ANALYSIS OF GROWTH AMONG THE INDIAN STATES IN THE POST LIBERALIZATION PERIOD

A Thesis submitted to the Goa University for the

Award of the Degree of

DOCTOR OF PHILOSOPHY

IN

ECONOMICS

By

APARNA P. LOLAYEKAR

GOA UNIVERSITY

Taleigao Plateau, Goa

2017

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Research Guide

Prof. PRANAB MUKHOPADHYAY

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CERTIFICATE

This is to certify that Ms. Aparna P. Lolayekar has worked on the thesis entitled "Analysis of Growth among Indian States in the Post Liberalization Period" under my supervision and guidance. This thesis being submitted to Goa University, Taleigao Plateau, Goa, for award of the degree of Doctor of Philosophy in Economics, is a record of the original work carried out by the candidate herself and has not been submitted elsewhere for the award of any degree or diploma of this or any other University.

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DECLARATION

I declare that the present thesis entitled "Analysis of Growth among Indian States in the Post Liberalization Period" is a consolidation of original work which has been carried out by me under the guidance of Prof Pranab Mukhopadhyay, Department of Economics, Goa University, and that the same has not been submitted to any university or institute for the award of any degree, diploma or other such title.

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Aparna P. Lolayekar

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

Chapter I

Introduction

1.1 An Overview of Economic Growth and Regional Convergence

Economic growth has been one of the major objectives of majority of the nations in the world. However there are economies which are very rich and some which are extremely poor. Not all of these economies were in a position to attain the sustained growth because in case of most of the economies, technological improvements and capital investments were overtaken by the growth of population. In fact diverse growth experience has been seen in the world, where, only certain countries in the Western Europe and North America could attain the sustained growth rate in the nineteenth and the twentieth century. In contrast, for the third world nations, growth began only in the post World War II period with the end of colonialism. Of exceptional interest has been the rise of the East Asian economies between the period 1965-1990 (Ray, 1998).

The key economic issue is whether these rich nations will remain rich and the poor remain poor for various decades or whether the initially laggard ones will ever grow faster and catch up with the rich ones in per capita terms. This also points towards an important question whether the inequality among the nations will continue to grow or ever decline in the future. This gives rise to the notion of convergence in growth economics. Growth theory suggests that if regions have unequal incomes to start with then they will experience unequal growth rates in the short run but will converge towards a common steady state rate of growth in the long run. Solow, (1956) gave a basic framework which explains this negative relation between the initial income per capita and the growth rates. The convergence hypothesis is based on standard neo classical production function, that focuses on the diminishing returns to reproducible capital. Poor countries or regions with low ratios of capital to labor have a higher marginal product of capital. This attracts greater investment and therefore grow at a higher rate. The economy experiences growth in the capital stock and level of output along the transition path to the steady state level. The equilibrium steady state income level is in turn determined by the rate of technological progress. In this model technology is exogenously given. Convergence suggests that poorer countries will grow faster than the rich ones. The process of catching up envisages two related concepts of convergence: The β convergence, states that poor regions tend to grow at a faster rate than the richer regions, thus catching up with the rich ones. The σ convergence focuses on decrease in cross regional dispersion (inequalities). The neoclassical economists while predicting β convergence focused on a strong notion of convergence called "absolute" or "unconditional" convergence. The parameters like the saving rate, technological progress, depreciation and the rate of growth of population is same across the regions and countries. In reality, it is unlikely that these parameters will be same across countries. This led to the notion of conditional convergence, where each country need not converge to one common steady state but towards different steady state levels determined by the parameters of each country.

Though these issues were discussed in the earlier decades, only in 1980s the convergence debate caught the attention of macroeconomists for two reasons: firstly to judge whether the modern theories of growth are valid as the existence of convergence across the economies had to be tested and secondly because there was an availability of data sets for international comparisons of GDP levels for many countries from the mid-1980s. With these data sets it was possible to see the evolution and compare the GDP levels across large number of economies over time (Sala-i-Martin, 1996). Further, the emergence of new econometric methods and the development of the new growth theories, led to the investigation of the pattern of convergence in different national and regional samples.

The other popular method to test for convergence is based on dispersion (variance of incomes). Economies are said to converge (in terms of "σ") if the dispersion in per capita levels of GDP decreases over time. The σ-convergence hypothesis assumes that there is a one-time shock to the cross-section of economies in the initial period. Thereafter the economies move towards their steady state following a smooth and monotonic path.

Quah (1993a, 1993b) argued that regression based methods do not capture the transition in income dynamics and the presence of convergence clubs (Durlauf, 1996). Quah (1997) proposed the kernel based approach that could separate the trends in the growth as well as distribution. This technique was used to analyze the long-run behavior in the inter and intra country context to find degree of polarization among the regions.

Besides, apart from these traditional ways of analyzing inequality among regions, new findings suggest that geographic space may also acquire an important role. Because of the similarities among the neighboring regions, we cannot consider the regional data as independently generated.Thus location and spatial interaction has recently gained an important place in applied and theoretical econometrics.

Studies assessing conditional convergence adopt a mean regression estimation method which implies that the impact of a change in a policy variable say, human capital, on a rich country's GDP growth rate should be the same as the impact on a poor country's GDP growth rate. However, this necessarily need not be the case. The interaction between policy variables and growth rates could be more complex than what is known by an average correlation. Thus a need was felt to have a technique that could address the issue of income convergence by providing a more complete picture of the association between policy variables and growth performance (Durlauf, 1996). Quantile regression methods were employed to address the determinants of economic growth across different income groups (Cuaresma, et al, 2011). This estimation procedure yields quantile coefficients; one for each sample quantile, thus on a conditional distribution of growth rates, each slope coefficient represents a different response of the GDP growth rate.

Beyond the data on per capita income, socio indicators like quality of life and quality of opportunity are very important(see Fischer, 2003). There are numerous economic and social indicators that have been used to measure different aspects of socio-economic progress, the improvement in the performance of these social indicators would provide an encouraging picture and imply convergence in economic as well as social indicators.

1.2 Economic Growth and Convergence in India

India accounts for 17.5 percent of the world population (Census of India, 2011). Along with China, India accounts for 36.9 percent of the world population. Because of its large demographic size and its changes in income distribution, India's growth performance has been important in shaping the evolution of world distribution of income (Bourguignon & Morrisson, 2002).The theory of growth anticipates that in the long run there will be an equalization of incomes with movement of factors of production and technology. Many had expected that the market forces in the post-liberalization period would free the economy from the shackles of licensing to promote growth and in turn reduce regional inequality and poverty in the Indian economy.

Economic planning in India has focused on reducing inequalities – both inter-and intra-regionally. A system of Five Year plans has articulated the Indian government's strategies in which two organizations have played a crucial role – the Planning Commission (now in a new avatar called the NITI Aayog) and the Finance Commission. They have different mandates – the Finance Commission has a Constitutional mandate to evolve a mechanism for raising and sharing of tax revenues between the Centre and States. The Planning Commission was tasked with estimating the funds requirement for implementing programmes and distributing Plan funds from the Centre to the states in a manner that would best serve the targets set out in each plan.

India's growth performance, both at the national level as well as its spatial distribution (across the states), has been the subject of considerable research interest (Basu & Maertens, 2012; Ghate, 2012). From a closed economic set-up, India moved to a liberalized and a globalised economy from the mid-1980s but more rapidly after the early 1990s economic crisis. As has been the worldwide experience (see Barro, 1991), not all regions and states in India have grown at the same pace nor has the decline in poverty rates been uniform. The states have experienced different pace of economic growth, with some states showing fast progress and others languishing behind, although the national growth has been remarkable for the past two decade. For example, certain regions like Goa, Punjab and Maharashtra, Delhi havecontinued to be at the top of the income distribution and on the other hand regions like Bihar, Rajasthan, Orissa, Madhya Pradesh, the per capita income has still been at the bottom of the distribution. The continuation of growth stagnation in most of the *BIMARU*[1] states poses a challenge to received theories of growth convergence and raises developmental concerns. The increased play of market forces in the Indian economy has not been able to overcome the problem of low initial incomes of some states and non-income inequalities. Under such circumstances economic reforms can by-pass the poorer states. Thus conditions of pro poor growth can reduce the disparities in access to human and physical capital that create inequalities (Ravallion, 2001).

The progress made in terms of the Human Development Index (HDI) is often considered as a benchmark of a nation's development. HDI is an index of relative performance, as such improvement in all the regions would imply convergence in social and economic progress across the regions (Fischer, 2003). The high growth story of India is conflicting with the poor performance on the HDI front. This raises the question whether the benefits are reaching all the sections of the society or not. India is in the category of countries with 'Medium Human Development', with a global HDI value of 0.586, it is 187th among countries and territories, much less than the world average of 0.702 (UNDP, 2014).

India has fallen behind in social indicators when compared to many of its South Asian counterparts. With life expectancy at birth at 66.4 years in 2013, India was much lower than Bangladesh, Bhutan, Nepal and Pakistan (UNDP, 2014). Its infant mortality rate in 2012 was 44 per 1000 live births, which is even higher than some

[1]BIMARU states is an abbreviation for Bihar, Madhya Pradesh, Rajasthan and Uttar Pradesh given by demographer Ashish Bose in 1980, because these states lagged behind other states in terms of economic conditions and were responsible in dragging down the growth rate of India's GDP.

poorer countries in the world. Thus India's health and social indicators have been lagging behind despite the increasing growth rates (Suryanarayana,et al, 2011).

In human development terms, at the interstate level there is a large amount of diversity. Some states in India, via: Kerala, Himachal Pradesh, Tamil Nadu have performed better than the other South Asian countries. Many of the North Indian states like Bihar, Madhya Pradesh, Odisha, Uttar Pradesh fair badly in terms of the development indicators like poverty, health and education and are in the same category as some of the poorer African nations (Dreze & Sen, 2013). Women experience enormous kinds of disadvantages and discrimination in health, education and employment (UNDP, 2014). Though India has seen fast growth its reach among different states and people has been limited. The public revenue generated from the economic growth has not been used to increase the physical and social infrastructure in all the states in a well- planned manner. In case of essential social services right from medical facilities and education to safe drinking water, immunisation and sanitation, there have been tremendous differences among the states in India.

Again the Indian economy is socially diverse with different religions, languages, castes and cultures which have added to inter - state economic differentiation. Up to mid-1990s, in the national data sets, population in India was divided into three broad categories; Scheduled Castes (SCs), Schedule Tribes (STs) and the 'Others' (which meant everyone else). After mid 1990s this classification further divided 'Others' into Other Backward Classes and the remaining ‘Others’ or the General (Upper) caste. The Constitution refers to this additional category of disadvantaged citizens as Other Backward Classes (a large and heterogeneous category which contains castes very close to the SCs in social and economic backwardness). The SCs STs and the OBCs constitutes the lower caste and are considered to be inferior than the upper caste (Deshpande, 2011).

Because of the caste based inequalities, Affirmative Action Programme was been initiated by the Government of India. As a result all states in India have quotas for the SCs, STs and the OBCs with respect to seats in legislatures, public sector jobs and even educational institutions.

It was expected that these social differences would diminish with economic development. However, over the years, though there has been some amount of convergence in literacy and primary education, among the backward categories and the General classes, continued divergence was seen in all educational categories after the middle school level, regular wage salaried jobs and in white-collar jobs except for the youngest group. Again the documentation of the change in the living conditions of the SC, ST is seen in some studies, but for the OBC's due to the lack of data, the evidence is unclear. Certain studies (see Deshpande & Ramachandran, 2014; Deshpande, 2013) have seen that affirmative action increased the share of OBCs with secure public sector jobs but OBCs have been unable to make use of the quotas in higher education. Before 1990s there were cases of indifference on the part of the appointing authorities, insufficient publication of vacancies which made many of the quotas to remain unfulfilled. Iyer, et al, (2013) found that though the OBCs have made progress in entrepreneurship, SCs and STs have remained underrepresented in the entrepreneurial sphere.

The constitutional amendments (73^{rd} and 74^{th}) of 1990s, made the lower castes (SCs, STs and OBCs) an important force in Indian politics at the local, state and national levels,. Whether this change in political arena will be accompanied by the subsequent change in traditional economic hierarchies (General caste at the higher economic hierarchy) needs a closer look. Thus by focusing on these social diversity, interstate differences can be known in a better form. Besides, a common approach that has now been adopted is to highlight the role of political factors and its influence on the economic growth.

Issues of economic growth in India has to be seen in the larger context of reduction in poverty and inequality, as there are instances of rise in inequality, even though the incomes have gone up, both at the top and the bottom levels (see Cherodian & Thirlwall, 2013; Radhakrishna & Panda, 2006; Fischer, 2003). The growing inequalities do not let the benefits of growth to reach the poor; thus all regions and states in India have grown at the different pace and the reduction in the poverty has also not been the same all over. Thus, along with maintaining a high rate of economic growth, ensuring equity and sustainability is a must.

1.3 Statement of the Problem

From a closed economic set-up, India moved towards being a liberalized and a globalized economy with centralized planning. Many policy reforms were followed and this opened up the economy and integrated it with the international markets. Although Indian states share common political institutions and national economic policies, and there are no trade barriers to technology transfers, there has been dispersion in per capita incomes and social development. It is a matter of considerable research interest to know the manner in which states have behaved vis-a-vis one another over time. Even though India has much to learn from its international counterparts, more importantly it can learn from the diverse nature of growth within the economy itself. This study thus seeks to analyze the growth performance across states in India for 1981-2013, a period that marked economic liberalization in 1991 and examine the convergence/divergence hypothesis. In order to explore and assess how rapid economic growth in India has been and how this has shaped regional income inequalities, the performance of all the regions in India in the post reform period is compared with the performance in the previous decade.

Development Indicators:

Income is only one dimension of economic wellbeing, In analysing the convergence hypothesis, along with income other dimensions also have to be taken into consideration. To measure inequality in non-income dimensions there are two approaches; one views inequality as variation of an outcome indicator across individuals while the other views inequality as disparities across socioeconomic groups (Chakraborty, 2002). Thus along with the income convergence, this study tries to analyse if there exists convergence in development indicators also.

In regional growth studies, factors like initial income, human capital, investments, infrastructure and institutions, population are said to influence economic growth. All these factors like trade between regions, movement of technology and knowledge, regional spillovers have made these regions geographically dependent. Thus, while analyzing inequality among regions, geographic space does acquire an important role. Although a number of empirical studies have emerged in other countries, evidence on the role of spatial interaction in India has been researched less. This study uses the exploratory and the confirmatory spatial data analysis to analyse patterns of spatial association for different indicators of economic performance in India.

1.4 Objectives of the Study

The following are the objectives of the study:

1) To compare the trends in growth rates among Indian states in the pre and post liberalisation period.

2) To examine the factors that influence growth among Indian states including the social characteristics and development policy.

1.5 Research Questions

After reviewing the literature on convergence in the Indian context, a number of issues remain to be adequately addressed. This study proposes to address the following research questions:

(i) Is there evidence of convergence in per capita incomes over the last thirty years?

(ii) Is there validity in the claim that the growth process in India exhibits twin peak (bimodal) behavior?

(iii) Why are different states showing differences in inequality and poverty reduction?

(iv) How do social heterogeneity influence growth outcomes?

(v) Does public policy (government expenditure in social sectors) foster development equitably across its states?

(vi) Are the neighbourhood spillover effects important in the Indian context?

1.6 Data sources and Methodology

In this section we discuss the data sources and the methodology.

1.6.1 Data sources

There are multiple sources of National Income data in India including the CSO and the RBI. In our study we have used the series of Net State Domestic Product (NSDP) per capita at current prices for the period of 1981 to 2012 provided by Economic and Political Weekly Research Foundation (EPWRF). For our study we have made the income data comparable not only across states (cross section) but also over time.We controlled for price variability by generating a NSDP constant price series. In order to do this, we divided each state's NSDP at current prices by the NDP deflator for that year. The NDP deflator was generated by taking the ratio of NDP at current prices to NDP at constant prices (Dornbusch, et al, 2002). This ratio is in the nature of a price inflation index. By dividing the NSDP (at current prices) of each state by the corresponding value in this index we derived the NSDP at constant prices (base 2004-5 prices) of each state.

In 2000 by a constitutional amendment three new states were created (Chhattisgarh bifurcated from Madhya Pradesh, Jharkhand bifurcated from Bihar and Uttarakhand – initially called Uttaranchal, bifurcated from Uttar Pradesh). For the period 1981-82 to 2000-2001, 28 states and union territories are considered and from 2001-2, 31 states are considered.

For the club convergence hypothesis in particular, the per capita NSDP at constant prices of each state has been normalised by using the sum of NSDP per capita of all the states in our sample, for the corresponding years. With this normalisation the distribution dynamics controls for the aggregate growth effect of the states and reflects only the state specific (relative) distribution effects.

Apart from the data on per capita income, social indicators like quality of life and quality of opportunity is analyzed in different states of India. Adult literacy rate (7+ literacy rate) is considered as variable good indicator for quality of opportunity and Infant Mortality Rate (IMR) is considered as a good indicator of quality of life. Besides these variables, the Gender Ratio, the percentage of Urban Population to the total population, Expenditure on Health, Expenditure on Education, and the Political Variable is used.

The data on literacy rate, Gender ratio, percentage of urban population is obtained from Census of India, various years. The data on IMR is obtained from EPWRF and Compendium of India's Fertility and Mortality Indicators 1971-2007 based on SRS Office of the Registrar General & Census Commissioner India, Ministry of Home Affairs. New Delhi, India. Similarly the data on Expenditure on Education and Health is obtained from the EPWRF. For the Political Variable, the data from the Election Commission of India is employed.

The data on caste for the years 1981- 95 is from the Census of India, while from 1999-00 onwards, the data from the 55th (1999–2000), 61st (2004–2005), 66th (2009–2010) Round of NSSO is used. As far as the poverty rates are concerned, the Planning Commission data from NSSO Rounds [38th (1983), 43rd (1987–1988), 50th (1993–1994), 55th (1999–2000), 61st (2004–2005), 66th (2009–2010) and 68th (2011-12)] is used.

1.6.2 Methodology

The analysis in this thesis uses a number of methodological approaches. The convergence hypothesis is tested using the regression techniques with the level of initial income as the pivotal explanatory variable. The growth rate of PCI is also regressed on a broad set of explanatory variables (including the initial level of PCNSDP. We relied on panel data techniques. We split the time period of analysis into three time units. Each unit was a ten year sub-period, namely 1981-90, 1991-00 and 2001-10. We also tried with six time units where each five year sub periods were 1981-85, 1986-90, 1991-95, 1996-00, 2001-05 and 2005-10. Various econometric methods offering improvements over the classical convergence model is used in this study. The reader will find the use of quantile regression estimation, the bimodality and the multimodality tests that arise in the distribution, the instrumental variable approach and the spatial econometric techniques. .

1.7 Structure of the Thesis

The present thesis consists of ten chapters, and has been organized in the following manner. Chapter one is the Introduction. It provides the background and the design of the thesis.

In chapter two, the theories underlying economic growth and convergence are discussed along with different notions of convergence. it has a detailed discussion on the application of the classical convergence model as well as the problems and limitations of it along with new improvements.

Chapter three is devoted to a discussion of data and methodology. It discusses problems of heterogeneity, non-linearity, spatial dependence that are encountered in the in the convergence models. In the last section of this chapter the sources of the data and the different software used for analysing the techniques have been presented.

In chapter four, the phenomenon of convergence among the states of India is discussed in details by using the cross section, pooled and the panel data estimation techniques.

Chapter five focuses on the application of the quantile regression approach. This is an improvement over the OLS technique that relies on mean regression estimation. OLS estimates fail to capture relations away from the mean.

Chapter six, makes use of two and three dimensional kernel density plots, transition matrices, and tests for multimodality to capture the transition in income dynamics.

Chapter seven is devoted to spatial econometric methods. We advance the standard OLS regression approach to convergence by correcting for the problem of spatial dependence.

Chapter eight moves from the income dimension which is focused in the previous chapter to discussion and use of the various other dimensions of well-being. As income is only one dimension of economic well-being, convergence in terms of social indicators like IMR, literacy rates are discussed in this chapter.

In chapter nine, we improve on OLS by using the instrumental variable approach to correct for endogeneity problem that arises in the β convergence estimation. This chapter focuses on two important issues, the link between growth, poverty and inequality and the influence of politics and social discrimination (caste system) on economic growth.

Chapter ten summarizes the major findings of the study and concludes the thesis.

Chapter II

Literature Review

2.1 Introduction

Analyzing economic growth and convergence has been a popular research theme among economists. Empirical research has used different growth models to investigate the process of convergence. Solow (1956) proposed one of the most popular and simple growth model using only two covariates to understand why some countries flourished while the others lagged behind. Later, Mankiw, Romer and Weil (1992) included human capital and investigated the issue of convergence. Based on these models different empirical evidences of convergence within and across the countries have been provided. (see Barro 1991; Barro et al. 1991; Barro and Sala-i-Martin 1992; Barro 1989). Certain pitfalls were identified in this model that led to the development of new theories and econometric methods. These developments ranges from the usage of non-parametric specification to spatial econometrics as being more precise explanations of economic growth. In this chapter, we begin with the discussion of the neo classical growth model followed by the empirical evidences of convergence or divergence across different countries as well as regions within same countries. It is followed by a discussion of more methods and empirical evidence in the growth literature.

2.2 Neoclassical Growth Model

Solow(1956) in his seminal paper on economic growth described how savings, population growth and technological progress affect the long run economic growth. With this model we can understand why the living standards differ among the countries and how to use economic policies to improve the standard of living. The model assumes that there is a closed economy and the production function is a *Cobb-Douglas* constant returns to scale type:

(2.1) $$Y = F(K, L) = K^{\alpha} L^{1-\alpha} \text{ where } 0 < \alpha < 1.$$

The total output produced in an economy depends on K-accumulated stock of capital, and L- labour, with α as the share of the output paid to the capital. The output per worker is $y = \frac{Y}{L}$ and capital per worker is $k = \frac{K}{L}$.

Equation 2.1 above can be rewritten as $y = k^{\alpha}$ to show that the output per worker can be defined in terms of capital per worker. The firms will employ labour and capital till the marginal products of labour and capital is equal to their wages and rent paid respectively thus,

(2.2) $$w = (1-\alpha)\frac{Y}{L} \text{ and } r = \alpha\frac{Y}{K}$$

There are no economic profits earned as the factor payments exhaust completely the value of the output produced. Thus we have,

(2.3) $$wL + rK = Y$$

If we increase the absolute amount of capital the output will rise, but as capital per worker increases at a decreasing rate, adding more capital would not increase the output proportionately. The growth of population is exogenous and so the labour force growth rate can be assumed to grow at $\frac{\dot{L}}{L} = n$. It appears that if we increase the level of capital per worker the output would increase. Thus to understand the rate of growth of output, understanding the growth rate of capital is important.

This gives us the *capital accumulation equation*;

(2.4) $$\dot{K} = sY - dK$$

The Solow model assumes a closed economy. Further Solow assumes that this is not a demand determined system, therefore all savings are equal to investments and adds to the accumulation of capital. The annual investment in capital is thus given as $I = s.Y$Investments would increase the capital stock ($\dot{K}$). At the same time a certain fraction (d) of the capital stock will depreciate each year. Some of the new stock of capital is required to replace the worn out capital stock and this is referred to as the 'replacement investment'. The difference between the gross investment and the replacement investment gives us the net investment in an economy. By deducting the amount of depreciation dK from the gross investments sY, we get the change in the capital stock $\dot{K}$ or the growth of capital stock per worker per year. This shows how the total stock of capital evolves every year. The rate of saving also determines how the output is allocated between the consumption and investment. The equation below represents how the capital per worker is evolved over time.

(2.5) $$\dot{K} = sy - (n + d)K$$

The stock of capita per worker over time will increase with investments but rate of depreciation and growth of labour supply will reduce the rate of accumulation. The difference between the two will decide whether the capital per worker rises, falls or remains constant.

If $sy > (n + d)K$, then capital per worker is increasing, if $sy < (n + d)K$, then it is decreasing. When$sy = (n + d)K$, the capital per worker and therefore the output per worker is constant, and this is called the *steady state* by Solow. Unless the rate of savings, depreciation or the labour force growth rate change, the capital and output per worker will remain at the steady state level. After reaching steady state level there is no growth in output. As the saving rates rise, economy would converge to a higher steady state level.

Thus different countries differ in terms of their living standard is because of the differences in the rate of savings and the labour force growth rates. Based on the above theoretical framework it was predicted that if nations had low levels of capital stocks, the output - capital ratio would be high, with the per capita stocks expanding quickly. In contrast, nations with high capital stocks, the output - capital ratio would be low, and the rate of per capita stocks expansion would be low. Thus the states would converge to a common steady state irrespective of where they started in the initial period.

By incorporating the human capital in production function Mankiw et al, (1992) extended the Solow model. The steady state level of income is then determined by investment in the physical as well as the human capital. By examining the cross country Summer Hestons data (1988), Mankiw et al, (1992) found that inclusion of human capital to the Solow model improved its performance. They argued that variation in the rate of savings, education and growth rate of population across the countries are responsible for the differences in income per capita.

The endogenous growth theory originated in the work of Arrow (1962), and was further developed by Lucas (1988). They made different predictions from the Solow model about convergence. The central focus of these models is the human capital. In these models, the steady state did not exists as such, rather, the differences between developed and developing countries with regard to productivity either remained constant or even increased over time. The reason being the economies of scale that arise with the acquisition of technical knowledge. The accumulation of knowledge helped to increase productivity at the aggregate level even when individual firms were facing diminishing returns to capital. Thus, the diminishing returns to scale disappear, and the growth paths of developing economies diverge from those of developed countries. Based on the concept of endogenous growth the convergence is viewed as a technological catch-up effect(Kumar & Managi, 2012). The argument is that imitations are faster and less costly than innovations. Thus, poor countries, which lie below the world technology frontier, may make technological progress more rapidly than the more technologically advanced. These theories gave importance to international trade, movements of capital and technology across different countries which would make the low income countries grow faster.

Two main concepts of convergence are discussed in classical growth literature.

2.2.1 β -Convergence

There is β when the growth rates of an economy are inversely related to its initial level of income – so initially rich countries are expected to grow relatively slowly vis-à-vis the initially poor one. The linear regression model to test this relationship:

$$Y_t = \beta_0 + \beta_1 Y_0 \tag{2.6}$$

where Y_t = Income in time period "t", and Y_0= Income in initial time period t=0. If β_1<0 then we expect convergence in incomes over time. Equation (2.6) measures the 'unconditional or absolute convergence' . In absolute β-convergence, all the economies converge to the same steady-state. In the Solow model different steady states are predicted for the economies which differ in terms of the rate of population growth, human, physical capital, and the level of technological progress. This gives rise to another notion of convergence called the 'conditional convergence', which means countries will return to their individual steady state rather than a common steady state level.

2.2.2 σ -Convergence

The other popular method to test for convergence is based on dispersion (variance of incomes), where a group of economies are said to be converging in terms of σ. This procedure measures the dispersion around determined average. If the dispersion is decreasing, then the countries are becoming increasingly similar to each other in terms of the income per capita and there is (sigma) convergence.

(2.7) $$\sigma_{t+T} < \sigma_t$$

Where$T > 0$ $and t + T > t$

The existence of σ-convergence implies a tendency of per capita income to be equal across regions over time (Sala-i-Martin, 1996).

Where,

(2.8) $$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_\mathrm{i} - \mu)^2}$$

Herex_1, $x_{2,...}$ x_n are the observed values of the sample, μ is the mean of these observations, while the denominator N stands for the sample size.

The concepts of β and σ convergence are strongly related. However, β-convergence is a necessary but not a sufficient condition for the reduction in the disparity of per-capita income over time. If the GDP levels of the economies become more similar over time, it means that the poor economy is growing faster. Thus the existence of β convergence will tend to generate σ-convergence (Barro & Sala-i-Martin, 1992). But it is also possible that the initially poor countries grow faster than rich ones, without the decline in the cross-sectional dispersion over time.This happens if the poor economy grows faster than the rich (β-convergence) but, the growth rate of poor economy is so much larger than that of the rich that at time $t+T$, the poor economy is richer than the rich economy. As the dispersion between these two economies is not fallen, there is no σ-convergence. Thus β-convergence, though necessary, is not a sufficient condition for σ-convergence (Sala-i-Martin, 1996).

β and σ do not capture the intra-distributional dynamics of the income distribution, because of the shortcomings of these two methods. (Quah, 1993a, 1996a, 1997) introduced a new concept of convergence, where the income is normalized by dividing the income of a particular economy by the weighted average of the aggregate of all the economies (economies with larger population have higher weights)

(2.9) $$h_{i,t} = \frac{\log(y_{i.t})}{\sum_{i=1}^{N} w_i \log(y_{i,t})}$$

$\sum_{i=1}^{N} w_i = 1$,convergence takes place when $h_{i,t} \rightarrow 1$, as $t \rightarrow \infty$

With this normalization the distribution dynamics controls for the aggregate growth effect of the states and reflects only the state specific (relative) distribution effects.

2.3 Cross Country Evidence of Convergence

The basic idea behind the neoclassical growth theories was that the marginal product of capital is low in high-income countries as they have high capital labour ratio, however, it is high in developing countries, where the capital labour ratio is low (Ray, 1998). If countries are similar in terms of structural parameters like preferences and technology, then poor countries will tend to grow faster than rich ones (Baumol, 1986).

With Baumol's (1986) pioneering work, efforts have been made to investigate the convergence process using different national and regional samples. The new econometric methods, ideas of new growth theories and availability of large data (Summers and Heston 1991; Maddison 1989) led many economists to focus on the convergence debate. Empirical evidence has shown that the distribution of output per worker has changed during the past decades across the globe. Interestingly some studies did report convergence; while others showed divergence across economies with different initial conditions.

Barro (1991), Barro et al. (1991), Barro & Sala-i-Martin, (1992), Sala-i-Martin, (1996)performed the convergence test by using cross-countries data, with the initial income the independent variable and growth rate of income as the dependent one. These were followed by studies like Islam (1995), Evans & Karras (1996) which used the pooled and/or panel estimation methods. Panel techniques were used because of the increasing number of observations and one could capture the existence of country specific and even time-specific effects.

There have been many cross country and within country analysis which have seen absolute or conditional convergence when certain factors are controlled for. Regional convergence over long sample periods and also over shorter sub-periods within the same sample was evident. Using the data from Summers-Heston (1988), Barro (1991) for 98 countries found that the average growth rate of per capita real GDP from 1960- 85 was unrelated to the 1960 value of real per capita for a cross section of countries. However, the poor countries showed tendencies to catch up with rich countries only if the poor countries have high human capital per person (in relation to their level of per capita GDP). Besides, different proxies of human capital like 1950 values of the school-enrolment rates, student-teacher ratios and adult literacy rate, physical investment to GDP and political variables were considered. Each of these factors had different impact on the growth rates,. Though there were no signs of absolute convergence across the countries, conditional convergence was confirmed.

For the regional data of 48 contiguous U.S. states, clear evidence of absolute convergence was found by Barro and Sala-i-Martin (1992) for Personal Income since 1840 and on Gross Domestic Product since 1963. With regions and sectoral composition, speed of convergence was around 2 percent irrespective of the time period and whether it is the personal income or the GDP data. For 20 homogeneous original members of the OECD, the per capita growth rate was inversely related to the log of initial per capita GDP. As far as σ convergence is concerned, except for the years 1920 (adverse shock to agriculture) and for 1976 (oil shock) dispersion in per capita income had declined from 1880 onwards. Thus the phenomenon of convergence both β and σ has been noticed for the U.S. states from 1840 to 1988.

To analyze whether the poor countries of Africa, South Asia and Latin America will grow faster than the developed countries, whether the poorer southern Italy will become like its richer north, or how fast would the eastern regions of Germany will attain the prosperity of the western regions, the above study on U.S states was extended by Barro et al, (1991) to examine the growth and dispersion of personal income since 1880 and relate the patterns for individual states to the behavior of regions. In this study, for 47 U.S. states, over nine sub periods from 1880 to 1988 there was an evidence of convergence. The correlation between average growth rate from 1880 to 1988 and log of per capita income in 1880 was seen to be negative. The Southern states had low PCI in 1880 but high average growth rate thereafter. The western states had above average PCI in 1880 and below average growth rate thereafter. Convergence pattern between regions (East, South, Midwest, and West) was similar to within regions.

The same framework was applied to patterns of convergence across 73 regions of 7 European countries (11-Germany, 11-U.K, 20-Italy, 21-France, 4- Netherlands, 3-Belgium, 3-Denmark) since 1950. The data showed a negative relation between growth rate of Per Capita Gross Domestic Product (PCGDP) from 1950-1985 and the log of initial PCGDP. The process of convergence within the European regions was similar to that for U.S states; the same 2% annual rate of convergence applied to even European Regions. Behavior of "σ " for the regions within 4 largest European countries showed that dispersion is highest in Italy, followed by Germany, France and U.K. Overall pattern showed decline in " σ " over time, with little net change since 1970 for Germany and U.K.

Sala-i-Martin (1996) applied the concepts of σ-convergence, absolute and conditional β convergence to a variety of data sets like 110 countries, OECD countries, the states within the United States, Japanese prefectures and regions within European countries, for the period 1960-1990. The four main findings were a) the cross-country variance of world GDP between 1960 and 1990 did not shrink, there was no σ-convergence nor absolute β-convergence, b) there was conditional β-convergence, by holding constant variables that proxy for the steady state of the various economies, for the sample of 110 economies. The estimated speed of conditional convergence is close to 2 % per year, c) for the sample of OECD economies, absolute convergence at a speed close to 2 % per year and σ-convergence over the same period (though σ-convergence stopped for a decade in the mid-1970s) and d) the regions within the United States, Japan, Germany, the United Kingdom, France, Italy, Spain, and other countries display absolute and conditional -convergence, as well as σ-convergence with a speed close to 2 % per year.

The convergence tests carried so far in the above empirical studies consists of running cross section regressions with the growth rate as the dependent variable and the initial income as the main explanatory variable, with many other variables appearing on the right hand side which control for the differences in the steady state levels. These studies have assumed that the different regions have common intercept and thus will converge to common steady states (after controlling for the variables). But in cross section regressions it is not possible to take into account many unobservable and immeasurable factors. Panel data approach can overcome this problem. More recent work have thus employed the panel data approach. Islam (1995) used cross section, pooled regression and the dynamic fixed effect panel data model and found similar results for pooled and cross section but significantly different results for the least square dummy variable (LSDV)[2] estimation for the Non-Oil sample of 96 countries, INTER-75 countries and OECD 22 countries. With panel data the convergence rate was higher.

Thus the studies on developed countries like Europe, Canada, U.S.A and Japan reveal convergence, both β and σ.

But for the developing countries the observations were not the same. In China, Kanbur & Zhang, (2005)confirmed that inequality seemed to have matched with different political–economic periods in its history. The development strategy emphasizing heavy-industry led to enormous rural–urban gap in the pre-reform

[2]A dummy variable is a binary variable that is coded to either 1 or zero. It is commonly used toexamine group and time effects in regression analysis.Panel data models examine fixed and random effects of entity (individual or subject) or time.The main difference between fixed and random effect models lies in the role of dummy variables.If dummies are considered as a part of the intercept, we have a fixed effect model, in a random effect model, the dummies act as an error term.Fixed effect models use least squares dummy variable (LSDV) and within effectestimation methods.

period, while, in the reform period(1980-90s) openness and decentralization worsened the disparity in the inland–coastal areas.

Similarly, Sanchez and Rodriguez (2002) found trade reforms to be the cause for increased regional income inequalities in the Mexican regions from 1980-2000, with the β and σ convergence being lost with trade liberalization. In contrast to the above finding, across 26 Brazilian states from 1985-2004, Daumal (2010) found Brazil's trade openness contributing to the decline in the regional income inequalities, more particularly because of the composition of trade. Brazil being an exporter of agricultural products than the industrial ones, the poorer agricultural regions benefited more from trade. Again trade openness fostered the dispersion of economic activities which led to the growth of the peripheral regions. For a panel data of 24 Chinese provinces from 1985-98 Demurger (2001) found the infrastructure endowments and geographical location influenced growth performances of the provinces.

2.4 β and σ Convergence literature in India

Like the cross country convergence studies, income convergence across Indian states has been explored using neoclassical growth regressions. Some studies do have reported convergence among the Indian states. Most of these studies relied on the ordinary least square method to test for convergence. One of the earliest papers in this area by Dholakia (1994) employed the kinked trend line techniques and switching regression for the time series data of 20 Indian states over the period 1960-90, it showed tendencies of convergence of long-term economic growth rate, with growth acceleration seen among the less well-off states. Cashin & Sahay (1996)used the cross-sectional estimation of Barro's regression to find transfers from

Central Government to the states responsible for weak absolute convergence among the 20 Indian states from 1960-1991. Analyzing a sample of 19 Indian states for the period 1961-1993 - divided into three sub periods, Bajpai, & Sachs (1996)measured the standard deviation of the log real per capita SDP across regionsand did not find statistically significant results of convergence for the period as a whole, except for the sub-period 1961-71.Mitra & Marjit (1996) studied the issue of regional convergence in 24 Indian states (1961-62 to 1989-90). On the basis of real PCNSDP, they find no evidence of convergence of PCNSDP among Indian states. Other empirical studies like Ghosh,, et al (1998); Rao, et al (1999); Kurian (2000), found increasing disparities since the launching of economic reforms in 1991, with the increasing role of the private sector having caused the disparity. Private investments were attracted towards the states with better infrastructure. Besides, the inadequacy of the inter-governmental transfers has brought about inequitable public expenditures across the states and is considered to be responsible for increasing the inequality.

Some of the studies have focused on the sectoral analysis. Shand & Bhide (2000) found convergence of the states in the share of the sectors in SDP though there has been a clear tendency of divergence in terms of per capita SDP. Dasgupta et al,(2000) examined variations in the size, income and structural characteristics of Indian states analyzing NSDP and PCNSDP for the period 1970-71 to 1995-96. A sectoral analysis shows that reform in agriculture yields the most benefit as growth in this sector is positively and significantly related to overall growth, followed by reform in infrastructure and human development. Rao and Singh (2001) examined a sample of 14 major states over the period 1965-1994, divided into various sub periods. Strikingly, they find an evidence of absolute and conditional divergence in every sub-period they consider. In another study, for the period from 1990-91 to

1998-99, Ahluwalia (2000) analyzed the performance of 14 major states during the post reform period vis-a-vis the pre reform period. In a recent study by Kumar and Subramanian (2012), growth performance of 21 Indian states during 2001-09 was examined. Interestingly it was reported that growth in the main states except for Himachal Pradesh, Rajasthan and West Bengal, increased in 2001-09 compared to 1993- 2001.For the span 2001-10, convergence was markedly evident for all states (non-special category and special category considered together) and non-special category states, while convergence among the special category states was slightly weak (Raju, 2012). Nagaraj, et al (1998) combined the panel data estimation techniques, principal component analysis and the instrumental variable approach for a sample of 17 Indian states from 1970-1994.

Though number of convergence and divergence studies have emerged some of these studies have covered the period before 1990 (Cashin & Sahay, 1996; Dholakia, 1994; Mitra & Marjit, 1996) and some looked into only the post reforms period (Kumar and Subramanian 2012; Astha, and Rangotra 2011) Again, most of the studies have covered few states of the country. Very rarely the smaller states and the special category states are considered. The ground stated for exclusion is twofold, one; these states represent a very small fraction of total population and income of India, and two, that these states have significantly different economic and geographical conditions.

2.5 Club Convergence across the World and within India

While many researchers have used the Barro (1991) regression equation, Quah (1993a, 1993b) pointed out the critical problem associated with this method as a researcher tests only whether the initial income is negatively correlated with a subsequent growth rate, and does not consider the dynamics of income. Thus an alternative approach that studies the evolution of economies where the behavior of any economy is studied as the evolution of an entire distribution, rather than through a cross-section regression which looks for average behavior in the cross-section is used. Quah (1997) has outlined a number of ways to study the evolution of cross sections, and conclude that conventional convergence findings can mask the presence of convergence clubs and the polarization of a population into rich and poor (Durlauf, 1996). Accordingly some studies have focused on this intra distributional mobility that detects the presence of convergence clubs at different parts of the income distribution (Kar, et al, 2011). This idea of club-convergence is best understood as an alternative to the idea of conditional convergence. In the case of conditional convergence, regions that have a common steady state (that is determined by the conditioning variables) converge towards this steady state. Thus, it is possible that while the regions as a group exhibit divergence, sub-groups of regions that have a common steady state exhibit convergence. Such within-group convergence in the midst of overall divergence is also possible within the club-convergence framework. However in this framework, such sub-groups are differentiated by the initial values of some important variables lying below or above a critical threshold value. In other words, regions with initial conditions above this threshold converge to form a club with a higher income while those below the threshold converge to form another club with a lower income.

There may be multiple threshold values leading to multiple clubs, but the most important case is the one where there is one threshold leading to the formation of two clubs. It is easy to understand in such a case, the regions within an economy get distributed into two groups over time, leading to the ‘Polarization’ of the economy

(Jha, et al , 2009). This increased polarization could give rise to social conflicts. As when some countries or regions grow faster than others, persistent disparities in income across countries and across regions lead to wide disparities in welfare and this could be a source of social and political tension, particularly so within national boundaries. Thus, apart from documenting convergence, it is necessary to consider the social, political, and economic implications of convergence (or divergence) among the states.

This study thus models the evolution of relative income distribution for Indian states using the 'distribution dynamics' methodologies proposed by (Quah, 1996b, 1996c), wherein the evolution of income is modeled as a Markov process[3]. The advantage of this methodology is that it formulates a law of movement for the entire distribution of incomes between the periods under analysis, allowing us to model the existence of convergence clubs in the data. This Markov process for relative incomes is modeled as a discrete formulation that uses transition matrices, and as a continuous formulation, known as a 'stochastic kernel', which avoids the problems associated with the discretization of the transition process in the estimation of transition matrices. Thus unlike standard regression approaches this approach allows us to identify specific distributional characteristics such as polarization and stratification.

For a sample of 118 economies, (Quah, 1993a, 1993b) provides an alternative framework for studying the long run dynamics of a rich panel of cross country incomes and constructs the transition matrix, estimated by averaging the observed one year transition over every year, from 1962-63 to 1984-85. The cross country incomes tend towards extremes at both high and low points with greater persistence.

