	-0.73	0.024	0
Z_VillHealth_subcntr_num__2005	0.197	0.757	0.252	0.549	0.151	0
Z_VillCommunity_health_num__2005	0.404	-0.212	0.857	-0.239	-0.022	0
ZVillcommunicabledisfaclty_2005	0.559	-0.322	-0.275	0.18	0.689	0
Z_Govtmatcentr_2005	0.587	-0.128	-0.249	0.276	-0.708	0

Table A8.2.c: Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Unexplained
Z_Vill_primary_Hlthcntr_2005		0.511	0.448
Z_VillHealth_subcntr_num__2005		0.757	0.287
Z_VillCommunity_health_num__2005	0.404		0.645
ZVillcommunicabledisfaclty_2005	0.559		0.314
Z_Govtmatcentr_2005	0.587		0.348

Table A8.2.d: SEs assume multivariate normality SE(Rho) = 0.0010

Eigenvalues	Coefficient	Std.err	z	P>z	[95% conf. interval]	
Comp1	1.833	0.008	222.52	0	1.817	1.849
Comp2	1.118	0.005	222.54	0	1.109	1.128
Comp1						
Z_Vill_primary_Hlthcntr_2005	0.375	0.004	89.24	0	0.367	0.384
Z_VillHealth_subcntr_num__2005	0.197	0.005	37.35	0	0.186	0.207
Z_VillCommunity_health_num__2005	0.404	0.004	110.56	0	0.397	0.411

ZVillcommunicabledisfaclty_2005	0.559	0.003	197.68	0	0.554	0.565
Z_Govtmatcentr_2005	0.587	0.002	265.17	0	0.582	0.591
Comp2						
Z_Vill_primary_Hlthcntr_2005	0.511	0.007	77.15	0	0.498	0.524
Z_VillHealth_subcntr_num__2005	0.757	0.005	147.64	0	0.747	0.767
Z_VillCommunity_health_num__2005	-0.212	0.009	-22.76	0	-0.23	-0.194
ZVillcommunicabledisfaclty_2005	-0.322	0.005	-60.03	0	-0.333	-0.312
Z_Govtmatcentr_2005	-0.128	0.006	-22.78	0	-0.139	-0.117

LR test for independence: chi2(10) = 50147.56 Prob > chi2 = 0.0000

LR test for sphericity: chi2(14) = 50150.33 Prob > chi2 = 0.0000

Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	1.833	0.367	0.001	0.367	0.001	0
Comp2	1.118	0.224	0.001	0.591	0.001	0
Comp3	0.82	0.164	0.001	0.755	0.001	0
Comp4	0.742	0.149	0.001	0.904	0	0
Comp5	0.48	0.096	0	1	0	0

Table A8.2.e: Testparm

- [Comp2]Z_Vill_primary_Hlthcntr_2005 + [Comp2]Z_VillHealth_subcntr_num__2005 = 0

- [Comp2]Z_Vill_primary_Hlthcntr_2005 + [Comp2]Z_VillCommunity_health_num__2005 = 0

- [Comp2]Z_Vill_primary_Hlthcntr_2005 + [Comp2]ZVillcommunicabledisfaclty_2005 = 0

- [Comp2]Z_Vill_primary_Hlthcntr_2005 + [Comp2]Z_Govtmatcentr_2005 = 0
chi2(4) = 3.1e+05
Prob > chi2 = 0.0000

Table 9.f: Pairwise correlation

Variables	Z_Vill_primary_Hlthcntr_2005	Z_VillHealth_subcntr_num__2005	Z_VillCommunity_health_num__2005	ZVillcommunicabledisfaclty_2005	Z_Govtmatcentr_2005
Z_Vill_primary_Hlthcntr_2005	1				
Z_VillHealth_subcntr_num__2005	0.2207*	1			
Z_VillCommunity_health_num__2005	0.1081*	0.0444*	1		
ZVillcommunicabledisfaclty_2005	0.1681*	-0.0045	0.2580*	1	
Z_Govtmatcentr_2005	0.2255*	0.1128*	0.2490*	0.5065*	1

Table A8.2.g: Scoring coefficients: sum of squares(column-loading) = 1

Variable	Comp1	Comp2
Z_Vill_pri~5	0.375	0.511
Z_VillHeal~5	0.197	0.757
Z_VillC~2005	0.404	-0.212

ZVillco~2005	0.559	-0.322
Z_Govtm~2005	0.587	-0.128

Table A8.2..h: Matrix of correlations

Variables	V4_2005	V5_2005
V4_2005	1	
V5_2005	0	1

Table A8.2..i: Rotation: orthogonal varimax (Kaiser off) Rho = 0.5910

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.737	0.522	0.348	0.348
Comp2	1.215	.	0.243	0.591

Rotated components

Variable	Comp1	Comp2	Unexplained
Z_Vill_primary_Hlthcntr_2005	0.162	0.613	0.448
Z_VillHealth_subcntr_num__2005	-0.095	0.777	0.287
Z_VillCommunity_health_num__2005	0.454	-0.049	0.645
ZVillcommunicabledisfaclty_2005	0.639	-0.095	0.314

Z_Govtmatcentr_2005	0.593	0.096	0.348

Component rotation matrix

	Comp1	Comp2
Comp1	0.93	0.367
Comp2	-0.367	0.93

Table A8.2..j: Anti-image covariance coefficients --- partialing out all other variables

Variables	Z_Vill_primary_Hlthcntr_2005	Z_VillHealth_subcntr_num__2005	Z_VillCommunity_health_num__2005	ZVillcommunicabledisfaclty_2005	Z_Govtmatcentr_2005
Z_Vill_primary_Hlthcntr_2005	0.9032				
Z_VillHealth_subcntr_num__2005	-0.19	0.9396			
Z_VillCommunity_health_num__2005	-0.0368	-0.0182	0.9123		
ZVillcommunicabledisfaclty_2005	-0.0588	0.0729	-0.1262	0.7169	
Z_Govtmatcentr_2005	-0.1063	-0.0788	-0.1044	-0.328	0.7037

Table A8.2.k: Principal component loadings: component normalization: sum of squares(column) = 1

Comp1	Comp2
0.375	0.511
0.197	0.757

0.404	-0.212
0.559	-0.322
0.587	-0.128

Table A8.2..l: Residual covariance matrix

Variables	Z_Vill_primary_Hlthcntr_2005	Z_VillHealth_subcntr_num__2005	Z_VillCommunity_health_num__2005	ZVillcommunicabledisfaclty_2005	Z_Govtmatcentr_2005
Z_Vill_primary_Hlthcntr_2005	0.4482828				
Z_VillHealth_subcntr_num__2005	-0.3480108	0.286679			
Z_VillCommunity_health_num__2005	-0.0491256	0.0778323	0.645033		
ZVillcommunicabledisfaclty_2005	-0.0323489	0.066605	-0.2328177	0.3141879	
Z_Govtmatcentr_2005	-0.1054162	0.0093958	-0.216844	-0.1409334	0.3480187

Table 9.m: Squared multiple correlations of variables with all other variables

Variables	SMC
Z_Vill_primary_Hlthcntr_2005	0.097
Z_VillHealth_subcntr_num__2005	0.06

Z_VillCommunity_health_num__2005	0.088
ZVillcommunicabledisfaclty_2005	0.283
Z_Govtmatcentr_2005	0.296

Table 9.n: Estimation sample PCA   Number of obs =   99,028

Variable	Mean	Std. dev.	Min	Max
Z_Vill_primary_Hlthcntr_2005	0.0006119	0.9994876	-0.3611111	14.7904
Z_VillHealth_subcntr_num__2005	-0.0003991	0.9995101	-0.6234483	15.92828
Z_VillCommunity_health_num__2005	0.001249	0.9971852	-0.141844	6.950355
ZVillcommunicabledisfaclty_2005	0.002444	1.002031	-0.1868132	5.307693
Z_Govtmatcentr_2005	0.0025304	0.9986297	-0.1777778	10.93333

A8.3: PCA and post estimation for infrastructure facilities in the village 2005

Table 10.a: Initial extraction of Components

Principal components/covariance Number of obs = 99,028

Number of comp. = 4 Trace = 3.999955

Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.516	0.503	0.379	0.379
Comp2	1.012	0.161	0.253	0.632
Comp3	0.852	0.232	0.213	0.845
Comp4	0.62	.	0.155	1