[3]A Markov chain is a mathematical model for stochastic systems whose states, discrete or continuous, are governed by a transition probability.

Quah (1996a)uses a model of growth and imperfect capital mobility across multiple economies to characterize the dynamics of cross-country income distributions. There is little cross-country convergence; instead, the important features are persistence, immobility, and polarization. Again the distribution dynamics approach as presented by Quah (1997) encompasses both time series and cross section properties of the data simultaneously. The intra-distribution dynamics information is encoded in a transition probability matrix and the ergodic distribution associated with this matrix describes the long term behavior of the income distribution. Following the above papers, Bandyopadhyay (2012)adopts the distribution dynamics approach covering the period of 1965 to 1997 and has shown the convergence in 1960s and emergence of 'twin peaks' and 'polarization' in the early 90s among 17 major Indian states. She establishes the superiority of the distribution dynamics approach over the panel data regression approach in the Indian context, and identifies infrastructural inequality as the main factor responsible for the emerging twin peaks. Similarly, Gunji & Nikaido (2010) used two alternative methods, i.e., Markov matrix estimations and SURADF[4] tests, to investigate the convergence hypothesis of per capita income across 14 Indian states in 1970-2000. The estimated Markov matrix suggest that, in the full sample period, the long-run distribution of per capita income scatters and does not vary, although it tends to rise slightly to a higher level. On the other hand, there was a split into two sub-samples at break points in 1985 and 1991, when the government induced economic liberalization, implying that lower income states were able to rise in status before the economic liberalization, but not afterwards. That is, in the recent period, low-income states continue to be poor and high-income states to be rich. Laurini et al, (2005)analyzed the evolution of relative per capita income distribution

[4]SURADF is an augmented Dickey-Fuller test based on the panel estimation method of seemingly unrelated regression (SUR). The SURADF tests a separate unit-root null hypothesis for each individual panel member andthus identifies how many and which series in the panel have stationary processes.

of Brazilian municipalities over the period 1970–1996.The results show the formation of two convergence clubs, a low income club formed by the municipalities of the North and Northeast regions, and another high income club formed by the municipalities of the Centre-West, Southeast and South regions.

Another important contribution in the context of convergence club formation is given by Esteban & Ray (1994). They have tried to conceptualize and measure the concept of polarization, which they argue is fundamentally different from inequality. The model throws sufficient light on the theory of convergence club formation and the consequences of polarization in the form of social tension. In India, a lot of interesting growth dynamics involving the states in the middle has been observed. A number of recent contributions to the growth literature have shown that such relative movements of regions can lead to club convergence, and most importantly, the polarization of regions over time. Kar, et al, (2011)show that the middle income states moved up (relatively) towards the higher income states.

A number of recent contributions to the growth literature have shown that such relative movements of regions can lead to club convergence, and most importantly, the polarization of regions over time. A number of states have shown a constant upward or downward movement from the national average and these movements have led to the formation of clubs over time. The study had developed a framework that analyses the evolution of the complete cross section of income distribution over time. The literature has thus used a non-parametric approach based on the estimation of a kernel density function and studied its dynamics over time. The distribution dynamics framework studies the evolution of the distribution of per capita income over time by analyzing the kernel density plots of initial, final and the long run distributions identifying the formation of convergence clubs, polarization or persistent inequality. It also tested for the robustness of these results by repeating the exercise for alternative groups of states and identified the group of states that play important role in the process of this transition and the formation of convergence clubs. Mobility or persistence within the distribution was studied using the 3-dimemsional plots of a stochastic kernel and its corresponding 2 dimensional contour plots.

2.6 Growth, Poverty and Inequality link

Issues of economic growth in India have been seen in the larger context of reduction in poverty and inequality. A general consensus is that growth alone cannot bring down poverty; it is the distribution of income that is important. Ravallion & Datt (2002), Kakwani & Son (2003). The growing inequalities do not allow the benefits of growth to reach the poor; as a result not all regions and states in India have grown at the same pace nor has the decline in poverty rates been uniform. In the late 1990s the term pro-poor growth became popular as economists began to analyze policy packages that could achieve more rapid poverty reduction through growth and distributional change(Kakwani & Son, 2003).The extent to which growth reduces poverty depends on the degree to which the poor participate in the growth process and share in its proceeds. Thus, both the pace and pattern of growth matter for reducing poverty. High inequality affects the pace and pattern of growth and its effectiveness in reducing economic poverty.

Whether the economic growth of a nation brings down the inequality in the distribution of income has been well debated in many studies initiated by Kuznets (1955) with his well-known hypothesis of "inverted U- shape pattern of income inequality". By comparing five countries (India, Sri Lanka, Puerto Rico, the United

Kingdom and the United States) it was confirmed that the inequality first increases and then decreases with the level of economic development. Ahluwalia (1976) for a sample of 60 countries (40 developing countries, 14 developed countries and 6 socialist countries) estimated the cross country regression using the income shares and the log of PCGNP for different quantile groups. The study confirmed statistically significant relationship between the income inequality and the level of development, and also emphasized that for the poorest income group the process of reversal of inequality would be more prolonged.

However, Kuznets hypothesis has been strongly challenged with the emergence of quality datasets and testing on individual nations. Deininger & Squire (1996) with 682 observations for 108 countries presented a new data set on inequality. Along with Gini coefficient (aggregate measure) income shares by quintiles were adopted. Although the authors did not find any significant link between growth and changes in inequality, strong positive relation was seen between aggregate growth and reduction in poverty (changes in the income of all quintiles except the top quintile). Kanbur (2010) focused on developing countries and found tendencies of increasing inequalities in growing economies. He also highlighted the importance of distribution policy of the government in bringing down the level of poverty. Deaton & Drèze (2002) found increasing inequalities in 1990s in India, with the southern and western regions doing much better than the northern and eastern regions. Kanbur & Zhang (2005)noted three peaks of inequality in China right from the Communist Revolution till the global integration in the late 1990s.

The relationship between growth and poverty is complex and is greatly determined by the level and changes in inequality (Kakwani & Son, 2003). The debate on poverty, inequality and growth has been discussed widely across the countries. Using the standard decomposition techniques, Kraay (2004) found that the pro-poor growth could bring down the level of relative and absolute poverty. The determinants of pro poor changes in relative income differ among countries. Ravallion (2001) with two successive household surveys for about 50 developing countries highlights how large differences between the countries could determine the share of the poor in growth. Greater openness to external trade has different effects on the inequality depending on whether it is a rich or a poor country. High initial level of inequality in the country could bring down the prospects of pro-poor growth. More particularly the inequality in the asset distribution adversely affects the growth (Deininger & Squire, 1998). Weak comparability of cross country data on poverty measurement and growth made (Ravallion & Datt (2002) compare the evolution of poverty measures across the 15 major Indian states with 20 rounds of NSSO household surveys spanning from 1960-94. Higher farm yields, development spending by the state Governments, lower inflation were poverty reducing. Poverty elasticity to non-farm output growth varied across the states. Though non-farm economic growth did not reduce the poverty for the states with poorer initial condition of rural development, states with higher initial literacy, higher farm productivity, improved rural living standards and low infant mortality did benefit from non-farm economic growth.

Besides this empirical work on poverty, growth and the inequality link, certain studies have focused specifically on the policies of the government that are responsible in the reduction in poverty. Structural and policy changes like declining returns to education, rural-urban convergence, increases in social transfers targeted to the poor; and decline in racial inequality, have been responsible for the falling inequality in Brazil from 1981 to 2004, and this has made a substantial contribution to poverty reduction (Ferreira & Leite, 2007).

2.7 Social-Political Indicators and Convergence

It is generally being argued that the focus on income as an indicator for economic inequality is too narrow and should be substituted by a broader concept of welfare (see Gachter & Theurl, 2011). Convergence is basically the end result of the process of changes in the similarities or dissimilarities across the states, expenditures, policies and social indicators which is a reflection of policy outcomes. Though the economic growth in India has increased significantly, certain sections of society remain excluded, especially in terms of improvements in human capabilities and entitlements (Mukherjee et al, 2014). There is high degree of inequality in human development across Indian States. Kerala, Himachal Pradesh, Tamil Nadu have been the better performers, while Bihar, Madhya Pradesh, Odisha, Uttar Pradesh have fared badly in development indicators like poverty, health and education (Dreze & Sen, 2013).

In India, besides economic, religious and linguistic disparities, caste system still prevails as one of the key drivers of poverty and inequality (Rao, 2010). In the past three decades, there has been sharp macroeconomic takeoff in India. The Affirmative Action (AA) programme undertaken in India was necessarily caste based as the most deprived had to face the various aspects of stigmatization, exclusion and rejection. The affirmative action measures have been strongly criticized as they are said to go against the consideration of merit and efficiency by allowing candidates access to preferred positions in higher education and public sector jobs that they would otherwise have no access to. The caste system has been widely researched by all of the social sciences except economics (Deshpande, 2011).

However, there has been extensive literature on affirmative action, with many focusing on its impact on the material well-being of the deprived class. The impact of social discrimination on growth among and within the countries has been recognized in few studies. Hnatkovska & Lahiri (2011) analyzed the cross state variations in the economic fortunes of SC/ST in contrast to the non-SC/ST population with the data from NSSO rounds between 1983-05. Interestingly, they found that that the gap between the SC/ST and the non-SC/ST has narrowed in wages, consumption and education attainment rates and quota have played a significant role in this convergence. Similarly, using the expenditure surveys from 1983-10, across time, and between rural and urban areas for major states in India, Panagariya & Mukim (2014), noted accelerated decline in the poverty rates which has been sharper for the socially disadvantaged than the upper income classes between 2004-10. Besides, acceleration in the growth rates in the same period, has been accompanied by acceleration in poverty reduction. Atsushi (2004) using growth regressions for 14 major states during 1980-97, examined the impact of social diversity on the growth through expenditure policy. He found that though public expenditure has positive influence on growth, social diversity retards public expenditure policy. Ghosal (2012) examined the cross state time behavior of growth, inequality and poverty from 1973-10 using the panel data estimation for 16 major states in India. He found that the social sector expenditures and the growth rate of PCNSDP are responsible in bringing down the incidence of poverty. Besides, the service sector led growth has also brought down the incidence of poverty. Only Annett (2000) presented a endogenous model which linked fiscal policy and social conflicts and concluded that higher Government consumption has brought down the political instability caused by fractionalization for low, middle and high income countries between 1960-90.

Drèze & Sen (2002) highlighted the major rise in the economic and political power of the backward castes. The abolition of Zamindari, the introduction of adult franchise, economic progress among the cultivating castes (as a result of green revolution), with various political movements have challenged the upper-caste dominancein rural areas. At the same time, the universal elementary education, improvements in gender relations and the growing participation of women in local politics have been some major developments in recent years. Zacharias and Vakulabharanam (2011) employed the data on household wealth of the All India Debt and Investment Survey (AIDIS) conducted in 1991–92 and 2002–03 (two rounds), to analyze the relationship between wealth inequality and caste divisions in India. The results showed that an average SC/ST had lower wealth than General class, while OBC and the non-Hindus occupied positions in the middle. However there was an emergence and strengthening of a "creamy layer," or relatively well-off group within the ST, as with globalization the disadvantaged groups has narrowed the gap with the privileged groups because the rent-seeking state is pushed back by the less discriminating global markets. Iyer et al, (2013) documented substantial caste differences in entrepreneurship across India for 19 states, with an under-representation of SC and ST. While the OBC were well represented and had shown progress from 1998-2005, with the share of firm ownership rising from 37.5% to 43.5% and the share of employment from 33.8% to 40%. Prakash (2009) analyzed the effect of employment quota on labor market outcomes for 16 main states using the NSSO Rounds (1983, 1987, 1993, and 1999) and found that the SC benefited much more than the STs. Employment quotas for the SCs increased the probability of acquiring a salaried job. This in turn had many positive benefits in terms of rise in household consumption expenditure, their children's school enrolment and decline in the incidence of child labor. These benefits were less for STs as there was a mismatch between where STs reside and location of the public sector jobs. From 1960-1992 for 16 major Indian states, Pande(2003)provides evidence that political reservation for disadvantaged minorities allows them greater influence on policy-making.

In sharp contrast, there have been studies that have highlighted the standards of living, poverty rates, health status and educational attainment. They find that occupational outcomes has not changed effectively indicating that the disparities between SC-ST,OBC and the Others (upper castes) are persistent and systematic. The extensive reservations in public sector jobs, in higher education institutions and political reservations have not been able to prevent SC, ST households from being overrepresented among the country's poor, illiterate and landless (Iversen, et al, 2014). NSSO data from 1983 to 2000 for fourteen major states suggests thatthe rate of decline of absolute poverty has been higher for the general class, with the rural poverty being stagnant for the ST in 1990s. In addition to this poverty was seen to be concentrated among the SC and ST, with the magnitude of the social disparities being state specific. The ST and SC are concentrated more in the poorer states. With regard to the occupational status of the SC, ST, OBC and Others, for the three rounds of National Family Health Survey (NFHS) in 1992-3, 1998-9 and 2005-6, Deshpande (2011) concludes that there has been continuing dominance of the upper caste in prestigious occupations, with no reversal of economic power and occupational hierarchy. SC and ST are occupying the lower rung jobs and that the gap between the OBCs and the Others for the upper most occupations is positive. With respect to the educational attainments there have been wide regional variations. She found that different state governments have given differing importance for education, while making it accessible to the disadvantaged groups. The southern and the western states have shown better educational outcomes, then comes the eastern states, while the northern states have displayed poor performance. The north eastern states, despite of having poor infrastructure and low levels of development have shown exceptionally good outcomes. Kerala, Maharashtra, Tamil Nadu displayed good outcomes even for SCs. Though landholdings are considered to be an important indicator of wealth, the backward classes are deprived of this and the distribution of land has been quite unequal across the caste groups. Even the states like Kerala and West Bengal (despite of better land records) have SCs who are landless. In contrast, Rajasthan and Uttarakhand had better and equal distribution of land (Deshpande, 2011).

On the political front, heterogeneous set of political variables are tested in growth regressions in a large number of studies across and within the countries. Certain studies have identified the relationship between political decision making process and economic growth (Kohli, 2006). Different aspects are focused as far as the debate on the politics-growth link is concerned. Measures of democracy (see Barro 1989;Alberto & Perotti 1996; Dasgupta, 1989), Government stability, political violence[see Barro, 1989, Barro, 1991,Alberto & Perotti, 1996], political volatility (see Dollar, 1992) and subjective measures of politics (see Brunetti et al, 1997) are focused as explanatory political variable in certain studies. On the local grounds, Asher & Novosad(2016)tried to find out if politics had an impact on local economic outcomes using the data for Economic Censuses in 1990, 1998 and 2005. The dataset linked economic and population outcomes to legislative elections. It was found that having a local politician who is aligned with the party in control of the state government had increased private sector employment growth between 1 to 2 percent percentage points per year. Besides there was a rise by 12-15% cumulative abnormal return to the firms because of this alignment. However in case of the supply of public infrastructure or public sector jobs, politician alignment had no measurable effect. The firms which were most affected by political alignment were those who were highly dependent on bureaucratic inputs, and who frequently met government officials. Ghosh (2010), analyzed the impact of political competition on economic performance and fiscal variables at the state level for 14 major states from 1980-04. The political competition had positive effect on state PCI and the politicians increased the developmental spending so as to improve their re-election prospects.

2.8 Convergence Across Quantiles

Most of the above empirical research on growth has relied on the least square methodology that models the mean of the growth rate on certain set of explanatory variables. The classical OLS model minimizes the sum of squares and estimates the conditional mean function models. The quantile regression analysis on the other hand, estimates the models for the conditional quantile functions and thus provides a complete statistical analysis of the relationship between the independent and the dependent variables. This analysis was first introduced by Koenker and Bassett (1978), as the conditional mean was not be able to fulfill the robustness requirement of the model. The quantile methodology estimates either the conditional median or other quantiles of the response variable. Thus each slope coefficient can be interpreted as a different response of the GDP growth rate to a change in a policy variable corresponding to a different position on the conditional distribution of growth rates. Again, as a result of heteroskedasticity in the model, the quantile regressions can characterize the complete conditional distribution that is useful and interesting (Koenker and Bassett, 1978). If the data is homoskedastic then the slope coefficients of the quantile functions are identical with the OLS slope coefficients (Canarella & Pollard, 2004). Based on this methodology many contributions exists across the countries and regions which use the cross sectional data for the estimation of the quantile regressions. Analysis such as Mello and Novo (2002) have used the Barro-Lee data set for 98 countries from 1960-85 for estimating regression quantiles over the complete conditional distribution of the growth rate of GDP to identify the different responses of the GDP to the regressors. This study also employed the inferential procedures to test if the policy variables affect the scale or the location of the distribution of the growth rate of GDP. Only the higher 35% quantiles show signs of convergence with human capital playing a major role on the GDP growth. Similarly, Canarella and Pollard (2004) applied the quantile regression approach to the Mankiw, Romer and Weil model across 86 countries from 1960-00. There were no signs of convergence for the countries belonging to the lower quantiles and these countries responded differently to investments in physical and human capital as compared to the countries in the higher quantiles. Barreto & Hughes (2004)employed around 37 variables from Barro and Lee(1994) and Leveine and Renault (1992) datasets for 119 countries from 1960-90 to analyze the long-term growth at different quantiles in a conditional distribution. Trade, demographic factors, social expenditures were determining the growth of the over -achieving countries, while the civil liberties, social infrastructure were important for the growth of the low performing countries. To see the impact of trade openness on the per capita growth rate across different quantiles, Dufrenot, et al (2010) applied the two-stage quantile regression methods to address the endogeneity issue that arises in growth regressions. For 75 developing nations from 1980-2006 it was found that the effect of trade openness is higher on countries with lower growth rates compared to the ones with high growth rates. Besides there are certain studies carried out at the regional levels. Laurini (2007) applied the "quantile smoothing spline" for the Brazilian municipalities from 1970 -1996, to replace the linear form of quantile regression into a nonparametric form. With this switch it was found that there has been divergence among the municipalities and formation of convergence clubs. Cuaresma et al, (2009) combined the quantile regression technique with the Bayesian Model Averaging across the 255- NUTS 2 European Regions, from 1995-05. The growth determinants were found to be different across different quantiles, the initial per capita GDP was not seen to be robust when country effects were considered. Again for 14 Member States of the EU, (Andrade et al, 2014) examined the convergence process across different quantiles, it was noted that incorporating the parameter heterogeneity was necessary as the influence of growth determinants like the exchange rates, Government consumption, interaction between the absorptive capacity and technological catch-up. Non tradable sectors' share varied over the distribution. Further, these result were applied to study the specific case of Portuguese economy, it was found that after the EC accession, the growth pattern of the Portugal has been varying, with higher growth rates between the 1986-98 and low growth rate from 1999 onwards.

A general conclusion that can be drawn from these results is that the influence of different growth determinants seems to vary across quantiles and secondly, even if a variable is found robust across the quantiles, the estimated impact on growth rates of that particular variable is generally found to be differing quantitatively across the quantiles. This is irrespective of the time periods of the analysis, set of growth determinants, the type as well as the number of countries or regions focused. Importantly all these papers have applied the quantile regressions methods by adopting the cross-sectional versions. As discussed earlier, the cross-sectional β-convergence model is affected by the unobserved region or the country-specific effects on income levels. The panel versions of the quantile regressions are used in to control for parameter heterogeneity and unobserved state specific or country effects (Islam, 1995).

One of the first and the best known approaches of introducing individual effects to account for unobserved individual heterogeneity in the quantile regression models was by Koenker (2004). As quantile regression model is a nonlinear model, switching to the panel version could result in inconsistent estimates, thus the shrinking of the ‘fixed effects' was carried out by introducing a penalty by Koenker (2004). Following this strategy, Kostov & Gallo (2015)applied the panel quantile regression to test for conditional β convergence for 120 countries from 1955-2010. It was found that the impact of the initial level of per capita income, the investment rate, growth of population as well as the human capital on growth rates varied with the estimated quantiles. Recognizing the importance of space, the spatial models were incorporated in this analysis. Besides the endogenous spatial effects seemed to be affecting the convergence process. Billger & Lamarche (2010) adopted the technique proposed by Koenker (2004) to examine the differences in earnings among the native and the immigrants in England and the United States.Theindividual heterogeneity was important in determining the earnings in both the countries. Another approach to estimate the quantile panel regression was introduced by Abrevaya & Dahl (2008). A particular structure is imposed on the relationship that exists between the individual effects and the regressors. This is known as a quantile regression model with the correlated-random-effects (CRE). This approach was used by Abrevaya & Dahl (2008) to estimate the impact of smoking on the distribution of birth weights. From the above literature review quantile regressions it can be concluded that very few studies have focused on the panel quantile regression models. This study would contribute to the quantile literature by applying panel quantile regressions to β-convergence across the states in India, which would be one of the first attempt in the Indian context.

2.9 Spatial Effects in the Analysis of Regional Income Convergence

Features of open economies speeds up the process of convergence (Barro and Sala-i-Martin 1992). Features like technology diffusion, factor mobility and transfer payments which drive the regional convergence phenomenon have explicit geographical components. The importance of spatial autocorrelation and spatial relations was first recognized with the publication of a small volume entitled *Spatial econometrics*, a first comprehensive attempt by Paelinck and Klaassen in 1979 (Anselin, 2010). More recently, focus on location and spatial interaction has gained a central place in various areas of economics. The growth regression approach has now started to consider the role of space in econometric analysis. Studies like (Ramirez & Loboguerrero, 2002)found strong evidences of spatial interdependence across 98 countries over the period 1965-95 both under the Maximum Likelihood and by two stage least square estimation. The rate of convergence was found to be similar in the OLS and the spatial model. By ignoring the spatial dependence, the spillover effects and externalities across the countries are underestimated.Using different specifications as well as different measures of proximity, for 93 countries over 1965 to 1989 period, Moreno and Trehan (1997) found that the demand and technology spillovers are responsible for a particular country's growth to be determined by its neighbors. Besides, most of the studies on spatial dependence have been carried out at the regional level(see Rey & Montouri, 1999; Elias and Rey 2011; Baumont et al, 2002; Fischer and Stumpner 2008; Ertur et al, 2007). These studies have used the cross section regression and have tried to show how the unconditional regression model is misspecified as a result of ignoring the spatial dependence. Rey & Montouri (1999)found strong evidences of spatial autocorrelation in the levels of PCI for the United States between 1929- 94. The states seem to converge in terms of relative incomes and their movements are similar to that of their neighbors.

Many studies are conducted across the European regions. Vaya, et al (2000) argued that there are strong technological spillovers so high incomes of neighboring regions affects the growth of a particular region, for the period 1975-1992. Similarly, Baumont, et al, (2002) for 138 regions from 1980-1995 also detected spatial dependence and heterogeneity along with strong spatial spillovers. Again for the same regions, Ertur, et al (2007),used the Bayesian Spatial approach to global and local convergence in a continuous fashion to see the impact of sub sample size. With maximum likelihood estimation it was found that there is spatial dependence across many regions and the β varies among countries and regions. There was convergence for 31 regions in Spain, Portugal & southern France. Ramajo, et al (2005) identified the general effects of European Union regional policies as a whole on the regional convergence process in terms of the Cohesion/Non Cohesion countries. The pattern of economic growth is explained by the geographic localization and proximity in the EU. It was found that there was faster convergence in the per capita income levels for the Cohesion countries than the non-cohesion ones. Convergence of a region seems to be also dependent on the initial values of per capita GDP of the neighboring regions. For Brazilian states, over the 1970-95 period, Magalhaes et al, (2005) followedRey & Montouri(1999) approach to find the presence of strong spatial autocorrelation. (Alessandrini, et al, 2008)during 1980-02, noted that liberalisation and openness to trade in India has divided the states into the slow and fast growing ones. Most of these studies discussed above have limited themselves to cross section spatial lag and the error specifications.

Instead of focusing on initial level of income and its influence on the growth rate, (Ades & Chua, 1997)for 118 countries over the period 1960 to 1985, showed how political instability in the neighboring countries, could have a strong negative impact on the country's economic performance. The magnitude of this negative spillover would result in an equivalent increase in the size of the domestic political instability. By disrupting the trade flows (as merchandise and trade of manufactures in such countries are lower) and increasing the defense expenditure (thus diverting the share of Government expenditures on education) political instability brought down the economic performance of the country.

Certain studies have moved beyond focusing only on the income aspects and have highlighted the geographical dynamics of the social indicators. Elias & Rey (2011) analyzed the spatial patterns in educational convergence for the Peruvian Provinces form 1993-2005. They found a positive autocorrelation for the socio economic indicators and a strong spatial dependence in the error term.

In recent years, some studies have taken into account the spatial panel data models. This has been possible since more data sets have been made available for different spatial units over time. The panel data models are considered to be more informative, with more variation and less amount of collinearity among the variables. Panel data models offer greater degrees of freedom and increase efficiency in the estimation. It also incorporates different effects that are not considered in pure cross section framework (Elhorst, 2014). Piras & Arbia (2007), noted that the simple cross section methods do not take into account the heterogeneity as well as the spatial effects, similarly though the classical panel data model consider the individual heterogeneity and the omitted variables, it does not consider the spatial dependence. Spatial panel data models also controls for spatial autocorrelation. The spatial panel model was used for 125 regions of 10 European Countries over the period 1977-02, to test for growth. Inclusion of a spatially lagged dependent variable resulted in the reduction of the coefficient value on the initial GDP per capita, with a considerable improvement in the estimated values of the rate of convergence among the European regions. These results confirm the influence of geographical spillovers, factor mobility and trade relationships on regional convergence. Similar analysis was conducted for the 92 Italian provinces from 1951-2000 by Arbia et al, (2005), here again after controlling for spatial effects it was found that spatial panel data models represents a genuine case of regional interaction effects. Chatterjee (2016) adopted the spatial econometric techniques to analyze if the per capita income from agriculture has been converging across 17 Indian states from 1967-2011. In addition to the state-contiguity and inverse-distance based matrix, shared border and district-contiguity based matrices were employed in this analysis. Spatial panel models seemed to explain the convergence pattern better than the non-spatial models. The spill-over across states were driven by rural literacy, roads and irrigation. It was found that the agriculture growth in India can be aided with increase in investments in human capital, physical infrastructure and incentives towards growing crops.

Within view of these considerations of the spatial dependence and spatial heterogeneity, our study estimates the convergence in per-capita NSDP across Indian states by making use of spatial cross section and the spatial panel data models.

2.10 Summary

In this chapter the growth theories that underline the discussion on growth convergence have been highlighted. As a result of the development of new econometric techniques and availability of large datasets, studies across the countries and within the countries have tried to analyze if there has been convergence among the growth rates. Within India, there is been no consensus on whether the growth rate of per capita income among the states has been converging or moving apart.

In the next chapter we discuss in detail the data sources and different methodologies used in this study.

Chapter III

Research Methodology

3.1 Introduction

In this chapter we discuss two things- data sources and methodology. There is now a reasonably large literature available for us to draw from. To investigate the convergence process Barro (1991), Barro & Sala-i-Martin (1992) and Sala-i-Martin (1996) have converted the economic notion of convergence into a statistical hypothesis that employs a growth regression with the level of initial income as the pivotal explanatory variable. This is known as β-convergence where the growth of per capita income is regressed on the logarithm of the initial level of per capita income. For convergence to occur, we anticipate a negative value of "β". A negative correlation between growth and initial income implies a tendency for poor countries to catch up (Baumol, 1986). The variability in growth across states has been analyzed from various theoretical perspectives wherein many of the studies have used cross section or pooled and panel data estimation techniques.

3.2 Data Sources

Our data is entirely from the secondary sources. We have used multiple variables from variety of sources. We discuss these briefly below.

1) Per Capita Income:

Studies on convergence typically track per capita incomes. In India the lowest sub-national level income data that is available is at the state level. There is one series available at district level but it is not widely accepted or used. There are few official sources for data- RBI, CSO. However they do not provide long term constant series.

Therefore the series of Net State Domestic Product (NSDP) per capita at current prices for the period of 1981 to 2013 provided by Economic and Political Weekly Research Foundation (EPWRF- Domestic Products of States India module) has been used. State level income data prior to 1981 is available for the major states but not for all the states and union territories considered in this study. We have also used the Net Domestic Product (NDP) series for both current prices and constant prices from the same database (EPWRF-National Accounts Statistics of India module).

The per capita income data was made comparable not only across states (cross section) but also over time. We controlled for price variability by generating a NSDP constant price series. In order to do this, we divided each state's NSDP at current prices by the NDP deflator for that year. The NDP deflator was generated by taking the ratio of NDP at current prices to NDP at constant prices (Dornbusch, et al., 2002, pg. 34). This ratio is in the nature of a price-inflation index. By dividing the NSDP (at current prices) of each state by the corresponding value in this index we derived the NSDP at constant prices (base 2004–5 prices) of each state.

In India, in the last 30 years not only has income and population grown but so have the number of states due to their administrative and political re-organization. For club convergence, data for 25 states and 3 Union Territories (UT) are used till 2000-2001. For the period 1981-82 to 2000-2001, we have considered 28 states and union territories. In 2000 by a constitutional amendment three new states were created (Chhattisgarh bifurcated from Madhya Pradesh, Jharkhand bifurcated from Bihar and Uttarakhand – initially called Uttaranchal, bifurcated from Uttar Pradesh). So, from 2001-2, we have 31 states.

Many studies on convergence in India have concentrated only on the major states (like Ahluwalia, 2000; Cashin & Sahay, 1996; Ghosh, 2008; Kar & Sakthivel, 2006; Kumar & Subramanian, 2012). Choosing only the major states have its advantages – the data availability is for a longer period, but this may lead to problems of selection bias. As we will see in the analysis below, it might leave us with a limited understanding of regional inequality as we would miss a lot of the action in terms of mobility evident in the smaller as well as special category states which has important political implications.

For the club convergence hypothesis in particular, the per capita NSDP at constant prices of each state has been normalized using the per capita NDP at constant prices of aggregate of all the states in the sample, for the corresponding years. With this normalization the distribution dynamics controls for the aggregate growth effect of the states and reflects only the state specific (relative) distribution effects.

2) Socio Economic Indicators:

Beyond the data on per capita income, socio indicators like quality of life and quality of opportunity is analyzed in different states of India. The most acceptable indicator for quality of life is life expectancy at birth or at age 1. Unfortunately, we do not have life expectancy data for all the states and UTs from 1981 onwards. Therefore Infant mortality rate (IMR) is used as the dimensional variable for quality of life. IMR is considered as a good indicator of the health status of a population. Education or knowledge is a core dimension of human wellbeing because it provides the opportunity to an individual to live a productive and socially meaningful life (UNDP, 2014). Adult literacy rate (Age 7+ literacy rate) is considered as an ideal variable for quality of opportunity (Census of India, 2011).

The gender ratio is an indicator of the composition of the population. It is defined as the number of females per 1,000 males. It is an important and useful social indicator that measures the extent of prevailing equity between males and females in a given population at that point of time (Government of India, 2011).

In India, the urbanization level is measured by the percentage of population living in urban areas. Different states in India have a diverse pattern of urbanization, but economically advanced states more or less show higher levels of urbanization (Bhagat, 2011). In our analysis we have used the gender ratio and the percentage of population in urban areas as the explanatory variables. The data on literacy rate, Gender ratio, percentage of urban population is obtained from Census of India, various years. The data on IMR is obtained from EPWRF and Compendium of India's Fertility and Mortality Indicators 1971-2007 based on SRS Office of the Registrar General & Census Commissioner India, Ministry of Home Affairs. New Delhi, India.

To see the relationship between political decision making process and the economic growth, the political variable employed in this study is the number of years the state party ally at the centre. This variable has been used as a dummy variable, if the state party ally at the centre then the value is 1, and 0 otherwise. The data on the political variable is from the Election Commission of India.

3) Public Finance:

To see the link between the components of government expenditure and economic growth across the states in India, the study includes two components of social services expenditures, 1)Education, Sports, Art and Culture (henceforth referred to as education expenditures) and 2) Medical and Public health, (medical expenditures). The data on these variables is from the EPWRF (Finances of the state Government module).

4) Social Stratification:

The data on caste for the years 1981- 95 is from the Census of India, while from 1999-00 onwards, the data from the 55th (1999–2000), 61st (2004–2005), 66th (2009–2010) Round of NSSO is used.

As far as the poverty rates are concerned, the Planning Commission data from NSSO Rounds [38th (1983), 43rd (1987–1988), 50th (1993–1994), 55th (1999–2000), 61st (2004–2005), 66th (2009–2010) and 68th (2011-12)] is used.

3.3 Software

The study has relied on a multiple set of softwares. In order to generate the 3D graph and for estimating panel quantiles the R-stat is used. To generate the GIS maps, the QGIS has been used. For spatial analysis, the Geoda software is employed and for the rest of the graphs and econometric analysis we used Stata (v12).

3.4 Panel data estimation

Most empirical work on convergence includes running cross section regressions with the growth rate of income as the dependent variable and initial income level as the main independent variable. There are explanatory variables in these regressions that control for the steady-states differences across countries (Mankiw, et al, & 1992). But the major limitation of these cross section regressions is that only the differences in technology and preferences which are observed and measured are taken into account. But, the differences in preferences and technology could have variables that cannot be measured or even observed over time (Islam, 1995). In a way cross section regressions have assumed a common intercept for different regions over time, which is unrealistic. The panel data model can overcome this drawback and bring about improvement in the robustness of empirical estimation as compared to the cross sectional analysis (Nayyar, 2008). In this study to decide between a random effects regression and a simple OLS regression, the Breusch-Pagan Lagrange multiplier (LM) test is employed. The null hypothesis in the LM test states that there is no significant difference across units that are there are no panel effects. Our results rejected the null hypothesis; as such we could use a random effect regression.

With panel data it is possible to control for variables that cannot be observed or measured. Panel data models examine the cross-sectional (group) and the time-series (time) effects. These effects may be fixed and/or random. Fixed effects assume that individual group/time have different intercept in the regression equation, while random effects assume that individual group/time have different disturbance but a common intercept. The core difference between fixed and random effect models lies in the role of dummy variables. If dummies are considered as a part of the intercept, this is a fixed effect model. In a random effect model, the dummies behave as an error term (Park, 2009). To select between the two effects the Hausman specification test is used. The Hausman test compares the fixed versus random effects under the null hypothesis that the individual effects are uncorrelated with the other regressors in the model. If this hypothesis is rejected, a random effect model produces biased estimators, violating one of the Gauss-Markov assumptions; therefore a fixed effect model is preferred (Park, 2009).

The most widely used model to test for convergence (as adopted by Barro, 1991) takes the following form.

$$(3.1) \qquad Y_{i,t,t-\tau} \equiv \frac{ln(y_{i,t}) - ln(y_{i,t-\tau})}{\tau} = \beta_0 + \beta_1 \, ln\left(y_{i,t-\tau}\right) + \varepsilon_{i,t}$$

Where $Y_{i,\,t,\,t-\tau} \equiv ln(\gamma_{i,t})- ln\ (\gamma_{i,t-\tau})/\ \tau$ is the *ith* region's annual average growth rate of per capita income between period t-τ and t. .

$ln(\gamma_{i,t})$ and $ln\ (\gamma_{i,t-\tau})$ are the natural logarithms of the ith region's per capita income at time t-τ and t respectively, γ stands for real PCNSDP, τ is the length of the time period.

A value of β in the range of −1< β < 0 would be an evidence of β -convergence that is the nearer the value of β to –1, the higher the speed of convergence and the nearer to zero the lower the speed of convergence. If β is zero means no convergence and a positive value for β indicates divergence.

When economies are converging to the same level of steady state, we have *unconditional or absolute* convergence. Absolute β convergence assumes that states differ only in their levels of capital. However it has been observed that economies differ in other respects like technology, population, savings as such there could be different steady states for different economies, which gives us the concept of *conditional convergence* (Sala-i-Martin, 1996b).Thus economies can converge to different levels of steady-states. Conditional β-convergence is possible only when other factors, which cause variations in steady states across regions, are accounted for. This is done by including in regression equation certain variables that control for the variation in steady states across regions. Thus, testing for the hypothesis of conditional β-convergence involves estimation of the following equation, in which we control for other variables which might influence the steady-state level of income.

$$(3.2) \qquad Y_{i,t,t-\tau} \equiv \frac{ln(y_{i,t}) - ln(y_{i,t-\tau})}{\tau} = \beta_0 + \beta_1\, ln(y_{i,t-\tau}) + \Psi X_{i,t-\tau} + \varepsilon_{i,t}$$

In addition to the above variables, we have X as a vector of explanatory variables. The selection of control variables depends on economic theory, availability of data and the priori belief on growth process (Ghosh, 2008).

3.5 Club Convergence

It has been pointed out that neither beta nor sigma convergence provide a complete insight into the convergence process (Quah, 1993a). The evolution of relative income distribution for Indian states is modeled using the 'distribution dynamics' methodology proposed by Quah (1993a, 1996b, 1997). This method assumes that each region's income follows a first-order Markov process with time-invariant transition probabilities. A Markov chain is a mathematical model for stochastic systems whose states, discrete or continuous, are governed by a transition probability. The current state (in a first order Markov chain) only depends on the most recent previous state (Kemeny, 2003).The advantage of this methodology is that it formulates a law of movement for the entire distribution of incomes between the periods under analysis, allowing us to model the existence of convergence clubs in the data.

3.5.1 Models of Distribution Dynamics

The stochastic kernels (continuous) and transition probability matrices (discrete) are the two main empirical models used to estimate distributional mobility of countries or regions. In both cases, it is assumed that an economy or region over a given time period (say, one year or five years) either remains in the same position, or changes its relative position in the income distribution (Bandyopadhyay, 2004a).

The density distribution "ϕ_t" is expected to evolve in accordance with the following equation

(3.3) $$\emptyset_t = M \, . \, \emptyset_{t-1}$$

where, "M" maps the transition between the income distributions for two consecutive periods "t" and "t-1". This is a first-order Markov process as the density distribution

"ϕ" for the period "t+1" only depends on the density "ϕ" for the immediately preceding period "t". In our estimates below we have assumed that the distribution "ϕ" has a finite number of states.

In estimating the dynamics of the income distribution, there are three possibilities for an economy's behaviour over a given period of time-

a) it may move ahead (poor catch up with the richer states),
b) it may stay where it was,
c) or even fall behind.

3.5.1.1 Transition Probability Matrix

For the Markov transition matrices we assume that the probability of variable s_t taking a particular value depends only on its past value s_{t-1} according to the first-order Markov chain

(3.4) $$P\{s_t = j \mid s_{t-1} = i\} = P_{ij}$$

where Pij indicates the probability that state i will be followed by state j. As

(3.5) $$P_{i1}+P_{i2}+....+P_{in}=1$$

The transition matrix constructed is as follow,

(3.6) $$P = \begin{bmatrix} P_{11} & P_{12} & \cdots P_{1n} \\ P_{21} & P_{22} & \cdots P_{2n} \\ \cdots. & \cdots. & \cdots\cdots \\ \cdots. & \cdots. & \cdots\cdots \\ P_{n1} & P_{n2} & \cdots P_{nn} \end{bmatrix}$$

where row i and column j indicates the probability that state i will be followed by state j.

By iterating the equation (3.3) and leaving out the error term, we get

(3.7) $$\phi_t = M^s . \phi_{t-s}$$

as s $\rightarrow \infty$, we can get the long term distribution of income known as the ergodic distribution. If the distribution after ϕ_t or ϕ_∞ period tends to be unimodal then there is convergence over time, bimodality would mean that then the distribution is polarized, and if more than two peaks emerge then there is stratification.

When we use the Markov chains to model the evolution of relative incomes distribution we are considering each state of this matrix as the category of relative income. We thus identify the position of the economy at the income distribution in the starting period. This is done by dividing the income distribution into "income states". Income states are a range of income levels.We then observe how many of the economies which are in an income state say between 0.75 and 1 in the initial period remain in that very state, or shift elsewhere in the next time period. If they end up in another income state, there is said to be mobility, ending up in the same state represents persistence.

The probabilities obtained, give us the percentages of economies or regions (in our case, Indian states) which given a starting state, have moved on to a different state.

The transition probability matrix measures in each cell the transition from one state of relative income to the same or another state of relative income. It therefore, measures the probability with which the income level in a country or region rises, falls, or remains unchanged between two periods (Magrini, 2007). These probabilities are normalized so that the sum of each row probabilities adds up to 1. We need to observe how many such transitions take place in the given time period.

Transition matrices are said to encounter the problem of discretization of the transition process into pre-determined ranges. Thus unlike standard regression approaches this method allows us to identify specific distributional characteristics such as polarisation and stratification, as discussed earlier. In the transition matrix, the income states selected are arbitrary; with different income classes we could have different results.

This Markov process for relative incomes can be modeled not only as a discrete formulation that uses transition matrices, but also as a continuous formulation using a 'stochastic kernel'. The stochastic kernels are able to overcome the problem of discretization of the transition process into pre-determined ranges. A stochastic kernel amounts to a transition matrix with an infinite number of infinitely small ranges. The stochastic kernel thus replaces the discrete income states by a continuum of states.

3.5.1.2 Kernel Density Estimator

The probability density function is estimated in a non-parametric form and the relative densities are estimated using kernel estimates. While the parametric approach forces a distribution to follow pre-determined distributional features, a non-parametric density estimation overcomes this and provides full information on the entire income distribution.

The most simple and frequently used non-parametric density estimator is the histogram. However, this instrument suffers from two limitations. First, histograms are not smooth, and second, the class frequencies would change depending on end points of the class-intervals selected to cover the data values (Silverman, 1986).

The kernel density estimators overcome both these problems quite easily. Under this method, each data point is the centre of normalized density function, referred to as the kernel. Densities are then added vertically to produce the estimation of the distribution (Monfort, 2008). The distribution of relative per capita incomes is then studied through the visualization of probability density functions which are estimated using kernel estimates (Laurini et al., 2005).

A probability density function *f(x)* of a random variable *X* is defined as

$$(3.8) \quad f(x) = \lim_{h\to 0} \frac{1}{2h} P(x - h < X < x + h)$$

For any given "h", we can estimate $P(x - h < X < x + h)$ by the proportion of the sample falling in the interval $(x - h, x + h)$. Thus a natural estimator $\hat{f}$ of the density is given by choosing a small number "h" ,where n refers to the real observations and setting

$$(3.9) \quad \hat{f}(x) = \frac{1}{2hn} P\ (number of X_1, \ldots\ldots, X_n falling in\ (x - h, x + h))$$

This is described as the naive estimator. To express the estimator more transparently, a weight function *w* is defined

$$(3.10) \qquad w(x) = \begin{Bmatrix} \frac{1}{2},\ if|x| < 1 \\ 0, otherwise \end{Bmatrix}$$

This suggests that the naive estimator can be written as

$$(3.11) \qquad \hat{f}(x) = \frac{1}{n} \sum_{i=i+1}^{n} \frac{1}{h} w\left(\frac{x - X_i}{h}\right)$$

To generalize the naive estimator, the weight function "w" is replaced by a kernel function *K* which satisfies the condition

$$(3.12) \qquad \int_{-\infty}^{\infty} K(x)dx = 1$$

By analogy with the definition of the naive estimator, i.e. *kernel estimator* with kernel *K* is defined by

$$(3.13) \qquad \hat{f}(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where "*h"* is the *window width,* also called the *smoothing parameter* or *bandwidth.*

There are two choices to be made here –

a) appropriate kernel function and
b) The bandwidth "h".

Kernel functions like the Uniform, Triangular and Epanechnikov kernels are commonly used but the Gaussian kernel is most popular as it has certain properties that are not present in the other kernels (Wand & Schucany, 1990).

First, the Gaussian kernel is said to be "universal", that is, it approximates bounded, continuous functions arbitrarily well. Secondly, Gaussian kernels are considered to be smooth and are used when additional information about the data is not available. Thirdly, being a squared exponential kernel, it can provide access to all analytical functions and with more data it can represent more complex relationships. The Gaussian kernel (see Martinez & Martinez, 2002) is represented as:

(3.14) $$K(x;\ \sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{x^2}{2\sigma^2}}$$

The width of the Gaussian Kernel "σ" is the standard deviation of probability density function and its square (σ^2) is the variance. The exponential power term indicates that this Gaussian kernel is normalised and the total area under the curve integrates to unity.

Silverman (1986) argued that the choice of kernel is not crucial since any kernel would be optimal for large enough samples. In contrast the selection of the bandwidth "*h*" is more complicated as it involves a trade-off between bias and variance (Wang, 2004). In keeping with the literature we choose a bandwidth that minimizes the asymptotic mean integrated square error (*AMISE*), in order to balance between the bias and the variance of the estimation (Kar et al, 2011).

3.5.2 Population Weighted Estimators

The sum "k" in equation 3.13 above, is now replaced by the weighted product "*wk"*. The weighted estimator given below, are expected to alter the height of the individual bumps (Gisbert, 2003).

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} wK\left(\frac{x - X_i}{h}\right) \qquad (3.15)$$

3.5.3 Cluster Analysis

In cluster analysis, groups or clusters in data can be identified. Besides, multimodality in a distribution occurs due to the presence of a cluster structure (Everitt et al, 2011). Hierarchical clustering is one of the methods in which clusters can be formed. The hierarchical classification clustering can be created by computing the distance matrix between individual observations in the raw data. There are three types of hierarchical clustering techniques namely;

a) Single linkage clustering which sees the distance between the closest pair of observations, b) Complete linkage clustering considers the distance between the most remote pair of observations, and c) Average linkage in which the average of distances between all pairs of observations is taken.

Cluster analysis is often graphically shown with the help of a tree diagram known as a dendrogram.

3.5.4 Dendrograms

The dendrograms groups observations at various levels of similarity or dissimilarity. At the bottom of the dendrogram, each observation is considered its own cluster. The observations combine until, at the top of the dendrogram, all observations are grouped together. The height of the vertical lines and the range of the (dis)similarity axis gives visual clues about the strength of the clustering. Long vertical lines at the top of the dendrogram indicate that the groups represented by those lines are well separated from one another. We need not use just intuition to decide on how many clusters to form. There are formal stopping rules.

3.5.5 Stopping Rules

One stopping rule common in cluster analysis is the Duda-Hart test (complete linkage). It works with hierarchical cluster analysis (as it wants to know at each level of hierarchy which group is to be split and how) and accordingly identifies the number of clusters.

The Duda–Hart test (Duda, et al, 2001, pg. 29) statistics is = Je(2)/Je(1), where, Je(1) = sum of squared errors within the group that is to be divided. Je(2) = sum of squared errors in the two resulting subgroups.

With this rule we have a "distinct clustering" statistic that we can visually compare between cluster and thus decide for the different numbers of clusters. In addition to checking for clusters, we can also test for presence of multi-modes in a distribution.

3.5.6 Silverman Test for Multimodality

There are many tests for testing presence of multimodality in the distribution. Here we have used the Silverman's test of multimodality that uses nonparametric kernel density estimation techniques to determine the most probable number of modes. In the equation 3.13, the selection of the bandwidth h is very important as a small value of h will give a very noisy density estimate, while a large value gives a over smoothed one. But in the test for multimodality what we are really concerned about is identifying the number of modes. The Silverman's test for multimodality, relies on a null hypothesis that a kernel density distribution "f " for "k" number of modes, (where "k" is a non-negative integer, see equation 3.12). If this is rejected then the distribution has more than "k" modes. When the kernel density distribution is constructed, the degree of smoothness is controlled by the value of the bandwidth "h" – the larger "h" is, the smoother the curve and more likely for the distribution to be uni-modal (Silverman, 1981). The critical window width "$h_{critical}$" is the smallest "h"that produces a density with "k"modes and is stated as:

$h_{critical}$ (k)= inf {h: $\hat{f}$ (..,h) has at most k modes}. Therefore, for all $h \leq h_{critical}$ (k), the estimated density distribution "f" has atleast "k+1" modes. The value of the critical bandwidth is computed using the Stata program developed by Salgado-Ugarte et al, (1997). Further, we use bootstrap tests which are used based on the concept of critical bandwidth introduced by (Silverman, 1981).

3.6 Quantile Regression Approach

A major limitation of using OLS to study inequality is that it ignores the fact that the explanatory power of the regressor may differ at different locations of the distribution. Two features of quantile regression are relevant to the estimation of the neoclassical growth model. First, the classical properties of efficiency and minimum variance of the OLS estimator are obtained under the restrictive assumption of independently, identically and normally distributed errors. When the distribution of errors is non-normal, the quantile regression estimator may be more efficient than the OLS estimator. Second, the quantile regression estimator is robust to the outliers and to the long tails with respect to the distribution of the residuals (Canarella & Pollard, 2004; Koenker & Bassett, 1978).

3.6.1 Quantile Regression Model

The quantile regression method was introduced by Koenker & Bassett (1978), and is described in the following equation

(3.16) $$y_{\mathrm{i}} = x'_{\mathrm{i}}\beta_q + e_{qi}$$

where y_{i} is the dependent variable, x_i the independent variable. Instead of having one coefficient β , we have sets of coefficients β_{q}, where these coefficient would be associated with the qth quantile of the dependent variables and e_{qi} is the unknown error term, that satisfies the constraint;

(3.17) $$Quant_q(\, e_{qi}/x_{\mathrm{i}}) = 0$$

with errors having the zero conditional mean.

As far as the estimation procedures are concerned, we know that the OLS minimises the sum of squares, $\sum_{\mathrm{i}} e_{\mathrm{i}}^2$ of the model prediction error e_{i}. so we minimise the sum of those e_{i} that is $\sum_i e_i^2$ squares.

In median regression also called as the *least absolute-deviation regression* we minimise the summation of the absolute values of the e_i , that is $\sum_i |e_i|$, which is different from the above sum of squares.

Thus the quantile regression will minimise the following;

(3.18) $$\sum_i q|e_i| + \sum_i (1-q)|e_i|$$

Along with e_i, the absolute value, we have q and 1-q, a sum that would give the asymmetric penalties q$|e_i|$ for under prediction and (1- q)$|e_i|$ for over prediction. We thus have $\beta_{q \text{ instead}}$ of β to emphasize that the different choices of "q" estimate different values of β. If we expand the above expression, we have, the "qth" quantile estimator$\widehat{\beta q}$ that minimizes βq over the objective function;

(3.19) $$Q(\beta_q) = \{ \sum_{i:y_i \geq x`_i\beta q}^{N} q|y_i - x`_i\beta_q| + \sum_{i:y_i < x`_i\beta q}^{N} (1-q)|y_i - x`_i\beta_q|\}$$

The expression 3.18 is expanded form of expression 3.17, except the error is substituted from the above equation 3.18. We have a penalty of "q" for under prediction, where the actual value of y is higher than the predicted value and we have a penalty of 1-q, when the actual value is lower than what we predicted by the model, this is a penalty for over prediction.

As we keep on increasing q, the quantile from 0 to 1, we can get a complete picture of the entire conditional distribution. Thus the entire distribution of the per capita growth rate which is conditional on the explanatory variables can be traced.

3.6.2 Quantile Regression Coefficient and Marginal Effects

In the equation 3.20, we specify the standard quantile to be linear:

(3.20) $$Q_q(y_i|x_i) = x'_i\beta_q$$

for the jth regressor, we take the derivative of the expression $x'_i\beta_q$ with respect to x_i or x_j we would find the coefficient β_{qj}

(3.21) $$\frac{\partial Q_q(y_i|x_i)}{\partial x_j} = \beta_{qj}$$

A quantile regression parameter β_{qj} estimates the change in a specified quantile "q" of the dependent variable "y" produced by a one unit change in the independent variable x_j. Importantly, every time we interpret these marginal effects we have to specify the particular quantile or percentile, say at the 25th quantile. In OLS we look at only the mean coefficient, but are not focused on any quantile as such. We notice that if the parameter q is changed from the interval 0 to 1, we can get the entire distribution of the growth rate of NSDP per capita. For example, if our dependent variable is the per capita NSDP growth rate and we considering two quantiles, q=0.10, i.e. states on the left tail of the distribution of the NSDP growth rates (the low income states) and q=0.90, the states on the upper tail of the distribution of NSDP growth rate, we would have different estimates for q=0.10 and q=0.90. This means, the marginal change in the explanatory variable will affect differently the per capita NSDP growth rate, depending on whether we are considering the10th or the 90th quantile. This is in sharp contrast to the conditional mean method, wherein it is not possible to see the different impact of the explanatory variables on the states concerned.

In the quantile regression approach, two types of significance are important for the QR coefficient: firstly, quantile coefficients can be significantly different from zero, and these are similar to the standard significance that are in OLS models. Secondly, Quantile coefficients can be significantly different from the OLS coefficients, showing different effects along the distribution of the dependent variable.

3.6.3 Panel Quantile Models and Estimation Issues

Though there exists many studies that use both the panel data methods and the quantile regression methods individually across the countries and regions, less work has been carried out combing both these methodologies. There are two methods for estimating quantile regression for panel data. One is correlated-random-effects type model given by Abrevaya & Dahl (2008) and the other is penalized fixed-effects model by Koenker (2004). According to (Koenker, 2004) as the quantile regression models are non-linear, when the individual effects are introduced to take into account the unobserved individual heterogeneity in these models some complications might arise. In the linear models to eliminate the state specific or the country specific effects, certain transformations like within transformation, time differencing are used. All these are not present for non-linear models and as such the individual effects cannot be ruled out. Only with the individual dummies these can be estimated. With panel data, the cross section dimensions will rise with the sample size leading to inconsistent estimates. To overcome this bias a penalty term L1 is introduced by shrinking the fixed effect coefficient to zero. With individual effects the variability of the estimates increases. The shrinking of this type towards a common value would reduce this variability. The other alternative to the fixed effect approach has been the correlated-random-effects model. In this case a particular structure is imposed on the relationship between the individual effects and regressors that would result in correlated-random-effects (CRE) quantile regression model. With this, a correlated random coefficients model is obtained that could be estimated using the standard quantile regression techniques.

This study employs the Regression Quantile for Panel Data (rqpd) package in R to estimate the quantile regression model with panel data.

3.7 Instrumental Variable Approach

Variables under econometric models are divided into exogenous and the endogenous variables. "Exogenous" variables are those whose values are determined outside the model and are assumed to be statistically independent of all stochastic disturbance terms of the model. While, the "endogenous" variables are not statistically independent of stochastic disturbance terms (Castineira & Nunes, 1999).

One of the assumption of the OLS regression is that there is no correlation between the explanatory variable and the error term that is $E(u / x) = 0$. A multiple regression model suffers from functional form misspecification when it does not take into account the relationship between the dependent and the observed explanatory variables. (Wooldridge, 2009). Thus a regression is said to be inconsistent if there is correlation between the explanatory variables and the error term

$$Y_i = \beta_0 + \beta_1 X_i + U_i \qquad (3.22)$$

One of the problems in growth studies is the likely endogeneity that may come up in the right hand side variables. There are three reasons for endogeneity;

a) Omitted variable bias (Model misspecification) - from a variable that is correlated with X but is unobserved, so cannot be included in the regression or there is another variable which is correlated with both x and y) so that after fitting the model above there is still a relationship with this other variable and the residuals. e.g, earnings depend on the years of schooling and ability. We cannot measure ability, but included in the error term, thus omitted variable.

b) Simultaneous causality bias (reverse causality) - changes in the LHS variable may cause changes in a RHS variable or that the LHS variable and a RHS variable are being jointly determined, then there is simultaneity

c) Measurement error- this arises when relevant explanatory variables may be poorly measured.

To obtain consistent estimators of β_0 and β_1, when the regressor and the error term are correlated we need an additional variable or an instrument (say Z) that will eliminate the bias caused by the above three sources. For an instrumental variable (an "instrument *Z*") to be valid, it must satisfy three conditions(Wooldridge, 2009).

1. Instrument relevance: $\text{corr}\ (Z_i X_i) \neq 0$

The instrumental variable Z_i should be strongly correlated with the endogenous variable. If we have instruments that are completely irrelevant and uncorrelated with the endogenous variable than there is no point in having those instruments.

2. Instrument exogeneity: $\text{corr}\ (Z_i u_i) = 0$

The instrument Z should be uncorrelated with the error term. The goal here is to find out those instruments that are not correlated with the error term that influences the regressors.

3. $\text{corr}\ (Y_i, Z_i | X_i) = 0$

The instrument Z_i is not the direct cause of dependent variable Y_i. Z_i is not in the Y_i equation. The main issue in real life is to find relevant instrumental variable.

If we have a valid instrument, Z_i , we can regress X_i on Z_i, obtain the predicted values for X_i, regress *Yi* on predicted X_i. The instrumental variable estimator employed in the context of endogeneity, is known as two-stage least squares method. The coefficient $\hat{\beta}_1$ on predicted X_i is the two stage least square (TSLS) estimator, which is a consistent estimator of β_1. The instrumental variables technique can readily be extended to the case of multiple regression and any number of additional exogenous variables can be used in the equation.

3.7.1 Two Stage Least Square Estimation Procedure

Endogeneity occurs when one or more independent variables are correlated with the error term, which means corr (X_i,u_i) ≠ 0, and this causes the estimated coefficient to be biased. We can rewrite the linear regression model

$$Y_i = \beta_0 + \beta_1 X_i + u_i \quad (3.23)$$

in the form of the following structural equation;

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 \gamma_2 + u_i \quad (3.24)$$

Yi is the dependent variable, γ_2 is the endogenous variable, with X_i and u_i as the exogenous variable and the error term respectively. The structural equation model thus involves a combined set of both the endogenous and the exogenous variables, (X_i, γ_2)

We need to find a set of instruments Z that would be associated with X but not with error term u. Instrument Z could be used to correct for the endogeneity and accordingly estimate coefficients which have been corrected for the endogeneity problem.

The Two Stage Least Square estimation replaces the endogenous variable with the predicted value of this endogenous variable when regressed on the instruments. In the first stage or the reduced form of equation with only the exogenous regressor thus we have

(3.25) $$\gamma_2 = \alpha_0 + \alpha_1 Zi + e_i$$

Two stage least square proceeds by first regressing γ_2 on Zi to get $\widehat{\gamma_2}$, then regressing Y_i on $\widehat{\gamma_2}$. $\widehat{\gamma_2}$ is regressed on the exogenous variable as well as on the instrument which occurs only in this equation, but does not belong to the original equation. We then save the predicted value of the endogenous variable $\widehat{\gamma_2}$ and substitute it in the structural equation model (3.23). Instead of the original variable γ_2, we use the predicted value $\widehat{\gamma_2}$ that is derived from first stage least square estimation.

3.7.2 Selection of the Instrumental Variables

If statistically sound and theoretically reliable instrumental variables are available than the instrumental variables estimation will generate consistent parameter estimates (Angrist & Krueger, 2001). A reliable instrumental variable should satisfy two important conditions:

1) It should be correlated significantly to the endogenous variable, this determines the strength of the instrument and,
2) It should be exogenous in the structural equation. This is referred to as the validity condition.

Selection of weak instruments needs to be avoided. If the variations in the endogenous variables are not explained sufficiently well by the instrumental variables, there could be large standard errors in the IV estimates (Stock & Yogo, 2001).With weak instruments, the results will be biased towards the OLS estimation. Adding more and more instruments also does not solve the problem.

3.7.3 Identification Issues

In econometrics, if a parameter is constructed from the joint distribution of the random variables, it is referred to as an identified parameter (Angrist & Krueger, 2001). In the IV approach, the relation between the number of instruments (Z) and the number of endogenous regressors (k) decides whether the coefficients are identified or not. We require at least one instrument for one endogenous variable. There could be three possibilities wherein the coefficients could be;

1) Just or Exactly Identified: *($Z=k$)*

If there is one instrument for each of the endogenous variable. In this case the estimator would be unbiased.

2) Under-identified; *($Z>k$)*

There are few instruments to estimate the endogenous regressors.

3) Over-identified *($Z<k$)*

In this case there are more instruments than the endogenous variables. This is a desirable. However it is important to test if the instruments are valid. If we have more instruments than the endogenous variables then we could use two efficient estimators in this model.

Thus in the instrumental variable approach, a valid instrument would isolate the part of the endogenous variable that is not related with the error term and this part is used to estimate the impact of change in the endogenous variable on the dependent variable.

In this section we discuss issues of spatial dependence.

3.8 Spatial Econometric Framework

When we discussed the notion of convergence, we considered each region or the state as an independent entity, while completely ignoring the interactions with the other states. Spatial dependence among the observations if ignored could give rise to model misspecification(Anselin, 1988). This spatial dependence is quantified through Spatial Weight Matrix. Recent developments in spatial econometrics have offered different procedures to test for these interactions (see Anselin, 1995, 2010; Elhorst, 2014). In our study, the exploratory spatial data analysis (ESDA), that uses innovative techniques is applied to find the evidence of spatial autocorrelation and spatial heterogeneity. We then apply the confirmatory spatial analysis that constructs and estimates the econometric equations based on the formal growth theories.

3.8.1 Spatial Weight Matrix

In time series analysis, the dependence among the observations is seen over time, whereas spatial econometrics focuses on dependence of the observations across space and uses the Spatial Weight Matrix (SWM) to describe the spatial arrangements of the geographical units. Each spatial unit is represented as a row and a column. SWM thus shows the spatial relationship among the observations, which are considered as neighbours and also how their values are related to each other. If two observations are close to each other they will influence each other a lot more than the ones which are located far away from each other. We need to account for this spatial dependence in the regression model. The Spatial weight matrix is given by

(3.26) $$W = (W_{ij}, \text{ where } i \text{ and } j = 1,...,n)$$

and shows the spatial relation between *n* spatial units. The spatial weight W_{ij} reflects the "spatial influence" of unit *j* on unit *i* . Each unit's value is the weighted average of its neighbor's. The SWM is row standardized, thus weights add up to 1 on each row. Each row represents the value for a unit as a weighted average of the neighbor's. This is done to create proportional weights when regions do not have equal number of neighbours. Each row standardized weight is the *fraction* of all spatial influence on unit *i* attributable to unit *j*. The diagonal elements of the matrix are equal to zero. The non diagonal elements are non zero for observations that are close spatially and zero for those that are far away.

1) ***Contiguity***:

Contiguity is when the observations touch, share a border, a line or vertex (points). With the help of Geographic information systems (GIS) software we can recognize the contiguity and use the data. W_{ij} is equal to one if *i* is contiguous to *j* and zero otherwise. All neighbours get the value of 1 and non neighbours get the value of 0. The diagonal elements are equal to 0 since a unit cannot be a neighbour of itself (W_{ii}=0).

In general,

(3.27) $$Y_i = \sum W_{ij} Y_j$$

Yj is the value of the neighbour and *Wij* is the influence of the neighbours. When this matrix is row standardized, each row represents the unit value as a weighted average of the value of its neighbours. The weights based on boundaries are classified as under;

a) *Spatial Contiguity Weights.*

Contiguity-based weights matrices are divided into rook and queen contiguity. In the case of rook contiguity, areas are neighbours if they share borders, and not vertices(for example on a grid, only the cells to the North-South and East-West are neighbours).

While in case of queen contiguity, areas are neighbours if they share either a border or point (like, on a grid, in addition to the four cells included under rook, the four cells sharing a corner with the central location are also counted as neighbours).

b) *Shared-Boundary Weight*:

In this case, weights are assigned according to the length of the border shared between two states. The length of shared borders between states is used since the spatial spill-over is expected to be proportional to the possibility of connectivity between two states.

2) ***Distance***:

In contrast to contiguity-based weights, which are based on common borders (and/or vertices), distance-based weights rely on the distance between points. We need to know the location of the observations (X and the Y coordinates or the latitudes and the longitudes) to calculate the distance between observations. For the state level data, we can use the distance between the centroids or the centre points of the states. If two states are close to each other, the distance is smaller than for those who are located far away. Thus the Dij can be distance between observations i and j. We assume that there are no spatial effects beyond a particular distance band. Thus the *Dij* is one if the distance between i and j is less than the distance band and it is zero otherwise. The SWM is constructed based on distance where the units within a specified radius have a spatial weight that is equal to one (neighbours) and zero otherwise. Higher weight is assigned to states which are closer to each other and vice-versa. An alternative way of constructing a SPW based on distance would be where this distance D_{ij} receives a weight that is inversely proportional to the distance between the units and zero if they are beyond a certain distance band D. So if we have Wij, the elements are equal to 1/dij, if the distance between i and j< D and zero otherwise. Thus farther they are from each other less is the influence.

We can thus have the following weight matrices based on the centroid distances, *Dij* between each pair of spatial units *i* and *j*.

a) *K-Nearest Neighbour Weights*: K-Nearest Neighbours is a distance-based definition of neighbours wherein “k" refers to the number of neighbours of a location. It is computed as the distance between a point and the number (k) of nearest neighbour points (i.e. the distance between the central points of polygons). It is applied when areas such as states, have different sizes to ensure that every location has the same number of neighbours, independently how large the neighboring areas are. We thus choose the k nearest points as neighbours. Positive weights are assigned to all *ij* pairs for which at least one is among the *k*-nearest neighbours of the other.

b) *Radial Distance Weights*: Distance bands are created by drawing a radius (of the defined minimum threshold distance) around each point and counting every point within the radius as a neighbor. The default threshold distance ensures that every observation has at least one neighbor. If *d* denotes a threshold distance or the bandwidth, then beyond *d*, there is no direct spatial influence between spatial units.

c) *Inverse-distance based matrix*: The inverse of the Euclidean distance between the geographical centroid of two states is used as the weight. This form of weighing ensures that higher weight is given to states which are closer to each other and vice-versa.

3.8.2 Methods of Estimation

Different methods like maximum likelihood (ML) or quasi-maximum likelihood (QML), instrumental variables (IV) or generalized method of moments (GMM) Bayesian Markov Chain Monte Carlo methods (Bayesian MCMC) are used to estimate the spatial econometric models (see Elhorst 2014). In this study we use the maximum likelihood estimation method.

3.8.2.1 Maximum Likelihood Estimation

The least square method and the maximum likelihood method are the two methods that are generally used for parameter estimation. The ordinary least squares (OLS) estimation however is inappropriate for models with spatial effects. In the case of spatial error autocorrelation, the OLS estimator of the response parameters remains unbiased, but it is inefficient.

While in case of a spatially lagged dependent variable, the OLS estimator of the response parameters loses its property of being unbiased and also becomes inconsistent. Thus to overcome these problems maximum likelihood technique for spatial regression models including SAR, SDM, SEM and SAC is been used for both, the cross section and the panel data estimation.

Since we are using the MLE in estimating the spatial process models, the following three testing procedures are employed;

a) Likelihood Ratio (LR) Test,

b) Wald Test,

c) Lagrange multiplier Test (Score Test)

In order to know whether the model with more predictor variables or with few predictors fits significantly well, we can employ three test; the likelihood ratio (LR) test, the Wald test, and the Lagrange multiplier test.

The null hypothesis for all three tests is that the smaller model is the "true" model. The goal of a model is to find the set of parameter estimates that make the data most likely. The likelihood is a function of the coefficient estimates and the data. As the data cannot be changed, one can change the estimates of the coefficients in such a way as to maximize the probability (likelihood). Different parameter estimates, or sets of estimates give different values of the likelihood. Generally instead of employing the likelihood itself, the log of the likelihood is adopted. The log likelihood is always negative and if there are higher values then it is a better fitting model.

1) The Likelihood Ratio Test

To perform the LR test, two models are estimated and the fit of one model to compared to the other. Removing predictor variables from the model makes it have a lower log likelihood, but we need to test if the observed difference in model fit is statistically significant. The LR test does this by comparing the log likelihoods of the two models, if this difference is statistically significant, then the less restrictive model (the one with more variables) is said to fit the data significantly better than the more restrictive model.

2) The Wald Test

The advantage of the Wald test over the LR test is, it requires estimating only one model. The Wald test works by testing the null hypothesis that a set of parameters is equal to some value. The null hypothesis in the model being tested here, is that the two coefficients of interest are simultaneously equal to zero. If the test fails to reject the null hypothesis, this suggests that removing the variables from the model will not substantially harm the fit of that model, since a predictor with a coefficient that is very small relative to its standard error is generally not doing much to help predict the dependent variable.

3) Lagrange Multiplier or Score Test

Like the Wald test, Lagrange multiplier test also requires estimating a single model. The only difference is that, in Lagrange multiplier test, the model estimated does not include the parameter(s) of interest.The test statistic is calculated based on the slope of the likelihood function at the observed values of the variables in the model.This estimated slope or "score" is the reason the Lagrange multiplier test is sometimes called the score test. The scores are then used to estimate the improvement in model fit if additional variables were included in the model. The test statistic is the expected change in the chi-squared statistic for the model if a variable or set of variables is added to the model. Because it tests for improvement of model fit if variables that are currently omitted are added to the model, the Lagrange multiplier test is sometimes also referred to as a test for omitted variables.

We notice that all three tests address the same basic question of whether leaving out certain predictor variables reduce the fit of the model. The difference between the tests lies in how the issue is addressed. To perform a likelihood ratio test, one estimates both the models it needs to compare. In contrast to only one model that is estimated for Wald and LM test. The values of the Wald and LM test statistics will become increasingly close to the test statistic from the lr test as the sample size becomes infinitely large. With finite samples, though all the three test could generate different test statistics, they arrive at the same conclusion. An interesting relationship between the three tests is that, when the model is linear, the three test statistics have the following relationship Wald ≥ LR ≥ LM. To select the right model we can use the LR test. Wald or LM tests can be used to test if the model is a SAR or a SEM, once that the (unrestricted) SDM model has been estimated (Belotti, et al 2013).

3.8.2.2 Model Comparison and Selection

To test for spatial interaction effects in a cross-sectional setting, Burridge and Anselin (1988)developed Lagrange Multiplier (LM) tests for a spatially lagged dependent variable and for spatial error correlation. Later Anselin in 1996, introduced a robust LM tests to test for a spatially lagged dependent variable in the presence of spatial error autocorrelation and for spatial error autocorrelation in the presence of a spatially lagged dependent variable.

3.8.2.3 Selection of Models based on Information Criterion

The AIC and the BIC are two popular measures for comparing maximum likelihood models. AIC and BIC are defined as,

(3.28) $$\text{AIC} = \boldsymbol{-2 * ln(likelihood) + 2 * k},$$

(3.29) $$\text{BIC} = \boldsymbol{-2 * ln(likelihood) + ln(N) * k}$$

Where, K is the number of parameters estimated and N= number of observations.AIC and BIC can be viewed as measures that combine fit and complexity. Fit is measured negatively by $-2 * ln(likelihood)$; the larger the value, the worse the fit. Complexity is measured positively, either by $2 * k(AIC) or ln(N) * k\ (BIC)$.The difference between AIC and BIC is that AIC uses the constant 2 to weight k, whereas BIC uses $ln(N)$.

3.9 Summary

The Solow's and the Baumol's work has inspired extensive research and discussion on the quality and validity of classical convergence models. In this chapter, various econometric methods offering improvements over the classical convergence model were discussed. These methods form the basis for the empirical analysis that follows in the subsequent chapters. To control for variables that cannot be measured or observed, the panel data estimation techniques are required, the first section discussed this methodology. Quantile regression methods for both cross section as well as panel data are used to analyze heterogeneity in the distribution (see Koenker & Bassett, 1978; Koenker, 2004).Many studies have identified the neglected nonlinearities (which renders the β-convergence to be invalid for different types of data sets). A nonparametric alternative, (see Quah, 1997) like using the kernel plots, transition matrices are discussed. To address the issue of endogeneity, the instrumental variable approach is also attempted. While discussing convergence, regions are viewed as independent entities, the dependence that exists, between the regions is not emphasized in the classical models. Spatial dependence among the observations if ignored could give rise to model misspecification. Recent developments in spatial econometrics have offered different procedures to test for these interactions. The exploratory spatial data analysis (ESDA), which uses innovative techniques, is applied to find the evidence of spatial autocorrelation and spatial heterogeneity were discussed in this chapter.

In the next chapter we first provide an analytical description of the economic performance of Indian states in terms of their per capita NSDP in the pre and the post reform period. Convergence hypothesis is then tested across the states in India.

Chapter IV

Growth and Convergence across Indian States: Pre and Post Liberalization Period

4.1 Introduction

India with its vast diversity in terms of geography, language, demography, political and social norms, has experienced different levels of economic development across its states. Since Independence the major objectives of planned development strategy in India has been to accelerate economic growth and also to achieve regional balance. Numerous policies and programmes were adopted to achieve regional balance in the economy. All states have not been able to achieve similarity in their economic performance. The economic reforms in 1991, initiated major structural adjustment and liberalization programmes. Critics of economic reforms argue that the reforms were responsible for greater disparities (Ghosh, 2008; Kurian, 2000; Rao, et al, 1999). While, some argue that these reforms have benefited both the poor as well as the rich states in India (Ahluwalia, 2000). Others have argued it was possible to sustain the growth trend of 1980s because of the liberalization of the 1990s (Panagariya, 2004). We first look at the performance of states in the pre and the post-reform period in terms of per capita NSDP and the growth rates (see Table 1).Studies on regional disparities generally have not considered the special category states (see Rao et al, (1999); Ahluwalia (2000); Ghosh (2008); Nayyar (2008). The reasons given for their exclusion has been that these states have a small proportion of population with geographical and economic conditions different from the mainstream. Many studies have thus either used the data for non-special category states because of their similarities or only the major states.

Table 1: Per Capita NSDP and its Annual Growth Rates across the States (1981-82 & 2013-14 at 2004-05 Constant Prices)

State	1981-82(Rs)	State	2013-14(Rs)	Annual Growth Rate(%)
Delhi	23442	Goa	120226	6.20
Goa	17700	Delhi	117995	5.13
Punjab	16386	Sikkim	94668	8.13
Puducherry	15966	Pondicherry	79807	5.49
Andaman & Nicobar	14957	Haryana	71569	5.26
Maharashtra	14043	Maharashtra	61359	4.67
Haryana	14017	Tamil Nadu	60432	6.17
Gujarat	12483	Andaman & Nicobar	57618	5.52
Arunachal Pradesh	10718	Gujarat	57304	5.40
Jammu & Kashmir	10350	Kerala	55688	6.78
Himachal P	10261	Punjab	49690	3.64
West Bengal	10140	Himachal P	49507	5.14
Tamil Nadu	9331	Andhra Pradesh	47672	5.65
Karnataka	8968	Arunachal Pradesh	45523	5.25
Sikkim	8937	Karnataka	45437	5.19
Manipur	8811	Nagaland	41586	5.55
Andhra Pradesh	8726	Mizoram	40830	5.52
Nagaland	8695	Uttar Pradesh	40231	5.44
Assam	8537	Tripura	37389	5.22
Kerala	8280	West Bengal	37233	4.03
Meghalaya	7965	Rajasthan	34918	5.21
Tripura	7891	Meghalaya	33013	4.48
Odisha	7581	Jammu & kashmir	31429	3.81
Madhya Pradesh	7550	Madhya Pradesh	30126	4.33
Rajasthan	7313	Orissa	28192	4.38
Mizoram	7266	Assam	24863	3.83
Uttar Pradesh	7030	Manipur	22299	3.18
Bihar	5485	Bihar	20748	5.18
India	11107	India	40455	4.13

Source: EPWRF and Authors' calculations.
States are arranged according to ascending order of ranking of per capita NSDP 2013–14.

Our study has taken into account both the special as well as the general category states. Table 1 shows widening disparities in growth rates as well as the per capita NSDP in the post reforms period. Sikkim, Kerala, Goa, Tamil Nadu, and Andhra Pradesh had impressive growth rates, and, among them, Goa, Sikkim, Pondicherry, Haryana, Maharashtra also had higher per capita income in 2013-14. Among the major states, Jammu & Kashmir, Madhya Pradesh, Orissa, Assam have lagged far behind both on per capita NSDP as well as growth in the post reform period, on the other hand, though Bihar has shown a better performance in terms of growth rate even though its per capita NSDP was the lowest in the latter period. Among the north eastern states, Sikkim is like an island in the north east and has shown a remarkable improvement.

Did all the richer states get richer and the poor states get poorer in the post reforms period? The answer is No! Punjab, one of the well performing states earlier has shown deceleration in growth rates. In contrast, Rajasthan, an earlier low income state has shown good improvement in the growth rates.

With heterogeneity in per capita income and growth rates, do the Indian states exhibit any tendency to converge toward a common steady-state path? Do Indian states reveal presence or absence of convergence? And if there is convergence, is it absolute or conditional?

4.2 Absolute and Conditional β - Convergence

We first begin with a simple framework as adopted by Barro, (1991). There is *absolute β convergence* if the poor regions grow faster than the rich ones. A relationship between the growth of per capita income and the initial level of income is modeled as below:

Thus,

(4.1) $$Gr_{i,t=} \beta_0 + \beta_1 \, lnpcnsdp_{\,i,t-\tau} + \varepsilon_{it}$$

Absolute β convergence assumes that states are homogenous and differ only in their levels of capital stock.Only if all regions converge to the same steady state, prediction of the classical growth model that poor regions should grow faster than rich ones holds true. However states in India differ in terms various factors like population growth rate, level of technology, investment rates, human capital, political, natural, social and historical factors. These could lead to different steady states for different regions or states- conditional convergence. Thus to test for *conditional convergence*, one has to hold the steady state of each region constant(Sala-i-Martin, 1996b). Classical economists tried to hold the steady state constant by identifying certain variables that proxy for the steady state in the regression equation. We expand the earlier model to a multiple regression equation,

(4.2) $$Gr_{it} = \alpha + \beta_1 \, lnpcnsdp_{i,\, t-\tau} + \psi X_{i,t-\tau} + \varepsilon_{it}$$

Where $X_{i,\ t-\tau}$ can be vector of variables that hold the steady state of an economy constant. Once we control for these vectors of variables and we estimate β to be negative, then we can affirm that there is conditional β convergence. We therefore need to find such variables that would proxy for the steady state. In the Indian context many such variables are identified, but the major point here is once some variables that proxy for the steady state are controlled for, the estimate of β can become positive and significant. If this is the case then this would be a robust finding (Sala-i-Martin, 1996b). Thus based on the availability of the data and past survey of literature, this study has identified certain variables that could proxy for the steady states across different regions in India(Ahluwalia, 2000; Barro & Sala-i-Martin, 1992; Barro, 1991; Ghosh et al., 1998; Nayyar, 2008).

4.3 Variables Considered in the Model

1) Human Capital:

With the inclusion of human capital within the traditional Solow model, we can yield conditional convergence. The importance of human capital in economic growth is recognized by many studies across the world (Barro et al., 1991; Lucas, 1988; Mankiw et al., 1992) as well as within India (Ghosh, 2008; Ravallion & Datt, 2002; Trivedi, 2002) With higher initial stock of human capital, countries tend to grow faster as it could generate new idea and new products(Barro, 1991). The type and the level of human capital in India could result in differences in growth rates among states. Low basic education attainments gives rise to income inequality and influences how much the poor can participate in skill-demanding non-farm growth (Ravallion & Datt, 2002). Literacy and education play a central role in human and overall social-economic development. Literacy rate is thus employed in this study as a proxy to human capital. In India, the Census obtains information on literacy for every individual. In the population census, a person aged seven years and above who can both read and write in any language, is treated as 'literate'. In the Censuses prior to 1991, children below five years of age were treated as illiterates. Since the ability to read and write with understanding is not ordinarily achieved until one has time to develop these skills, therefore in the 1991 Census, all children in the age group of 0-6 years were treated as illiterate by definition and population aged seven years and above only were classified as either 'literate' or 'illiterate'. India's literacy rate stood at 74. % in 2011, in comparison to a mere 44% in 1981. Over the years literacy rate has been increasing but with variations among states. Kerala and Mizoram were above national average and Bihar with a dismal rate of 64% in 2011(Census of India, 2011).

2) Political Factor:

Certain studies have identified the relationship between political decision making process and economic growth (Kohli, 2006). Different aspects have been examined as far as the politics-growth debate is concerned. Measures of democracy (Alberto & Perotti, 1996; Barro, 1991; P. Dasgupta, 1989), Government stability, political violence (Alberto & Perotti, 1996; Barro, 1989, 1991b), political volatility (Dollar, 1992),and subjective measures of politics (Brunetti, et al, 1997) have been used as explanatory political variables in earlier studies. In the Indian context it has been argued that the development of a state could be expedited if the same party ruled in both state and Centre. In India, for most of the years since independence, the federal government has been guided by the Indian National Congress (INC). The two largest political parties have been the INC and the Bharatiya Janata Party (BJP). Although the two parties have dominated Indian politics, regional parties also exist. From 1950 to 1990, barring two brief periods, the INC enjoyed a parliamentary majority. States in India have their own elected governments, whereas Union Territories are governed by an administrator appointed by the President. The central government exerts greater control over the Union Territories than over the States, although some territories have gained more power to administer their own affairs. There could be considerable center-state conflict when ruling political party in a state is different from the national ruling party. One such political variable employed in this study is the number of years the state party ally at the centre. This variable has been used as a dummy variable, if the state party ally at the centre then the value is 1, and 0 otherwise. In the regression model we have also used the square of political variable to accommodate a quadratic nonlinear relationship between growth and the political factor.

3) Components of Expenditure:

Government budget policy can influence the long-term growth rate through its decisions on priority based public spending in different sectors. This can influence the growth rate by way of increased saving (Harrod - Domar Model) or as anticipated in the endogenous growth models. We need to see the link between the components of government expenditure and economic growth across the states in India. In this chapter the total of the revenue and the capital expenditure on Education, Sports, Art and Culture (pceduexp) and Medical and Public health (pcmedexp) is considered.

The revenue expenditures of the Central and State budgets are divided into development and non-development expenditures. The development expenditure by the states includes expenditure on general, social and economic services. Within this, social services include education sports, art and culture, medical and public health, family welfare, water supply and sanitation, housing, urban development, labor and labor welfare, social security and welfare, nutrition, and relief for natural calamities. The economic services include agriculture and allied activities, rural development, special area programs, irrigation and flood control, energy, industry and minerals, transport and communications, science, technology and environment. The study includes two components of social services expenditures, 1)Education, Sports, Art and Culture(henceforth referred to as

Education expenditures) and 2) Medical and Public health, (referred as health expenditures), to analyze the long-run relationship between public expenditure on education, health and economic growth. There are three ways of examining trends in social sector expenditures. The first is to look at social sector expenditure as a proportion of GDP, the second is to calculate it as a percentage of overall government expenditure, and the third option is to look at real per capita social sector expenditure. Our analysis focuses on the real per capita social sector expenditure for states under consideration.

4) Urbanization:

Certain studies has viewed urbanization necessary for achieving high growth, increase in productivity and efficiency through specialization and diffusion of knowledge (Lucas, 1988; Spence, et al, 2009). Urbanization should be seen as a positive factor for overall development as higher growth rate of GDP can be attained if cities are made inclusive, bankable, and competitive (Planning Commission, 2008). In India, the urbanization level is measured by the percentage of population living in urban areas. In the Census of India, two criteria are adopted to decide the urban areas. a) When municipal status is granted by the state government, and b) the settlement has a population of more than 5,000, a density of 400 persons per Square Kilometre and 75% male workforce is in the non-agricultural sector. The urban population of India rose from 27.8 % of the total population in 2001 to 31.16% in 2011.Different states in India have a diverse pattern of urbanization, but economically advanced states more or less show higher levels of urbanization (Bhagat, 2011). However, urbanization may also deter firms from locating in larger cities due to negative spillovers including congestion and high land prices leading to dampening effect on economic growth. Urbanization is included in the analysis to provide evidence if it supports income growth.

5) Gender Composition:

Gender ratio is the number of females per thousand males. It is an important and useful social indicator to measure the extent of prevailing equity between males and females in a given population at that point of time. Gender differentials can arise due to difference in mortality rate, migration, sex ratio at birth and also due to the undercounting of women during population enumeration. Most of the populous countries like U.S.A(1026), Indonesia (1003), Russian Federation(1165) and Japan(1054), the women tend to outnumber men. Even among the Asian countries, India has much lower sex ratio than Myanmar (1048), Sri Lanka (1032), Nepal (1014), and even Bangladesh (978) in 2010.This inequality across the world highlights to the social factors responsible for low female to male ratios in Asian countries (Sen, 1992).

In India, sex ratio is skewed favouring males that have continued to rise and expand in various forms. As per Census 2011, India has a sex ratio of 943, slightly better than China (927). For rural India this ratio is 949 and for urban areas this is 929 females per 1000 males. More precisely, there has been a declining trend in the child sex ratio (0-6 years) in our country, which deteriorated from 927 in 2001 to 914 in 2011, as compared to the overall sex ratio.