Table 10.b: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Z_Vdistnrsttown2005	0.402	0.55	-0.708	0.184	0
Z_Vdist_frmpucca_road2005	0.63	-0.249	-0.026	-0.735	0
Z_Vdist_clst_busstop2005	0.549	-0.525	0.073	0.646	0
Z_Vdist_clst_rlwystn_2005	0.373	0.601	0.702	0.091	0

Table 10.c: Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Unexplained
Z_Vdistnrsttown2005	0.402	0.55	0.449
Z_Vdist_frmpucca_road2005	0.63		0.336

Z_Vdist_clst_busstop2005	0.549	-0.525	0.263
Z_Vdist_clst_rlwystn_2005		0.601	0.424

Table 10.d: SEs assume multivariate normality SE(Rho) = 0.0011

Eigenvalues	Coefficient	Std.err.	z	P>z	[95% conf interval)	
Comp1	1.516	0.007	222.52	0	1.502	1.529
Comp2	1.012	0.005	222.56	0	1.004	1.021
Comp1						
Z_Vdistnrsttown2005	0.402	0.006	69.27	0	0.391	0.414
Z_Vdist_frmpucca_road2005	0.63	0.003	197.4	0	0.624	0.637
Z_Vdist_clst_busstop2005	0.55	0.005	117.3	0	0.54	0.559
Z_Vdist_clst_rlwystn_2005	0.373	0.006	61.48	0	0.361	0.385
Comp2						
Z_Vdistnrsttown2005	0.55	0.013	40.87	0	0.523	0.576
Z_Vdist_frmpucca_road2005	-0.249	0.007	-36.34	0	-0.262	-0.235
Z_Vdist_clst_busstop2005	-0.525	0.006	-85.73	0	-0.537	-0.513
Z_Vdist_clst_rlwystn_2005	0.6	0.013	45.36	0	0.575	0.626

LR test for independence: chi2(6) = 20805.17 Prob > chi2 = 0.0000						
LR test for sphericity: chi2(9) = 20805.30 Prob > chi2 = 0.0000						
Explained variance by components						
Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	1.516	0.379	0.001	0.379	0.001	0
Comp2	1.012	0.253	0.001	0.632	0.001	0
Comp3	0.852	0.213	0.001	0.845	0.001	0
Comp4	0.62	0.155	0.001	1	0	0
Prob > chi2 = 0.0000						

Table 10.e: Testparm

- [Comp2]Z_Vdistnrsttown2005 + [Comp2]Z_Vdist_frmpucca_road2005 = 0
- [Comp2]Z_Vdistnrsttown2005 + [Comp2]Z_Vdist_clst_busstop2005 = 0
- [Comp2]Z_Vdistnrsttown2005 + [Comp2]Z_Vdist_clst_rlwystn_2005 = 0

chi2(3) = 4.5e+05

Prob > chi2 = 0.0000

Table 10.f: Pairwise correlation

Variables	Z_Vdistnrsttown2005	Z_Vdist_frmpucca_road2005	Z_Vdist_clst_busstop2005	Z_Vdist_clst_rlwystn_2005
Z_Vdistnrsttown2005	1			
Z_Vdist_frmpucca_road2005	0.1778*	1		
Z_Vdist_clst_busstop2005	0.0728*	0.3610*	1	
Z_Vdist_clst_rlwystn_2005	0.1486*	0.1475*	0.0716*	1

Table 10.g: Scoring coefficients: sum of squares(column-loading) = 1		
Variable	Comp1	Comp2
Z_Vdistnrsttown2005	0.402	0.55
Z_Vdist_frmpucca_road2005	0.63	-0.249
Z_Vdist_clst_busstop2005	0.549	-0.525
Z_Vdist_clst_rlwystn_2005	0.373	0.601

Table 10.h: Matrix of correlations

Variables	V6_2005	V7_2005
V6_2005	1	
V7_2005	0	1

Table 10.i: Rotation: orthogonal varimax (Kaiser off) Rho = 0.6320

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.352	0.177	0.338	0.338
Comp2	1.176	.	0.294	0.632

Rotated components

Variable	Comp1	Comp2	Unexplained
Z_Vdistnrsttown2005	0.018	0.681	0.449
Z_Vdist_frmpucca_road2005	0.66	0.155	0.336

Z_Vdist_clst_busstop2005	0.75	-0.118	0.263
Z_Vdist_clst_rlwystn_2005	-0.036	0.706	0.424

Component rotation matrix

	Comp1	Comp2
Comp1	0.822	0.569
Comp2	-0.569	0.822

Table 10.j: Anti-image covariance coefficients --- partialing out all other variables

Variables	Z_Vdistnrsttown2005	Z_Vdist_frmpucca_road2005	Z_Vdist_clst_busstop2005	Z_Vdist_clst_rlwystn_2005
Z_Vdistnrsttown2005	0.953			
Z_Vdist_frmpucca_road2005	-0.1311	0.8364		
Z_Vdist_clst_busstop2005	-0.0063	-0.2987	0.8693	
Z_Vdist_clst_rlwystn_2005	-0.1203	-0.0985	-0.0173	0.9624

Table 10. k: Principal component loadings: component normalization: sum of squares(column) = 1

Comp1	Comp2
0.402	0.55
0.63	-0.249
0.549	-0.525
0.373	0.601

Table 10. l: Residual covariance matrix

variables	Z_Vdistnrsttown2005	Z_Vdist_frmpucca_road2005	Z_Vdist_clst_busstop2005	Z_Vdist_clst_rlwystn_2005
Z_Vdistnrsttown2005	0.4485459			
Z_Vdist_frmpucca_road2005	-0.0681999	0.3355617		
Z_Vdist_clst_busstop2005	0.0297279	-0.2960313	0.2632891	
Z_Vdist_clst_rlwystn_2005	-0.4129275	-0.057343	0.0803181	0.4245128

Table 10.m: Squared multiple correlations of variables with all other variables

Variables	SMC
Z_Vdistnrsttown2005	0.047
Z_Vdist_frmpucca_road2005	0.164
Z_Vdist_clst_busstop2005	0.131
Z_Vdist_clst_rlwystn_2005	0.038

Table 10.n: Estimation sample PCA Number of obs = 99,028

Variables	Mean	Std.dev.	Min	Max
Z_Vdistnrsttown2005	0	1	-1.261	6.553

Z_Vdist_frmpucca_road2005	0	1	-0.383	11.993
Z_Vdist_clst_busstop2005	0	1	-0.592	11.267
Z_Vdist_clst_rlwystn_2005	0	1	-1.008	3.577

A8.4 PCA and post estimation for infrastructure facilities nearby 2005

Table 11.a: Initial component extraction

Principal components/covariance Number of obs = 99,028

Number of comp. = 4 Trace= 4.000106

Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.716	0.56	0.429	0.429
Comp2	1.156	0.482	0.289	0.718
Comp3	0.674	0.219	0.168	0.886
Comp4	0.455	.	0.114	1

Table 11.b: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Unexplained
Z_Vdistnear_primary2005	0.409	0.561	-0.719	-0.002	0
z_DIsttoclosestMatcentr_km2005	0.587	-0.397	0.023	0.705	0

Z_Vdistnear_subcntr_2005	0.368	0.62	0.693	0.019	0
Z_Vdisnear_comdis2005	0.593	-0.38	0.043	-0.709	0

Table 11.c: Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Unexplained
Z_Vdistnear_primary2005	0.409	0.561	0.349
z_DIsttoclosestMatcentr_km2005	0.587		0.227
Z_Vdistnear_subcntr_2005		0.62	0.324
Z_Vdisnear_comdis2005	0.593		0.23

Table 11.d: SEs assume multivariate normality SE(Rho) = 0.0009

Eigenvalues	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
Comp1	1.716	0.008	222.52	0	1.701	1.731
Comp2	1.156	0.005	222.53	0	1.146	1.166
Comp1						
Z_Vdistnear_primary2005	0.409	0.005	80.79	0	0.399	0.419
z_DIsttoclosestMatcentr_km2005	0.587	0.004	165.97	0	0.58	0.594
Z_Vdistnear_subcntr_2005	0.369	0.005	67.67	0	0.358	0.379