The sex ratio in India is biased towards boys, particularly in the northern and western states. Technological developments permitting sex-selective abortions has seriously aggravated the imbalances in these states (Bhaskar &

Gupta, 2007). This declining child sex ratio can have a cascading effect on population over a period of time leading to diminishing sex ratio in the country. The diversity in overall sex ratio among the States and Union territories is phenomenal. Puducherry (1037) and Kerala (1084) recorded the highest sex ratio in 2011, while the regions of Daman and Diu (618) and Haryana (879) had the lowest density of female population.

This biased sex ratio in an economy could have a detrimental impact on the income and growth of the economy as it affects the labour force participation rate, changes in fertility rates, educational outcomes. Several studies have noted undesirable consequences like rising proportion of unmatched males with the families boys competing to match their sons with scarce girls, trafficking in women and increased rates of crime in the countries with declining sex ratios. Gender ratio is thus considered in this study as one of the variables determining growth (Edlund & Zhang, 2007; Golley & Tyers, 2012).

Many studies have employed these variables in their estimation of results on convergence across the states in India. For example, (Sachs, et al, 2002) has explained conditional convergence after controlling for the degree of urbanization. (Ghosh, 2008)employed production structures, public investment in human capital and infrastructure as explanatory variables. (Nayyar, 2008) using a dynamic panel data model , employs the literacy rate and public and private investment as control variables. (Karnik & Lalvani, 2012) focused on the contribution of educational attainment (social sector capital) to the growth process.

In testing for conditional convergence, therefore, we have explanatory variables like: (i) initial per capita Net State Domestic Product (initial log PCNSDP); (ii) Literacy rate (literacy); (iii) Gender ratio i.e. the number of females per thousand males (Gender); (iv) Urbanisation, the percentage of population living in urban areas. (Urban); (v) Per capita social sector expenditure on Education, Sports, Art and Culture in log (lnpceduexp), (vi) Per capita social sector expenditure on Medical and Public health in log (lnpcmedexp), and (vii) Political variable, the number of years the state party allies at the Centre (pol).

4.4 Estimation Results

Thus most empirical work on the conditional convergence uses cross section or pooled regressions with growth rate of income as the dependent variable and a host of factors as independent variables. However, a cross section or pooled OLS method reduces time series to a single or average observation. Another major limitation of the cross section estimation is that only the differences that can be measured or observed are taken into consideration. The estimated coefficients derived from regression may be subject to omitted variable bias. This is a problem that arises when there are unknown that cannot be controlled for that affect the dependent variable. With panel data, it is possible to control for some types of omitted variables even without observing them, by observing changes in the dependent variable over time. This controls for omitted variables that differ between cases but are constant over time(fixed effect). It is also possible to use panel data to control for some omitted variables that may be constant over time but vary between cases, and others that may be fixed between cases but vary over time (random effects). To switch from single cross section to panel data framework, the entire period of analysis is divided into several shorter time spans of five year time intervals. We use data up to 2010 as it allows us to take 5-year averages, since PCNSDP up to 2015 is not available yet.

Thus we have , six, 5-year spans namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10 (τ = 05). The compare it with a longer period the data is also divided into, three , 10-year spans, namely 1981-90, 1991-00 and 2001- 10 (τ =10). We first run the cross section regressions, followed by the pooled regression on the basis of the five year averaged data and then compare these results with the panel data estimation results.

4.4.1 Cross Section Regressions

To test for unconditional convergence, the simple OLS cross section regression takes the form of the following equation.

(4.3) $$Gr_{i} = \alpha + \beta_1 \, lnpcnsdp_i + \varepsilon_i$$

A negative relationship between the growth rate (Gr_i) and the initial per capita NSDP is the indication of unconditional convergence. Table 2 shows the relationship across 28 regions in India. For the cross section regression, the data set is divided into five sub periods viz; 1981-90 (pre reform), 1991-2000, 2001-13, 1991-2013 (post reform period) and the entire time period 1981 to 2013.

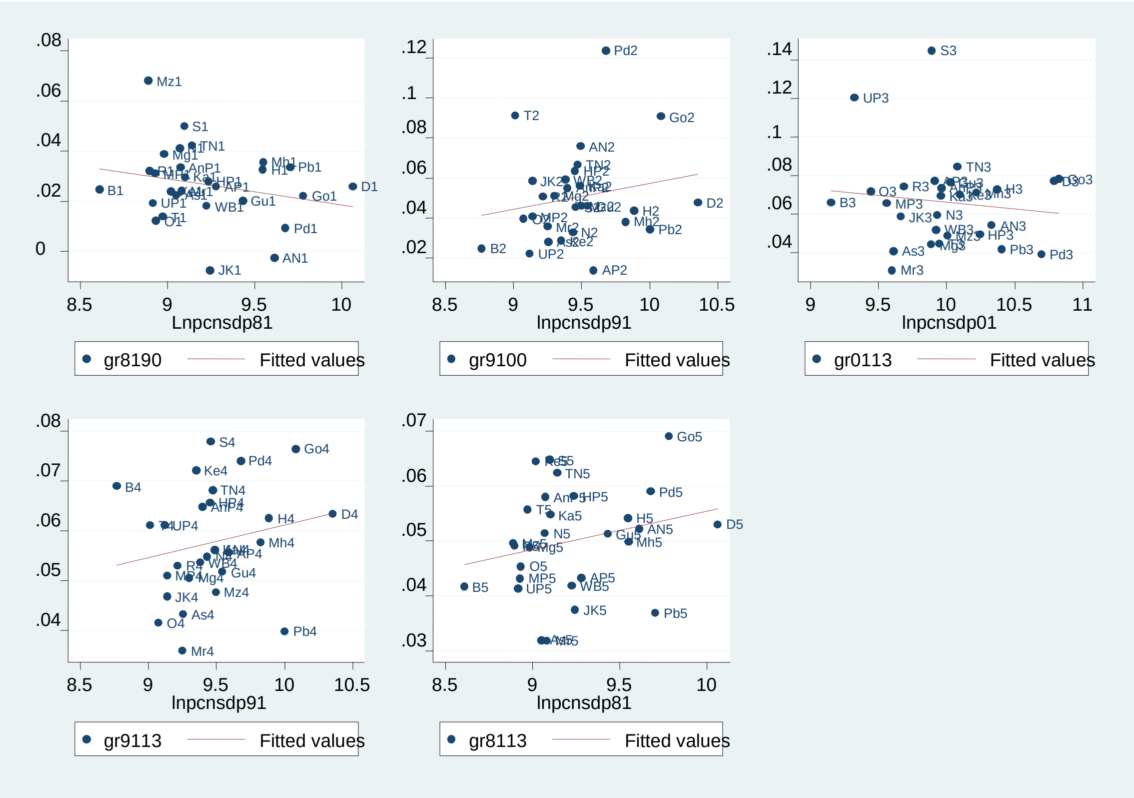
It can be seen that the results are not statistically significant for any of the periods taken into consideration. The hypothesis that the poor regions tend to grow faster than the rich ones seems to be inconsistent with the cross state evidence in India. The β coefficient is not significantly different from zero, so there is no evidence of convergence or divergence among the states when we use OLS estimation.

Table 2: Unconditional Convergence / Divergence

	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
Dependent Variables →	GR81_90	GR91_00	GR01_13	GR81_13	GR91_13
Independent Variables ↓	OLS (Cross Section Regression)				
lnpcnsdp81	-0.01 (0.007)			0.006 (.004)	
lnpcnsdp91		0.012 (0.013)			0.006 (0.006)
lnpcnsdp01			-.007 (0.01)		
Constant	0.122* (0.07)	-0.07 (0.12)	0.138 (0.112)	-0.014 (0.044)	-0.004 (0.063)
R-square	0.05	0.03	0.01	0.05	0.04
No of Observations: 28 Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1.					

Source: EPWRF data and Authors' calculations.

Figure 1: Per Capita Growth Rate and the Initial Per Capita Net State Domestic Product



Source: EPWRF data and Authors' calculations.

Though the slope of the curves for the post reform period (1991-13) and the entire period (1981-13) is positive in the Figure 1, the slope coefficient between growth rate and the initial per capita is not significant. Similarly for periods 1981-90, 1991-00, 2001-13 the results are insignificant. By employing control variables across the states we can estimate β that is significant and the correlation between growth rates and the initial income can turn out to be negative as predicted by the neo classical models (see Barro, 1991). Thus for the conditional convergence the regression equation employed is given as follows.

(4.4) $Y_{i} = \alpha+\beta_1\ lnpcnsdp_i + \beta 2\ Literacy_i + \beta 3\ Gender_i + \beta_4\ Urban_i + \beta_5\ lnpceduexp_i + \beta_6\ lnpcmedexp_i + \beta_7\ Pol_i + \varepsilon_i$

Since human capital is said to play a crucial role in a number of models (Barro et al., 1991; Lucas, 1988),proxy for human capital, literacy rate, for initial periods of 1981, 1991 and 2001 is considered. Per capita expenditure on education (lnpceduexp) and health (lnpcmedexp) have been taken as proxies for public expenditures. The two main proxies for social factors are gender ratio (gender) and the percentage of urban population(urban). The political variable (pol) employed in this study is a dummy variable(value =1 if the state party ally at the centre and 0 otherwise). The set of variables that are included in the model have been influenced by the findings in earlier literature as well as by the data availability across the 25 states and 3 Union Territories. We present below (Table 3) the cross section results and then compare it with the panel data model results. The OLS cross section regression results are shown for the period 1981-91, 1991-00, 2001-13, 1991-13 and 1981-2013, even when we control for variables under cross section analysis, there seem to be no significant relationship between the dependent and the independent variables. Only the per capita education expenditure seems to be significant.

Table 3: Cross Section Regression Results

Independent Variable	Dependent variable – Growth rate				
	Equation 1 Gr81-90	Equation 2 Gr91-00	Equation 3 Gr01-13	Equation 4 Gr81-13	Equation 5 Gr91-13
lnpcnsdp	-0.01 (.012)	0.004 (.01)	-0.005 (0.02)	0.004 (0.009)	0.004 (.010)
literacy	0.0002 (.0003)	-0.0001 (0.0004)	-0.0002 (0.0007)	0.0003* (.0001)	0.00009 (0.0001)
gender	-0.00003 (0.00004)	0.0002*** (0.0007)	-0.00009 .0001	0.00002 (0.00003)	0.00005 (0.00005)
urban	0.0001 (.0001)	0.0002 (.0002)	0.00002 (0.0004)	-0.00008 (0.0001)	-0.00001 (0.0001)
lnpceduexp	0.005 (0.006)	-0.03** (0.013)	0.016 (.015)	0.002 (.0004)	-0.013 (0.008)
lnpcmedexp	-0.001 (0.007)	0.03** (0.01)	-0.013 (0.016)	0.002 (0.004)	0.014 (0.01)
pol	-0.003 (.006)	0.009 (.007)	0.006 (0.01)	0.002 (.006)	-0.00002 (0.005)
Constant	0.190 (0.127)	-0.14 (0.16)	0.17 (0.24)	-0.03 (.100)	-0.029 (0.12)
R-squared	0.32	0.59	0.14	0.29	0.20
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1. N=28					

Source: EPWRF and Authors' calculations.

4.4.2. Pooled Estimation

Pooled data analysis combines the cross section data at a time and treats it as belonging to a single time period. We employ the pooled data formulation by dividing the growth period into five year spans and see if there is any significant relationship. The results from the estimation are given as under.The pooled regression results are slightly different from the cross section results. Equation 1 suggests divergence with positive significant coefficient. But when we control for "literacy" in equation 4 and 5, we find that literacy is positively related to the growth rate of per capita, whichsuggests that states with higher amount of human capital can grow faster. Besides, the expenditure made by the government on health and education (equation 3 and 5) alsohas a significant impact on the growth rates.

Table 4: Pooled Regression Results

Independent Variable	Dependent variable – Growth rate				
	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
lnpcnsdp	0.018*** (0.005)	0.019*** (0.005)	0.016*** (.005)	0.01 (0.009)	0.01 (0.007)
literacy				0.0008** (0.001)	0.0006** (0.0002)
political		0.003 (0.005)			
sq_political		-0.0008 (0.001)			
lnpceduexp			0.019*** (0.005)		0.01** (0.006)
lnpcmedexp			-0.01*** (0.006)		-0.012* (0.007)
genderratio				-9.38e-07 (0.00006)	
urbanr				-0.0005** (.0002)	-0.0003 (0.0002)
Constant	-0.12 (0.05)	-0.13*** (0.05)	-0.13** (0.05)	-.213 (.101)	-0 .10 (0.07)
Observations	168	168	151	168	151
R-squared	0.05	0.08	0.14	0.11	0.16
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1					

Source: EPWRF data and Authors' calculations.

However, the medical expenditures seem to be negatively associated with the growth rates. Besides these variables all other variables are having no impact on the rate of growth. Thus dividing the data into shorter time spans have not shown any significant improvement in the results. We thus switch on to the panel data estimation to see how the results changes.

4.4.3 Panel Data Estimation

There are many advantages of using panel data technique (Temple, 1999). With panel data, we can control for persistent omitted variables over time. We can use several lags of the regressors as instruments wherever required and thus alleviate the measurement error and endogeneity bias. We rewrite the above equation as a panel data model in which growth rate is regressed on initial per capita income and a set of control variables. The fixed effects formulation allows us to control for unobserved differences between the steady states of regions. We use a panel of five-year spans (ie, $\tau = 5$). Hence, we only consider the period 1981-2010, with six panels.

The estimated model to test for unconditional convergence is given below

$$(4.5) \qquad Gr_{it} = \alpha + \beta_1 \, lnpcnsdp_{i,t-\tau} + \varepsilon_{it}$$

Here the subsequent growth rate $Y_{it}$is the dependent variable and log of initial *PCI* ($lnpcnsdp_{i,t}$) is the prime explanatory variable.If the coefficient on initial level of *pcnsdp* has a statistically significant negative sign, then absolute β - convergence exists. When $\beta < 0$ implies that the states with lower initial levels of per capita income grow faster than states with higher initial per capita income.

$$(4.6) \quad Gr_{i,t} = \alpha + \beta_1 \, lnpcnsdp_{i,t-\tau} + \beta_2 \, Literacy_{i,t-\tau} + \beta_3 \, Pol_{i,t-\tau} + \beta_4 \, Pol\_sq_{i,t-\tau} + \beta_5 \, lnpceduexp_{i,t-\tau} + \beta_6 \, lnpcmedexp_{i,t-\tau} + \beta_7 \, Genderatio_{i,t-\tau} + \beta_8 \, Urban_{i,t-\tau} + \varepsilon_{it}$$

The standard error component in the regression equations assumes homoskedasticity in the regression disturbances with the same variance across time and individuals. However this may be a restrictive assumption for panels. With the presence of heteroskedasticity the standard errors of the estimates will be biased. We thus compute robust standard errors to correct for the possible presence of heteroskedasticity. We have calculated a modified Wald statistic for group-wise heteroskedasticity in the residuals of a fixed-effect regression model. The results ($P < 0.05$) indicate that we must reject the null hypothesis of homoskedasticity.In the Table 5 below, we first test for unconditional convergence in equation (1). We find that the coefficient of initial income is highly significant and has a positive sign. This indicates that there is unconditional divergence (see Figure 2) and the Indian states are not converging to identical steady states. The implied rate of divergence, "λ" measures the rate of divergence (absolute or conditional) over the period of our analysis. This rate is calculated by dividing the β estimate by 5, which represents the panel of five-year spans. The implied rate of divergence is 0.005;the rate of absolute divergence among the states is low at 0.5 %.

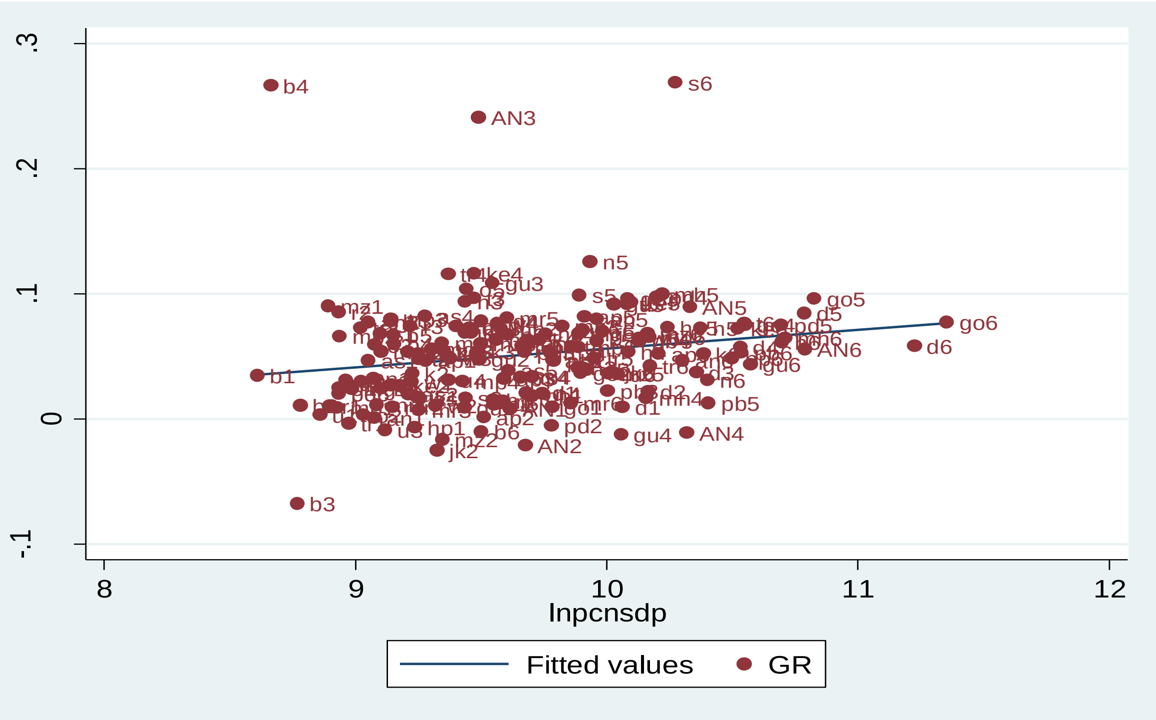
Table 5: Panel Regression Results (Fixed Effects Model - 5 Years Span)

Independent Variable	Dependent variable – Growth rate				
	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
lnpcnsdp	0.027*** (0.007)	0.02*** (0.007)	-0.05*** (0.02)	0.01 (.010)	-0.07*** (0.02)
literacy			0.002** (0.001)		0.003*** (0.001)
political		0.008 (0.005)			
sq_political		-0.001* (0.0007)			
lnpceduexp			.04*** (0.01)		0.03* (0.01)
lnpcmedexp			-0.006* (0.01)		-0.002 (.019)
genderratio				0.0005*** (0.0001)	
urban				0.0009 (.001)	0.002 (0.001)
Constant	-0.21*** (.072)	-0.15** (.08)	0.16 (0.14)	-0.65*** (0.18)	0.34*** (0.14)
Observations	168	168	151	168	151
No of states	28	28	27	28	27
R-squared	0.05	0.04	0.10	0.01	0.06
Implied rate of divergence (λ)	0.005	0.004	0.01	0.002	0.014
Modified Wald test for groupwise heteroskedasticity Prob>chi2	0.00	0.00	0.00	0.00	0.00
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.					

Source: EPWRF and Authors' calculations.
Note:The robust standard errors corrects for standard errors in the presence of heteroskedasticity. With the robust option, the point estimates of the coefficients are exactly the same but there is are changes in the standard errors and t-tests.

In the panel data model, with the inclusion of literacy rate as a proxy to human capital, given the initial level of PCNSDP, the state's subsequent growth rate is positively related to the initial level of literacy. Moreover, given the literacy rate, growth rate is now substantially negatively related to the initial PCNSDP in equation (3).

Figure 2: Relationship between Growth Of PCNSDP and Initial Level of PCNSDP (5- Years Span)



Source: EPWRF and Authors' calculations.

Thus in this modified sense, the data does support the convergence hypothesis. A poor state will grow faster than a rich one only if the quantity of human capital is higher.Economists have long stressed the importance of human capital to the process of growth. With human capital, either the theoretical modelling or the empirical analysis of economic growth could alter (Mankiw et al., 1992).At the theoretical level, even if there are decreasing returns to physical-capital accumulation, when human capital is held constant, the returns to all reproducible capital (human plus physical) are constant (Lucas, 1988). Allowing for human capital in a regression eliminates the high coefficients on investment and on population growth. Our finding is in line with the above literature, even in Barro (1991)with the inclusion of initial measures of human capital β turns negative and the data supports convergence hypothesis in a modified sense. Again by examining the cross country Summer Hestons data (1988), Mankiw et al, (1992) found that inclusion of human capital to the Solow model improved its performance.

Similarly, if we control for the expenditures by the Government on education and health, there seems to be convergence in the growth rates among the states. In equation (5) in this fixed-effects model, coefficients on literacy, per capita education expenditures are positive and statistically significant at the 1 significance levels. However for the medical expenditures the coefficient is negative and significant at 5%, indicating that poor states incur more on health expenditures. In equation (4), we control find that there is a positive relationship between growth rate and the gender ratio in the states. While in equation (2), proxy to political variable is insignificant, showing no significant relationship between growth and political variable. However, when we consider the square of the political variable we find a significant and negative relationship with the growth rate. Thus we can conclude that there is strong and consistent evidence of conditional β-convergence among the states.

We extend the same panel data analysis by considering a 10 year span.Dividing the period into 10 years span, the results obtained differ in some way to those obtained for 5 year span.

Table 6: Panel Regression Results (Fixed Effects Model - 10 Years Span)

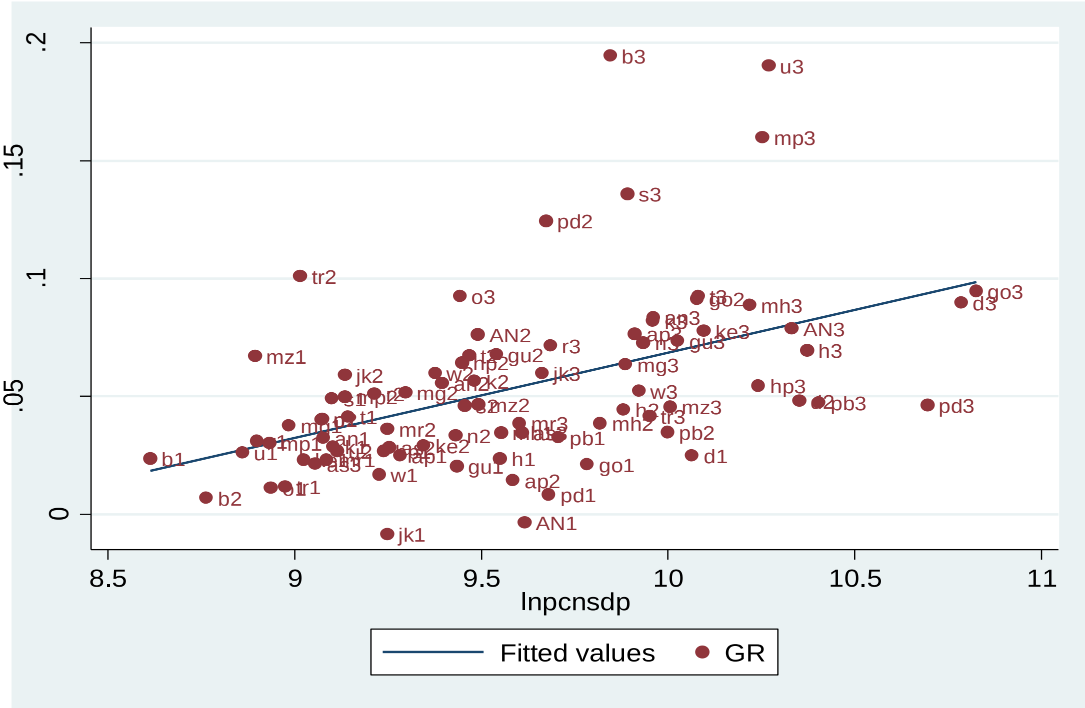
Independent Variable	Dependent variable – Growth rate				
	Equation 1	Equation 2	Equation 3	Equation 4	Equation 5
lnpcnsdp	0.05*** (0.012)	0.05*** (0.01)	0.059*** (0.02)	0.05*** (.021)	0. 021 (.038)
literacy					0.002** (.001)

political		-0.006*** (.002)			
sq_political		0.006*** (.0002)			
lnpceduexp			0.005 (0.012)		-0.010 (.010)
lnpcmedexp			-0.09 (0.012)		-0.007 (.010)
genderratio				0.0004 (0.0003)	0.0003 (.0003)
urban				-0.0002 (.001)	0.0002 (.001)
Constant	-0.52*** (.122)	-0.500** (.107)	-0.505 (0.180)	-0.842 (.24)	-0.60 .33
Observations	84	84	151	168	151
No of states	28	28	28	28	27
R-squared	0.23	0.23	0.23	0.21	0.11
Modified Wald test for groupwise heteroskedasticity Prob>chi2	0.00	0.00	0.00	0.00	0.00
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.					

Source: EPWRF and Authors' calculations.

For the 10 year span, positive coefficient on initial per capita indicates unconditional divergence. In equation (2), Political variable is however negative and significant at 1%, suggesting that if same political party rule at the state and Centre will have negative influence on growth rate in the long term (this factor was insignificant for the 5 years span). In equation (3), proxies to public investment- lnpceduexp has insignificant but positive influence on growth rate; however, lnpcmedexp is negative and insignificant. Proxies to social variables also do not seem to affect average decadal the growth rate (equation 4). Only in equation (5), we notice that the literacy rates have a positive influence on the growth rates.

Figure 3:Relationship between Growth of PCNSDP and Initial Level Of PCNSDP (10 Year Span)



Source: EPWRF and Authors' calculations.

4.4.4 σ - Convergence

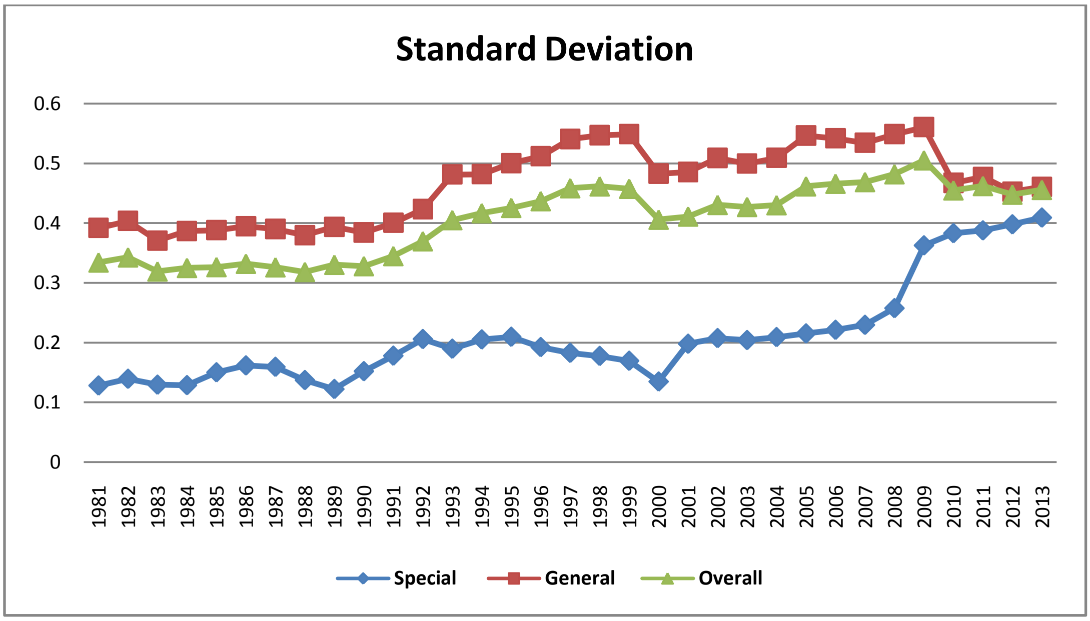
The concepts of β- and σ-convergence are strongly related. β-convergence is a necessary but not a sufficient condition for the reduction in the disparity of per-capita income over time. If the GDP levels of the economies become more similar over time, it means that the poor economy is growing faster. Thus the existence of β - convergence will tend to generate σ -convergence. But it is also possible that the initially poor countries grow faster than rich ones, without the decline in the cross-sectional dispersion over time. This happens if the poor economy grows faster than the rich (β-convergence) but, the growth rate of poor economy is so much larger than that of the rich that at time t+T , the poor economy is richer than the rich economy. As the dispersion between these two economies is not fallen, there is no σ-convergence (Barro & Sala-i-Martin, 1992; Sala-i-Martin, 1996). Thus the β convergence is not a sufficient condition for the standard deviation (SD) of per capita incomes to converge because of random shocks. Even the conditional β convergence is not a sufficient condition for σ convergence as the steady-state levels of per capita income may diverge through time.

The above findings on conditional convergence does not imply that states are converging in terms of levels of income. For analyzing whether or not poor states are catching up with richer ones over time we also need to evaluate the changing distribution of state incomes over time. To test for σ convergence, we estimate the time trend of some measure of dispersion of PCI across the states. Standard deviation of per capita NSDP across the states is thus computed. A declining value of the standard deviation over time would reflect σ convergence.

The Indian states are classified into special (14^{th} FC-states with hilly and difficult terrain, low population density with sizeable share of tribal population, strategic location along borders with neighbouring countries; economic and infrastructure backwardness and non-viable nature of state finances) and general category states. The special category states are granted concession and awards in the form of central plan assistance so that they can catch up with the genera category.

In the figure 4, σ convergence is analyzed by looking at the plots of standard deviation of the log of per capita NSDP (at 2004-05 constant prices) across special and general category as well as general and special category together.

Figure 4: Standard Deviation of Log Of Per Capita NSDP at 2004-5 Constant Prices



Source: EPWRF and Authors' calculations.

The results clearly point to increasing standard deviation of the log of per capita NSDP. This indicates that the disparity has risen, and Indian states have experienced divergence in regional incomes. The combined special and general category plot depicts three phases of dispersion, from 1981-1990, the standard deviation shows relatively stable levels of deviation between 1991-1999, there is a sharp and a steady increase in standard deviation in the general category indicating divergence among the states (with the exception of 1998). The third and the most recent phase is from 2000 onwards which shows a steady rise in deviation till 2009, and a steady level thereafter. In the special category states, there is a mixed trend. During 1981-2005 the standard deviation keeps alternately increasing or decreasing. But from 2005 onwards there has been a steady rise in the standard deviation.

4.5 Summary

From the above analysis it is evident that there are substantial variations in the per capita NSDP as well as the average annual growth rate among the states and the

U.Ts in India. The statistical analysis reveals that there has been unconditional divergence. The richer states have been growing significantly faster than poorer states. New growth theory suggests that even if there is no unconditional convergence, there may be conditional convergence. Each state may converge to its own steady-state level of income, once the factors that affect steady-state levels of income are controlled for. The poor states would grow faster on average than the rich ones. The inclusion of literacy as a conditional variable, makes the state's per capita growth rate to be inversely related to its initial level of income.

By holding constant the measure of initial human capital-literacy rate, there is evidence that states with lower per capita NSDP tend to grow faster.Similar is the case with social expenditures by the Government in each states. This is indicative of Indian states converging to increasingly divergent steady-states.

There is an increase in the dispersion of per capita incomes across states over time which again is logically consistent with our finding of absolute β-divergence, i.e, states are not converging in levels of per capita income over time.We can thus conclude that inequality in per capita income levels between Indian states is rising over time and this is more so with respect to the special category states.

Chapter V

Regional Economic Growth by Quantiles

5.1 Introduction

The neo classical growth model predict unconditional β- convergence if the economies have same technological parameters and preferences, but differ only in terms of the initial level of income in the short run and converge to a common steady state level in the long run. While, if the countries differ in various microeconomic specifications and consequently have different steady-state levels of per capita income, then after controlling for these steady-state differences, poor countries or regions should grow faster than the rich countries or regions for conditional β- convergence to occur. Earlier critics have used different policy variables as control variables to test for conditional convergence like the measures of openness, terms of trade, investment rate, proxies for human capital etc (Barro & Sala-i-Martin, 1992; Islam, 1995; Lucas, 1988; Mankiw et al., 1992). However, there are serious statistical pitfalls in this empirical growth literature.

Firstly, the OLS regression gives rise to what is termed as the "Galton's fallacy", wherein Galton examined the heights of fathers and sons, and found that the sons of tall fathers tended to be shorter than their fathers, similarly, the fathers of tall sons tended to be shorter than their sons, i.e. regressed toward the mean (Friedman, 1992; Quah, 1993b). It has been pointed out that the inverse relationship between the average growth rate and the initial level of per capita income reflects regression to the mean but is not convergence of the growth rates. One could find the inverse relationship between average rate of growth and initial income, but, when we replace the latter by final period income, one finds no relationship between the dependent variable and the average growth rate. This regression fallacy is been largely ignored in the growth literature (Friedman, 1992). Thus one should be careful while interpreting the negative relationship between the growth rate and initial per capita using OLS regressions as an evidence of convergence.

Secondly, studies on conditional convergence have employed the mean regression estimation methods which implies that the impact of a change in a particular policy variable say for example, the human capital, on a rich state's NSDP per capita growth rate is the same as the impact on a backward state's NSDP per capita growth rate. However, this necessarily need not be the case. The simple OLS captures how the mean of the growth rate of NSDP per capita changes with the change in human capital. Many a times a single mean curve may not be informative enough. The explanatory power of the regressor may differ at different locations of the distribution. Thus the interaction between policy variables and growth rates could be more complex than what is captured by an average correlation. The growth regressions have assumed that there is parameter homogeneity among the countries or regions. This effectively assume that the impact of population growth, physical and human capital , the initial level of PCI on the per capita growth rates will be the same across all countries or regions. Evidently, this assumption is unrealistic. Thus accounting for the parameter heterogeneity is necessary in empirical growth models (Canarella & Pollard, 2004; Durlauf, Kourtellos, & Minkin, 2000).

Thirdly, OLS regressions do not reveal where on the distribution of the dependent variables the effects of the explanatory variables are likely to occur. Finding the effects of the independent variables at the tails of the distribution is useful.

In this chapter we extend the discussion on income convergence beyond the mean values to all levels of distribution between the growth and policy variables. we employ the Quantile regression approach to do this.

5.2 Quantile Regression Approach: An Overview

Quantile regression is an alternative to the conditional mean modeling of OLS that is commonly used. In traditional regression analysis, the focus is on the mean or the average. The relationship between the dependent and the independent variable is summarized by describing the conditional mean of the response variable given certain values of the predictor variables. In quantile regression methods (QRM) on the other hand we estimate either the conditional median or other quantiles of the dependent variable, like the quartiles divide the observations into four segments, quintiles into five and the deciles into ten segments. The quantile regression estimation procedure yields quantile coefficients; one for each sample quantile, thus providing a complete picture of the relationship between the dependent and the independent variables. The median is considered as a special quantile, which describes the central location of a particular distribution. A special case of quantile regression is the conditional median regression. In the empirical growth model, each slope coefficient can be interpreted as a different response of the GDP growth rate to a change in an explanatory variable depending on the position of the dependent variable. So, we may have smaller effects for lower quantiles or higher effects for higher quantiles and vice-versa.

5.3 Advantages of employing Quantile Regression

In recent years, many studies have made use of quantile regression or the conditional median modelling to address the determinants of economic growth across different quantiles (Andrade, et al, 2014; Canarella & Pollard, 2004; Cuaresma, et al, 2009; Laurini, et al, 2005; Mello & Novo, 2002).

For analyzing growth or the economic inequality among the states, what is of interest is to examine the effect on a poor or rich state (lower or upper tail of the distribution). Thus using conditional-mean models to address these questions are inefficient (Hao & Naiman, 2007) especially since heavy tailed distribution is a common social phenomena. When the distribution is highly skewed the median can be more informative than the mean (Cuaresma et al, 2009). In quantile regressions, the estimator is robust to outlying observations of the dependent variable. This is a particular advantage where there is a heterogeneity in growth rates and the distribution is characterized by long right tails. Such observations can have a marked effect on OLS results. In quantile regression, since any quantile can be used, the researchers can select those quantiles which are relevant for their specific inquiries. For example, poverty studies would focus more on the low income population, while studies on taxation would concentrate on the high income people. Another important advantage of the quantiles is its robustness. While the least square models could magnify the effects of the outliers, quantile estimator is robust as far as the outliers are concerned in the dependent variable.

5.4 Convergence and Quantile Regression Analysis

In a linear regression model,

(5.1) $$Gr_{i} = \alpha + \beta_{1} x'_{i} + e_{i}$$

" Gr_i " is the growth rate of per capita income (dependent variable), "x'_i" is the vector of explanatory variables and e_i is the error term. The least square estimator can be found by minimizing the sum of the squares residuals.

As discussed earlier (see sub section 3.5.1) in the following quantile regression equation

(5.2) $$Gr_i = \alpha + \beta_q x'_{\mathrm{i}} + e_{qi}$$

Instead of having one coefficient β, we have set of coefficients β_q where these coefficients are associated with the q^{th} quantile of the dependent variables and e_{qi} is the unknown error term, that satisfies the constraint;

(5.3) $$Quant_q(\, e_{qi}/x_{\mathrm{i}}) = 0$$

with errors having the zero conditional mean.

In case of quantile regression, the quantile regression estimator, "q", (where 0 < q < 1), solves the following minimization problem;

(5.4) $$\boldsymbol{Q(\beta_q) = \{\sum_{i:y_i \geq x`_i\beta q}^{N} q \mid y_i - x`_i\beta_q\mid + \sum_{i:y_i < x`_i\beta q}^{N}(1-q)\mid y_i - x`_i\beta_q\mid\}}$$

The objective function above is a weighted sum of absolute deviations, which can be interpreted as an asymmetric linear penalty function (Koenker & Bassett, 1978). A special case of the quantile regression estimator is the least absolute deviation estimator (LAD) or median regressor.

Therefore in equation (5.2) if we vary the parameter "q" on the (0,1) interval we have the entire conditional distribution of GDP growth rates. Thus, the quantile regression approach allows us to identify the effects of the covariates at different points on the conditional distribution of the dependent variable.

In this study instead of using OLS, we use quantile regression to examine how initial PCI affects slow-growing states and fast-growing states. The slow-growing states are those in the 10th quantile or the left tail of the conditional distribution of growth rates and the fast-growing countries as those in the 90th quantile or right tail of the conditional distribution of PCNSDP growth rates.

5.5 Quantile Cross Section Regressions

The method of least squares provides estimates that approximate the conditional *mean* of the response variable given certain values of the predictor variables. Quantile regression methods (QRM) on the other hand aims at estimating either the conditional median or other quantiles of the response variable, that is, we use quantiles to describes the distribution of the dependent variable. The quantile regression estimation procedure yields quantile coefficients; one for each sample quantile. Each slope coefficient can be interpreted as a different response of the PCNSDP growth rate to a change in a explanatory variable corresponding to a different position on the conditional distribution of growth rates. The results for the cross section and the pooled data are presented below. In the sub section below we also plot the dependent variables by quantiles.

5.5.1 Quantile Graphs for the Dependent Variable

Figure 5 below shows the quantiles of the dependent variable- growth rate of PCNSDP, across the pre and post reforms periods viz; a) 1981-90, b) 1991-2000, c) 2001-2013 and d) 1981-2013. On the y-axis we plot the values of the dependent variable - growth rate of PCNSDP, while on the x-axis we plot the quantiles after sorting the data from minimum to maximum. We have very low growth rates at the lower quantiles, while the growth rate keeps on increasing as we move on the higher quantiles. For 1981-90, the median growth rate is 0.02, with very low growth rates in lower quanitles (the lowest growth rate is -0.007) and growth rate is increasing as we move towards the higher quantiles (highest is 0.06). Similarly for the other periods, we find the growth rate varying across different quantiles. Particularly for the period 2001-13, the growth rates are rapidly increasing at the higher quantiles (0.14 at the highest percentile). Thus when we refer to different quantiles we are referring to the dependent variables and not the independent variables.

Figure 5: Dependent Variable by Quantiles (1981-90 and 1991-2000)

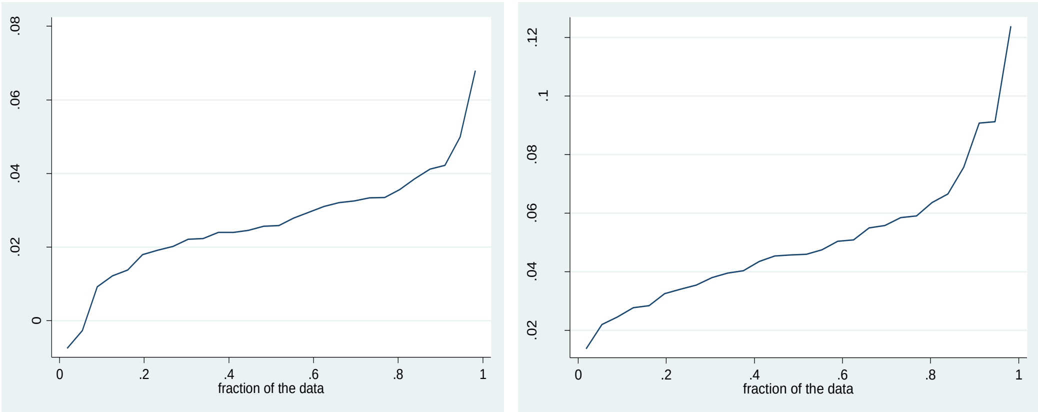


Figure 6: Dependent Variable by Quantiles (2001-13 and 1991-13)

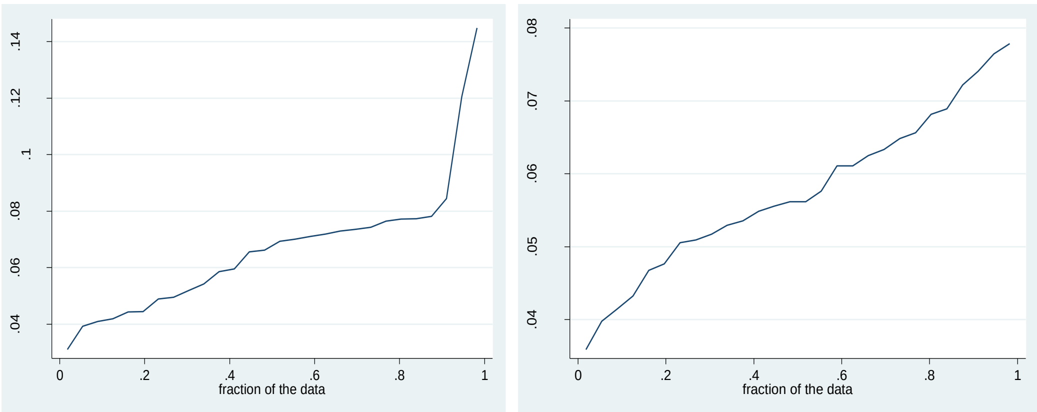
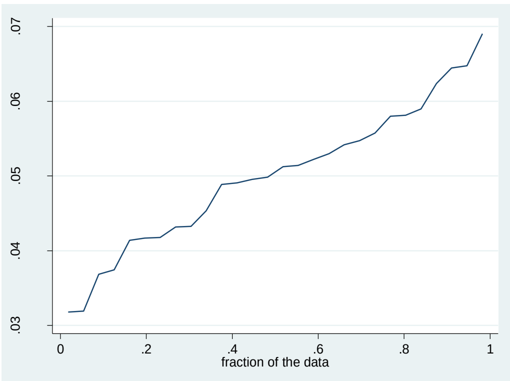


Figure 7: Dependent Variable by Quantiles (1981-2013)



Source: Author's calculations based on EPWRF data

5.5.2 Cross Section Regressions by Quantiles

We first begin with the unconditional convergence model for three time periods. The model is given as ;

(5.5) $$Gr_{i=}\ \alpha + \beta_1 lnpcnsdp_{i} + e_i$$

Here we regress the average per capita growth rate for the period 1981-90 on initial GDP per capita.