Z_Vdisnear_comdis2005	0.593	0.003	173.41	0	0.587	0.6
Comp2						
Z_Vdistnear_primary2005	0.561	0.005	105.68	0	0.551	0.572
z_DIsttoclosestMatcentr_km2005	-0.397	0.005	-75.77	0	-0.407	-0.386
Z_Vdistnear_subcntr_2005	0.619	0.005	124.12	0	0.61	0.629
Z_Vdisnear_comdis2005	-0.379	0.005	-71.76	0	-0.39	-0.369

LR test for independence: chi2(6) = 49325.39 Prob > chi2 = 0.0000
LR test for sphericity: chi2(9) = 49325.68 Prob > chi2 = 0.0000
Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	1.716	0.429	0.001	0.429	0.001	0
Comp2	1.156	0.289	0.001	0.718	0.001	0
Comp3	0.674	0.168	0.001	0.886	0.001	0
Comp4	0.455	0.114	0.001	1	0	0

Prob > chi2 = 0.0000

Table 11. e: Testparm

(1)-[Comp2]Z_Vdistnear_primary2005 + [Comp2]z_DIsttoclosestMatcentr_km2005 = 0
(2) - [Comp2]Z_Vdistnear_primary2005 + [Comp2]Z_Vdistnear_subcntr_2005 = 0
(3) - [Comp2]Z_Vdistnear_primary2005 + [Comp2]Z_Vdisnear_comdis2005 = 0
chi2(3) = 3.7e+05
Prob > chi2 = 0.0000

Table 11.f: Pairwise correlations

Variables	Z_Vdistnear_primary2005	z_DIsttoclosestMatcentr_km2005	Z_Vdistnear_subcntr_2005	Z_Vdisnear_comdis2005

Z_Vdistnear_primary2005	1			
z_DIsttoclosestMatcentr_km2005	0.143*	1		
Z_Vdistnear_subcntr_2005	0.325*	0.104*	1	
Z_Vdisnear_comdis2005	0.150*	0.545*	0.117*	1

*** p<0.01, ** p<0.05, * p<0.1

Table 11.g: Scoring coefficients:sum of squares(column-loading) = 1

Variable	Comp1	Comp2
Z_Vdistnear_primary2005	0.409	0.561
z_DIsttoclosestMatcentr_km2005	0.587	-0.397
Z_Vdistnear_subcntr_2005	0.368	0.62
Z_Vdisnear_comdis2005	0.593	-0.38

Table 11.h: Matrix of correlations

Variables	V8_2005	V9_2005
V8_2005	1	
V9_2005	0	1

Table 11.i: Rotation: orthogonal varimax (Kaiser off) Rho = 0.7179

Component	Variance	Difference	Proportion	Cumulative

Comp1	1.547	0.223	0.387	0.387
Comp2	1.324	.	0.331	0.718

Rotated components

Variable	Comp1	Comp2	Unexplained
Z_Vdistnear_primary2005	0.034	0.694	0.349
z_DIsttoclosestMatcentr_km2005	0.709	-0.009	0.227
Z_Vdistnear_subcntr_2005	-0.032	0.72	0.324
Z_Vdisnear_comdis2005	0.704	0.008	0.23

Component rotation matrix

	Comp1	Comp2
Comp1	0.836	0.549
Comp2	-0.549	0.836

Table 11.j:Anti-image covariance coefficients --- partialing out all other variables

Variables	Z_Vdistnear_primary2005	z_DIsttoclosestMatcentr_km2005	Z_Vdistnear_subcntr_2005	Z_Vdisnear_comdis2005
Z_Vdistnear_primary2005	0.8784			
z_DIsttoclosestMatcentr_km2005	-0.0489	0.6988		
Z_Vdistnear_subcntr_2005	-0.2744	-0.0208	0.8891	
Z_Vdisnear_comdis2005	-0.0528	-0.3716	-0.0378	0.6962

Table 11.k: Principal component loadings: component normalization: sum of squares(column) = 1

Comp1	Comp2
0.409	0.561
0.587	-0.397
0.368	0.62
0.593	-0.38

Table11.l: Residual covariance matrix

Variables	Z_Vdistnear_primary2005	z_DIsttoclosestMatcentr_km2005	Z_Vdistnear_subcntr_2005	Z_Vdisnear_comdis2005
Z_Vdistnear_primary2005	0.348618			
z_DIsttoclosestMatcentr_km2005	-0.0117038	0.2266664		
Z_Vdistnear_subcntr_2005	-0.3357823	0.0168434	0.3235563	
Z_Vdisnear_comdis2005	-0.0203673	-0.2267337	0.0140186	0.2297572

Table 11.m: Squared multiple correlations of variables with all other variables

Variables	SMC
Z_Vdistnear_primary2005	0.122
z_DIsttoclosestMatcentr_km2005	0.301
Z_Vdistnear_subcntr_2005	0.111
Z_Vdisnear_comdis2005	0.304

Table 11.n: Estimation sample pca				
Variable	Mean	Std. dev	Min	Max
Z_Vdistnear_primary2005	0.0000388	1.000025	-0.9660568	7.254574
z_DIsttoclosestMatcentr_km2005	0.0000116	0.9999966	-0.9934155	4.307628
Z_Vdistnear_subcntr_2005	0.0000866	1.000039	-0.5596877	15.87754
Z_Vdisnear_comdis2005	-0.0000238	0.9999918	-0.9883274	3.812077

A8.5 Short and major morbidity doctors advice and treatment 2012

Table 1.a: Covariance matrix with initial PCA extraction	
Principal components/covariance	Number of obs = 99,028
Number of comp. = 8	
Trace = 7.995947	
Rotation: (unrotated = principal)	Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.903	0.582	0.363	0.363
Comp2	2.322	1.054	0.29	0.653
Comp3	1.267	0.341	0.159	0.812
Comp4	0.927	0.733	0.116	0.928
Comp5	0.194	0.036	0.024	0.952
Comp6	0.158	0.037	0.02	0.972
Comp7	0.121	0.016	0.015	0.987
Comp8	0.104	.	0.013	1

Table 1.b: PCA eigen vectors

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Comp8	Unexplained
Z_SMfirstadvice_2012	0.227	0.427	0.511	-0.134	0.516	-0.258	0.366	-0.143	0
Z_SMplacefirst_treatment2012	0.241	0.442	0.472	-0.11	-0.531	0.256	-0.377	0.147	0
Z_SMsecondadvice_2012	0.227	0.452	-0.478	0.123	0.369	-0.195	-0.541	0.183	0
Z_SMplacesecond_treatment2012	0.231	0.451	-0.476	0.125	-0.335	0.181	0.565	-0.192	0
Z_MBfirstadvice_2012	0.432	-0.228	0.129	0.517	0.261	0.483	0.134	0.397	0
Z_MBfirstplace_treatment2012	0.449	-0.239	0.106	0.458	-0.257	-0.504	-0.14	-0.426	0
Z_MBsecondadvice_2012	0.444	-0.228	-0.127	-0.488	0.194	0.413	-0.189	-0.504	0
Z_MBsecondplace_treatment2012	0.448	-0.232	-0.129	-0.474	-0.177	-0.373	0.198	0.543	0

Table 1.c : Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Comp3	Unexplained
Z_SMfirstadvice_2012	0.427		0.511	0.097
Z_SMplacefirst_treatment2012	0.442		0.472	0.096
Z_SMsecondadvice_2012	0.452		-0.478	0.085
Z_SMplacesecond_treatment2012	0.451		-0.476	0.084
Z_MBfirstadvice_2012		0.432		0.316
Z_MBfirstplace_treatment2012		0.449		0.268
Z_MBsecondadvice_2012		0.444		0.285