In the Tables below we provide results of the unconditional OLS regression as well as the quantile regressions for the 10^{th} , 25^{th} ,50^{th} , 75^{th} 90^{th}, 95^{th} and 99^{th} quantiles for three periods; a) Pre reform period (1981-90), b) Post reforms period 1991-2013 and c) overall time period in the analysis (1981-2013). The OLS regression in the Table 7 indicates a negative relationship between the growth rate of PCI from 1981-90 and the initial PCI in 1981, however the results are not statistically significant for this period. For the period 1991-13 as well as for 1981-13, there is insignificant relationship between growth rate and initial PCI.

When we consider quantile regression, we find interesting results at different quantiles. For the period 1981-90, the signs of the estimated coefficients of the regressor do not change across quantiles (except for the 50^{th} quantile). But the results show that the quantitative importance of the β-coefficients differ across the growth rate distribution for the period taken into consideration.Though the coefficient on initial per capita income is not significant across the entire conditional distribution, there has been a negative relationship between the growth rate of PCI in 1981-90 and the initial PCI in 1981.

These results provide strong evidence of unconditional convergence at the lower most quantile (10^{th}) as well as the upper quantiles (95^{th} and 99^{th}).

Table 7: Unconditional Convergence – OLS and Quantile Regressions

Variable	OLS/ Quantile	1981-90			1991-13			1981-13		
		Coefficient	Std Error	R^2/ Pseudo R^2	Coefficient	Std Error	R^2/ Pseudo R^2	Coefficient	Std Error	R^2/ Pseudo R^2
Constant	OLS	0.12	0.07		-0.004	0.05		-0.01	0.05	
	0.10	0.24**	0.11		0.05	0.05		0.04	0.04	
	0.25	0.11	0.16		-0.07	0.10		-0.04	0.07	
	0.50	0.024	0.07		-0.03	0.08		0.001	0.08	
	0.75	0.13	0.13		-0.03	0.15		0.01	0.08	
	0.90	0.24*	0.13		0.01	0.02		-0.03	0.04	
	0.95	0.027	0.11		0.01	0.01		0.01	0.01	
	0.99	0.038***	0.004		-0.04***	0.003		0.01***	0.002	
Initial PCI	OLS	-0.01	0.008	0.05	0.006	0.006	0.04	0.006	0.005	0.05
	0.10	-0.02**	0.012	0.18	-0.001	0.005	0.02	-0.001	0.004	0.07
	0.25	-0.01	0.01	0.004	0.01	0.01	0.06	0.01	0.008	0.02
	0.50	0.0001	0.008	0.0003	0.009	0.008	0.06	0.005	0.009	0.05
	0.75	-0.01	0.01	0.008	0.01	0.016	0.009	0.004	0.009	0.02
	0.90	-0.02	0.01	0.10	0.005*	0.003	0.08	0.01**	0.004	0.05
	0.95	-0.02**	0.01	0.18	0.005***	0.001	0.05	0.005***	0.001	0.05
	0.99	-0.03***	0.0004	0.28	0.012***	0.0003	0.004	0.006***	0.0003	0.17

Standard errors in parentheses *** $p<0.01$, ** $p<0.05$, * $p<0.1$
N=168
R^2- for OLS, Pseudo R^2- for Quantiles

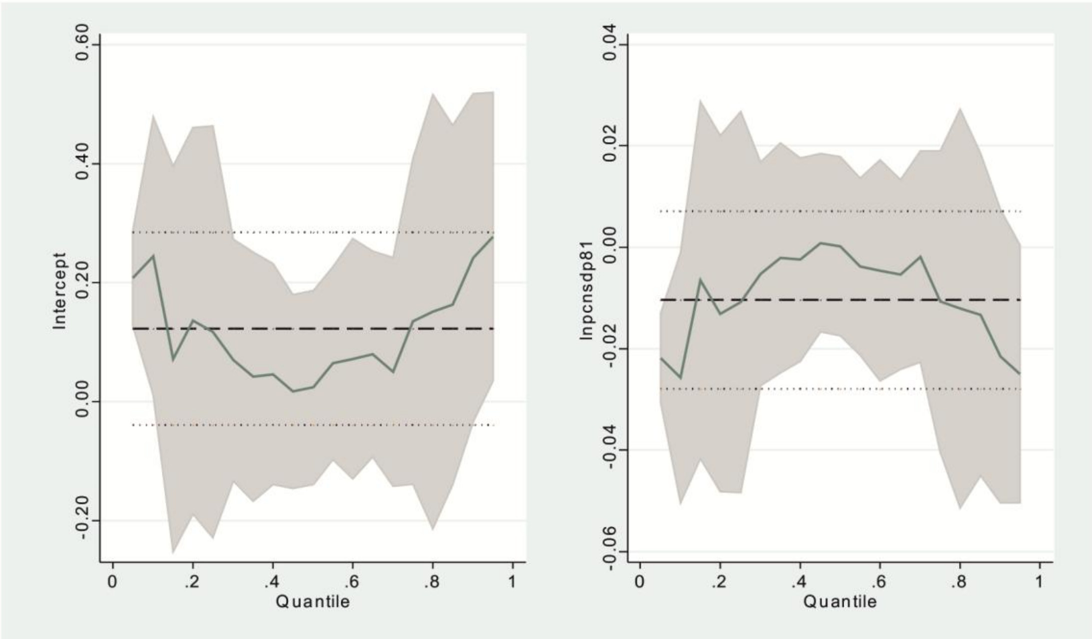
Source: Author's calculations based on EPWRF data

However, for the periods 1991-13 and 1981-13, we do not find evidenceof convergence for any of the quantiles. In fact for the upper quantiles though the results are significant, there is a positive relationship between the growth rates of PCI and the initial PCI confirming divergence.

In the figures below we plot the graphs of Ordinary Least Squares and Quantile Regression estimates to show the differential effects of using the quantiles. Each of these figures (8, 9, 10) exhibits the entire quantile regression process on the initial PCI, the 95% confidence interval for the quantile regression estimate for the periods 1981-90, 1991-13 and 1981-13.

The second plot shows the initial per capita NSDP and its coefficients of how it affects the growth rates of per capita NSDP. The OLS coefficient is plotted as a thick horizontal dashed line with confidence interval as two dotted lines around the coefficient line. The OLS coefficient does not vary across quantile. The quantile regression coefficient is plotted as thick line varying across the quantiles with confidence interval around them. In quantile regression, the estimated coefficients can be interpreted as the marginal effects. We have different estimates for the slope coefficients.

Figure 8: Plots of the Quantile Regression (1981-90)

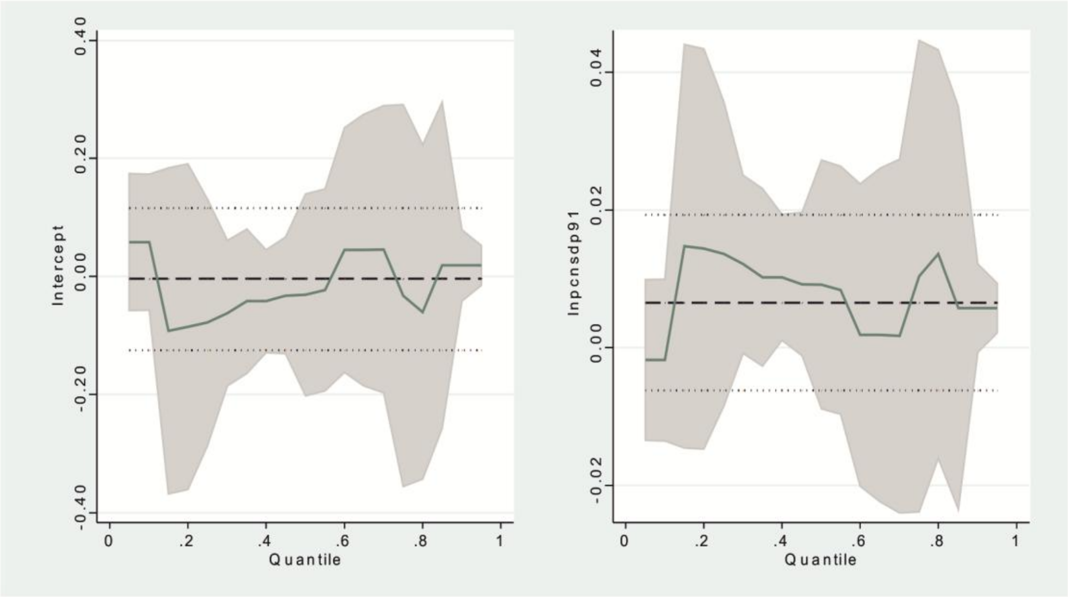


Source: Author's calculations based on EPWRF data

If the quantile coefficient is outside the OLS confidence interval, then we have significant differences between the quantile and the OLS coefficient. It is important to note that the coefficients at 10th and 25th quantiles are significantly lower than the

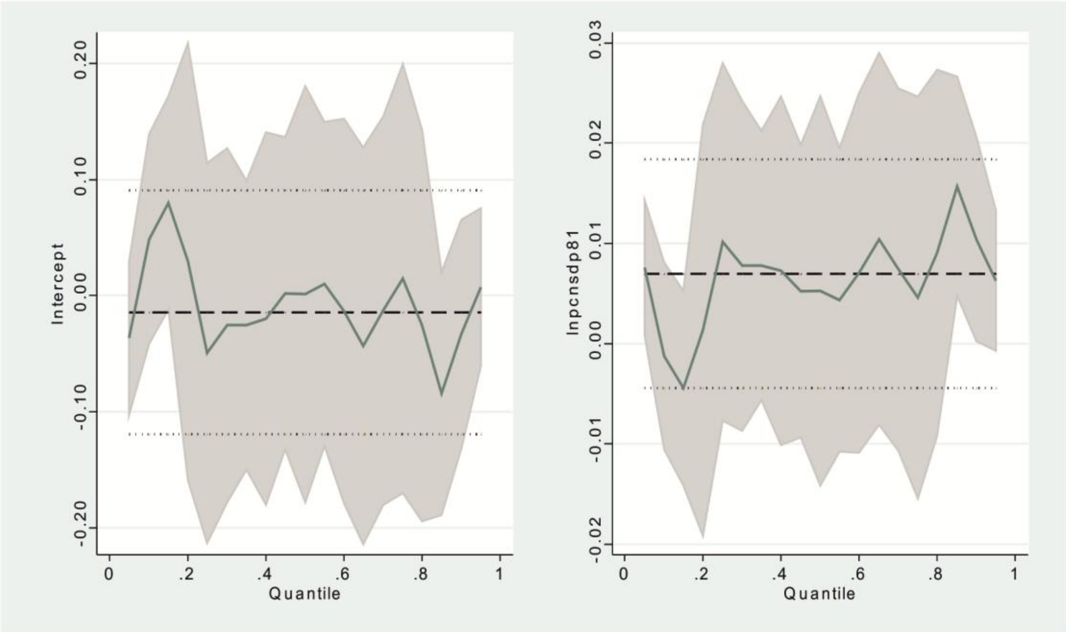
OLS coefficients,, similarly after the 75th (higher) quantiles the coefficients are again lower than the OLS.

Figure 9: Plots of the Quantile Regression (1991-13)



Source: Author's calculations base on EPWRF data

Figure 10: Plots of the Quantile Regression (1981-13)



Source: Author's calculations base on EPWRF data

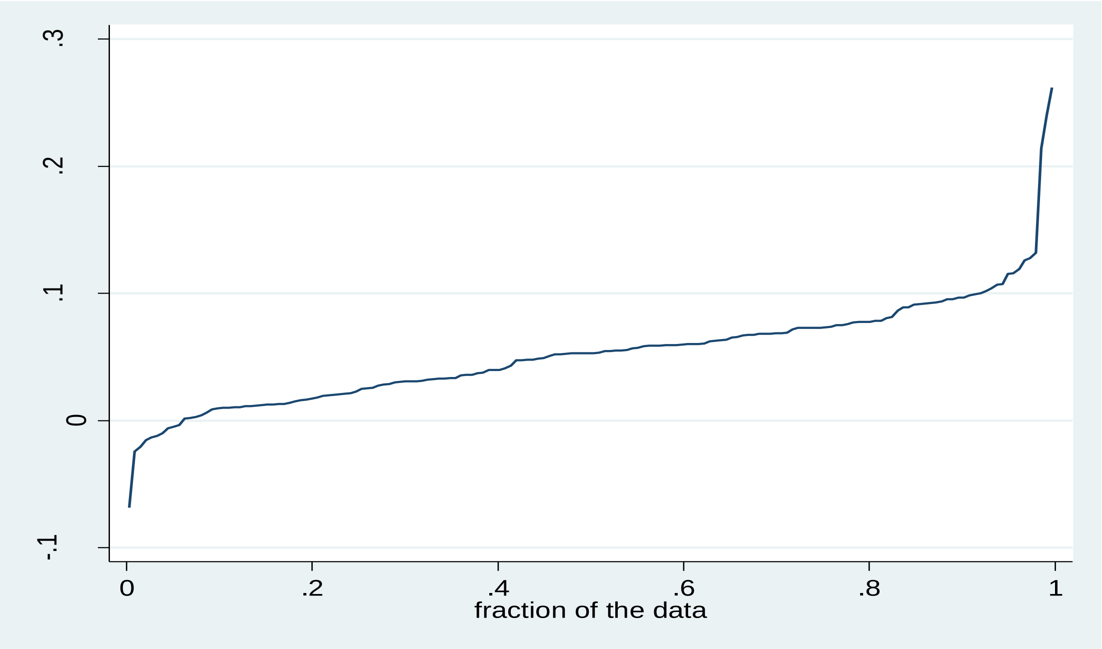
5.6 Pooled Regressions by Quantiles

In this section we employ the pooled data formulation by dividing the growth period (1981-2010) into five year time intervals, thus we have six, five year spans - namely 1981-85, 1986-90, 1991-95, 1996-2000, 2001-05 and 2006-10.

5.6.1 Quantile Coefficients for the Dependent Variable

As the quantile regression approach gives one solution to each quantile, it is useful to observe the distribution of per capita income growth across quantiles.Figure 11 below on the y-axis we plot the values of the dependent variable - growth rate of PCI, while on the x-axis we plot the quantiles.

Figure 11: Quantile Coefficients for the Dependent Variable



Source: Author's calculations based on EPWRF data

By sorting the data from minimum to maximum, we notice very low growth rates at the lower quantiles, while the growth rate keeps on increasing as we move on the higher quantiles. In fact the growth rates at the 10th quantile has been negative (-0.06) while at the highest quantiles it has been high (0.26). The quantile regression results in the next section will consider the determinants of economic growth for each quantile.

5.6.2 Quantile Pooled Regressions

For the pooled regression the unconditional convergence model is given as ;

(5.6) $Gr_{it=} \alpha + \beta_1 lnpcnsdp_{i,t-\tau} + e_{it}$

Here we regress the average per capita growth rate on initial PCNSDP; we also test the conditional convergence model with control variables as given below

(5.7) $Gr_{it=} \alpha + \beta_1 lnpcnsdp_{i,t-\tau} + \beta_2 lnpceduexp_{i,t-\tau} + \beta_3 genderratio_{i,t-\tau} + \beta_4 Urban_{i,t-\tau} + \beta_5 pol_{i,t-\tau} + \beta_4 Sq\_Pol_{i,t-\tau} + \varepsilon_{it}$

The pooled and quantile results for the test of unconditional convergence among the growth rates are presented in Table 8.

Table 8: Unconditional Convergence – Pooled and Quantile Regressions

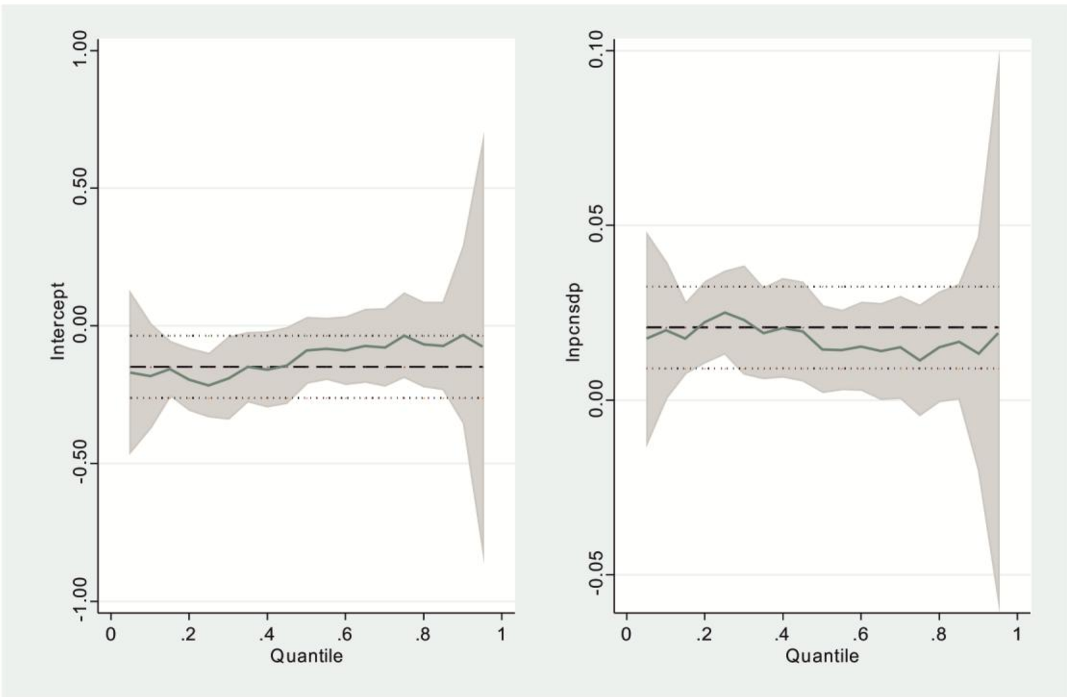
Variable \Quantile	Pooled Regression	Quantile Regression						
		0.10	0.25	0.50	0.75	0.90	0.95	0.99
lnpcnsdp	0.02*** (0.005)	0.01** (0.009)	0.02*** (0.005)	0.01** (0.006)	0.01 (0.007)	0.01 (0.016)	0.01 (0.03)	0.03*** (0.006)
Constant	-0.14*** (0.57)	-0.18** (0.09)	- 0.21*** (0.05)	-0.08 (0.06)	-0.03 (0.07)	-0.03 (0.16)	-0.07 (0.37)	-0.59*** (0.075)
Adjusted R^2/ Pseudo R^2	0.06	0.04	0.06	0.04	0.01	0.01	0.01	0.08
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 N=168 Adjusted R^2- for Pooled, Pseudo R^2- for Quantiles								

Source: Author's calculations base on EPWRF data

The coefficients of pooled regression the independent variable (log of initial PCNSDP) is significant and positive confirming divergence in the growth rates. However, the coefficients of the initial per capita income variables are positive and significant, for the median quantiles as well as the lower quantiles (10^{th} and 25^{th}), reflecting the diverging growth of the low income states.On the other hand, beyond the median quantile, the magnitudes are different across percentiles, with positive but insignificant relationship between growth rates and initial PCI. Only for the 99th quantile we find a positive and significant relationship confirming divergence in the higher income states as well.

Figure 12 below display the regression quantile processes for the unconditional growth equation (5.6).

Figure 12: Plots of the Quantile Regression for NSDP Per Capita



Source: Author's calculations base on EPWRF data

The figure exhibits the entire quantile regression process on the initial income variable, the pooled estimate on the initial income (dashed line), the 95% confidence interval for the pooled (dotted line) and the quantile regression estimate (thick line). we then estimate the growth equation by using different conditional variables.

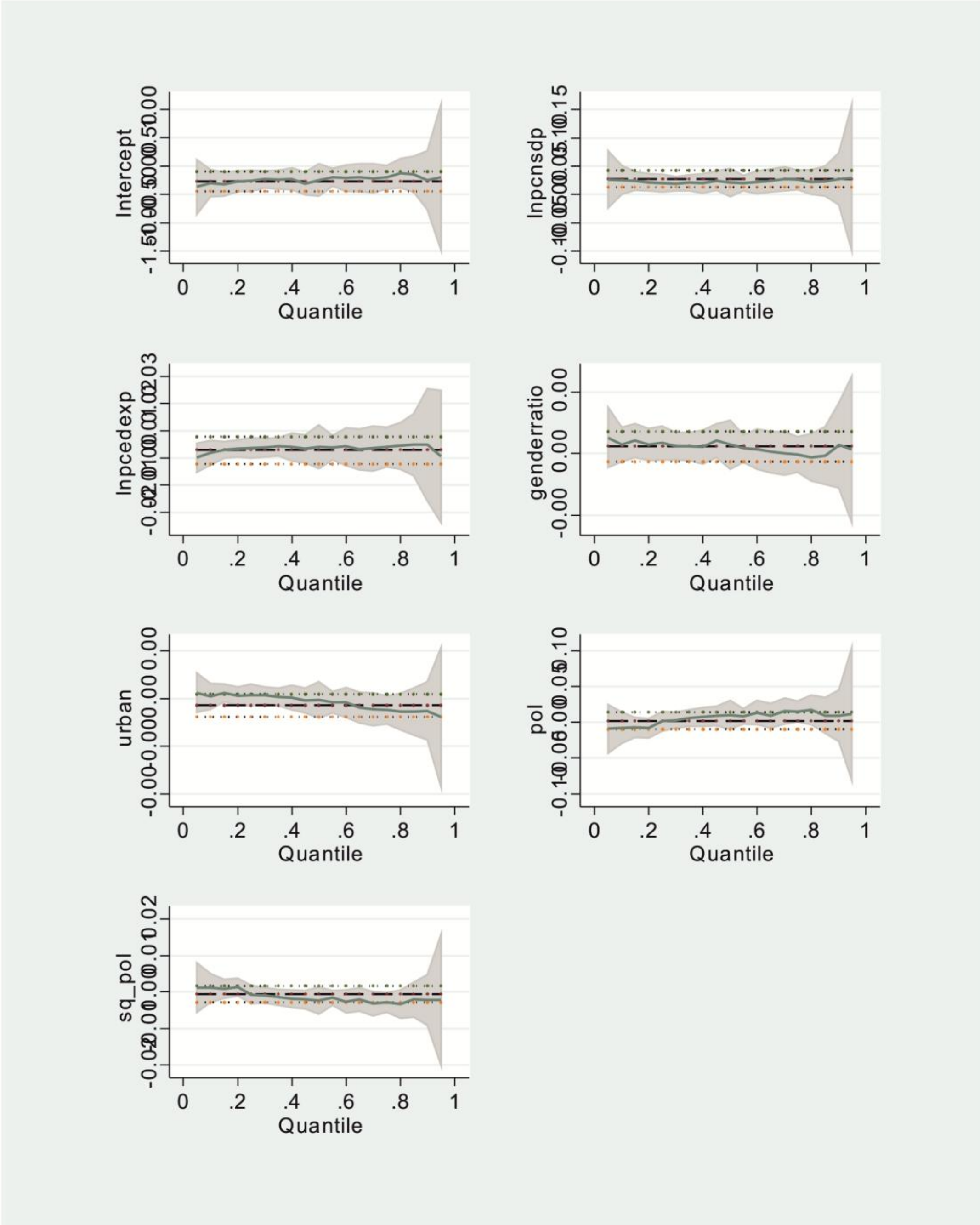
Table 9: Conditional Convergence – Pooled and Quantile Regressions

Variable \Quantile	Pooled Regression	Quantile Regression						
		0.10	0.25	0.50	0.75	0.90	0.95	0.99
lnpcnsdp	0.02*** (0.007)	0.02** (0.012)	0.01** (0.007)	0.02* (0.01)	0.01 (0.007)	0.02 (0.023)	0.02 (0.06)	0.06*** (0.001)
pcedexp	0.002 (0.002)	0.001 (0.002)	0.003** (0.001)	0.004 (0.004)	0.02*** (0.008)	0.004 (0.01)	0.0005 (0.01)	-0.001** (0.0005)
Pol	0.002 (0.006)	-0.007 (0.01)	0.001 (0.006)	0.01 (0.009)	0.01** (0.007)	0.009 (0.01)	0.01 (0.04)	-0.03*** (0.001)
Sq_pol	-0.0006 (0.001)	0.001 (0.001)	-0.0006 (0.001)	-0.002 (0.001)	-0.002** (0.001)	-0.002 (0.003)	-0.002 (0.009)	0.009*** (0.0002)
Urban	-0.0002 (0.0002)	-0.00008 (0.0002)	0.0001 (0.0002)	-0.00006 (0.0003)	-0.0004* ((0.0004)	-0.0005 (0.0006)	-0.0007 (0.001)	-0.001*** (0.0005)
Gender	0.00006 (0.00006)	0.00007 (0.00007)	0.00008 (0.00006)	0.0007 (0.0001)	-5.15e-06 (0.0007)	0.00006 (0.0001)	0.00003 (0.0003)	2.69e-07 (0.00001)
Constant	-0.14*** (0.57)	-0.30** (0.12)	-0.26*** (0.09)	-0.24 (0.14)	-0.19** (0.10)	-0.25 (0.26)	-0.20 (0.64)	-0.37*** (0.02)
Adjusted R^2 Square / Pseudo R^2	0.06	0.12	0.13	0.09	0.06	0.05	0.08	0.40
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1 N=157 Adjusted R^2- for Pooled, Pseudo R^2- for Quantiles								

Source: Author's calculations base on EPWRF data

Table 9 shows the results for the quantile regressions for the conditional case. Similar to the unconditional case, the coefficients of the initial per capita income are positive among quantiles. The coefficients of the other independent variables show significance across different quantiles. The political, square of political and urban variables are significant at 75th quantile. While the per capita education expenditure is significant at the 25th and the 75th quantiles.

Figure 13: Plots for Conditional Convergence



Source: Author's calculations based on EPWRF data

Figure 13 shows the quantile coefficients, the standard deviations and the pooled regression results, from which we can observe that the quantile coefficients are not significantly different from the OLS results.

In the next section we rewrite the above equation as a panel data model in which growth rate is regressed on initial per capita income and a set of control variables. The panel data analysis was performed using the R- software as Stata software did not have this provision.

5.7 Panel Regressions by Quantiles

We estimate the growth equation by employing the panel data with 28 regions (25 states, 2 Union Territories and Delhi as the National Capital Territory) from 1981-10. The entire period is divided into six time periods of five year span namely,1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10. The model to test for unconditional convergence is given in equation

(5.8) $$Gr_{it} = \alpha_{it} + \beta_1 lnpcnsdp_{i,t-\tau} + \varepsilon_{it}$$

Equation (5.8) above, represents the key relationship investigated in this study. With Gr_{it} as the dependent variable, growth rate of per capita NSDP with the initial per capita as the explanatory variable. ε_{it} is the error term. The above equation is estimated using both the traditional conditional mean regression model as well as the conditional quantile regression model.

We estimate three equations for quantile regression. For the unconditional convergence, the following quantile regression model is used;

(5.9) $$Gr_{it} = \alpha_{it} + \beta_q lnpcnsdp_{i,t-\tau} + \varepsilon_{qit}$$

The equation (5.9) is without the inclusion of the other control variables. β_q is the vector of parameters associated with the qth quantile and ε_{qit} is the random error term.

The Table 10 below presents the estimates using both the traditional conditional mean regression model as well as the conditional quantile regression model for the 25^{th}, 50^{th} , 75^{th} and the 99^{th} quantiles.

Table 10: Regression Quantiles for Panel Data (Unconditional Growth Convergence)- Model 1

Model 1 Dependent variable - Growth Rate					
Independent Variables	Panel Fixed effect model	Quantile Regression			
		25^{th}	50^{th}	75^{th}	99^{th}
1	2	3	4	5	6
lnpcnsdp	0.027*** (0.007)	0.024*** (0.0034)	0.016*** (0.005)	0.01 (0.009)	0.02 (0.04)
Constant	-0.21*** (0.072)	-0.20*** (0.03)	-0.10*** (0.05)	-0.06 (0.08)	-0.02 (0.046)
Number of states=28 Observations=168					

Source: Author's calculation based on the EPWRF data

We find that the coefficients are varying with the quantiles confirming that the initial level of per capita income has different impact on the growth rate of per capita NSDP. The coefficients on the initial income are positive for all the concerned quantiles but are significant only for the 25^{th} (lower quantile) and the 50^{th} quantile suggesting that states with lower growth rates are exhibiting divergence. These results suggest that the unconditional divergence is stronger for the bottom 25 percent and the 50 percent slow growing states in our data sample. Though there is unconditional divergence among the states, it depends on whether the states are in the upper or the lower quantile of the distribution. In the states with higher growth rate, the initial income is not a significant determinant.

We now extend the analysis to conditional convergence. We estimate different growth regressions one that includes human capital (literacy rate), and another one where we include the impact of public expenditures on health and education as well as other social and political factors. This analysis is expected to capture the influence of these different factors at different points on the growth distribution.

The model we estimate by controlling for the literacy rate is given as under;

(5.10) $$Gr_{it} = \alpha_{it} + \beta_q lnpcnsdp_{i,t-\tau} + \beta_q lit_{i,t-\tau} + \varepsilon_{qit}$$

Where $lnpcnsdp_{it}$ and lit_{it} is the log of PCNSDP and the literacy rate respectively for initial time periods namely 1981, 1986, 1991, 1996, 2001 and 2006. β_q is the vector of parameters associated with the q^{th} quantile and ε_{qit} is the random error term.

Table 11: Regression Quantiles for Panel Data (Conditional Growth Convergence)- Model 2

Model 2 Dependent variable - Growth Rate					
Independent Variables	Quantiles				
	Panel Fixed effect model	0.25	0.50	0.75	0.99
1	2	3	4	5	6
Constant	-0.03 (0.06)	-0.12*** (0.04)	-0.02 (0.08)	0.07 (0.09)	0.004 (0.33)
lnpcnsdp	0.004 (0.007)	0.01*** (0.005)	0.004 (0.01)	-0.005 (0.01)	-0.0003 (0.041)
Literacy	0.0007*** (0.0002)	0.0005*** (0.0002)	0.0006 (0.0004)	0.001*** (0.0004)	0.003*** (0.001)
Number of states=28 Observations=168					

Source: Author's calculation based on the EPWRF data

In model 2, we use two variables, the initial level of PCNSDP and the literacy rate which is a proxy to human capital. By taking into account an additional factor to test for conditional convergence in model 1, it is seen that the signs of the initial level of PCI estimated coefficients changes across quantiles for the 75^{th} and the 99^{th} quantiles (fast growing states), however, the results for these quantiles are insignificant. For the literacy rate the coefficient is positive across all the growth quantiles indicating that increase in the human capital will improve the growth across the states (except the 50th quantile) and is highly significant for the 25th , 75th and the 99th quantile.

In the next equation we include the social and political variables.

(5.11) $Gr_{it} = \alpha_{it} + \beta_q lnpcnsdp_{i,t-\tau} + \beta_q lit_{i,t-\tau} + \beta_q Gender\ ratio_{i,t-\tau} + \beta_q Urban_{i,t-\tau} + \beta_q Pol_{i,t-\tau} + \beta_q\ Sq\_pol_{i,t-\tau} + \varepsilon_{qit}$

In equation (5.11), along with per capita NSDP and literacy rate we incorporate social, political factors. The two main proxies for social factors are the number of females per thousand males (gender ratio) and the percentage of urban population to total population (urban). The political variable employed in the above equation (5.11) is the number of years the state party ally at the centre. This variable has been used as a dummy variable, if the state party ally at the centre then the value is 1, and 0 otherwise. We have also used the square of political variable to accommodate a quadratic nonlinear relationship between growth and the political factor across different quantiles.In the model 3 (Table 12), the initial PCI is now significant only at the lowest quantile (25th), showing divergence in the rate of growth among the low income states, this is in line with our model 1. The literacy rate is significant only at the 75th quantile. The rise in the percentage of urban population seems to have a negative influence on the growth rates of the states. This is significant across the faster growing states (upper quantiles, 50th, 75th,and the 99th). This is in line with the studies on urbanization (Cali, 2008) which indicates that urbanization or rather over urbanization may have negative spill over including congestion and high land prices that would lead to a dampening effect on economic growth.

Table 12: Regression Quantiles for Panel Data (Conditional Growth Convergence) - Model 3

Model 3 Dependent Variable Growth Rate					
Independent Variables	Panel Fixed effect model	Quantiles			
		0.25	0.50	0.75	0.99
1	2	3	4	5	6
Constant	-0.11 (0.23)	-0.23*** (0.10)	-0.15 (0.13)	-0.02 (0.14)	0.16 (0.30)
lnpcnsdp	-0.03 (0.02)	0.01*** (0.007)	0.01 (0.01)	0.01 (0.013)	0.02 (0.03)
literacy	0.002*** (0.0009)	0.00002 (0.0003)	0.00048 (0.00042)	0.001*** (0.0005)	0.001 (0.0014)
Gender ratio	0.0003** (0.0001)	0.00009 (0.00007)	0.00007 (0.00007)	-0.00006 (0.0008)	-0.00027 (0.0003)
Urban	0.0004 (0.001)	-0.00013 (0.00017)	-0.00034* (0.0002)	-0.00078*** 0.0003	-0.001* (0.001)
Political	0.006 (0.004)	-0.00245 (0.0064)	0.00965 (0.006)	0.01*** (0.006)	-0.023 (0.015)
Sq_pol	-0.001 (0.0008)	0.00001 (0.0011)	-0.002* (0.001)	-0.003)*** (0.001)	0.006*** (0.003)
R-square	0.04				
Number of states=28 Observations=168					

Source: Author's calculation based on the EPWRF data

With regard to the political factor, the coalition between the state and central ruling party does influence the growth rates. The coefficient for political variable increases for the higher quantiles and is highly significant at the 75th quantile suggesting that the if the state and the centre parties are allies it would have a stronger impact to an extend on the higher income states than the lower ones. The square of the political variable showing the nonlinear relationship is also significant across the higher quantiles.

In the next extension we estimated quantile regression model by taking into account public sector investments as proxied by the per capita expenditure on education (pceduexp) and the per capita expenditure on medical and health (pcmedexp) along with the initial per capita NSDP.

(5.12) $Gr_{it} = \alpha_{it} + \beta_q lnpcnsdp_{i,t-\tau} + \beta_q pceduexp_{i,t-\tau} + \beta_q pcmedexp_{i,t-\tau} + \varepsilon_{qit}$

Table 13:Regression Quantiles for Panel Data (Conditional Growth Convergence)- Model 4

Model 4 Dependent Variable Growth Rate					
Independent Variables	Panel Fixed effect model	Quantiles			
		0.25	0.50	0.75	0.99
1	2	3	4	5	6
Constant	-0.13 (0.23)	-0.19*** (0.10)	-0.05 (0.06)	0.005 (0.09)	-0.29 (0.27)
lnpcnsdp	-0.005 (0.008)	0.02*** (0.006)	0.01* (0.006)	0.005 (0.01)	0.05* (0.02)
pceduexp	0.00006*** (9.56e-06)	0.00002* (0.00001)	0.00002* (0.00001)	0.00004** (0.00002)	0.00004** (0.00002)
pcmedexp	-0.0005 (0.00002)	-0.00005* (0.00003)	-0.00002 (0.00003)	-0.0005** (0.00002)	-0.00013 (0.00001)
R-square	0.04				
Number of states=28 Observations=168					

Source: Author's calculation based on the EPWRF data

However, the proxies for social expenditures particularly the per capita education expenditure has been significant and positive across all the quantiles. This shows the fact that there is a positive relationship between the education expenditures and growth rates of the states and this is true for the low income as well as the high income states. With regard to the per capita medical expenditure, there has been a negative relationship with the growth rates, this is in the case of the 25th and the 75th quantile.

5.8 Summary

In this chapter, instead of employing the mean regression estimation methods and taking into account the parameter heterogeneity of the empirical growth models as well to have a complete picture at all levels of distribution between the growth and policy variables, quantile regression approach is adopted. We apply the quantile regression technique for the cross section, pooled and panel data estimation.

When we consider quantile regression for the cross section data, we find interesting results at different quantiles. Though the coefficient on initial per capita income is not significant across the entire conditional distribution, there has been a negative relationship between the growth rate of PCI in 1981-90 and the initial PCI in 1981. These results provides strong evidence of unconditional convergence at the lower most quantile (10^{th}) as well as the upper quantiles (95^{th} and 99^{th}). However, for the periods 1991-13 and 1981-13, we do not find evidence of convergence for any of the quantiles. In fact for the upper quantiles though the results are significant, there is a positive relationship between the growth rates of PCI and the initial PCI confirming divergence.

In case of pooled regression, for unconditional convergence the coefficients of the initial per capita income variables are positive and significant for the median quantiles as well as the lower quantiles (10^{th} and 25^{th}), reflecting the diverging growth of the low income states. In case of conditional convergence, the coefficients of the other independent variables show significance across different quantiles. The political, square of political and urban variables are significant at 75^{th} quantile. While the per capita education expenditure is significant at the 25^{th} and the 75^{th} quantiles.

In case of panel data estimation, it was found that at 25th, 50^{th} 75^{th} and the 99^{th} quantiles, the coefficients are varying with the quantiles confirming our expectation that the initial level of per capita income has different impact on the growth rate of per capita NSDP. The coefficients on the initial income are positive for all the concerned quantiles but are significant only for the 25^{th} (lower quantile) and the 50^{th} quantile suggesting that there is divergence in the growth rates for the states. By extending the model with the inclusion of more control variables, per capita income is significant only at the lowest quantile, showing divergence in the rate of growth among the low income states. An interesting finding of this analysis has been, the negative spillover effects of urbanisation leading to dampening effect on economic growth.

Chapter VI

Club Convergence

6.1 Introduction

Though there is a huge literature analyzing convergence and divergence based on the β and σ convergence approach, it has been pointed out that neither β nor σ convergence provide a complete insight into the convergence process (Quah, 1993b). The regression-based approach only tests whether the initial income is negatively correlated with the subsequent growth rate. Quah (1993a) has argued that regression based methods do not capture the transition in income dynamics and could mask the polarisation of a population into rich and poor masking the presence of convergence clubs (Durlauf 1996). The time paths of the economies are affected by continuous shocks, instability or volatility and thus the dispersion of their cross-section distribution does not diminish over time, but rather, remain more or less constant. Interestingly, while the overall dispersion is constant, there are various kinds of regional dynamics possible, which are of interest. These include criss-crossing, leapfrogging, persistence inequality and even poverty traps, all possible within a constant "σ" band. Clearly, σ-convergence is unable to capture all these possibilities (Kar et al. 2011).

An alternative proposed is a kernel-based approach that is able to separate the trends of growth and distribution and focus exclusively on the latter (Quah 1997). One is then able to separate different long term outcomes like:

a) *Polarisation* – when different regions converge at different peaks,
b) *Stratification*- when different regions converge at multiple two different peaks

c) *Persistence*- when different regions continue in their relative positions, i.e., if an economy is rich at time "t" and it continues to be rich at time "t +s" while others who were poor at "t" continue to be poor at "t+s",

d) *Mobility* - regions that are rich in time period "t + s" had begun poor while some of those poor at "t + s"had begun rich and

e) *Separating*- someeconomies close together at time period "t" have subsequently separated at time period "t+s", with some becoming much richer than others.

The *kernel-based* approach is a non-parametric technique of estimating the probability density function (PDF) of a continuous random variable. Density estimates are considered important as they can reveal skewness and multimodality in the data (Silverman 1986).

While the kernel-based approach assumes a continuous function, if one were only interested in comparing two states (periods), one could use the transition probability matrix. This is a square matrix which describes the probabilities of moving from one state to another in a dynamic system. In each row are the probabilities of moving from the state represented by that row, to the other states. All entries are between 0 and 1 as it represents probabilities and the sum of the entries in the row adds up to one. In a set of studies (Bandyopadhyay, 2004, 2011, 2012)examined the long term behaviour of the income distribution using the transition probability matrix and found evidences of two convergence clubs.

In this chapter these dynamics are investigated primarily using the transition matrix based on Markov Chains. The results are then compared with an alternative method - the stochastic kernels. As discussed in the chapter 3, the Kernel-based approach is a non-parametric technique of estimating the probability density function (PDF) of a continuous random variable. Density estimates are considered important as they can reveal skewness and multimodality in the data (Silverman, 1986).