Z_MBsecondplace_treatment2012	0.448	0.272

Table 1.d: VCE normal SE(Rho) SEs assume multivariate normality = 0.0006

Eigenvalues	Coefficient	Std. error	z	P>z	[95%	conf. interval]
Comp1	2.903	0.013	222.54	0	2.877	2.929
Comp2	2.322	0.01	222.55	0	2.301	2.342
Comp3	1.267	0.006	222.53	0	1.256	1.279
Comp1						
Z_SMfirstadvice_2012	0.227	0.006	35.52	0	0.214	0.239
Z_SMplacefirst_treatment2012	0.241	0.007	36.84	0	0.228	0.254
Z_SMsecondadvice_2012	0.227	0.007	33.98	0	0.214	0.24
Z_SMplacesecond_treatment2012	0.231	0.007	34.62	0	0.218	0.244
Z_MBfirstadvice_2012	0.432	0.004	120.96	0	0.425	0.439
Z_MBfirstplace_treatment2012	0.449	0.004	122.43	0	0.441	0.456
Z_MBsecondadvice_2012	0.444	0.004	125.35	0	0.437	0.451
Z_MBsecondplace_treatment2012	0.448	0.004	124.96	0	0.44	0.455
Comp2						
Z_SMfirstadvice_2012	0.427	0.004	100.81	0	0.419	0.435
Z_SMplacefirst_treatment2012	0.442	0.004	103.58	0	0.434	0.451
Z_SMsecondadvice_2012	0.452	0.004	109.5	0	0.444	0.46
Z_SMplacesecond_treatment2012	0.451	0.004	108.46	0	0.443	0.46
Z_MBfirstadvice_2012	-0.228	0.006	-35.37	0	-0.24	-0.215
Z_MBfirstplace_treatment2012	-0.239	0.007	-36.27	0	-0.252	-0.226
Z_MBsecondadvice_2012	-0.227	0.007	-34.66	0	-0.24	-0.215
Z_MBsecondplace_treatment2012	-0.231	0.007	-35.07	0	-0.244	-0.219
Comp3						
Z_SMfirstadvice_2012	0.511	0.003	177.63	0	0.505	0.517
Z_SMplacefirst_treatment2012	0.472	0.003	164.99	0	0.466	0.478
Z_SMsecondadvice_2012	-0.478	0.003	-164.55	0	-0.484	-0.473
Z_SMplacesecond_treatment2012	-0.476	0.003	-163.3	0	-0.482	-0.47
Z_MBfirstadvice_2012	0.128	0.006	22.71	0	0.117	0.14
Z_MBfirstplace_treatment2012	0.106	0.005	20.69	0	0.096	0.117
Z_MBsecondadvice_2012	-0.127	0.005	-23.62	0	-0.138	-0.117
Z_MBsecondplace_treatment2012	-0.129	0.005	-24.47	0	-0.14	-0.119

LR test for independence: chi2(28) = 573021.60 Prob > chi2 = 0.0000

LR test for sphericity: chi2(35) = 573025.53 Prob > chi2 = 0.0000

Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	2.903	0.363	0.001	0.363	0.001	0
Comp2	2.322	0.29	0.001	0.653	0.001	0
Comp3	1.267	0.159	0.001	0.812	0.001	0
Comp4	0.927	0.116	0.001	0.928	0	0
Comp5	0.194	0.024	0	0.952	0	0
Comp6	0.158	0.02	0	0.972	0	0
Comp7	0.121	0.015	0	0.987	0	0
Comp8	0.104	0.013	0	1	0	0

Prob > chi2 = 0.0000

Table 1.e: Testparm

- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_SMplacefirst_treatment2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_SMsecondadvice_2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_SMplacesecond_treatment2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_MBfirstadvice_2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_MBfirstplace_treatment2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_MBsecondadvice_2012 = 0
- [Comp3]Z_SMfirstadvice_2012+ [Comp3]Z_MBsecondplace_treatment2012 = 0

chi2(7) = 1.2e+10

Prob > chi2 = 0.0000

Table 1.f: Pairwise correlation

Variables	Z_SMfirstadvice_2012	Z_SMplacefirst_treatment2012	Z_SMsecondadvice_2012	Z_SMplacesecond_treatment2012	Z_MBfirstadvice_2012	Z_MBfirstplace_treatment2012	Z_MBsecondadvice_2012	Z_MBsecondplace_treatment2012
Z_SMfirstadvice_2012	1							
Z_SMplacefirst_treatment2012	0.833*	1						
Z_SMsecondadvice_2012	0.291*	0.305*	1					
Z_SMplacesecond_treatment2012	0.263*	0.341*	0.860*	1				
Z_MBfirstadvice_2012	0.085*	0.086*	0.030*	0.032*	1			

Z_MBfirstplace_treatment2012	0.065*	0.091*	0.030*	0.040*	0.855*	1		
Z_MBsecondadvice_2012	0.046*	0.048*	0.080*	0.076*	0.441*	0.464*	1	
Z_MBsecondplace_treatment2012	0.038*	0.049*	0.073*	0.084*	0.424*	0.504*	0.871*	1

*** p<0.01, ** p<0.05, * p<0.1

Table 1.g: Scoring coefficients, sum of squares(column-loading) = 1

Variable	Comp1	Comp2	Comp3
Z_SMfirstadvice_2012	0.227	0.427	0.511
Z_SMplacefirst_treatment2012	0.241	0.442	0.472
Z_SMsecondadvice_2012	0.227	0.452	-0.478
Z_SMplacesecond_treatment2012	0.231	0.451	-0.476
Z_MBfirstadvice_2012	0.432	-0.228	0.129
Z_MBfirstplace_treatment2012	0.449	-0.239	0.106
Z_MBsecondadvice_2012	0.444	-0.228	-0.127
Z_MBsecondplace_treatment2012	0.448	-0.232	-0.129

Table 1.h: Matrix of correlations: correlating predicted scores

Variables	V1_2012	V2_2012	V3_2012
V1_2012	1		
V2_2012	0	1	
V3_2012	0	0	1

Table 1.i: Rotation: orthogonal varimax (Kaiser off)

Rho = 0.8119

Component	Variance	Difference	Proportion	Cumulative
Comp1	2.778	0.908	0.347	0.347
Comp2	1.87	0.027	0.234	0.581
Comp3	1.844	.	0.231	0.812

Rotated components

Variable	Comp1	Comp2	Comp3	Unexplained
Z_SMfirstadvice_2012	-0.004	-0.009	0.703	0.097

Z_SMplacefirst_treatment2012	0.003	0.032	0.69	0.096
Z_SMsecondadvice_2012	-0.001	0.696	0.009	0.085
Z_SMplacesecond_treatment2012	0.002	0.695	0.012	0.084
Z_MBfirstadvice_2012	0.487	-0.095	0.096	0.316
Z_MBfirstplace_treatment2012	0.507	-0.082	0.078	0.268
Z_MBsecondadvice_2012	0.5	0.087	-0.084	0.285
Z_MBsecondplace_treatment2012	0.506	0.087	-0.086	0.272

Component rotation matrix

	Comp1	Comp2	Comp3
Comp1	0.886	0.323	0.332
Comp2	-0.463	0.64	0.613
Comp3	-0.014	-0.697	0.717

Table 1.j: Anti-image covariance coefficients: partialing out all other variables

Variable	Z_SMfirstadvice_2012	Z_SMplacefirst_treatment2012	Z_SMsecondadvice_2012	Z_SMplacesecond_treatment2012	Z_MBfirstadvice_2012	Z_MBfirstplace_treatment2012	Z_MBsecondadvice_2012	Z_MBsecondplace_treatment2012
Z_SMfirstadvice_2012	0.292							
Z_SMplacefirst_treatment2012	0.2362	0.2816						
Z_SMsecondadvice_2012	0.0515	0.0378	0.2508					
Z_SMplacesecond_treatment2012	0.0489	0.063	0.2104	0.245				
Z_MBfirstadvice_2012	0.0197	0.0135	0.0003	0.0007	0.2578			
Z_MBfirstplace_treatment2012	0.0187	0.0201	0.0014	0.0004	0.2042	0.2396		
Z_MBsecondadvice_2012	0.002	0.0016	0.0116	0.0088	0.0473	0.0297	0.23	
Z_MBsecondplace_treatment2012	0.0004	0.0014	0.0089	0.0119	0.0407	0.0618	0.1888	0.2206

Table 1.k: Principal component loadings

component normalization: sum of squares(column) = 1

Comp1	Comp2	Comp3
0.227	0.427	0.511

	0.241	0.442	0.472
	0.227	0.452	-0.478
	0.231	0.451	-0.476
	0.432	-0.228	0.129
	0.449	-0.239	0.106
	0.444	-0.228	-0.127
	0.448	-0.232	-0.129

Table 1.l:Residual covariance matrix

Variable	Z_SMfirstadvice_2012	Z_SMplacefirst_treatment2012	Z_SMsecondadvice_2012	Z_SMplacesecond_treatment2012	Z_MBfirstadvice_2012	Z_MBfirstplace_treatment2012	Z_MBsecondadvice_2012	Z_MBsecondplace_treatment2012
Z_SMfirstadvice_2012	0.0970195							
Z_SMplacefirst_treatment2012	-0.0688427	0.0957143						
Z_SMsecondadvice_2012	0.0030817	-0.0311043	0.0852752					
Z_SMplacesecond_treatment2012	-0.0285889	0.0004591	-0.0557855	0.0837069				
Z_MBfirstadvice_2012	-0.0575033	-0.0601339	0.0616734	0.0579159	0.316434			
Z_MBfirstplace_treatment2012	-0.0616349	-0.0407259	0.050248	0.0543695	0.1477825	0.2682634		
Z_MBsecondadvice_2012	0.0621168	0.0473199	-0.0517785	-0.0599913	-0.2162349	-0.2237114	0.285356	
Z_MBsecondplace_treatment2012	0.0568685	0.0508097	-0.0578334	-0.0516334	-0.2390098	-0.190127	0.1503464	0.2721551

Table 1.m: Squared multiple correlations of variables with all other variables

Variables	SMC
Z_SMfirstadvice_2012	0.708
Z_SMplacefirst_treatment2012	0.718
Z_SMsecondadvice_2012	0.749
Z_SMplacesecond_treatment2012	0.755
Z_MBfirstadvice_2012	0.742
Z_MBfirstplace_treatment2012	0.76
Z_MBsecondadvice_2012	0.77
Z_MBsecondplace_treatment2012	0.779

Table 1.n: Estimation sample pca

Variable	Mean	Std. dev.	Min	Max
Z_SMfirstadvice_2012	0.0000258	1.000103	-0.4031365	6.054428
Z_SMplacefirst_treatment2012	0.0003913	1.000443	-0.4070796	6.47591
Z_SMsecondadvice_2012	-0.0005059	0.9992735	-0.1471264	15.94483
Z_SMplacesecond_treatment2012	-0.0005335	0.9995289	-0.1501057	14.64905
Z_MBfirstadvice_2012	-0.0003191	1.000209	-0.3178017	8.045401
Z_MBfirstplace_treatment2012	0.0002197	0.999771	-0.3253968	5.847443
Z_MBsecondadvice_2012	0.0003902	0.9990847	-0.1696253	13.63708
Z_MBsecondplace_treatment2012	0.0005073	0.999559	-0.1756168	9.984035

Table 2.a :Intial extraction of Principal components(covariance matrix)

Number of obs = 99,028 Number of comp. = 5				
Trace = 4.999664				
Rotation: (unrotated = principal) Rho = 1.0000				
Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	2.346	1.213	0.469	0.469
Comp2	1.133	0.377	0.227	0.696
Comp3	0.756	0.218	0.151	0.847
Comp4	0.538	0.313	0.108	0.955
Comp5	0.225	.	0.045	1

Table 2.b: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Z_VillPrimary_health_num_2012	0.286	0.549	-0.781	0.08	-0.024	0
Z_VillHealth_subcntr_num_2012	0.506	0.011	0.102	-0.848	0.121	0
Z_Vill_Healthworkernum_2012	0.556	-0.259	0.045	0.428	0.662	0
z_MultiHlthwork_no2012	0.575	-0.23	0.097	0.247	-0.739	0
Z_GovtmatNo_2012	0.149	0.76	0.607	0.174	0.017	0

Table 5.c Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Unexplained
Z_VillPrimary_health_num_2012		0.5494	0.4645
Z_VillHealth_subcntr_num_2012	0.506		0.3982
Z_Vill_Healthworkernum_2012	0.5559		0.1992
z_MultiHlthwork_no2012	0.5754		0.1628
Z_GovtmatNo_2012		0.7605	0.2952

Table 5.d: VCE normal

Eigenvalues	Coefficient	Std. error	z	P>z	[95%	conf. interval]
Comp1	2.346	0.011	222.52	0	2.326	2.367
Comp2	1.133	0.005	222.53	0	1.123	1.143
Comp1						
Z_VillPrimary_health_num_2012	0.286	0.003	91.02	0	0.28	0.292
Z_VillHealth_subcntr_num_2012	0.506	0.002	297.18	0	0.503	0.509
Z_Vill_Healthworkernum_2012	0.556	0.002	353.56	0	0.553	0.559
z_MultiHlthwork_no2012	0.575	0.001	415.74	0	0.573	0.578
Z_GovtmatNo_2012	0.149	0.004	40.98	0	0.142	0.156
Comp2						
Z_VillPrimary_health_num_2012	0.549	0.006	88.37	0	0.537	0.562
Z_VillHealth_subcntr_num_2012	0.011	0.004	2.55	0.011	0.003	0.019
Z_Vill_Healthworkernum_2012	-0.259	0.003	-80.46	0	-0.265	-0.252
z_MultiHlthwork_no2012	-0.23	0.003	-75.06	0	-0.236	-0.224
Z_GovtmatNo_2012	0.76	0.005	157.4	0	0.751	0.77

LR test for independence: chi2(10) = 139659.32 Prob > chi2 = 0.0000
LR test for sphericity: chi2(14) = 139660.84 Prob > chi2 = 0.0000

Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	2.346	0.469	0.001	0.469	0.001	0
Comp2	1.133	0.227	0.001	0.696	0.001	0
Comp3	0.756	0.151	0.001	0.847	0.001	0
Comp4	0.538	0.108	0.001	0.955	0	0
Comp5	0.225	0.045	0	1	0	0

Prob > chi2 = 0.0000

Table 5.e Testparm

[Comp2]Z_VillPrimary_health_num_2012 +[Comp2]Z_VillHealth_subcntr_num_2012 = 0

[Comp2]Z_VillPrimary_health_num_2012+ [Comp2]Z_Vill_Healthworkernum_2012 = 0

[Comp2]Z_VillPrimary_health_num_2012 +[Comp2]z_MultiHlthwork_no2012 = 0

[Comp2]Z_VillPrimary_health_num_2012 +[Comp2]Z_GovtmatNo_2012 = 0

chi2(4) = 3.4e+05

Prob > chi2 = 0.0000

Table 5.f: Pairwise correlations

Variables	Z_VillPrimary_health_num_2012	Z_VillHealth_subcntr_num_2012	Z_Vill_Healthworkernum_2012	z_MultiHlthwork_no2012	Z_GovtmatNo_2012

Z_VillPrimary_health_num_2012	1				
Z_VillHealth_subcntr_num_2012	0.249*	1			
Z_Vill_Healthworkernum_2012	0.200*	0.483*	1		
z_MultiHlthwork_no2012	0.200*	0.555*	0.768*	1	
Z_GovtmatNo_2012	0.223*	0.154*	0.035*	0.068*	1

*** p<0.01, ** p<0.05, * p<0.1

Table 5.g:Scoring coefficients

sum of squares(column-loading) = 1

Variable	Comp1	Comp2
Z_VillPrimary_health_num_2012	0.286	0.549
Z_VillHealth_subcntr_num_2012	0.506	0.011
Z_Vill_Healthworkernum_2012	0.556	-0.259
z_MultiHlthwork_no2012	0.575	-0.23
Z_GovtmatNo_2012	0.149	0.76

Table 5.h:Matrix of correlations

Variables	V4_2012	V5_2012
V4_2012	1	
V5_2012	0	1

Table 5.iRotation: orthogonal varimax (Kaiser off) Rho = 0.6960

Component	Variance	Difference	Proportion	Cumulative
Comp1	2.239	0.999	0.448	0.448
Comp2	1.24	.	0.248	0.696

Rotated components

Variable	Comp1	Comp2	Unexplained
Z_VillPrimary_health_num_2012	0.11	0.609	0.465
Z_VillHealth_subcntr_num_2012	0.48	0.161	0.398
Z_Vill_Healthworkernum_2012	0.608	-0.082	0.199
z_MultiHlthwork_no2012	0.618	-0.049	0.163
Z_GovtmatNo_2012	-0.083	0.77	0.295