6.2 Sub National Incomes in India

In India, in the last 30 years not only has income and population grown but so have the number of states due to their administrative and political re-organization. In this chapter, we have used data for 25 states and 3 Union Territories (UT) till 2000-2001. For the period 1981-82 to 2000-2001 we have considered 28 states and union territories. In 2000 by a constitutional amendment three new states were created (Chhattisgarh bifurcated from Madhya Pradesh, Jharkhand bifurcated from Bihar and Uttarakhand – initially called Uttaranchal, bifurcated from Uttar Pradesh). So, from 2001-2 we have considered 31 states.

Many studies have concentrated only on the major states like (M. Ahluwalia, 2000; Cashin & Sahay, 1996; M. Ghosh, 2008; Kar & Sakthivel, 2006; U. Kumar & Subramanian, 2012).Choosing only the major states have its advantages – the data availability is for a longer period, but this may lead to problems of selection bias. As we will see in the analysis below, it might leave us with a limited understanding of regional inequality as we would miss a lot of the action in terms of mobility evident in the smaller and well as special category states.

6.3 Normalization of NSDP

As discussed earlier, the per capita NSDP at constant prices of each state has been normalized using the per capita NDP at constant prices of aggregate of all the states in the sample, for the corresponding years. With this normalization the distribution dynamics controls for the aggregate growth effect of the states and reflects only the state specific (relative) distribution effects.

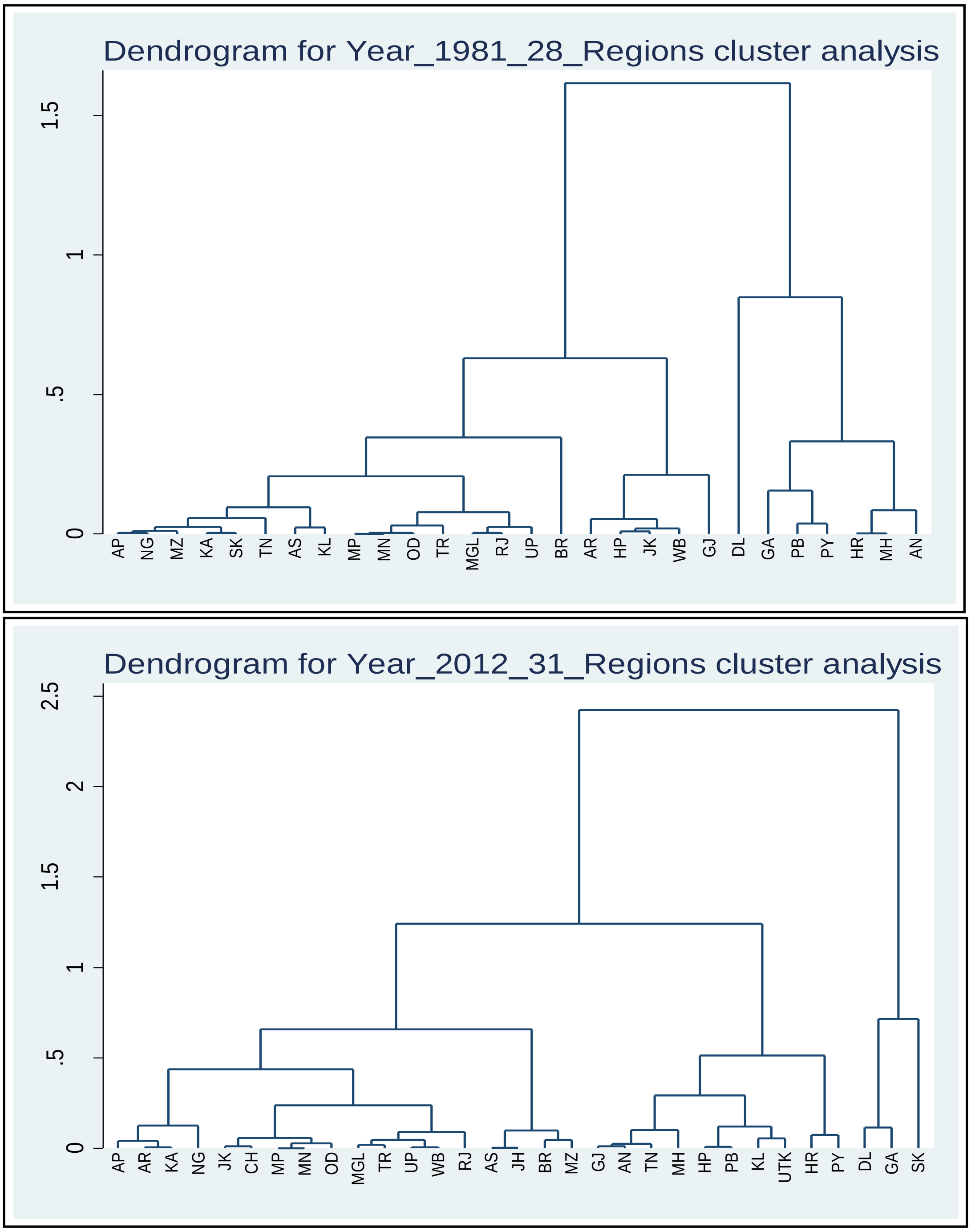
The analysis in this paper has relied on a set of econometrics softwares. In order to generate the 3D graph we use R-stat, for the India GIS maps we use QGIS and for the rest of the graphs and econometric analysis we use Stata. In the following section, we present the findings of our empirical analysis.

6.4 Cluster Analysis and Dendograms

We start with the discussion on the transition probability matrix. In order to determine the number of categories (rows and columns) to be used in the transition probability matrix we tested to see how many clusters are defined at the start and at the end of the period of analysis. Cluster analysis is often graphically shown with the help of a tree diagram known as a dendrogram. It groups observations at various levels of similarity or dissimilarity. At the bottom of the dendrogram, each observation is considered its own cluster. The observations combine until, at the top of the dendrogram, all observations are grouped together. The height of the vertical lines and the range of the (dis)similarity axis gives visual clues about the strength of the clustering. Long vertical lines at the top of the dendrogram indicate that the groups represented by those lines are well separated from one another.

We present the dendrograms for 1981 with 28 regions and 2012 with 31 regions (Figure 14). In 1981, Delhi (DL) is in a league by itself (highest per capita income) and Goa (GA) was clustered with Punjab (PB), Puducherry (PY), Haryana (HR), Maharashtra (MH), Andaman and Nicobar (AN). At the lower end Bihar (BR) stood by itself while Uttar Pradesh (UP), Rajasthan (RJ) and Meghalaya (MGL) clustered together. In 2012, the picture had changed. Delhi, Goa and Sikkim (SK) form a cluster at the right hand (top), while Bihar, Assam (AS), Jharkhand (JH) and Mizoram (MZ) form a cluster at the lower end of the spectrum (Figure 14)

Figure 14 : Dendrogram cluster analysis



Source: Author's calculations based on EPWRF data

We used the Duda-Hart test (complete linkage) common in cluster analysis to statistically identify the number of clusters. The results clearly indicate that there were four clusters in 1981 and five clusters in 2012 (see Table 14).

Table 14 :Cluster Analysis using Duda Hart test (Complete Linkage) for 1981-82 and 2012-13

	1981-82 (28 regions)			2012-13 (31 regions)	
Number of clusters	Je(2)/Je(1)	PseudoT-squared		Je(2)/Je(1)	PseudoT-squared
1	0.2514	77.42		0.3395	56.43
2	0.1625	25.78		0.2953	62.03
3	0.3805	30.93		0.0226	43.26
4	**0.5355**	**12.14**		**0.4432**	**20.1**
5	0.2113	14.93		0.303	18.4

Source: Author's calculations based on EPWRF data.

Note: Bold italics emphasize the number of groups (clusters) as per the Duda-Hart test. It uses the stopping rule that is the largest Je(2)/Je(1) value that corresponds to a low pseudo-T-squared value

In order to decide the number of groups (clusters) based on theDuda–Hart stopping-rule we have to find the largest Je(2)/Je(1) value that corresponds to a low pseudo-T-squared value. Accordingly in 1981–82, we find that the largest Duda–Hart Je(2)/Je(1) ratio is 0.5355, corresponding to four groups with the smallest pseudo-T squared value is 12.14. Similarly, in 2012–13, the largest Duda–Hart Je(2)/Je(1) ratio is 0.4432, corresponding to four groups and has a low corresponding pseudo-T-squared value of 20.1. Even though this is not the smallest pseudo-T-squared value (which would be 18.4 for the five-group solution), we choose the four cluster result since the stopping rule states that the deciding factor is the Duda-Hart Je(2)/Je(1) ratio. The pseudo-T-squared value for the four-group solution (20.1) is low and comparable to the lowest pseudo-T-squared value of 18.4.

In the transition probability matrix presented below, we therefore created four categories of relative PCI—less than 0.75 of average national PCI (normalised to 1), between 0.75 and 1, greater than 1 but less than 2, and greater than 2.

6.5 Transition Probability Matrix

We first analyse the period from 1981–82 to 2012–13 with the original 28 state and UTs. We observe mobility by many states. Sikkim and Kerala have outperformed all the other states with a two-step jump to the right of the diagonal (see Table 15).

Table 15: Relative Per Capita Income Transition Dynamics (1981-12)

		2012				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1981	States with starting level <0 .75	0.333 Bihar, M.P, Odisha	0.556 Meghalaya, Tripura U.P, Mizoram, Rajasthan	0.111 Kerala		9
	States with starting level =or >0 .75 but < 1 or = 1	0.182 Manipur, Assam	0.182 J&K, W.B	0.545 Andhra P.Arunachal P, H.P, Karnataka, Nagaland, T.N	0.091 Sikkim	11
	States with starting level >1 but < 2or =2			0.857 Gujarat, Haryana, Maharashtra, Punjab, Puducherry, A&N Islands	0.143 Goa	7
	States with starting level > 2				1 Delhi	1

Source: Author's calculations based on EPWRF data

Sikkim catapulted to the exclusive club (with Goa and Delhi) with double the relative per capita incomes. Even states like Meghalaya, Tripura, Mizoram, Nagaland, Arunachal Pradesh have shown improvement by moving higher than their 1981 levels. Goa, which was already in the category of higher income states has also moved a step ahead. However, Assam and Manipur, have shown a worrisome performance by moving below the diagonal, being the only two states that fall below their 1981 category.

However, the first decade of the 2000s has seen many changes and the demarcation of new states has been of significance to their parent state. The matrix for the period 2001–12 (see Table 16) represents just a decade's change.

Table 16: Relative Per Capita Income Transition Dynamics, 2001-12 (31 regions)

		2012				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
2001	States with starting level <0 .75	0.75 Assam, Bihar, M.P, Odisha, Jharkhand, Manipur	0.25 J&K, Chhattisgarh			8
	States with starting level =or >0 .75 but < 1 or = 1	0.09 Uttar Pradesh	0.36 Meghalaya, Rajasthan, Tripura, W.B	0.46 AP, Arunachal P, Karnataka, Nagaland, Uttarakhand	0.09 Sikkim	11
	States with starting level >1 but < 2or =2		0.11 Mizoram	0.89 Gujarat, Haryana, H.P, Kerala, Maharashtra, Punjab, TN, A&N		9
	States with starting level > 2			0.33 Puducherry	0.67 Delhi, Goa	3

Source: Author's calculations based on EPWRF data.

The most significant difference is that UP has now moved below the diagonal in the lowest income category signifying a slowdown. Joining UP below the diagonal are Mizoram and Puducherry but at higher income groups. The results of the transition matrix are similar to the findings of the dendogram presented earlier.

In the following tables we see if there is any difference in the dynamics observed between the pre and post reform period. The tables below depicts the transitions matrices for the pre reforms (1981-90)and the post reforms periods(1991-2012).

Table 17 : Relative Per Capita Income Transition Dynamics (1981-90)

		1990				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1981	States with starting level <0 .75	0.78 Bihar, MP, UP, Odisha, Kerala, Rajasthan, Tripura	0.22 Mizoram, Meghalaya	0	0	9
	States with starting level =or >0 .75 but < 1 or = 1	0.27 J&K, Manipur, Assam	0.73 An P, Arunachal P, H.P, Karnataka, Nagaland, Sikkim, T.N,West Bengal	0	0	11
	States with starting level >1 but < 2or =2	0	0.14 A& N Islands	0.86 Goa, Gujarat, Haryana, Maharashtra, Punjab, Puducherry,	0	7
	States with starting level > 2	0	0	1 Delhi	0	1

Source: Author's calculations based on EPWRF data.

The pre-reform decade 1981-90, shows strong persistence with rich states remaining rich, and the poor staying poor (see Table 17). Among the poorer states in that period, J&K, Manipur, Assam ended up in a lower state category as did the rich state of Delhi. Even Andaman & Nicobar moved lower. Mizoram and Meghalaya moved into the next higher category, while the rest of the states maintained their positions. This is indicative of polarization of income as discussed earlier.

When we look at the post reforms period 1991-2012 (see Table 18) we find greater mobility in the lower income category, with J&K, Rajasthan, UP and Tripura moving into higher income categories, and the states like Andhra, Gujarat, HP, Karnataka, Kerala, Nagaland, TN, A&N clubbing with the higher income groups.

Table 18: Relative Per Capita Income Transition Dynamics(1991-12)

		2012				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1991	States with starting level <0 .75	0.56 Assam, Bihar, MP, Manipur, Odisha	0.44 J&K, Rajasthan, UP Tripura	0	0	9
	States with starting level =or >0 .75 but < 1 or = 1	0	0.25 Meghalaya, Mizoram,WB	0.67 Andhra, Gujarat,HP, Karnataka, Kerala,Naga, TN, A&N	0.08 Sikkim	12
	States with starting level >1 but < 2or =2	0	0	0.83 Arunachal Pradesh, Maharshtra Haryana,Punjab, Puducherry	0.17 Goa	6
	States with starting level > 2	0	0	0	1 Delhi	1

Source: Author's calculations based on EPWRF data.

Interestingly though the composition of the income convergence clubs does not drastically differ over the time periods. The richer states have moved ahead, with the poor states making little progress even in the post-reform period. Some of the middle income states are found to be clubbing with the rich or the poor ones. Delhi, Goa, Punjab, Haryana, Gujarat Maharashtra, Puducherry, and A&N Islands have dominated the top ranks for all decades examined. On the other hand, Bihar, Orissa, Madhya Pradesh, J&K, Rajasthan, and Uttar Pradesh have had lower levels of income. Interestingly though Tamil Nadu, Himachal Pradesh, Karnataka, and Kerala clubbed with higher PCI level states. Among the north eastern states, Sikkim, Arunachal Pradesh, Nagaland have done better during certain periods whereas, Tripura, Assam, and Manipur moved backwards in some periods. The states that are in the highest income category at the beginning of the time period have shown a very high persistence in maintaining their position of affluence.

One of the criticisms levelled against the use of the Markov transition matrix is that the results are very sensitive to the choice of the discrete groups. Since these are determined in an ad hoc manner the results may not be robust (Kar et al., 2011). To overcome these shortcomings, stochastic kernel distributions are preferred and we now examine if these confirm or contradict the findings of the discrete dynamic models. In the following section with kernel density plots, the distribution of PCI in Indian states is seen.

6.6 Kernel Density

We track the distribution of per capita income in Indian states over four time-periods i.e. (1981, 1991, 2001 and 2012). A set of income distributions (kernel-smoothed densities obtained using a Gaussian kernel) across the states in India at roughly decade-long intervals is presented below (see Figure 15 and 16).

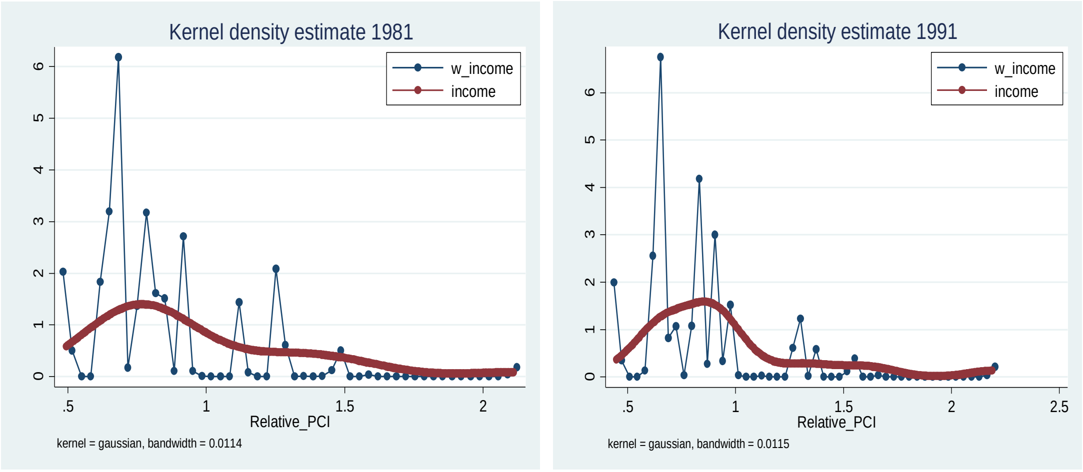
Visually, when compared across the four time periods, the smoothed density curves suggest that the highest modal frequency was achieved in 1991 and the lowest modal frequency was achieved in 2012. Expectedly, the largest spread is also noticed in 2012. In all the four years there seem to be more than one modal value. In the post-reform period, the modal frequencies declined when compared to the pre-reforms period and the peaks of the smoothed distribution have moved further apart in this period. This could lead us to believe that there is a 'twin peak' formation in the distribution of PCI among the Indian states in the post reform period as a result of the mobility of some middle income states towards low income values compared to the pre-reforms distribution as anticipated by Kar et al., (2011) andBandyopadhyay (2004).

This conclusion may be premature since the kernel density plots may have an inherent flaw – the unweighted kernel density estimates treat each observation with equal weight. However, states in India vary widely in demographic and geographic size – the population of Andaman and Nicobar is around 0.5 million in comparison to Uttar Pradesh which has a population above 200 million. Therefore, the unweighted analysis may not reflect the true degree of dispersion or convergence in PCI.

6.7 Population weighted Analysis

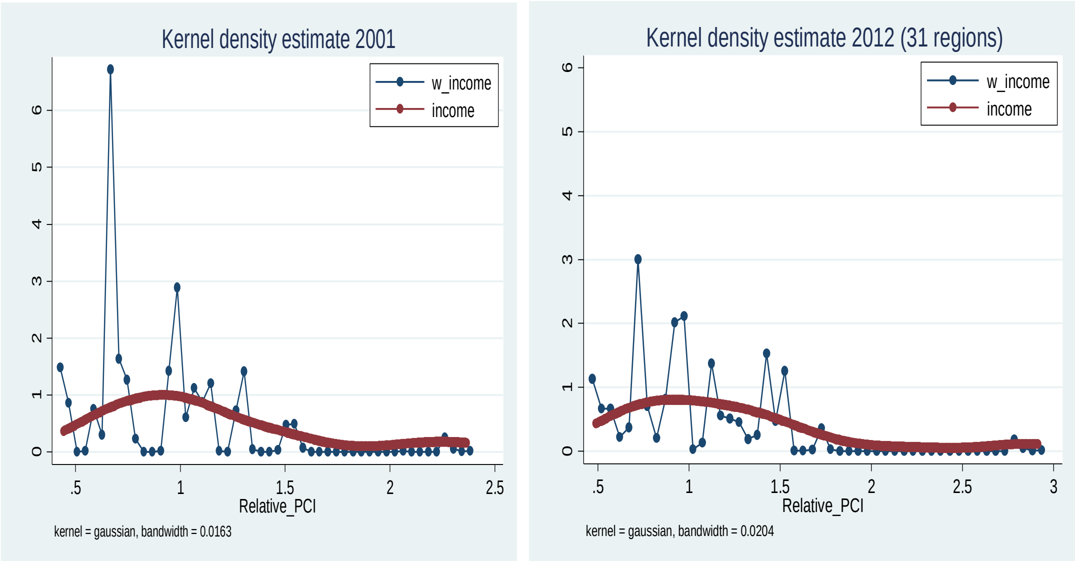
Attaching population weights to the observations would more accurately reflect the contribution of each observation in the given sample (Gisbert, 2003). If we compare the weighted kernel density estimates (jagged curve labelled *w_income*) with the the un-weighted estimates (smoothed curve labelled *income*) we find the possibility of multiple modes in the distribution (see Figure 15 and 16).

Figure 15: Weighted kernel density 1981 and 1991



Source: Author's calculations based on EPWRF data.
Note: The bandwidth is automatically estimated by the software (Stata 12).

Figure 16: Weighted kernel density 2001 and 2012



Source: Author's calculations based on EPWRF data.
Note: The bandwidth is automatically estimated by the software (Stata 12).

This would imply that polarization has increased in the middle income states as well in all the sub periods – an outcome not so clearly demonstrated in the un-weighted smoothed kernel analysis. In order to confirm the validity of the claim based on visual observation and to determine the number of modes in empirical non-parametric kernel density estimators we use the Silverman test (Silverman 1981,1986).

One of the first applications of the bootstrap multimodality tests and nonparametric density estimation techniques was by Bianchi (1997) followed by numerous others like Henderson et al, (2008) and Colavecchio et al, (2011) to name a few. To the best of our knowledge, this study is the first attempt to formally test for multi-modality statistically for convergence among the Indian states.

6.8 Testing for Multi-Modality

In order to verify whether the multimodality exists, we used a test of multimodality based on the bootstrap principle proposed by (Silverman, 1981). The multi-modality test relies on a null hypothesis that a kernel density distribution "f" for "k" number of modes, (where "k" is a non-negative integer) as given in Equation 6.1 below;

(6.1) $$\int_{-\infty}^{\infty} K(x)dx = 1$$

If this is rejected then the distribution has more than "k" modes. When the kernel density distribution is constructed, the degree of smoothness is controlled by the value of the bandwidth "h" – the larger "h" is, the smoother the curve and more likely for the distribution to be uni-modal (Silverman, 1981). The critical window width "$h_{critical}$" is the smallest "h" that produces a density with "k" modes and is stated as:

(6.2) $$h_{critical}(k) = \inf\{h: \hat{f}(..,h) \text{ has at most } k \text{ modes}\}$$

Therefore, for all $h \leq h_{critical}(k)$, the estimated density distribution "f" has atleast "k+1" modes. Further, bootstrap tests are used based on the concept of critical bandwidth introduced by (Silverman, 1981). The value of the critical bandwidth in this paper is computed using the Stata program developed by Salgado-Ugarte et al. (1997).

We perform the Silverman test for each year from 1981-2012, with the null hypothesis that there are one, two, three and four modes (alternate hypotheses implies that there are more than one, two, three and four modes, respectively). The results are displayed in Table below. The cell entries for any given year (row entries) indicate the values of "$h_{critical}(k)$".

Table 19: Silverman's Multimodality Test (28 Regions-1981-2000 and 31 Regions-2001 Onwards)

Critical bandwidth (p-values in parenthesis)					
Year	$h_{critical}$ *(1)*	$h_{critical}$ *(2)*	$h_{critical}$ *(3)*	$h_{critical}$ *(4)*	*K**
1981	0.21(0.34)	**0.16(0.10)**	0.09(0.22)	0.06(0.24)	1
1982	0.19(0.42)	0.14(0.22)		**0.08(0.06)**	5
1983	0.16(0.34)	**0.15(0.02)**	0.07(0.42)		3
1984	0.17(0.40)	0.11(0.36)	0.09(0.28)	**0.10(0.02)**	5
1985	0.22(0.22)	0.13(0.32)	**0.1(0.06)**	0.06(0.32)	4
1986	0.21(0.14)	0.1(0.50)	0.08(0.42)		1
1987	0.22(0.32)	0.12(0.26)	0.08(0.34)	0.06(0.44)	1
1988	0.21(0.36)	0.11(0.22)	**0.09(0.08)**	0.06(0.24)	4
1989	0.17(0.58)	0.12(0.44)	0.11(0.12)	0.07(0.18)	1
1990	0.17(0.48)	0.13(0.28)	0.08(0.26)	0.06(0.16)	1
1991	0.22 (0.48)	0.12 (0.42)	**0.13(0.02)**	**0.08(0.10)**	4
1992	0.17(0.62)	0.11(0.48)	0.08(0.36)	**0.09(0.04)**	5
1993	0.21(0.30)	0.13(0.50)	0.12(0.12)	**0.2(0.00)**	5
1994	0.23(0.44)	0.13(0.32)	**0.16(0.00)**	**0.1(0.02)**	5
1995	0.21(0.34)	0.14(0.30)	**0.12(0.04)**	**0.1(0.08)**	5
1996	0.22(0.44)	**0.17(0.08)**	0.1(0.38)	0.09(0.14)	3
1997	0.26(0.42)	0.15(0.40)	**0.14(0.08)**	**0.13(0.00)**	5
1998	0.25(0.64)		**0.24(0.00)**	**0.15(0.00)**	5
1999	0.28(0.50)	0.16(0.34)	**0.19(0.00)**	**0.12(0.02)**	5
2000	0.31(0.40)	0.13(0.58)	0.11(0.42)	0.09(0.30)	1
2001	0.3 (0.22)	0.12(0.46)	**0.23(0.00)**		4
2002	0.34(0.12)	0.12(0.48)	**0.14(0.08)**	**0.11(0.02)**	5
2003	0.32(0.16)	0.11(0.58)	**0.23(0.00)**	0.10(0.12)	4
2004	0.36(0.48)	**0.29(0.06)**	0.14(0.24)	**0.13(0.02)**	5
2005	0.4(0.26)	0.21(0.32)	0.14(0.24)	0.12(0.12)	1
2006	0.34(0.46)	0.20(0.32)	**0.21(0.00)**	**0.12(0.10)**	5
2007	0.36(0.42)	0.20(0.34)	0.16(0.22)	**0.13(0.06)**	5
2008	0.41(0.48)		0.18(0.12)	0.12(0.24)	1
2009	0.33(0.38)	0.25(0.16)	**0.19(0.04)**	0.13(0.20)	4
2010	0.35(0.38)	0.22(0.18)	**0.19(0.04)**	0.11(0.16)	4
2011	0.35(0.38)	**0.28(0.10)**	0.18(0.16)	**0.16(0.02)**	5
2012	0.39(0.16)	0.19(0.26)	**0.23(0.00)**	**0.12(0.10)**	5

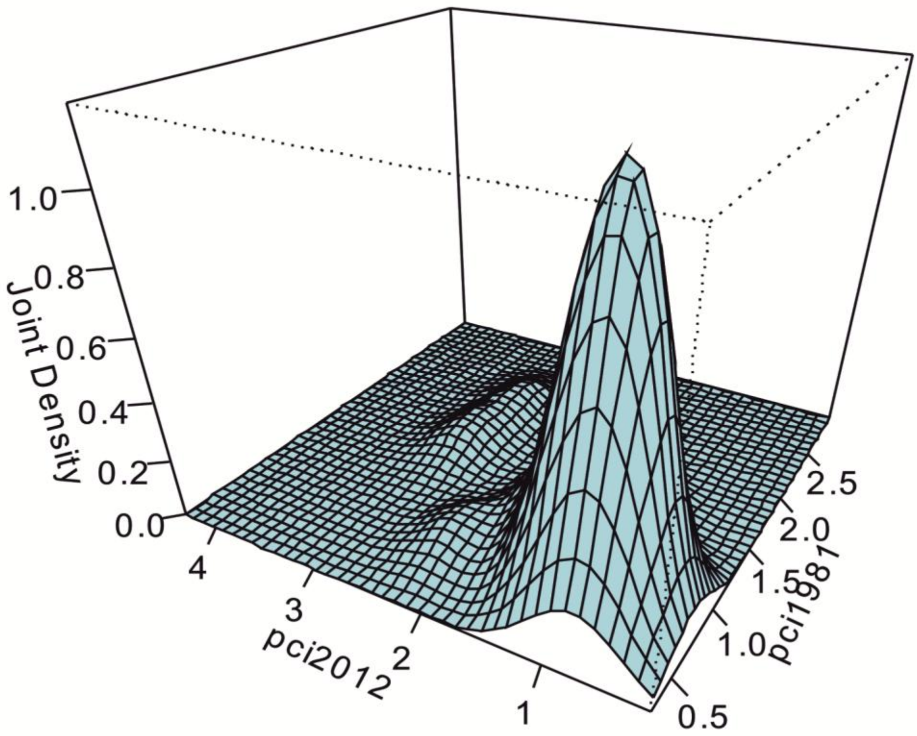
Source: Author's calculations based on EPWRF data.
Note: The critical values that are significant are shown in bold if $p \leq 0.1$

The p-values associated with the corresponding critical value widths are given in parentheses, and k* denotes the number of modes detected.In the period, 1981-90, we are unable to reject the null hypothesis of uni-modality in five of the 10 years under consideration. In contrast, between 1991-2000 (28 regions) and in 2001-12 (31 regions) there were only two years when there was uni-modality. Interestingly, Silverman's test reveals that in none of the years under consideration is there evidence of bi-modality (twin peaks). The presence of multi-modality is also visually validated by examining the kernel density estimates using a 3-dimensional representation.

6.9 Stochastic Kernels: Three Dimensional Plots

The three dimensional graph (Figure 17) is a representation of the standardised kernel density function and is a continuous version of a transition probability matrix as discussed earlier. It allows us to track distribution dynamics between two time periods. Its input is a distribution, while the output is a three dimensional graph that plots the evolution of a distribution between two time periods - in our study, 1981 and 2012. On the vertical axis we measure the density and on the horizontal axes are the two years under consideration (left axis 2012 and right axis 1981). The value at any point on the surface from the X-axis (marked "pci 1981")extending parallel to the Z-axis (marked "pci 2012"), is given by the stochastic kernel, which is a probability density function. It has a projection that is nonnegative and the area under the curve integrates to unity. (This projection is similar to a row of a transition probability matrix discussed earlier in the paper that has only nonnegative entries and sums up to 1).

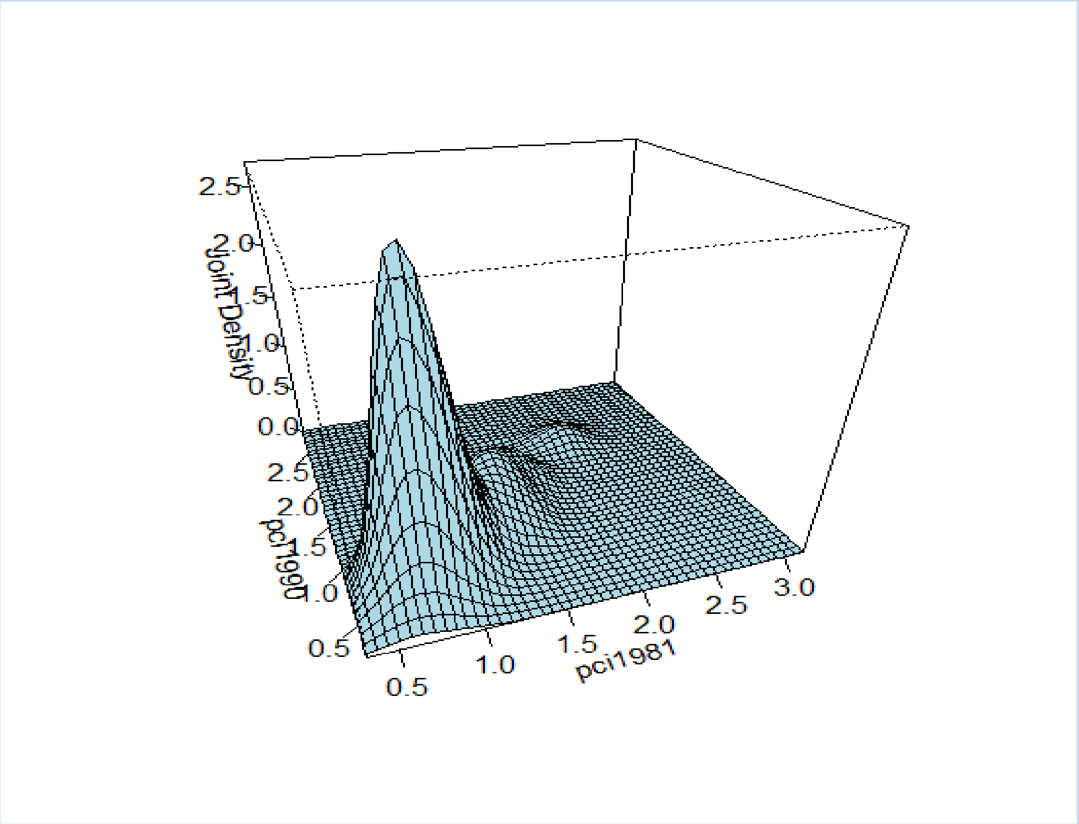
Figure 17: Three -dimensional representation of growth rates between 1981-2012



Source: Author's calculations based on EPWRF data.

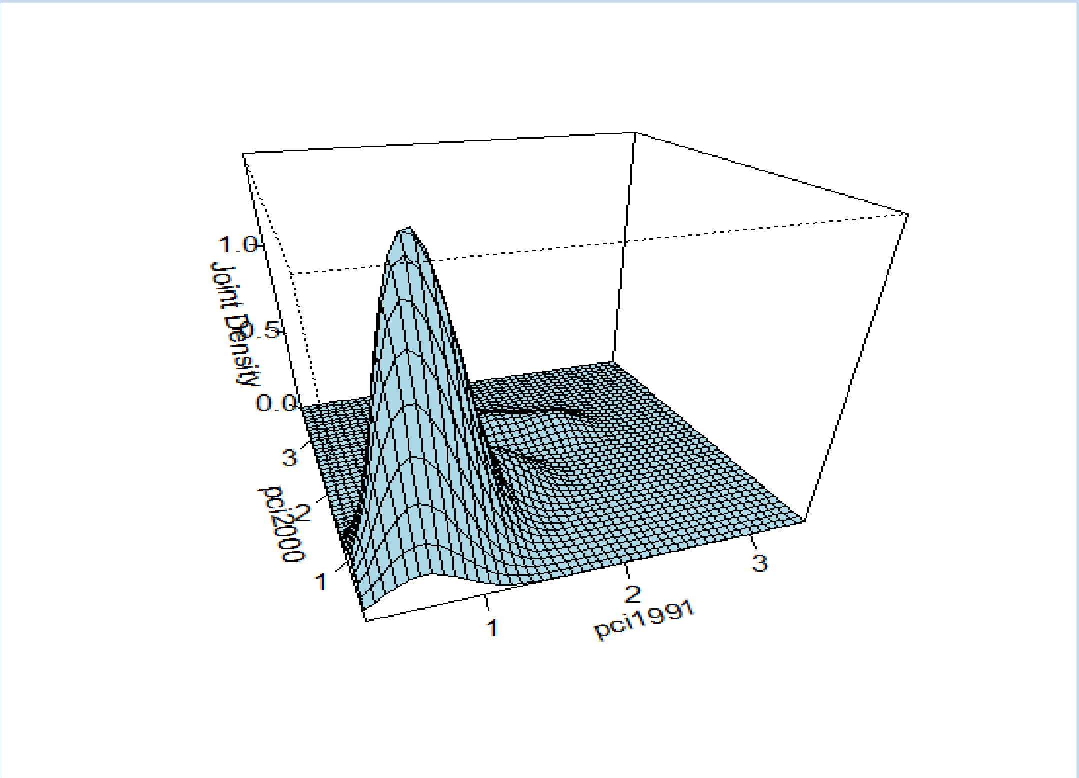
Since most of the surface is concentrated along the 45-degree diagonal, it means the elements in the distribution remain where they began. In the above figure, a large portion of the probability mass is clustered around the main diagonal, and along the principal ridge, and therefore multimodality can be clearly identified by observing the peaks.These results suggest that the hypothesis of bimodality of PCI can be rejected for the years under consideration (1981-2012). While the claim of divergence is validated, we find more than twin peaks in the distribution of income especially in the post-liberalization period. We can now turn to Figure 18 and 19 which shows the stochastic kernel estimates for the pre reform period(1981-1990) and the post reform period (1991-00) and (1991-2012).

Figure 18:Three -dimensional representation of growth rates between 1981-1990



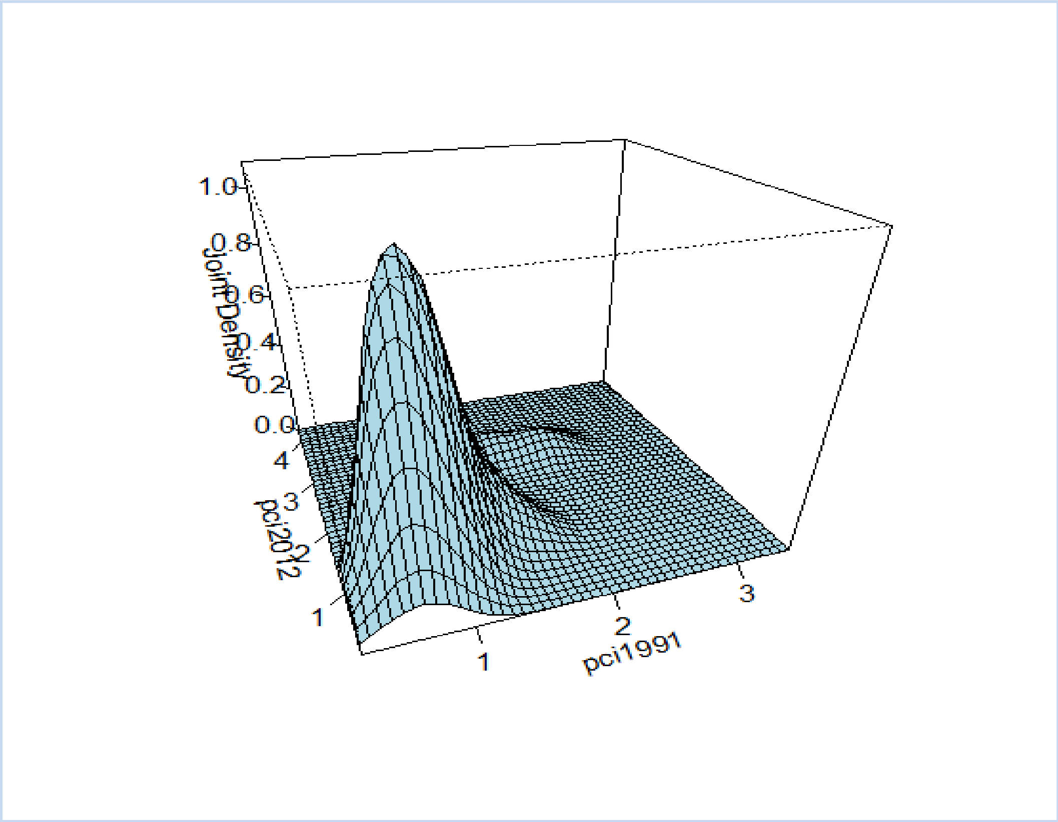
Source: Author's calculations based on EPWRF data.

Figure 19:Three -dimensional representation of Growth Rates between 1991-2000



Source: Author's calculations based on EPWRF data.

Figure 20:Three -dimensional representation of growth rates between 1991-2012



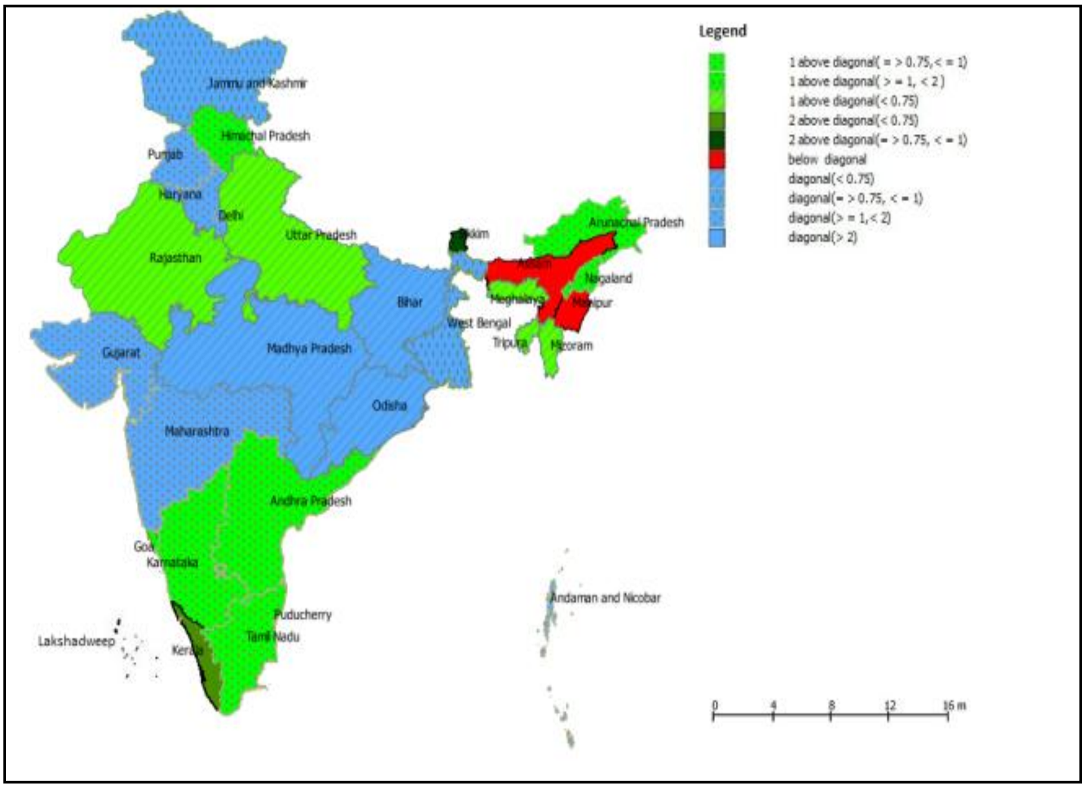
Source: Author's calculations based on EPWRF data.

The results are not much different even in the pre and the post reform period shown in the figures. A clear multimodality is observable in all the graphs. The main diagonal in all the plots below highlights persistence properties. We find that a larger proportion of states are concentrated in the lower income category, with very few states being the part of higher income category and a cluster of states in between these two extremes.