Component rotation matrix

	Comp1	Comp2
Comp1	0.955	0.297
Comp2	-0.297	0.955

Table 5.j: Anti-image covariance coefficients --- partialing out all other variables

Variables	Z_VillPrimary_health_num_2012	Z_VillHealth_subcntr_num_2012	Z_Vill_Healthworkernum_2012	z_MultiHlthwork_no2012	Z_GovtmatNo_2012
Z_VillPrimary_health_num_2012	0.8932				
Z_VillHealth_subcntr_num_2012	-0.104	0.6573			
Z_Vill_Healthworkernum_2012	-0.0396	-0.0518	0.4032		
z_MultiHlthwork_no2012	-0.0088	-0.1561	-0.2625	0.3657	
Z_GovtmatNo_2012	-0.1807	-0.0886	0.0331	-0.0058	0.936

Table 5.k:.Principal component loadings component normalization: sum of squares(column) = 1

Comp1	Comp2
0.286	0.549
0.506	0.011
0.556	-0.259
0.575	-0.23
0.149	0.76

Table 5. l:Residual covariance matrix

Variables	Z_VillPrimary_health_num_2012	Z_VillHealth_subcntr_num_2012	Z_Vill_Healthworkernum_2012	z_MultiHlthwork_no2012	Z_GovtmatNo_2012
Z_VillPrimary_health_num_2012	0.4644586				
Z_VillHealth_subcntr_num_2012	-0.0974726	0.3982163			
Z_Vill_Healthworkernum_2012	-0.0118275	-0.1739826	0.1991835		
z_MultiHlthwork_no2012	-0.0423783	-0.1253209	-0.0500658	0.1628428	
Z_GovtmatNo_2012	-0.3509721	-0.0322738	0.0636147	0.0645819	0.2951511

Table 5.m:Squared multiple correlations of variables with all other variables

Variables	smc
Z_VillPrimary_health_num_2012	0.107
Z_VillHealth_subcntr_num_2012	0.343
Z_Vill_Healthworkernum_2012	0.597
z_MultiHlthwork_no2012	0.634
Z_GovtmatNo_2012	0.064

Table 5.n:Estimation sample pca Number of obs = 99,028

Variables	Mean	Std. Dev	Min	Max
Z_VillPrimary_health_num_2012	0.001	0.999	-0.382	5.5
Z_VillHealth_subcntr_num_2012	0.001	1	-0.727	11.413
Z_Vill_Healthworkernum_2012	0	1	-0.269	13.721
z_MultiHlthwork_no2012	0	1	-0.292	13.774

Z_GovtmatNo_2012	0	1.001	-0.206	9.598

A8.6: Health facility in the village 2012

14: Infrastructure facilities in the village

Table 6.a: Initial extraction of Principal components/covariance

Number of obs = 99,028 Number of comp. = 5

Trace = 5.000443 Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.583	0.451	0.317	0.317
Comp2	1.132	0.295	0.226	0.543
Comp3	0.837	0.061	0.167	0.71
Comp4	0.776	0.103	0.155	0.866
Comp5	0.673	.	0.135	1

Table 6.b : Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Unexplained
Z_DistNrtownkm_2012	0.51	-0.219	0.427	-0.613	0.365	0
Z_DIstDstrctHQkm_2012	0.535	-0.213	0.385	0.457	-0.558	0
Z_VillpuccaRddist_2012	0.399	0.545	-0.41	-0.416	-0.449	0
Z_ Vrailstn_2012	0.542	-0.019	-0.501	0.421	0.526	0
Z_Vbusstp_vill2012	0.024	0.78	0.499	0.254	0.276	0

Table 6.c: Principal components (eigenvectors) (blanks are abs(loading)<.4)			
Variable	Comp1	Comp2	Unexplained
Z_DistNrtownkm_2012	0.51		0.534
Z_DIstDstrctHQkm_2012	0.535		0.495
Z_VillpuccaRddist_2012		0.545	0.411
Z_ Vrailstn_2012	0.542		0.534
Z_Vbusstp_vill2012		0.78	0.31

Table 6.d VCE normal Principal components/covariance

	SEs assume multivariate normality		SE(Rho) = 0.0010			
Eigenvalues	Coefficient	Std. err.	z	P>z	[95% conf. interval]	
Comp1	1.583	0.007	222.53	0	1.569	1.597
Comp2	1.132	0.005	222.55	0	1.122	1.142
Comp1						
Z_DistNrtownkm_2012	0.51	0.004	121.87	0	0.502	0.518
Z_DIstDstrctHQkm_2012	0.535	0.004	135.38	0	0.527	0.543
Z_VillpuccaRddist_2012	0.399	0.006	66.13	0	0.387	0.411
Z_ Vrailstn_2012	0.542	0.004	150.14	0	0.535	0.549
Z_Vbusstp_vill2012	0.024	0.008	2.99	0.003	0.008	0.039
Comp2						
Z_DistNrtownkm_2012	-0.219	0.009	-25.35	0	-0.235	-0.202
Z_DIstDstrctHQkm_2012	-0.213	0.008	-25.96	0	-0.23	-0.197
Z_VillpuccaRddist_2012	0.545	0.007	75.53	0	0.531	0.559
Z_ Vrailstn_2012	-0.019	0.009	-2.16	0.031	-0.036	-0.002

Z_Vbusstp_vill2012	0.78	0.006	132.37	0	0.769	0.792
LR test for independence: chi2(10) = 24323.36 Prob > chi2 = 0.0000						
LR test for sphericity: chi2(14) = 24323.54 Prob > chi2 = 0.0000						
Explained variance by components						

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	1.583	0.317	0.001	0.317	0.001	0
Comp2	1.132	0.226	0.001	0.543	0.001	0
Comp3	0.837	0.167	0.001	0.71	0.001	0
Comp4	0.776	0.155	0.001	0.866	0.001	0
Comp5	0.673	0.135	0.001	1	0	0
chi2(4) =62384.36						
Prob > chi2 = 0.0000						

Table 6.e: Testsparm

-[Comp2]Z_DistNrtownkm_2012 + [Comp2]Z_DIstDstrctHQkm_2012 = 0

- [Comp2]Z_DistNrtownkm_2012 + [Comp2]Z_VillpuccaRddist_2012 = 0

- [Comp2]Z_DistNrtownkm_2012 + [Comp2]Z_Vrailstn_2012 = 0

- [Comp2]Z_DistNrtownkm_2012 + [Comp2]Z_Vbusstp_vill2012 = 0

Table 6.f: Pairwise correlations

Variables	Z_DistNrtownkm_2012	Z_DIstDstrctHQkm_2012	Z_VillpuccaRddist_2012 Z_	Vrailstn_2012	Z_Vbusstp_vill2012
Z_DistNrtownkm_2012	1				
Z_DIstDstrctHQkm_2012	0.268*	1			
Z_VillpuccaRddist_2012 Z_	0.128*	0.095*	1		
Vrailstn_2012	0.192*	0.254*	0.208*	1	
Z_Vbusstp_vill2012	-0.048*	-0.022*	0.159*	-0.025*	1

*** *p<0.01*, ** *p<0.05*, * *p<0.1*

Table 6.g: Scoring coefficients: sum of squares(column-loading) = 1

Variable	Comp1	Comp2
Z_DistNrtownkm_2012	0.51	-0.219
Z_DIstDstrctHQkm_2012	0.535	-0.213
Z_VillpuccaRddist_2012 Z_	0.399	0.545

Vrailstn_2012	0.542	-0.019
Z_Vbusstp_vill2012	0.024	0.78

Table 6.h:Matrix of correlations

Variables	-1	-2
(1) V6_2012	1	
(2) V7_2012	0	1

Table 6.i:Rotation: orthogonal varimax (Kaiser off) Rho = 0.5430

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.559	0.403	0.312	0.312
Comp2	1.156	.	0.231	0.543

Rotated components

Variable	Comp1	Comp2	Unexplained
Z_DistNrtownkm_2012	0.547	-0.095	0.534
Z_DIstDstrctHQkm_2012	0.57	-0.085	0.495
Z_VillpuccaRddist_2012	0.263	0.622	0.411
Z_ Vrailstn_2012	0.532	0.106	0.534
Z_Vbusstp_vill2012	-0.157	0.765	0.31

Component rotation matrix

	Comp1	Comp2
Comp1	0.973	0.23
Comp2	-0.23	0.973

Table 6.j: Anti-image covariance coefficients --- partialing out all other variables

Variables	Z_DistNrtownkm_2012	Z_DIstDstrctHQkm_2012	Z_VillpuccaRddist_2012	Z_ Vrailstn_2012	Z_Vbusstp_vill2012
Z_DistNrtownkm_2012	0.9024				
Z_DIstDstrctHQkm_2012	-0.203	0.8849			

Z_VillpuccaRddist_2012 Z_	-0.0841	-0.0233	0.9195		
Vrailstn_2012	-0.1004	-0.1823	-0.1666	0.8875	
Z_Vbusstp_vill2012	0.0533	0.0092	-0.1637	0.0429	0.9673

Table 6.k: Principal component loadings: component normalization: sum of squares(column) = 1

Comp1	Comp2
0.51	-0.219
0.535	-0.213
0.399	0.545
0.542	-0.019
0.024	0.78

Table 6.l: Residual covariance matrix

Variables	Z_DistNrtownkm_2012	Z_DIstDstrctHQkm_2012	Z_VillpuccaRddist_2012 Z_	Vrailstn_2012	Z_Vbusstp_vill2012
Z_DistNrtownkm_2012	0.5342599				
Z_DIstDstrctHQkm_2012	-0.2167627	0.4952603			
Z_VillpuccaRddist_2012 Z_	-0.0592487	-0.1108033	0.4111429		
Vrailstn_2012	-0.2506374	-0.2096352	-0.1227931	0.534294	
Z_Vbusstp_vill2012	0.1256743	0.1471125	-0.3371036	-0.0288479	0.310251

Table 6.m: Squared multiple correlations of variables with all other variables

Variables	SMC
Z_DistNrtownkm_2012	0.098
Z_DIstDstrctHQkm_2012	0.115

Z_VillpuccaRddist_2012	0.081
Z_ Vrailstn_2012	0.113
Z_Vbusstp_vill2012	0.033

Table 5.n:Estimation sample PCA Number of obs = 99,028

Variable	Mean	Std.dev	Min	Max
Z_DistNrtownkm_2012	-0.0002061	1.000131	-2.19476	2.172052
Z_DIstDstrctHQkm_2012	0.0001752	0.99998	-2.936302	2.011132
Z_VillpuccaRddist_2012	0.0001857	0.9998069	-0.2212251	21.238
Z_ Vrailstn_2012	-4.54E-06	1.000012	-0.8319182	10.72009
Z_Vbusstp_vill2012	-0.000105	1.000291	-2.050214	1.154914

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Table 7.a: Initial extraction of Principal components/covariance

Principal components/covariance : Number of obs = 99,028

Number of comp. = 7 Trace = 7.0001

Rotation: (unrotated = principal) Rho = 1.0000

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	1.711	0.121	0.244	0.244
Comp2	1.591	0.556	0.227	0.472
Comp3	1.035	0.156	0.148	0.62
Comp4	0.878	0.133	0.126	0.745
Comp5	0.745	0.102	0.106	0.851
Comp6	0.643	0.246	0.092	0.943
Comp7	0.397	.	0.057	1

Table 7.b: Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Comp7	Unexplained
Z_VILhealthsubcentreDistnce_2012	0.304	-0.132	0.724	-0.021	0.601	0.051	0.041	0
Z_Vprimhlthcntrdist_2012	0.412	-0.117	0.275	0.664	-0.532	-0.13	-0.002	0
Z_Vcommhlthcntrdist_2012	0.447	-0.183	0.095	-0.615	-0.437	0.433	-0.034	0
Z_Vdisthosptdist_2012	0.51	-0.16	-0.314	-0.246	0.139	-0.732	0.009	0
Z_Vhlthwrkrdist_2012	0.234	0.666	-0.006	-0.031	-0.017	0.035	0.706	0
Z_vmltiprpsehlthwrkrdist_2012	0.238	0.665	0.023	-0.005	0.044	0.013	-0.706	0
z_GovtMatdist_2012	0.408	-0.154	-0.54	0.345	0.379	0.506	0.005	0

Table 7.c: Principal components (eigenvectors) (blanks are abs(loading)<.4)

Variable	Comp1	Comp2	Comp3	Unexplained
Z_VILhealthsubcentreDistnce_2012			0.7244	0.2715
Z_Vprimhlthcntrdist_2012	0.4123			0.6091
Z_Vcommhlthcntrdist_2012	0.447			0.5953
Z_Vdisthosptdist_2012	0.5099			0.4122
Z_Vhlthwrkrdist_2012		0.6665		0.1996
Z_vmltiprpsehlthwrkrdist_2012		0.6649		0.1994

z_GovtMatdist_2012	0.4078		-0.5396	0.3763		

Table 7.d:Principal components/covariance	Number of obs = 99,028					
	SEs assume multivariate normality		SE(Rho) = 0.0008			
Eigenvalues	Coefficient	Std.err.	z	P>z	[95% conf. interval]	
Comp1	1.711	0.008	222.72	0	1.696	1.727
Comp2	1.591	0.007	222.75	0	1.577	1.605
Comp3	1.035	0.005	222.58	0	1.025	1.044
Comp1						
Z_VILhealthsubcentreDistnce_2012	0.304	0.008	39.91	0	0.289	0.319
Z_Vprimhlthcntrdist_2012	0.412	0.006	63.48	0	0.4	0.425
Z_Vcommhlthcntrdist_2012	0.447	0.009	51.25	0	0.43	0.464
Z_Vdisthosptdist_2012	0.51	0.008	66.54	0	0.495	0.525
Z_Vhlthwrkrdist_2012	0.234	0.029	8.09	0	0.177	0.291
Z_vmltiprpsehlthwrkrdist_2012	0.238	0.029	8.25	0	0.181	0.295
z_GovtMatdist_2012	0.408	0.008	51.3	0	0.392	0.423
Comp2						
Z_VILhealthsubcentreDistnce_2012	-0.132	0.014	-9.12	0	-0.16	-0.103
Z_Vprimhlthcntrdist_2012	-0.117	0.018	-6.31	0	-0.153	-0.08
Z_Vcommhlthcntrdist_2012	-0.183	0.02	-9.25	0	-0.222	-0.144
Z_Vdisthosptdist_2012	-0.16	0.022	-7.14	0	-0.204	-0.116
Z_Vhlthwrkrdist_2012	0.666	0.01	64.94	0	0.646	0.687
Z_vmltiprpsehlthwrkrdist_2012	0.665	0.01	63.75	0	0.644	0.685

z_GovtMatdist_2012	-0.154	0.018	-8.41	0	-0.19	-0.118
Comp3						
Z_VILhealthsubcentreDistnce_2012	0.724	0.006	116.99	0	0.712	0.737
Z_Vprimhlthcntrdist_2012	0.275	0.014	19.42	0	0.247	0.303
Z_Vcommhlthcntrdist_2012	0.095	0.013	7.16	0	0.069	0.122
Z_Vdisthosptdist_2012	-0.314	0.008	-40.73	0	-0.329	-0.299
Z_Vhlthwrkrdist_2012	-0.006	0.006	-1.07	0.287	-0.017	0.005
Z_vmltiprpsehlthwrkrdist_2012	0.023	0.006	4.1	0	0.012	0.034
z_GovtMatdist_2012	-0.54	0.009	-61.43	0	-0.557	-0.522