6.10 Spatial Spread of Growth Rates

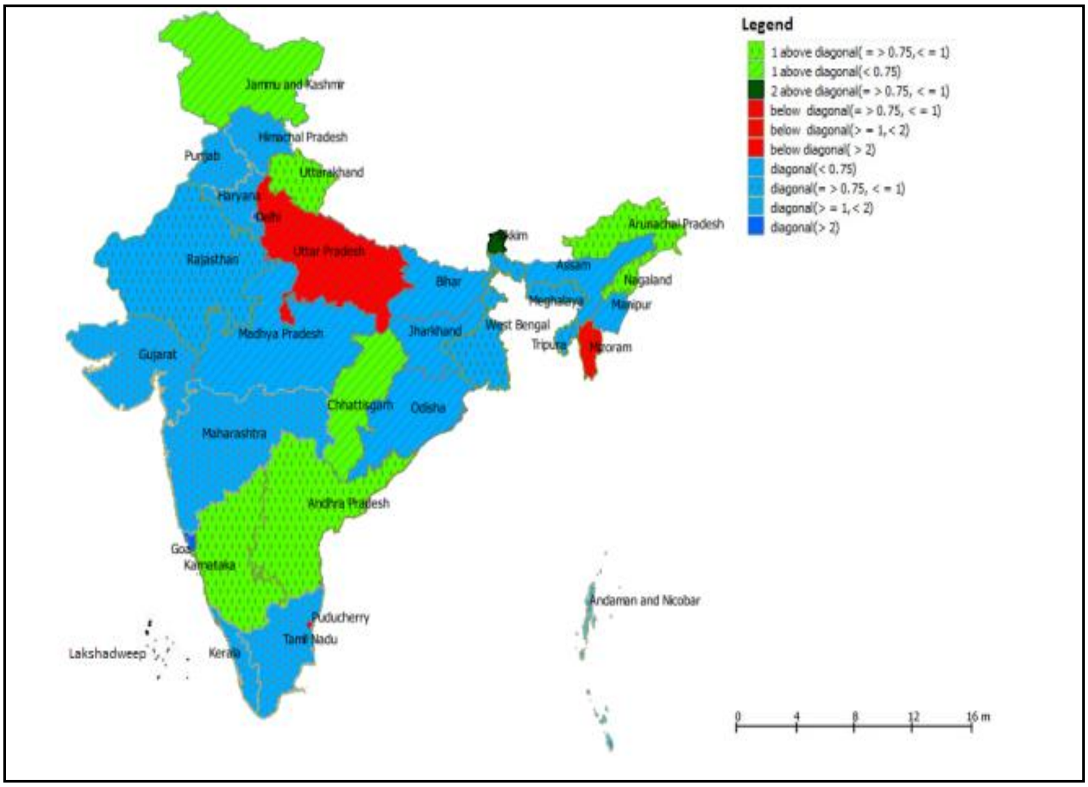
When we map the growth rates geographically (state-wise), we find an interesting spatial spread (Figures 21 and 22).

Figure 21: Spatial spread of growth rates - 28 regions between 1981-2012



Source: Author's calculations based on QGIS shape file

Figure 22: Spatial spread of growth rates, 31 regions between 2001-2012



Source: Author's calculations based on QGIS shape file.

The two maps indicate the transition matrix outcomes (Table 15 and 16 respectively) when we consider 28 regions for the period 1981-2012 (Figure 21) and when we consider 31 regions for the period 2001-2012 (Figure 22). The green coloured states (in different shades) are the ones who have moved beyond the category where they started in 1981-82 (above the diagonal on the transition matrix). The ones in blue are those who did not experience any change in relative position (on the diagonal of the transition matrix). The areas shaded in red are states which receded in terms of their relative starting category in the 30 year period under study (placed below the diagonal on the transition matrix). The colours are overlaid with symbols to indicate differences in transition among them. The areas with diagonal lines are in the lower category of the income levels, the areas with dashes have moved a step ahead in their respective category. The ones with dots have reached towards higher levels of income. The states without any symbols in the shades of blue and green have been the best performers over the entire period.

The low income states are mostly clustered in the northern and the eastern areas of India. Interestingly, Rajasthan has moved out of the BIMARU category along with two of the newly formed states – Uttarakhand and Chhattisgarh. What is left of the original BIMARUgroup are Bihar, Jharkhand, Madhya Pradesh (minus Chhattisgarh), Odisha, Uttar Pradesh (minus Uttarakhand) and the new entrants into this category are Assam, and Manipur.

6.11 Summary

This chapter examined the divergence in per capita incomes in the last 30 years, and tested the claim of polarisation (twin peak formation) in the distribution of incomes. We find that there is evidence of divergence in per capita incomes and the nature of divergence is not bi-modal but multi-modal especially in the last two decades. One of the main talking points about India's growth trajectory in the post-1991 phase has been the transition to a higher long run growth trajectory. We find that the spatial spread of growth has seen interesting outcomes whether we take a telescopic view of 30 years or the just the last decade which saw greater consolidation of market reforms. In the relative growth ranking of states while there has been change within the poorest group of states, their relative positions vis-à-vis the rest has not altered. Rajasthan is the exception. While we have not explored reasons for this, it is likely to have reaped some benefits of spatial proximity to better performing states in its neighbourhood like Gujarat, Punjab, Haryana and Delhi. Uttarakhand and Chhattisgarh havealso been able to accelerate their growth beyond their parent state's economic status. Uttarakhand was probably better off than the rest of UP to start with and the post separation data only confirms this. Additionally, it may have had the benefit of being in geographical proximity of Punjab, Haryana and Himachal Pradesh. Chhattisgarh shares its western boundaries with Maharashtra and Andhra Pradesh which are better performing states and has probably been able to overcome influences of bordering Odisha and Jharkhand which have shown little change in their relative position to the national average. The last decade has not been good for UP, Mizoram and Puducherry. Part of UP's falling behind could be due to the separation of Uttarakhand (with a higher growth rate) which has led to a fall in UP's relative income. While Mizoram has improved its relative status in the last three decades, it has seen a lowering of its relative position in the last decade. If we take the long run view, Assam and Manipur stand out as the only two states that have fallen below their starting levels. In the last decade, Sikkim has shown the largest acceleration while Andhra Pradesh, Arunachal Pradesh, Karnataka, Uttarakhand, Jammu and Kashmir and Chhattisgarh also moved out of their starting groups. The rest of the states have maintained their relative group positions including Goa, Delhi which have continued to exhibit the highest relative growth rates. The variation in sub-national growth outcomes suggests that regional inequality continues to be a concern and deepening of market forces in the economy has not resulted in convergence.

Chapter VII

Spatial Distribution of Growth

7.1 Introduction

The theory of economic growth postulates that in the long run there would be a convergence of growth rates due to a transfer of technology and factors of production (Solow, 1956). Wide regional variations in growth performance of the states in India has kept alive the research interest in this area (see Bajpai, & Sachs, 1996; Cherodian & Thirlwall, 2013; Dholakia, 1994; Ghosh, et al., 1998; Kurian, 2000). The post-independence era was characterized as a closed economic set up (Basu & Maertens, 2007). India became a liberalized open economy from the mid 1980s and more rapidly from early 1990s (Cashin & Sahay, 1996; B. Ghosh et al., 1998; Kalra & Thakur, 2015). It was expected that all the states and regions would benefit from the market oriented reforms (see Ahluwalia, 2000; Ghosh et al., 1998). Contrarily, dispersion in per capita incomes and social development has increased over time (Ahluwalia, 2000; Kar et al., 2011).

Empirical studies traditionally have typically highlighted that economic growth is influenced by certain factors like initial level of income, human capital, investment, physical infrastructure and institutions (Barro et al., 1991; Karnik & Lalvani, 2012; Mankiw et al., 1992; Nayyar, 2008).Oddly in all the studies mentioned above, the states have been viewed as independent entities and the possibility of dependence among them has been ignored. It is now increasingly recognized that geographic space and physical distances between regions play an important role in determining growth outcomes. Therefore a region's growth may not be generated independently(Anselin, 1988). Spatial dependence occurs when there is a dependence among the observations at different points in space..

Spatial dependence occurs when there is a dependence among the observations at different points in space. Spatial data may show dependence in the variables and error terms. The use of OLS, time series or panel techniques without controlling for neighbourhood effects could lead to serious bias and inefficiency in the estimation of the convergence rate (Arbia, et al 2005; Getis, 2008). In this chapter we a) test whether growth of Indian states exhibits spatial dependence and then b) estimate the convergence rate after controlling for spatial impacts.

7.2 Convergence and Spatial Dependence

In a linear regression analysis, the purpose is to find a linear relationship between the dependent variable and a set of independent variables. The ordinary least squares estimates the β coefficient by minimizing the sum of squared errors. Different assumptions are made as far as the random errors are concerned like; a) errors should be normally distributed, b) errors must have a constant variance, c) there should be no misspecification or bias in the regression equation. However, these assumptions may not be always satisfied in practice. When the value in one location depends on the value in another location, there is spatial dependence. The ordinary least square estimation is thus not suitable when there is spatial dependence between the observations (Anselin, 1988).This dependence could be present in the variables as well as the error terms. The consequence of ignoring this varies with the type of spatial dependence in the data. If there is presence of spatial lag (when the dependent variable y in state *'i'* is affected by the dependent variables in both place *'i'* and *'j'*) and we ignore it, we may encounter an omitted variable problem, akin to excluding an important explanatory variable. The OLS would then produce biased and inconsistent estimates. If there is spatial error, ignoring it would result in an efficiency problem and the OLS estimates would be unbiased but inefficient. These estimates would violate the BLUE assumptions.

Spatial econometrics accounts for the presence of spatial effects in regression analysis. Spatial econometrics provides a mechanism to overcome the problem of spatial dependence in the OLS and panel regression approach.

In terms of data requirement, spatial models require geo coding of observational units. These units could be cities, regions, municipalities, jurisdictions, states, countries and so forth (Elhorst, 2014). The observations which are close will influence each other more than those which are farther away.

One of the unique things about the spatial data is that it needs to be geo coded for locations. Basically every single observation in the data needs to have either coordinates, borders, distance or some other geo coded data to do spatial econometric modeling. Spatial econometrics, not only considers the characteristics of the individual regions, but also sees the influence of neighbors on the regions.

Spatial effects could be of two types:

1) Spatial Dependence (Spatial Autocorrelation)

When variables of one region depend on (or are correlated) to values observed in neighbouring regions it caused spatial autocorrelation. If a variable tends to cluster in area then spatial autocorrelation is high and when neighbouring geographical areas have uncorrelated values then spatial autocorrelation is low.

There could be least three possible explanations for such possibilities;

firstly, there is a simple spatial correlation relationship, showing what is causing an observation in one location, also causes similar observations in nearby locations.

Secondly, there is a possibility of spatial causality; that is something at a given location directly influences it in nearby locations.

Thirdly, there is spatial interaction as the mobility of individuals, goods or information creates relationships between locations.

2) Spatial Heterogeneity

Spatial heterogeneity is a special case of observed or unobserved heterogeneity that generally refers to the clumpy or patchy distribution of processes or events across a broad landscape. It is the variation in relationships across the space. For example, could be a cluster of forward States (rich regions or the core) and a cluster of backward States (poor regions or the periphery). Thus while analysing regional convergence all these issues need to be considered (Anselin, 1988).

As the traditional econometrics ignores these two issues, there is a violation of the Gauss-Markov assumptions. With spatial dependence the assumption that the explanatory variables need to be fixed in repeated sampling is violated. While with the spatial heterogeneity, the assumption of single linear relationship across the sample data observations is violated. Alternative estimation procedures are required if the relationship keeps on varying as we move across the spatial data sample. Thus while analyzing regional convergence all these issues need to be considered.

The simple cross section methods do not take into account the heterogeneity or the spatial effects. The panel data models with greater degrees of freedom, more variation and less amount of collinearity among the variables have more efficiency in the estimation (Elhorst, 2014). The classical panel data fixed effects models are able to overcome the problems of individual heterogeneity and omitted variables. However, they do not control for spatial dependence. This chapter provides the first estimates of regional income convergence in India controlling for spatial dependence.

We use the Exploratory Spatial Data Analysis (ESDA) to test for spatial effects in the data. Our analysis has relied on QGIS (v 2.0.1), Stata (v12) and Geoda software packages for the analysis.

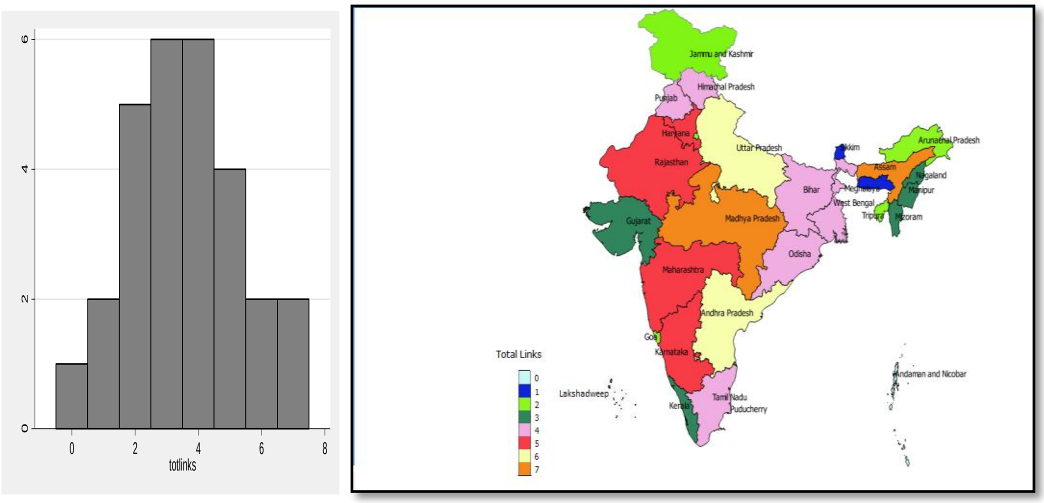
7.3 Spatial Weight Matrix

Spatial dependence is quantified through the Spatial Weight Matrix (SWM) W =[W_{ij}] (where*i* and *j*=1,...,n, which incorporates the spatial relationship among the 'n' observations that are considered as neighbours). The expectation is that if two observations are close to each other they will influence each other a lot more than observations which are located further away. The spatial weight W_{ij} reflects the “spatial influence” of unit *j* on unit *i*. Each unit's value is the weighted average of its neighbours. The SWM is row standardized, thus weights add up to 1 in each row. This is done to create proportional weights when regions do not have equal number of neighbours. Each cell's row standardized weight is the fraction of all spatial influence on unit *i* attributable to unit *j*. The diagonal elements of the matrix are equal to zero. The non - diagonal elements are non - zero for observations that are close spatially and zero for those that are far away. The SWM have different values and are based on contiguity and distance. Accordingly we have employed contiguity and inverse distance based matrix.

7.3.1 Contiguity Matrix from Geospatial Data

A contiguity or a normalized-contiguity matrix is constructed from the boundary information in a coordinates dataset of geospatial data. In contiguity matrix, contiguous units are assigned the weights of 1, while, non-contiguous units are assigned weights of 0. These contiguous units are known as neighbours.Contiguity can be further defined either as Queen, Bishop or Rook and they could be of first order or higher (second) order. We use rook contiguity of the first order – spatial units sharing a common border are considered first order rook contiguous (see Figure 23). This is a stronger condition that avoids the situation of a single shared boundary point being counted as neighbour.

Figure 23: Distribution of states with first order contiguity



In the histogram in Figure 23 (left hand-side) we present the distribution of states and their neighbours. It provides a count of the number of links (neighbours) that the 28 spatial units have. Diagnostic tests of the contiguity matrix for India show that we have two states Madhya Pradesh and Assam with 7 neighbours while Andaman and Nicobar being an island has no neighbour (zero link). The colour scheme on the India map (right had side of Figure 23) shows the geography of total links.

Three normalization techniques namely; row, minmax, and spectral are available in the software.

1) *Row-normalized matrix*- each element in row *i* is divided by the sum of row *i*'s elements.
2) *Minmax-normalized matrix*- each element isdivided by the minimum of the largest row sum and column sum of the matrix.
3) *Spectral-normalized matrix*- each element is divided by the modulus of the largest eigen value of the matrix.

The summary of contiguity based matrix used in the analysis is given as under;

Table 20:Contiguity Based Matrix

Matrix	Description
Dimensions	28x28
Stored as links	28x28
Total	100
minimum	0
mean	3.57
maximum	7

The table shows the information about the row normalized contiguity matrix. The number of neighbors found is reported as 100 with each state having around 4 on an average.The shortcoming with using the contiguity option is that only neighbouring units are taken into account. However, sometimes deeper knowledge about distance relationships is important (Anselin, 1988).We have therefore also used the distance-based matrix for our analysis, which we discuss next.

7.3.2 Inverse Distance Matrix from Geospatial Data

An inverse-distance spatial-weighting matrix is made up of weights that are inversely related to the distances between the units. With the help of the coordinate variables from the attribute data, the inverse-distance spatial-weighting matrix is created.

Table 21: Inverse Distance Matrix

Matrix	Description
Dimensions	28x28
Stored as links	28x28
Total	100
minimum	0
Min>0	.0003325
mean	.0011267
maximum	.0102623

This helps us to examine if the distance has any neighbourhood impacts. These distances between geospatial units are computed from the latitudes and longitudes of the unit's centroids.

There are different distance functions that can be used. The Euclidean, dhaversine and the rhaversine are the distance functions generally employed. When distance function rhaversine or dhaversine is specified, the haversine distance measure is applied to the two coordinate variables.The haversine equation is mostly employed in navigation, as it gives great-circle (spherical) distances between two points from their longitudes and latitudes. The first coordinate variable specifies longitude and the second coordinate variable, the latitude.

The coordinates are in radians when rhaversine is specified and in degrees when dhaversine is specified. The haversine distance measure is calculated in kilometers by default (Drukker, et al, 2013).It is useful when the units are located on the surface of the earth and the coordinate variables represent the geographical coordinates of the spatial units.

We find, following Drukker, et al (2013) that in India the centroids of the two closest states lie within 97 kilometers of each other (i.e. 1/.0102623), while the two most distant states are 300.7 kilometers apart (i.e. 1/0.003325).

7.4 Interaction Effects

The standard approach in most empirical work is to start with a non-spatial regression model and then to test whether or not the model needs to be extended with spatial interaction effects (Anselin, 1988;Elhorst, 2014).

In a spatial econometric model there are three kinds of interaction effects (Elhorst 2014)

a) Endogenous interaction effects: These are the effects among the dependent variables (Y). Here the dependent variable of a particular unit say, 'A' depends on the dependent variable of other units, say, 'B', and vice versa.

b) Exogenous interaction effects: here the dependent variable of a particular unit A, depends on independent explanatory variables of other units ay 'B'. These are the effects among the independent variables(X). For example, the growth of per capita income of an economy may depend on the other explanatory variables in the neighbouring states. In the empirical convergence literature, the economic growth of a particular country thus can depend not only on the initial income level, saving rates, population growth, technological change and depreciation of its one's own economy, but also on these variables in neighbouring countries.

c) Interaction effects among the error terms (e): here the omitted variable from the model are spatially auto correlated, or there could be situations where there is a spatial pattern in the unobserved shocks.

7.5 Exploratory Spatial Data Analysis

The Exploratory Spatial Data Analysis (ESDA) checks for the presence of spatial heterogeneity and autocorrelation. The test commonly used for detecting spatial autocorrelation is the Global Moran's I and Local Moran’s I (also called the LISA – Local Indicators of Spatial Autocorrelation) tests.

7.5.1 Global Moran's I

The Global Moran’s I test statistics to check for the presence of global spatial dependence among observation units is calculated as follows;

(7.1) $$I = \frac{N}{\Sigma_i \Sigma_j W_{ij}} \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} W_{ij} (X_i - \bar{X})(X_j - \bar{X})}{\sum_{i=1}^{n} (X_i - \bar{X})^2}$$

where N is the number of regions(points or polygons), W_{ij} is the relevant element (cell value) of the weight matrix W, X_i is the value of the variable in region i , X_j is the variable value in another region j, and $\bar{x}$ is the cross-sectional mean of X.

Moran's I involves only one variable - the correlation between variable, X, and its “spatial lag” calculated by averaging all the values of X for the neighboring polygons. The global measure uses a single value of Moran's I for the entire data set and the entire geographic area.The spatial models become relevant if these tests reject the null hypothesis of absence of spatial dependence. Presence of spatial dependence is confirmed if the correlation statistic is significant, suggesting that the distributional evolution of a variable is clustered in nature. High values of a variable will be located close to other high values and vice versa.

7.5.2 Local Moran's I

The local Moran's I test statistic on the other hand is computed for each location and is calculated as follows:

(7.2)
$$I_{\mathrm{i}} = \frac{(X_{\mathrm{i}} - \bar{X}) \sum_{j=1}^{n} W_{ij} (X_j - \bar{X})}{\sum_{i=1}^{n} (\mathrm{X}_{\mathrm{i}} - \bar{X})^2 / \mathrm{n}}$$

Local Moran's I indicates the location of local clusters and spatial outliers. We can also map the polygons having a statistically significant relationship with its neighbors, and show the type of relationship. Local Moran's I statistics identify the locations contributing most to the overall pattern of spatial clustering. The local statistics detects significant spatial clustering (referred as hotspots) around an individual location (Pisati, 2001).

In the presence of global spatial autocorrelation (GSA), the p-values of Local Moran's I local statistics should be regarded just as an approximate indicator of statistical significance. Like GSA, the Local Moran's I detects presence of both the positive and negative spatial autocorrelation. The sum of local values of all observations is proportional to global Moran's I (Anselin, 1995). With the Moran scatter plot we can visualize the type and strength of spatial autocorrelation.

The Moran's I test and LISA statistics detect if there is spatial dependence and thus justify the use of spatial econometric models. However, even if spatial autocorrelation statistics indicate a significant pattern of spatial clustering, it is only the first step in the analysis. The next step would be to model the relationship across the spatial units or the different interaction effects. This is what we discuss in the next section.

7.6 Spatial Dependence Models for Cross-Section Data

In order to test for β-convergence across regions in India, we would first begin with cross-sectional OLS approach followed by a diagnostics test for the presence of spatial effects. A linear regression model without any spatial effects is stated as follows;

$$Y_i = \alpha_i + \beta X_i + u_i \quad (7.3)$$

In the equation above, per capita income (PCI) growth "Y_i"is the dependent variable and the initial income level "X_i" is the explanatory variable in region "i".α and β are parameters to be estimated, and u is the error term.

7.6.1 Cross Section Models

We discuss four kinds of spatial models which are commonly used for cross section as well for panel data analysis.

a) The Spatial Lag Model or the Spatial Autoregressive (SAR) model contains endogenous interaction effects,

b) Spatial Error Model (SEM) considers the interaction effects among the error terms,

c) When endogenous interaction effects and the error interaction effects is considered together we have the Spatial Autocorrelation (SAC) model (Le Sage & Pace, 2009),

d) The Spatial Durbin Model includes both endogenous and exogenous interaction effects.

When all types of spatial interactions are considered in a cross section model it is referred to as the *General Nesting Spatial (GNS) Model*.

(7.4) $$Y_i = \alpha_i + \beta X_i + \rho W Y_i + \theta W X_i + u_i$$, where

(7.5) $$u_i = \lambda W u + e_i,$$ implying

(7.6) $$Y_i = \alpha_i + \beta X_i + \rho W Y_i + \theta W X_i + \lambda W u + e_i$$

In equation (7.4) and (7.6) *"WY"*, captures the spatial dependence in the dependent variables (endogenous interaction effects),"*WX*", denotes the exogenous interaction effects among the independent variables and "Wu" denotes the spatial dependence in the error term. The estimated parameter " ρ " is known as the spatial autoregressive coefficient (coefficient estimated for the spatial lag), " λ " is the spatial autocorrelation coefficient, while θ and β represent the fixed but unknown parameters and W is a non-negative spatial matrix, that describes the spatial arrangement of the units in the sample.

These cross section spatial models with interactions effects can be replicated for panel data models given in the section below.

7.6.2 Panel Data Models

Panel data models examine the cross-sectional (group) and the time-series (time) effects. Panel data models also offer different effects that may be fixed and/or random. Fixed effects assume that individual group/time have different intercept in the regression equation, while random effects assume that individual group/time have different disturbance but a common intercept. The cross section of "n" observations in the equations (7.4-7.6) can be extended for a panel of "n" observations over numerous time periods "T" , by adding a subscript "t" to all the variables and the error term in the model.

A simple growth equation using panel data without including any form of spatial effects is expressed in the following way;

(7.7) $$Y_{it} = \alpha_{it} + \beta X_{it-\tau} + \mu_i + \eta_t + u_{it}$$

With "i=1 ...n" denotes regions and "t=1 ...T", denotes time periods. The dependent variable Y_{it} is the annual growth rate of PCI and $X_{it-\tau}$ is the initial value of PCI in region "i" and time "t-τ". In the above equations, the intercept "μ_i" considers the omitted variables which are specific to each spatial unit, and "η_t" represents time specific effects. The spatial and the time effects can be divided into the fixed and random effects. In fixed effects models, a dummy variable is introduced for each of the spatial units and time periods, while in random effects model, both μ_i and η_t are considered as random variables that are independently and identically distributed (I.I.D) with zero mean and variance. Further, μ_i, η_t and u_{it} are assumed to be independent of each other.

Equation (7.7) represents a fixed effect panel data model, in which β is the fixed parameter estimated by a Least Square Dummy Variable process. It is time invariant and represents the region specific effects.

We can account for spatial dependence in the GNS model by extending equation 6 and 9 in the following way:

(7.8) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \rho WY_{i,t-\tau} + \mu_i + \eta_t + \theta WX_{i,t-\tau} + u_{it}, \text{ where}$$

(7.9) $$u_{it} = \lambda Wu + e_{it}, \quad \text{implying}$$

(7.10) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \rho WY_{i,t-\tau} + \mu_i + \eta_t + \theta WX_{i,t-\tau} + \lambda Wu + e_{it}$$

We can thus create different linear spatial econometric models by imposing restrictions on one or more of its parameters (Elhorst 2014). We next describe the different models popularly used briefly below.

7.6.2.1 Spatial Lag Model or Spatial Autoregressive Model (SAR)

The fixed effect SAR model considers the spatial dependence in the dependent variable. The spatial impact of error term and the independent variable is dropped here, so $\lambda = 0$ and $\theta=0$. Equation (7.10) reduces to

(7.11) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \rho W Y_{i,t-\tau} + \mu_i + \eta_t + u_{it}$$

In this model, spatial dependence is explained by interactions among the dependent variables across regions. Here, ρ is the spatial autoregressive coefficient.

In the context of convergence and economic growth of the states, it would imply that the growth rate of one state is related not only to its own initial level of per capita income but also on the current income levels in the other states.

7.6.2.2 Spatial Error Model (SEM)

The SEM considers only the spatial dependence in the error term, thus $\rho = 0$ and $\theta=0$. Equation (7.10) reduces to

(7.12) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \mu_i + \eta_t + u_{it}, \text{ where}$$

(7.13) $$u_{it} = \lambda W u + e_{it}$$

The error term here is not IID. Therefore like the GNS, the error term is adjusted to accommodate spatial dependence and a random error "e_{it}" that confirms to I.I.D requirements. This type of spatial dependence could be because of some missing variables as a result of an underspecified model. The parameter λ shows the intensity of the spatial relationship through the error term (Rabassa & Zoloa, 2016).

7.6.2.3 The Spatial Autocorrelation (SAC) model

The fixed effects SAC model includes interaction effects among endogenous variables and interaction effects among the error terms and thus $\theta=0$. The spatial impact of the other explanatory variable is dropped here and only the spatial impact of the dependent variable is used as an explanator. This specification is also known as the spatial autoregressive model with autoregressive disturbance (SARAR) model,

(7.14) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \rho WY_{i,t-\tau} + \mu_i + \eta_t + u_{it}$$, where

(7.15) $$u_{it} = \lambda Wu + e_{it}$$

This model implies that the growth rate of an individual region is affected by the growth of the neighbouring regions. Unlike the SDM model which we discuss the impact and the spatial dependence of the other factors is represented by the error term.

7.6.2.4 Spatial Durbin model (SDM)

The fixed-effects SDM includes both the endogenous and the exogenous interaction effects. It includes the spatial lags of the explanatory variables as well as the dependent variable, but assumes $\lambda = 0$ in equation 7.10.

The spatial impact of error term is dropped here and only the spatial impact of the dependent and independent variable is employed. Equation (10) reduces to

(7.16) $$Y_{it} = \alpha_{it} + \beta X_{i,t-\tau} + \rho WY_{i,t-\tau} + \mu_i + \eta_t + \theta WX_{i,t-\tau} + u_{it}$$

This model implies that the growth rate of one state depends on the growth rate of the neighbouring states. This completes our discussion on the different spatial models. In the next sub section we discuss the results of our empirical analysis.

7.7 Empirical Results

As discussed earlier, a common statistic that is examined in the spatial models is the Moran's I.

7.7.1 Moran's I statistics

The results of the Moran's *I* statistic for global spatial autocorrelation for the PCNSDP for 1981 and 2010, as well as for real per capita growth (from 1981 to 2010) are reported in the Table 1 below. Both the contiguity and distance based matrices are presented. The values of Moran's I show the degree of spatial dependence and its significance implies that geographically proximate regions exhibit spatial dependence in India.

Table 22: Moran's I Global Spatial Autocorrelation Statistic for Indian States

	Contiguity Matrix	Distance Weight Matrix
PCNSDP 1981	0.151*	0.070**
PCNSDP2010	0.219**	0.073***
Growth Rate 8110	0.226**	0.105***

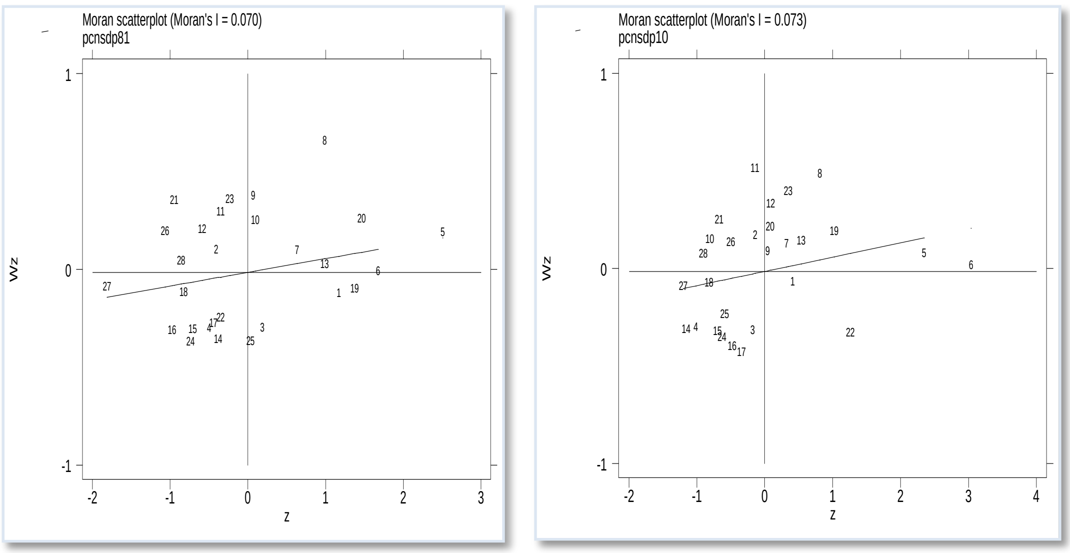
Source: Author's calculations based on EPWRF data using QGIS and Stata

Significance at ***1%, **5%, and *10% level

These results suggests that there is a strong positive and statistically significant spatial dependence in the PCI for both the years (1981 and 2010) and growth (1981-10) whether we use the contiguity measure or the distance measure.

Moran's scatter plot shows the correlation between variable X, andthe "spatial lag" of X. This lag is formed by averaging all the values of X used to identify the type of spatial association for the neighboring states (Anselin, 1996). The standardized income of a state (y-axis) is plotted against the weighted average of the incomes of its neighbouring states (x-axis). The weights are obtained based on the inverse distance and the contiguity matrices (discussed earlier).In Figure 1 below, on the vertical axis we represent "W_z" which is the lag of variable X and on the horizontal axis is "z" which is variable X. The slope of the regression line obtained by regressing "W_z" (lag of variable X) and "z" (variable X) gives us the Moran's I (I = 0.070 in 1981 and I=0.073 in 2010) based on the inverse distance matrix (Anselin, 1996, p. 116).

Figure 24: Moran's Scatter Plot of PCI 1981and 2010 (2004-5 Constant Prices) based on Inverse Distance Matrix



Source: Author's calculations
Note: 1-A&N Islands, 2-Andhra Pradesh, 3-Arunachal Pradesh, 4-Assam, 5-Delhi, 6-Goa, 7-Gujarat, 8-Haryana, 9-Himachal Pradesh,10-J&K, 11-Karnataka, 12-Kerala, 13-Maharashtra,14-Manipur,15-Meghalaya, 16-Mizoram, 17-Nagaland, 18-Orissa, 19-Puducherry, 20-Punjab, 21-Rajasthan,22-Sikkim,23-Tamil Nadu,24-Tripura,25-West Bengal,26-Uttar Pradesh,27-Bihar,28-Madhya Pradesh.

The Moran's scatter plot is divided into four quadrants, each representing different kinds of spatial association or dependence.

a) The first quadrant (upper right quadrant (HH)) shows the spatial clustering of regions with high income and surrounded with similar regions with high income neighbours. Thus, the locations are associated with positive values ofI_i.

b) The third quadrant (lower left quadrant (LL)) showsthe spatial clustering of low income states which have low income states as neighbours. These locations are also associated with positive values of I_i

c) The second quadrant (upper left quadrant (LH)) shows clustering of low incomes states surrounded by regions with high incomes. These locations have negative values of I_i.

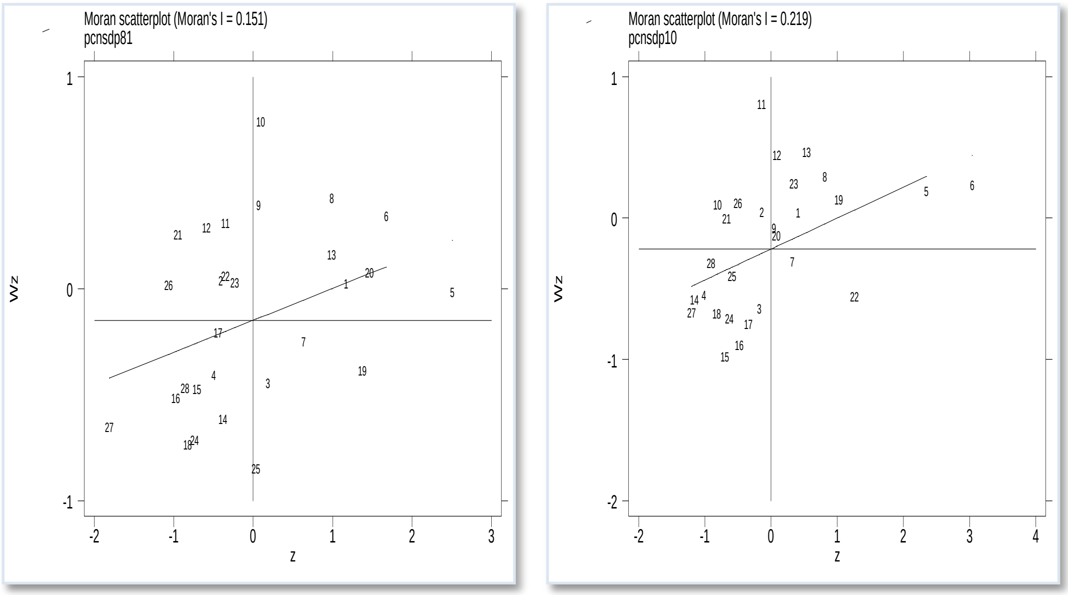
d) The fourth quadrant (lower right quadrant (HL)) shows spatial clustering of high income states surrounded by regions with low incomes. These locations arealso associated with negative values of I_iI.

If we examine the per capita incomes in the two periods 1981-82 and 2010-11, we find evidence of spatial concentration of the states. In 1981, Delhi, Goa and Punjab were the richest states surrounded by high income neighbours. Contrarily, Puducherry was a high income state surrounded by regions with low incomes. In quadrant 2, U.P, M.P, Rajasthan, Kerala and Andhra Pradesh were the low income states surrounded by richer neighbours. In the third quadrant Assam, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura (North eastern states) along with Bihar and Odisha were the poorest and also had poor neighbours.

In 2010, Delhi, Goa were the richest states and there has been an increase in the number of high income neighbours surrounding them. Kerala and Tamil Nadu, which earlier belonged to a lower income category, joined the cluster in quadrant 1 in 2010. Similarly, Puducherry which was surrounded by low income neighbours in quadrant 4, joined the cluster in quadrant 1 in 2010. Unfortunately Assam, Manipur, Meghalaya, Mizoram, Nagaland, Tripura (North eastern states) have continued to be in the third quadrant. Arunachal Pradesh and West

Bengal hasnow joined this cluster. Sikkim has been a remarkable outlier and moved from being a low income state to a high income state. It is however surrounded by low income neighbours and therefore is placed in quadrant 4. Our results confirm a strong regional concentration of per capita income in India, with most of the richer states located in the Southern and the Western parts of India, along with Delhi, Haryana, Punjab in the North (Lolayekar & Mukhopadhyay, 2016).

Figure 25: Moran Scatter Plot of PCNSDPin 1981 and 2010 (2004-5 Constant Prices) based on Contiguity Matrix



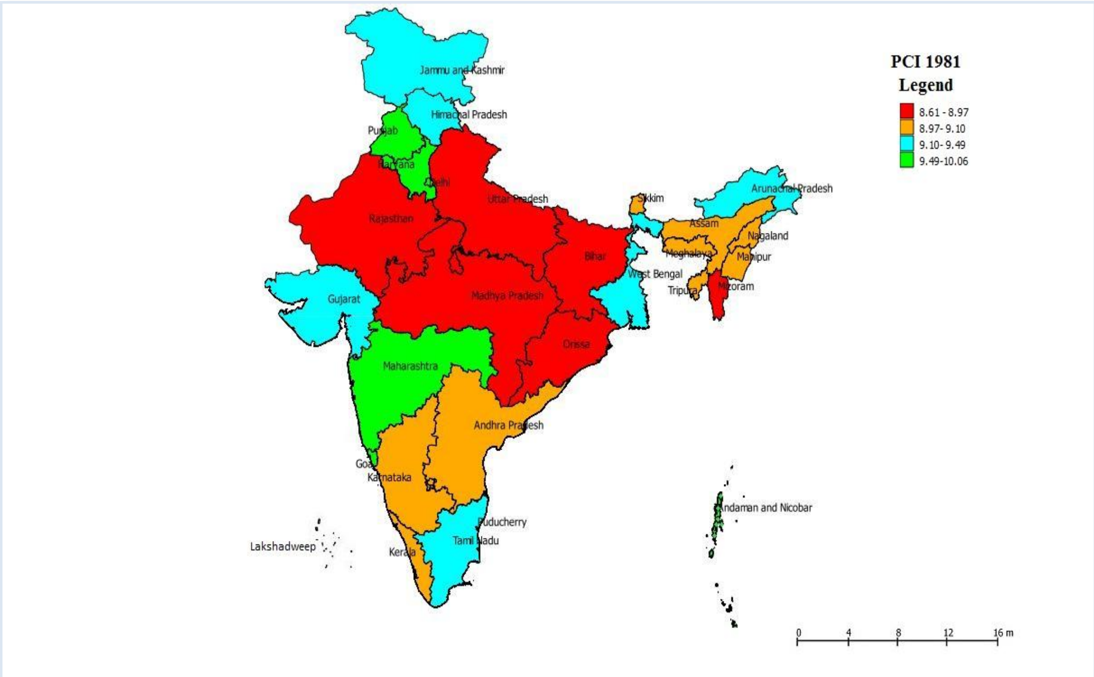
Source: Author's calculations using EPWRF data.

The scatter plots created from contiguity matrix reveal similar results (from inverse distance) with respect to the pattern of spatial concentration in India, with a few exceptions (see Figure 24). We find that Delhi, Goa, Haryana, Punjab and Maharashtra were the richer states surrounded by high income neighbours in 1981. In contrast (to the findings of the distance matrix), Gujarat is located in quadrant 4 surrounded by states with low income (in contrast to Figure 23).

7.7.2 Spatial Maps

A slightly different perspective from the scatter plots is in the maps below here the Local Moran's I is mapped for each state in the initial and terminal years of our data. These maps help to detect some possible spatial patterns that remain constant through time. The distribution of the states based on their per capita incomes is taken for two time slots 1981 and 2010. When we map the per capita incomes geographically (state-wise), we find an interesting spatial spread (Figures 25 and 26).

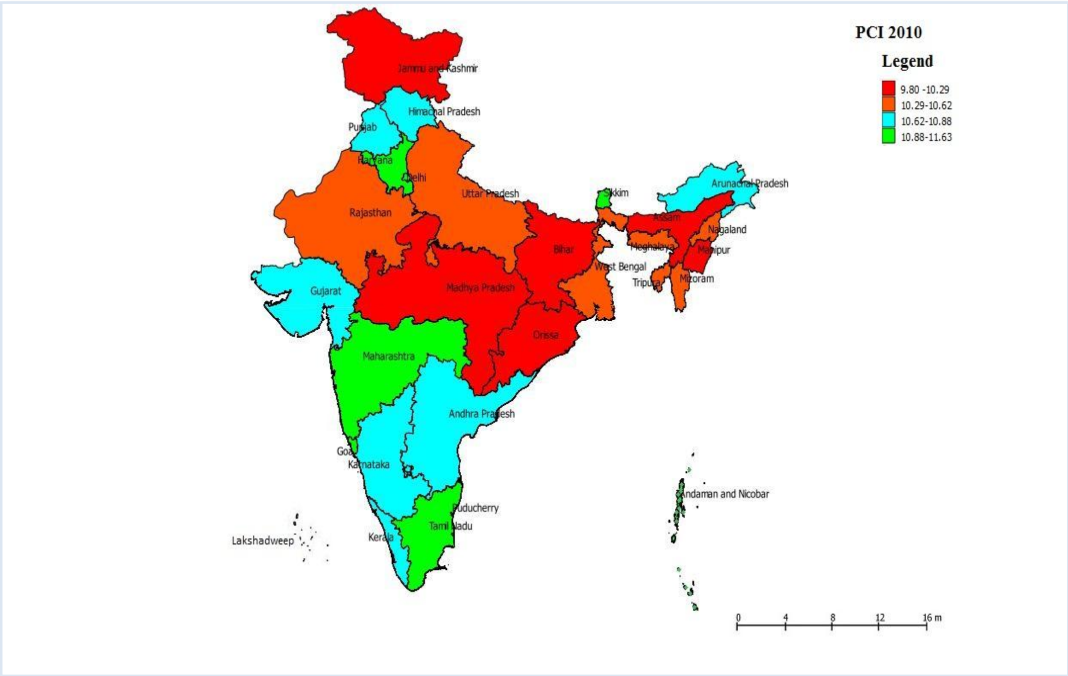
Figure 26: Spatial Spread ofPer Capita Income (1981)



Source: Author's calculations based on QGIS shape file.