LR test for independence: chi2(21) = 74683.07 Prob > chi2 = 0.0000

LR test for sphericity: chi2(27) = 74683.53 Prob > chi2 = 0.0000

Explained variance by components

Components	Eigenvalue	Proportion	SE_Prop	Cumulative	SE_Cum	Bias
Comp1	1.711	0.244	0.001	0.244	0.001	0
Comp2	1.591	0.227	0.001	0.472	0.001	0
Comp3	1.035	0.148	0.001	0.62	0.001	0
Comp4	0.878	0.126	0.001	0.745	0.001	0
Comp5	0.745	0.106	0.001	0.851	0.001	0
Comp6	0.643	0.092	0	0.943	0	0
Comp7	0.397	0.057	0	1	0	0

chi2(6) =28136.04

Prob > chi2 = 0.0000

Table 7.e: Testparm

(1) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]Z_Vprimhlthcntrdist_2012 = 0
(2) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]Z_Vcommhlthcntrdist_2012 = 0
(3) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]Z_Vdisthosptdist_2012 = 0
(4) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]Z_Vhlthwrkrdist_2012 = 0
(5) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]Z_vmltiprpsehlthwrkrdist_2012 = 0

(6) - [Comp2]Z_VILhealthsubcentreDistnce_2012 + [Comp2]z_GovtMatdist_2012 = 0

Table 7.f: Pairwise correlations

Variables	Z_VILhealthsubcentreDistnce_2012	Z_Vprimhlthcntrdist_2012	Z_Vcommhlthcntrdist_2012	Z_Vdisthosptdist_2012	Z_Vhlthwrkrdist_2012	Z_vmltiprpsehlthwrkrdist_2012	z_GovtMatdist_2012
Z_VILhealthsubcentreDistnce_2012	1						
Z_Vprimhlthcntrdist_2012	0.191*	1					
Z_Vcommhlthcntrdist_2012	0.172*	0.155*	1				
Z_Vdisthosptdist_2012	0.106*	0.163*	0.289*	1			
Z_Vhlthwrkrdist_2012	-0.017*	0.025*	0.007*	0.027*	1		
Z_vmltiprpsehlthwrkrdist_2012	0.011*	0.030*	-0.008*	0.028*	0.602*	1	
z_GovtMatdist_2012	0.020*	0.172*	0.135*	0.297*	0.002	0.004	1

*** p<0.01, ** p<0.05, * p<0.1

Table 7.g: Scoring coefficients: sum of squares(column-loading) = 1

Variable	Comp1	Comp2	Comp3
Z_VILhealthsubcentreDistnce_2012	0.304	-0.132	0.724
Z_Vprimhlthcntrdist_2012	0.412	-0.117	0.275
Z_Vcommhlthcntrdist_2012	0.447	-0.183	0.095
Z_Vdisthosptdist_2012	0.51	-0.16	-0.314
Z_Vhlthwrkrdist_2012	0.234	0.666	-0.006
Z_vmltiprpsehlthwrkrdist_2012	0.238	0.665	0.023

z_GovtMatdist_2012	0.408	-0.154	-0.54

Table 7.h: Matrix of correlations

Variables	V8_2012	V9_2012	V10_2012
V8_2012	1		
V9_2012	0	1	
V10_2012	0	0	1

Table 7.i: Rotation: orthogonal varimax (Kaiser off) Rho = 0.6195

Component	Variance	Difference	Proportion	Cumulative
Comp1	1.604	0.113	0.229	0.229
Comp2	1.491	0.25	0.213	0.442
Comp3	1.241	.	0.177	0.62

Rotated components

Variable	Comp1	Comp2	Comp3	Unexplained
Z_VILhealthsubcentreDistnce_2012	-0.01	-0.131	0.786	0.272
Z_Vprimhlthcntrdist_2012	0.034	0.201	0.466	0.609
Z_Vcommhlthcntrdist_2012	-0.02	0.347	0.349	0.595
Z_Vdisthosptdist_2012	0.017	0.619	0.038	0.412
Z_Vhlthwrkrdist_2012	0.706	0.005	-0.016	0.2
Z_vmltiprpsehlthwrkrdist_2012	0.706	-0.008	0.01	0.199
z_GovtMatdist_2012	-0.015	0.663	-0.204	0.376

Component rotation matrix

	Comp1	Comp2	Comp3
Comp1	0.338	0.783	0.522
Comp2	0.941	-0.273	-0.201
Comp3	0.015	-0.559	0.829

Table 7.jAnti-image covariance coefficients --- partialing out all other variables

Variables	Z_VILhealthsubcentreDistnce_2012	Z_Vprimhlthcntrdist_2012	Z_Vcommhlthcntrdist_2012	Z_Vdisthosptdist_2012	Z_Vhlthwrkrdist_2012	Z_vmltiprpsehlthwrkrdist_2012	z_GovtMatdist_2012
Z_VILhealthsubcentreDistnce_2012	0.9387						
Z_Vprimhlthcntrdist_2012	-0.1547	0.9185					
Z_Vcommhlthcntrdist_2012	-0.1212	-0.0761	0.8868				
Z_Vdisthosptdist_2012	-0.0438	-0.0669	-0.209	0.8393			
Z_Vhlthwrkrdist_2012	0.0265	-0.0091	-0.0118	-0.0081	0.6365		
Z_vmltiprpsehlthwrkrdist_2012	-0.0194	-0.0115	0.0193	-0.0121	-0.3831	0.6365	
z_GovtMatdist_2012	0.0382	-0.119	-0.0391	-0.225	0.0056	0.001	0.8929

Table 7.k:Principal component loadings : component normalization: sum of squares(column) = 1

Variables	Comp1	Comp2	Comp3
Z_VILhealthsubcentreDistnce_2012	0.304	0.1315	0.7244
Z_Vprimhlthcntrdist_2012	0.4123	0.1165	0.2749
Z_Vcommhlthcntrdist_2012	0.447	0.1831	0.09542
Z_Vdisthosptdist_2012	0.5099	0.1599	-0.3142
Z_Vhlthwrkrdist_2012	0.2342	0.6665	-0.005983
Z_vmltiprpsehlthwrkrdist_2012	0.238	0.6649	0.02294
z_GovtMatdist_2012	0.4078	0.1543	-0.5396

Table 7.l: Residual covariance matrix

Variable	Z_VILhealthsubcentreDistnce_2012	Z_Vprimhlthcntrdist_2012	Z_Vcommhlthcntrdist_2012	Z_Vdisthosptdist_2012	Z_Vhlthwrkrdist_2012	Z_vmltiprpsehlthwrkrdist_2012	z_GovtMatdist_2012
Z_VILhealthsubcentreDistnce_2012	0.2715483						
Z_Vprimhlthcntrdist_2012	-0.2543114	0.6091457					
Z_Vcommhlthcntrdist_2012	-0.1707848	-0.2215203	0.5952813				
Z_Vdisthosptdist_2012	0.0428219	-0.1375659	-0.1168062	0.4121644			
Z_Vhlthwrkrdist_2012	0.0053708	-0.014661	0.0227007	-0.0093902	0.1996402		
Z_vmltiprpsehlthwrkrdist_2012	0.0088267	-0.020828	0.0012648	-0.0026558	-0.1979645	0.1994241	
z_GovtMatdist_2012	0.1801607	0.0091333	-0.1690388	-0.2732523	-0.0014064	0.0136815	0.37632

Table 7.m:Squaredmultiplecorrelations of variables with all other variables

Variable	smc
Z_VILhealthsubcentreDistnce_2012	0.0613
Z_Vprimhlthcntrdist_2012	0.0815
Z_Vcommhlthcntrdist_2012	0.1132
Z_Vdisthosptdist_2012	0.1607
Z_Vhlthwrkrdist_2012	0.3635
Z_vmltiprpsehlthwrkrdist_2012	0.3635
z_GovtMatdist_2012	0.1071

Table 7.n : Estimation sample pca Number of obs = 99028

Variable	Mean	Std. dev.	Min	Max

Z_VILhealthsubcentreDistnce_2012	-0.0000151	1.000075	-0.5848787	17.34869
Z_Vprimhlthcntrdist_2012	-0.0000521	0.9999276	-1.042105	13.78369
Z_Vcommhlthcntrdist_2012	0.0000138	1.000029	-1.172111	8.281759
Z_Vdisthosptdist_2012	-0.0000146	0.9999983	-1.41265	8.219714
Z_Vhlthwrkrdist_2012	3.01E-06	1.000004	-0.1509128	17.62473
Z_vmltiprpsehlthwrkrdist_2012	8.29E-06	1.000008	-0.1796154	19.20522
z_GovtMatdist_2012	0.0000105	1.000008	-0.999056	5.956429