We have four categories of income. The green coloured states are the ones with highest per capita incomes in 1981. Followed by these we have the states in blue shades with higher per capita income as compared to the states with orange shade. The areas shaded in red are states are the ones with the lowest per capita incomes.

Figure 27: Spatial Spread Of Per Capita Income (2010)



Source: Author's calculations based on QGIS shape file.

There is positive spatial autocorrelation reflecting clustering of states. Two strong regional clusters seem to persist. The higher income states are clustered in the western and southern parts of India, along with some of the northern states like Punjab, Himachal Pradesh, Delhi and Haryana. While the low income states are mostly clustered in the northern and the eastern areas of India.

Since spatial dependence is confirmed by Moran's I and LISA statistics, we now proceed to set up the spatial econometric models to examine the growth relationship across the states.

7.7.3 OLS estimation and spatial cross section model

For the OLS estimation we use different period combinations in contrast to the panel estimation (time-period of 30 years split into six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10). We start by estimating the standard OLS regression model (equation 5) for four period combinations namely 1981-10, 1991-10, 1981-90 and 2001-10. Growth is regressed against initial income of the periods. The reason for choosing this time slots is

a) 1981-10, covers the beginning and the end of our period of study

b) 1981-90 and 1991-10 allows us to compare the pre and the post liberalisation period

c) 2001-10, this is the most accelerated period of liberalisation

After estimating the OLS regression we examine if there is spatial dependence using a number of diagnostic tests. We have earlier used the Moran's I to test for spatial dependence. In addition we use two Lagrange Multiplier (LM) tests to check for spatial dependence in "Error" and "Lag" terms using their robust versions to control for heteroskedasticity. The tests help us to decide which specification - spatial error or the spatial lag is the most appropriate (Anselin and Florax 1995). LM tests are asymptotic and follow a $\chi 2$ distribution with one degree of freedom and they test the null hypothesis of no spatial dependence against the alternative hypothesis of spatial dependence. To choose between the two models the values of Akaike Information Criteria (AIC) and Schwartz criteria (BIC) are considered. The model with the smaller value of the information criterion (either AIC or BIC) is considered to be better. The " speed " of convergence or divergence (calculated by dividing the β estimate by number of years in the period combinations namely 1981-10, 1991-10, 1981-90 and 2001-10) measures how fast states converge or diverge towards the steady state per annum (see Table 23). The result of these regression and diagnostic tests is presented below.In the pre reform period (1981-90) both the robust LM tests, (for the lag and error) are significant.

Table 23: OLS Estimation: Unconditional Convergence Model

Eqn	Dependent Variable	constant	Ln(pcn sdp)	Divergence speed	AIC	BIC	R2	Adj R^2	Moran's I (error)	Robust LM (error)	Robust LM(lag)
1	Gr81-10	-0.038 (0.053)	0.009 (0.005)	0.0002	-175.45	-172.79	0.09	0.05	1.45 (0.14)	0.615 (0.43)	0.000 (0.98)
2	Gr91-10	.004 (0.069)	0.005 (0.007)	0.0003	-161.21	-158.55	0.05	0.02	1.49 (0.13)	0.66 (0.41)	0.002 (0.96)
3	Gr01-10	.005 (0.107)	.0065 (0.01)	-0.0003	-131.56	-128.8	0.005	-0.03	1.61 (0.10)	0.40 (0.52)	0.006 (0.94)
4	Gr81-90	0.12 (0.078)	-0.010 (0.008)	0.0007	-154.3	-151.72	0.05	0.01	-1.32 (1.81)	4.93 (0.02)	3.14 (0.07)
Robust standard errors in parentheses , significance *** p<0.01, ** p<0.05, * p<0.1 No of observations 28									p-values are in the parentheses		

Source: Author's calculations based on EPWRF data using QGIS and Stata

The significance of Moran's I provide evidence of spatial dependence during the post reform period 1991-10. The above findings indicates the presence of spatial error as well as spatial lag. The results confirm that the OLS estimates suffer from a misspecification because of the omitted spatial dependence. In the case of spatial error autocorrelation, the OLS estimator of the response parameters remains unbiased, but it is inefficient. While in case of a spatially lagged dependent variable, the OLS estimator of the response parameters loses its property of being unbiased and also becomes inconsistent. This has implications for all the earlier studies on convergence in India which have used OLS estimates for testing convergence (Ahluwalia, 2000; Cashin & Sahay, 1996; Kurian, 2000; Mitra & Marjit, 1996).

The next step in our analysis involves controlling for spatial dependence in the cross model. Since the OLS estimation method is inappropriate for models with spatial effects. Thus we use the maximum likelihood technique for spatial regression models namely SAR, SDM, SEM and SAC. This is applicable for both, the cross section and the panel data estimation (to be discussed later in next section). We first present the test for spatial dependence using the inverse distance matrix (Table 25) followed by the contiguity matrix in (Table 26).

Table 24: Maximum Likelihood Estimation of Spatial Cross Section Models Based on Inverse Distance Matrix

Model specification	β (Initial lnPCNSDP)	λ	ρ	θ	Divergence speed	Moran's I(error)	Robust LM(error)	Robust LM(lag)
1	2	3	4	5	6	7	9	11
	1981-10							
SAR	0.008 (0.005)		-4.52 (6.19)		0.00018	24.83***	0.24	0.02
SAC	0.009 (0.007)	0.92*** (0.13)	-3.77 (6.96)		0.00018	644.3***	621.2***	462.4***
SEM	0.009* (0.005)	0.92*** (0.23)			0.00021	651.6***	757.42***	593.0***
SDM	0.008 (0.005)		5.53 (14.7)	-0.07 (0.68)	0.00018	21.9***	0.53	0.42
	1991-10							
SAR	0.006 (0.006)		-6.3 (6.26)		0.00036	4.28***	0.006	0.0017
SAC	0.006 (0.007)	0.81 (7.29)	-6.34 (6.48)		0.00036	576.4***	400.7***	360.6***
SEM	0.006 (0.007)	0.88			0.00066	217.0***	83.62***	180.9***
SDM	0.005 (0.006)		3.46 (15.23)	-0.063 (0.091)	0.00031	0.63	0.22	0.22
	2001-10							
SAR	.007 (0.010)		-23.1*** (8.70)		-0.0003	-23.5***	0.23	0.002
SAC	-0.004 (0.008)	-15.5 (15.89)	-10.24 (15.80)		-0.0004	458.4***	51.9***	191.8***
SEM	0.01** (0.006)	7.42			-0.0005	602.7***	628.4***	569.2***
SDM	.005 (0.009)		-7.82 (18.31)	-.10 (.11)	-0.0004	-30.5***	3.77	3.49*
	1981-90							
SAR	-0.006 (0.007)		-5.14 (9.25)		-0.00067	-56.1***	0.008	1.52
SAC	-0.007 (0.007)	.92*** (0.06)	-8.06 (9.67)		-0.0007	634.7***	519.3***	362.4***
SEM	-0.006 (0.007)	.88*** (0.14)			-0.0006	650.3***	758.6***	593.9***
SDM	-0.007 (0.005)		-53.8*** (14.35)	.25*** (0.063)	-0.0007	-94.0***	0.17	0.91

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1
Source: Author's calculations based on EPWRF data using QGIS and Stata

The results of the spatial dependence model for unconditional β convergence over the 4 periods of interest are presented in Table 24.The estimated coefficients of the spatial variable are reported in column 3, 4 and 5 for different models. We find that of all the models tested here, only the SEM model (in 1981-2010 and 2001-2010), has a significant β coefficients. In the SEM model, the coefficients on the error term are significant over two periods (1981-2010 and 1981-90). The SAC model reports a "λ" significant for the sub periods 1981-90 and 1981-2010, while the coefficient on the lag term "ρ" is not significant in any of the periods. In the SDM model, the coefficient on the spatial lagof initial level of income "ρ" and the spatial lag of growth rate "θ " is significant only in the pre reform period 1981-90.

Table 25: Maximum Likelihood Estimation of Spatial Cross Section Models based on Contiguity Matrix

Model specification	β (Initial lnPCNSDP)	λ	ρ	θ	DIvergence speed	Moran's I(error)	Robust LM(error)	Robust LM(lag)
1	2	3	4	5	6	7	9	11
	1981-2010							
SAR	0.009* (0.005)		0.09 (0.14)		0.0012	1.50	2.43	1.41
SAC	0.008 (0.006)	0.142 (0.28)	0.052 (0.24)		0.001	1.62*	3.20**	2.02
SEM	0.006* (0.004)	0.198 (0.21)			0.00021	1.70*	3.08*	1.71**
SDM	0.008 (0.005)		-0.20 (0.20)	-0.001 (0.001)	0.00018	1.60*	823.80***	822.96***
	1991-2010							
SAR	0.006 (0.005)		0.151 (0.14)		0.00036	1.85**	4.30***	2.65
SAC	.005* (0.002)	0.43*** (.18)	-0.22		0.00036	1.68*	4.48**	3.90**
SEM	.005* (0.002)	.22 (0.22)			0.00066	1.69*	5.32**	4.65**
SDM	.005 (0.006)		.228 (0.22)	-.001 (.001)	0.00031	1.66*	4.69e+04***	4.69e+04***
	2001-2010							
SAR	0.005 (0.01)		.17 (0 .18)		-0.00033	1.74*	5.21**	3.79**
SAC	.004* (0.002)	0.71*** (0.19)	-0.71* (0.39)		-0.0004	1.56	3.00*	2.12
SEM	0.005 (0.006)	0.24 (0.21)			-0.0005	1.77*	4.65**	3.17*
SDM	.004 (0.010)		.25 (0.224)	-0.001 (0.002)	-0.0004	1.79*	4313.6***	4312.1***
	1981-90							
SAR	-0.004 (0.006)		-0.64 (0.23)		-0.00067	-0.98	0.003	0.68
SAC	-.004 (0.006)	-.03 (0.06)	-.61 (0.74)		-0.0007	-1.0	0.004	0.70
SEM	-0.002 (0.005)	-.642 (.24)			-0.0006	-1.33	0.59	2.21
SDM	-0.005 (0.006)		-0.66*** (0.24)	.004*** (0.001)	-0.0004	-1.67*	0.34	0.14

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Source: Author's calculations based on EPWRF data using QGIS and Stata

We performed the same tests for the four models using the contiguity matrix. The results are presented in Table 25. We find that the "β" is significant only for the period 1991-2010 in the SEM model. A note of caution needs to be placed here. The cross section analysis has its limitations (Elhorst, 2014). This sets the analytical need to use panel models, which we present next.

7.7.4 Spatial Dependence Models for Panel Data

We generate the panel here by splitting the time-period of 30 years into six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10.The fixed effect model is used since the units of observations remain the same during the period. We start by presenting results of the simple panel fixed effect model (Table 26).

Table 26: Panel Data Fixed Effect Model Results

Variable		Coefficient
Initial Lnpcnsdp (β)		0.03*** (0.008)
constant		-0.24*** (0.077)
Observations (N)		168
R-sq:	within	0.094
	between	0.059
	overall	0.072
Convergence/Divergence speed		0.006
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1		

Source: Author's calculations based on EPWRF data using QGIS and Stata

The β - coefficient of initial income is significant at 1% level. The positive sign of the coefficient confirms that there is divergence in the rate of growth among the states in India. Over the period 1981-2010, the estimated coefficient of the initial per-capita income level is 0.03 which implies a rate of divergence is 0.006.

We will now extend the simple panel model to test for the presence of spatial dependence. This not only allows us to solve the problems associated with unobserved factors that influence growth, but also removes the bias introduced by spatial dependence in the error terms. For reasons discussed earlier, we use the maximum likelihood technique for the SAR, SDM, SEM and SAC for panel data estimation. Results of the four types of spatial models are presented in Table 27 using Contiguity Matrix.

Table 27: MLE Using Different Model Specifications (Spatial Panel Data Fixed Effects with Contiguity Matrix)

Dependent Variable- Growth Rate (Contiguity Matrix)								
	1	2	3	4				
	Lnpcnsdp (β)	ρ	θ	λ	Log-likelihood	AIC	BIC	Divergence speed
SAR	.021 *** (0.008)	.27*** (0.06)			310.59	-615.1	-605.8	0.004
SDM	-0.017 (0.02)	.21*** (0.07)	0.05*** (0.02)		317.52	-627.0	-614.5	-0.003
SEM	.022** (0.01)			0.23*** (0.10)	308.98	-611.9	-602.6	0.004
SAC	.020*** (0.006)	.37*** (0.1)		-0.14 (0.16)	310.84	-613.6	-601.1	0.004
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.								

Source: Author's calculations based on EPWRF data using QGIS and Stata

Interestingly now the β coefficient is positive in all models (except for the SDM) confirming that once we control for spatial dependence and missing variables there is strong evidence of income divergence. The significance of ρ, θ, λ values confirms that there is spatial dependence of growth rates and state *'j'* will influence the state 'i', independent of the impact of initial per capita income. This confirms our claims that estimate from previous studies are biased, inconsistent and inefficient. Expectedly therefore the values of β in all the spatial models (about 0.02) is less than the non-spatial panel model (0.03) confirming that the earlier econometric results overestimate the value of β if we do not control for spatial dependence.

The SDM model confirms the spatial dependence among the independent variables as well. The growth rate in a state *'i'* depends on the per capita income levels of the neighboring states *'j'*. The SEM model finds divergence in growth rates among the states as well as strong spatial dependence among the error term of the states. In contrast the SAC model finds that there is significant spatial dependence in growth among the states but no significant relationship is seen among the error terms.

Table 28: MLE using Different Model Specifications (Spatial Panel Data fixed effects with Inverse Distance Matrix)

Dependent Variable- Growth Rate (Inverse Distance Matrix)								
	Initial Lnpcnsdp (β)	ρ	θ	λ	Log-likelihood	AIC	BIC	Divergence speed
SAR	0.014 (0.01)	13.6 *** (2.99)			310.59	-615.1	-605.8	0.002
SDM	-0.017 (0.02)	1.58*** (0.07)	1.58*** (0.79)		315.3	-622.6	-610.1	-0.003
SEM	0.005 (0.28)			16.49*** (6.9)	309.2	-612.5	-603.1	0.001
SAC	.014 * (0.011)	14.94*** (2.92)		-3.91 (7.7)	310.6	-613.3	-600.8	0.002
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.								

Source: Author's calculations based on EPWRF data using QGIS and Stata

If we use the inverse distance matrix with same models (Table 28) the β is significant and positive only in the SAC model as is the 'ρ' coefficient. It also reaffirms that the 'β' value is much lower than what earlier results have found. This implies that the speed of divergence for the spatial models is much lower than that obtained in non-spatial fixed-effect panel model.

7.8 Summary

One of the criticisms in convergence data is the assumption that there is spatial independence of economies. Considering the fact that there are spill overs with respect to technology, capital labour, and different interaction effects viz; the endogenous, exogenous and within the error terms are discussed in this chapter. The exploratory spatial data analysis (ESDA) is employed to find the presence of spatial autocorrelation and heterogeneity. To test for spatial autocorrelation the Global Moran's I and Local Moran's I is used. The data reveals that there has been spatial dependence among the states in India; regions with similar per capita levels were geographically closer. There is a strong positive and statistically significant spatial dependence in the pcnsdp for all the years 1981, 1991, 2001and 2010. The NSDP per capita across the states are clustered over the period under analysis.

There are two strong regional clusters that seem to have persisted for above 30 years in India. The first one is the western, southern and some northern cluster of high income states which are located in quadrant 1. The second is the North eastern and Eastern cluster of low income sates located in the quadrant 3 of the Moran scatter plot. This preliminary analysis suggests that there is spatial dependence among the states and at the same time there are differences in the per capita incomes across the states.

The literature on convergence in India by a large majority has established that there is divergence in the growth rates. In this chapter we find confirmation of these findings. However, our results above suggest that the OLS and panel data estimates on convergence in these studies suffer from bias, inconsistency and inefficiency due to misspecification caused by the omitted spatial component in their analysis. Our estimates from the fixed effect spatial panel confirm that the process of growth in India is spatially dependent. Further, the impact of initial income on growth is much smaller than earlier anticipated once we control for spatial dependence. Our analysis suggests that neighbourhood effects play a significant role in determining growth outcomes of Indian states. We believe that this is the first attempt to demonstrate this in the Indian context and has important implications for policy making. Areas of low incomes could benefit from growth spill over effects from richer neighbours and be able to break the vicious circle of poverty and the drop of a low initial income. This raises hope that a virtuous circle of growth could emerge in India.

Chapter VIII

Human Development Indicators and Convergence

8.1 Introduction

Within the country we have seen that the regression on growth rates, the standard deviation has shown no signs of convergence among the states. It is generally being argued that the focus on regional income as an indicator for economic well being or inequality is too narrow and should be substituted by a broader concept of welfare (Gachter & Theurl, 2011). Income is only one dimension of economic well being. In analyzing convergence, other dimensions also have to be taken into consideration. Convergence is basically the end result of the process of changes in differences across the states, expenditures, policies and social indicators which is a reflection of policy outcomes. Thus convergence can represent the decrease in the variation across the states in social and economic indicators. It could also mean the catching up by less endowed states with the better off ones on certain economic and social indicators. The United Nations (UN) Human Development Index (HDI), is based on three equally weighted factors - life expectancy, education, and per capita income. The HDI is a composite outcome index that measures the average achievements in the outcome indicators in the following dimensions of human development;

1) *A long and health life* :- Infant Mortality Rate and Life Expectancy at age 1
2) *Knowledge* :- 7+ Literacy Rate and Mean Years of Education for 15+ age group
3) *Decent standard of living*:- Estimated Earned Income per capita per annum.

Three indices are constructed capturing these dimensions that is the Education Index, the Health Index, and the Income Index and then these are aggregated. Reduction in inequalities these dimensions, could bring about increase in economic growth, human development as well as reduction in poverty (Suryanarayana & Agrawal, 2013). The human development outcomes depend on economic growth, poverty reduction strategies and social policies. To achieve faster economic growth, it is necessary to enhance human capabilities. With investments in health and education, the human capabilities can be enhanced, which in turn will promote economic growth and reduce (income) poverty. The HDI is an index of relativeperformance, an improvement in the performance of social indicators would be encouraging and could mean economic and social convergence (Fischer, 2003). The UNDP Report annually tracks the performance of countries. In 2013, India ranked 135 among 187 countries across the world, with a medium level HDI of 0.586. Though PCI growth in India has increased significantly, certain sections of society remain excluded, especially in terms of improvements in human capabilities and entitlements (Mukherjee, et al 2014). The HDI of the economy depends on the performance of the states. There is a high degree of human development inequalities across Indian States, Kerala, Himachal Pradesh, Tamil Nadu have been the better performers, while Bihar, Madhya Pradesh, Odisha, Uttar Pradesh have fared badly in terms of the development indicators like poverty, health and education (Dreze & Sen, 2013).

Inequality in non-income dimensions can be viewed in two ways. Firstly, there could be variation of a particular outcome indicator across individuals and secondly, there could be disparities across socio-economic groups. This chapter we focus on the first view, convergence in outcome indicators. Poverty is the deprivation of a minimum level of living defined in income terms but it is multidimensional in nature. Apart from the income approach, there are other ways to conceptualise poverty. One could consider deprivations in areas such as literacy, schooling, life expectancy, child mortality, malnutrition, safe water and sanitation (Radhakrishna & Panda, 2006). The Human Development Report of the UNDP, based on capabilities approach considers some of these non-income dimensions of deprivation. This approach centres around the capability up gradation and enlargement of opportunities for the people. While income deprivation is an important element and in some cases closely associated with other types of deprivation, they are not all encompassing and might not always move together with other deprivations. Income becomes important in the capability approach to the extent it helps in expanding basic capabilities of people to function.

If the poorer states with high concentration of various marginalized groups, have started catching up with the rich ones in terms of these components of HDI, it suggests that the process of human development is socially inclusive.

8.2 Conceptualizing the Human Development Index

In this section we focus our attention on multidimensional convergence at a regional level in India for the period 1981-2011. As discussed earlier there is a vast literature that have focused on economics convergence in India. However studies focusing on social convergence are still sparse. (see Goli & Arokiasamy, 2013; Mukherjee et al., 2014; Mukhopadhyay, 2015).these studies have used measures like β convergence, σ convergence as well as spatial econometrics to check for convergence in social indicators. There are scores of economic and social indicators to measure the socio-economic progress. The choice of indicators generally depends upon the focus and the availability of data(GOI, 2011). Along with the data on per capita income, socio indicators like quality of life and quality of opportunity is analyzed in different states of India.

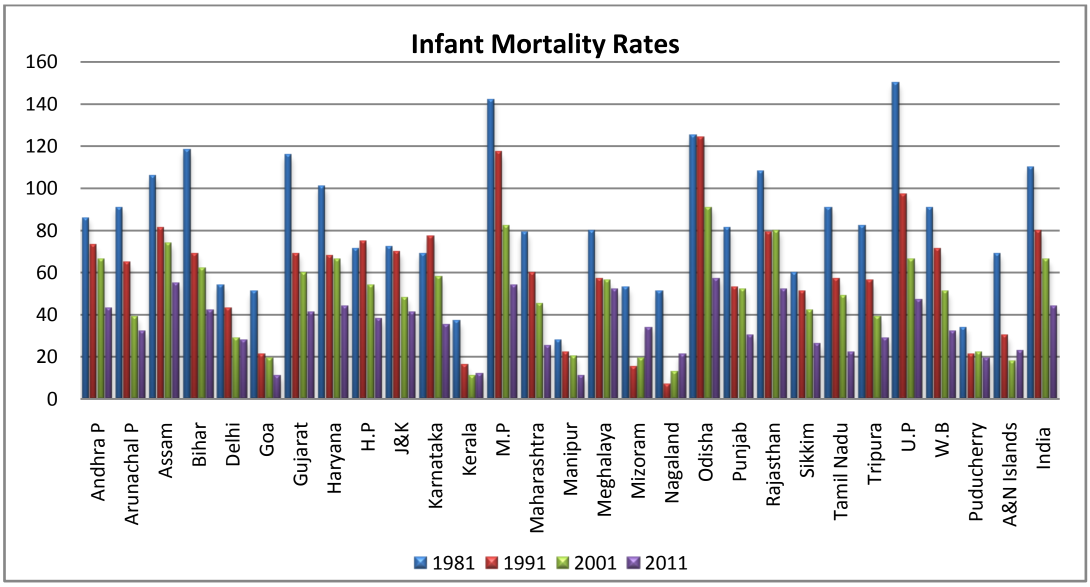
In this chapter we examine convergence hypothesis for non-income indicators across Indian states,using both β and σ convergence techniques. We focus on the convergence in select indicators i.e the Infant Mortality Rate, Literacy rate and the poverty rates.

8.2.1 Quality of life

An improved quality of life reflects socio economic development of the state. States with inadequate nutrition, water supply, improper sanitation and various health care services would have a poor health status (Goli & Arokiasamy, 2013). Life expectancy and mortality are considered as good indicators of quality of life in many studies. Preston (1975) analysed relation between income and longetivity among 30 countries between 1930 and 1960. For given levels of income, longevity had been rising upto 15 years, with the increasebeing greater for poor countries. ForPritchett & Summers (1996), rising per capita incomes are responsible for improvements in two measures of health- Infant Mortality Rate (IMR) and longetivity. As the PCI rises reduction in mortality rates is expected. Life expectancy is also expected to be higher in the developed countries than the poor ones. Besides income there are many factors that determine health and quality of life. Sen (1995) argued that though mortality rates are affected by poverty and economic deprivations, the quality of life of an individual does not depend only on the personal income but many other physical and social conditions.

Proper health care medical insurance, social services like basic education, proper urban living influences the life of the people. Thus both life expectancy and the morality are considered as valid measure of quality of life. Becker, et al, (2003) showed that life expectancy gains have been an important component of improvements in welfare throughout the world in the 30 years between 1965 and 1995. Both these variables have little variation in the short run. Significant changes are needed in social, health and demographic factors to bring about sufficient variation in mortality and life expectancy(Maynou, et al, 2015).Generally life expectancy at birth or at age 1 is used as a variable for quality of life. In India, we do not have life expectancy data for all the states and UTs from 1981 onwards. The Infant mortality rate (IMR) is therefore used as a dimensional variable for quality of life. Infant mortality rate (IMR) computed as the number of deaths of infants under age 1 in a given year per 1,000 total live births in the same year (Preston, 1975; Pritchett & Summers, 1996; Sen, 1995). It is probability of a child dying before attaining age one year.

Figure 28: Infant Mortality Rate across Indian States from 1981 to 2011



Note: For Mizoram, 1991 IMR is taken from DES, Mizoram.
Source: EPWRF, Compendium of India's Fertility and Mortality Indicators 1971-2007, based on Sample Registration System(SRS), Office of the Registrar General & Census Commissioner, India, Ministry of home Affairs, New Delhi.

The figure 28 shows the infant mortality rate among the states from 1981 to 2011. The trend for IMR indicates consistent decline in IMR during1981–2011for India and the states. The data on IMR is obtained from EPWRF and Sample Registration System- Office of Registrar General, India for 25 states and 3 Union Territories.

The IMR at all India level declined sharply from 110 per thousand live births to 44 per thousand live births, signifying a drop of 66 per thousand live births in 30 years.In 1981, Uttar Pradesh(150), Madhya Pradesh (142), Bihar (118), Odisha (125) and Gujarat(116), were higher than the national average 110 per 1000 live births. Kerala (37), Manipur (28) and Puducherry (34) had the lowest IMRs. In 2011, the average IMR for India as well as for individual states decreased substantially. Assam (55), M.P (54), Meghalaya (52), Odisha (57) and Rajasthan (52) had a higher IMR than the national average (44), while, Goa (11), Kerala (12), Manipur (11) and Puducherry (19) were among the better performers. Evidently, the progress in IMR transition is not uniform across all the states.

Most of the southern states are experiencing a faster decline in IMR as compared to the Northern states of India. even the gap in IMR between the states has declined substantially. Substantial gaps still exist between the demographically advanced states like Kerala, Goa, Puducherry and demographically weaker states like Bihar, Madhya Pradesh, Odisha, Rajasthan and Uttar Pradesh. Oddly Mizoram, Nagaland and Andaman and Nicobar Islands, saw increase in IMR in 2011 as compared to the previous years.

We will in the later section examine whether the reduction in IMR over the past 30 years has been accompanied by convergence in IMR among the states in India.

8.2.2 Education

The capability to read, write and count has a strong effect on the quality of our lives (Dreze & Sen, 2013). Education is a core dimension of human wellbeing because it provides greater capability to an individual to live a productive and socially meaningful life.

A reliable empirical literature suggests that there is a positive relationship between education and growth. Lack of education and related can be a deterrent for entry of high-tech industries and the effective imitation of innovation from other developed countries (Baumol, 1986). Drèze & Sen (2013) have emphasized that basic education plays a major role in reducing health problems in general and public health in particular. General education can influence a person's ability to think, generate social understanding which is required in times of certain epidemiological problems. School education has a bigger impact on health, as it tends to facilitate the implementation of public health measures like immunisation, sanitation and prevention of epidemics. It brings about changes in public perceptions of the human rights as well as legal rights.

The educational development in Kerala and of recent in Himachal Pradesh is said to be an important factor in increased demand for health care (Gandhi & Institute of Applied Manpower Research (India), 2011). It has also been argued that schooling of women enhances women's participation in decision making and can be catalytic in social change. Women empowerment is known to impact fertility and mortality rates (see Barro, 1991; Goli & Arokiasamy, 2013). However despite of the pro education movement in India, the expansion of school education has been slow in India as compared to many of the Asian countries.

Table 29 above illustrates that India at 81 percent of youth literacy rate has been lagging behind all the East Asian countries. Among south Asian countries, India is lagging behind even Nepal which has a low PCI than India. In the South Asia region India is ahead of only two countries - Pakistan and Bangladesh.

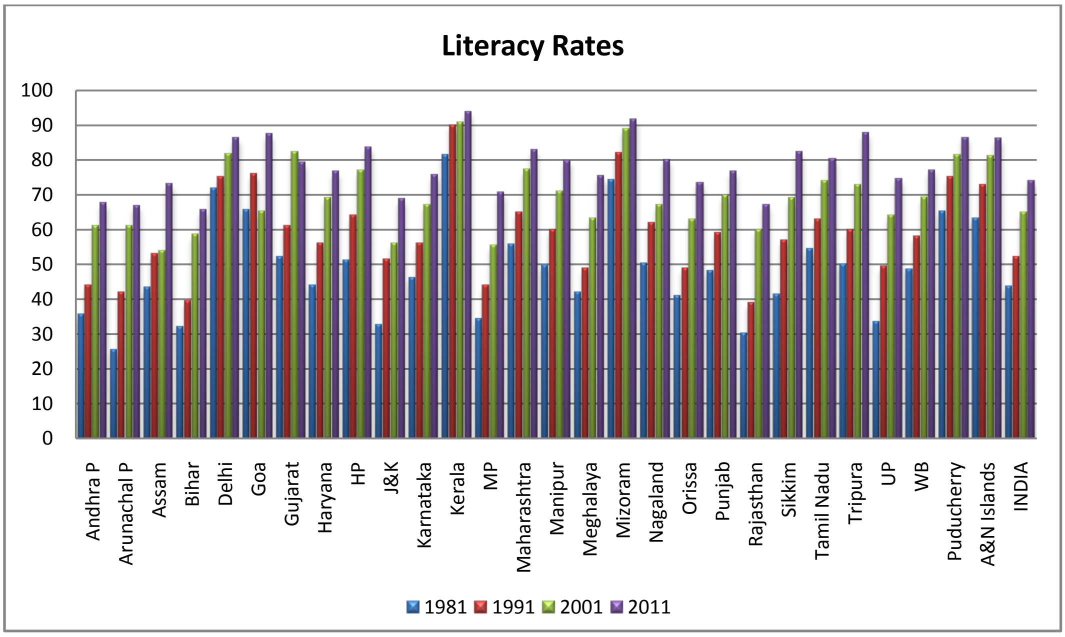
Table 29: Literacy Rate for 2005–13 in selected Asian Countries

Country	Youth Literacy Rate, % ages 15–24
Bangladesh	80
China	100
India	81
Indonesia	99
Malaysia	98
Nepal	82
Pakistan	71
Philippines	98
Sri Lanka	98
Thailand	97
Vietnam	97

Source: World Development Indicators (World Bank, 2015)

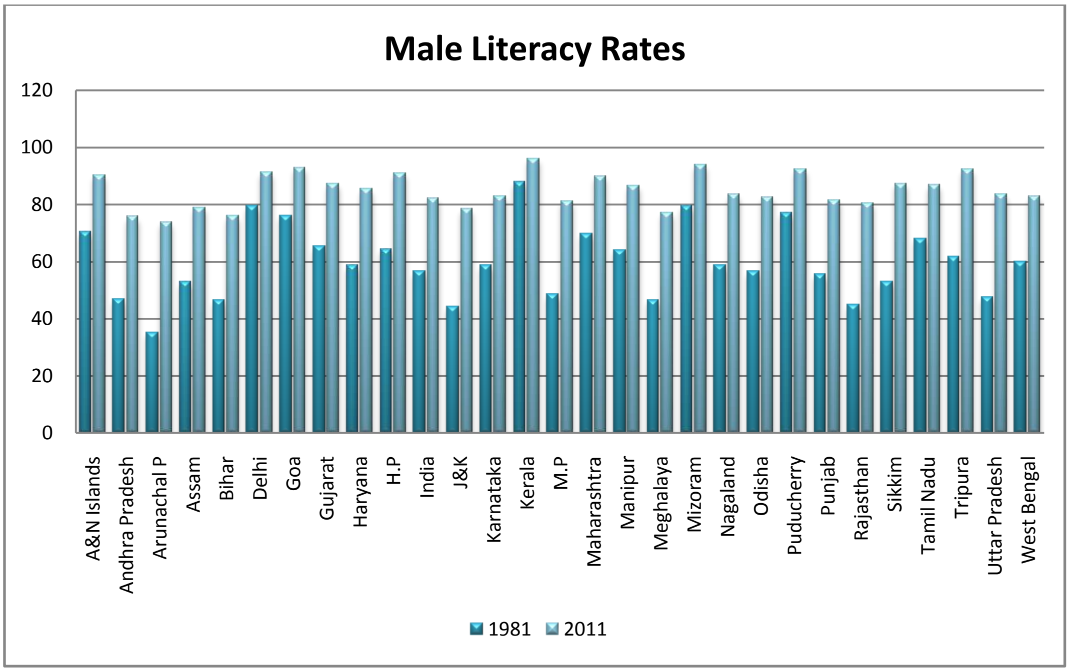
The trend in Literacy rates of population aged seven and above over years from 1981 to 2011 across smaller and larger states in India is seen below (Figure 28). The division between smaller and larger states is made on the basis of size of the population. We also see the male and female literacy rate from 1981 to 2011 across states in India (Figure 29and 30). The total Literacy rate in India has improved from 44% percent in 1981 to 74% in 2011 (Fig 28). Even female literacy (see figure 30) has shown considerable improvement from 29.8 percent to 66% in the same period. However, we see a regional divide in educational attainment. The southern states and the UTs, especially Kerala, Tamil Nadu, A &N Islands and Puducherry, have been more successful in driving up their literacy rates. Similarly the North eastern states like Mizoram, Tripura, Sikkim have shown considerable improvements, with Mizoram ranking second among all the states in India in the last two decades.

Figure 29: Literacy Rates across the States In India from 1981-2011



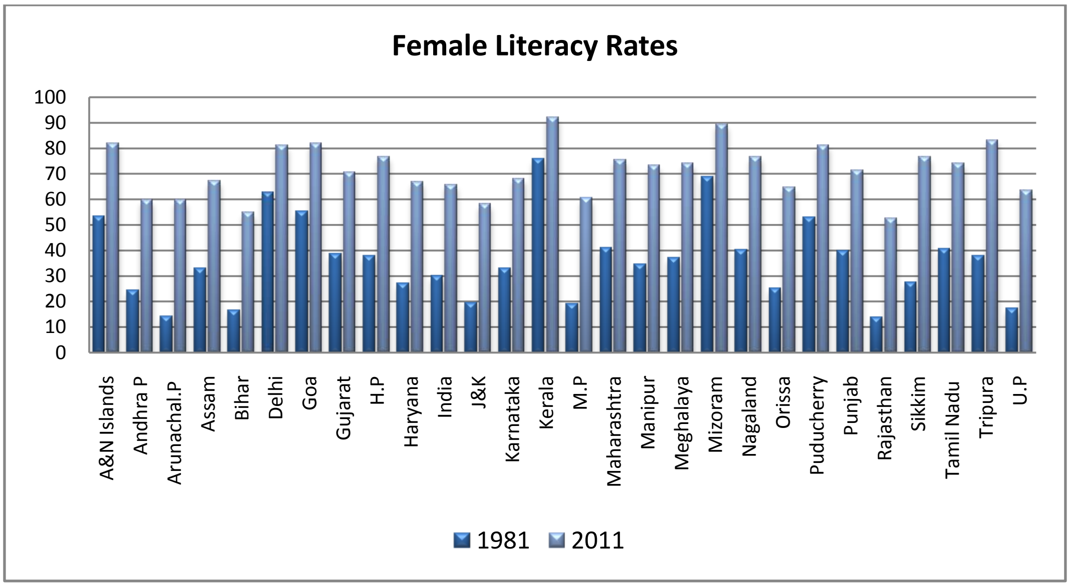
Source: Census of India (various years)
Note: Literacy rate for Assam in 1981 is the average of 1971 and 1991 literacy rate

Figure 30: Male Literacy Rates across States In India (1981-2011)



Source: Census of India (various years)
Note: Literacy rate for Assam in 1981 is the average of 1971 and 1991 literacy rate

Figure 31: Female Literacy Rates across States in India (1981-2011)



Source: Population Census India (Various years)
Note: Literacy rate for Assam in 1981 is the average of 1971 and 1991 literacy rate

Among the larger states, the state of Kerala is substantially ahead among all the states in school education. Even the female literacy rate in Kerala increased from 76 % in 1981 to 92% in 2011. Other states that have shown massive rise in literacy rates between 1981 to 2011 have been Gujarat (from 52% to 79%), Maharashtra (56% to 84%) and Tamil Nadu (54% to 80%). In 2011, Andhra Pradesh (68%), Assam (73%), Bihar (66%) Jammu and Kashmir (69%), Madhya Pradesh (71%), Odisha (74%) and Rajasthan (67%) had literacy lower than the national average, all these states had lower literacy rates even in 1981. We next see the position of small states in terms of literacy.

As far as the small states are concerned, all the states except Arunachal Pradesh at (67%) had literacy rate above the national average of (74%). Mizoram (92%) had the highest literacy rate among the small states in 2011. This was followed by Tripura (88%) and Goa (87%). Sikkim with a very low percentage of literacy at 42% showed remarkable improvement to 82% in 2011. Similar is the case with Himachal Pradesh, with a rise from 51% in 1981 to 84% in 2011. Mizoram is another state with high female literacy rate among all the smaller states, both in 1981 (69%) and 2011 (89%).

8.2.3 Standard of Living

HDI is a composite index of (Health and Knowledge) and standard of living. This third dimension determines people's command over resources, necessary to access food, shelter and clothing, as well as working in meaningful and rewarding activities (GOI, 2011).The lowest standard of living as highlighted by the PCI is seen in certain poorer states like Assam, Bihar, Madhya Pradesh, Orissa, and Uttar Pradesh. If convergence of PCI is an indicator of better growth by poorer states we should expect to see a convergence in poverty rates also.

There are different measures of poverty. The most common one is the headcount ratio (HCR). The HCR estimates the proportion of the population living in households with consumption or income below the poverty line. Another measure is the poverty gap, given by the average distance below the line expressed as a proportion of the poverty line, where the average is formed over the whole population. In India the Planning Commission used to estimate poverty lines and poverty ratios based on the quinquennial rounds of Household Consumer Expenditure conducted by the National Sample Survey Office (NSSO).The estimates of poverty derived from the NSS data uses the urban and rural poverty lines developed by the Planning Commission. These poverty lines were chosen to see that some predetermined nutritional requirements were met in the rural and urban areas. The nutritional requirements fixed were 2100 calories per in urban areas and 2400 person per day, for rural areas (Panagariya & Mukim, 2014). Accordingly, rural poverty line that was established was at Rs 49 in 1973-74 and Rs.57 was the urban poverty line, this was about 15 percent higher than the rural areas. The Planning Commission updated the official poverty line over time using the Consumer Price Index for Agricultural Labourers for rural poverty and the Consumer Price Index for Industrial Workers for urban poverty.

In India, the original official poverty estimates provided by the Planning Commission, were based on the Lakdawala poverty lines, however, recommendations of a 2009 expert committee (Tendulkar Committee), led to an upward adjustment in the rural poverty line compared to the Lakdawala Committee counterparts. Thus the earlier poverty estimates are based on the Lakdawala Committee and the new ones are based on the Tendulkar Committee recommendations. Only in two years, 1993–1994 and 2004–2005, we have official estimates based on both methodologies (Panagariya & Mukim, 2014).

The last quinquennial survey, the 66th NSSO round (2009-10), was not a normal year because of a severe drought in many parts of the country. Several studies suggested that the Tendulkar Poverty Line was too low, the NSSO therefore repeated the large scale survey in 2011-12, the 68th NSSO round (GOI, 2013). In this chapter we look at the poverty convergence by taking into account both the Rounds, 66th (2009-10) and (68th) 2011-12.

Accordingly while analyzing the incidence of poverty both at the national and at the state level, we have used the head -count ratio of poverty as is estimated by the planning commission based on the NSSO rounds [38th (1983), 43rd (1987–1988), 50th (1993–1994), 55th (1999–2000), 61st (2004–2005), 66th (2009–2010)and 68th (2011-12)].

The literature on the poverty in India is too large to summarize here except to say that the major controversies are regarding a) the magnitude of poverty, b) its rate of decline and c) various methodologies of estimation (Ghosal, 2012). With regard to the incidence of poverty, earlier analysts defined poverty in terms of a minimum required calorie intake. Others analysts considered poverty in monetary terms, which classified those people as poor whose income was less than a specified monetary amount corresponding to a minimum calorie intake (Bhalla, 2002; Deaton & Valerie, 2005). The choice of the poverty line has been greatly debated. As the base poverty line is adjusted across states and across time using the price indices, the selection and construction of these indexes is of central importance in measuring poverty. The lack of precision of the baseline year can have serious implications for estimation of poverty rates and head count ratios. The poverty lines used between 1970s and 1990, ignored the interstate differentials and rural-urban differentials in price levels (Deaton & Valerie, 2005; Sala-i-Martin, 2006). The comparability of different NSSO rounds was also a controversial issue. Most of the quinquennial surveys seem to collect information on relatively infrequently purchased items including clothing and consumer durables on the basis of both 30-day and 365-day reference periods. For other categories, including all food and fuel and consumer services, they have used a 30-day reference period. There are two alternative measures of monthly per-capita expenditures (MPCE) :a) uniform reference period (URP)- all expenditure data used to estimate MPCE are based on the 30-day reference period, and b) mixed reference period (MRP), here expenditure data used to estimate the monthly per-capita expenditure are based on the 365-day reference period in the case of consumer durables and clothing and the 30-day reference period in the case of other items. Generally, MPCE associated with the MRP is higher than that associated with the URP.

The Planning Commission's initial estimate of poverty based on Lakdawala poverty lines relied on the URP monthly per-capita expenditures. But sometime prior the Tendulkar Committee report, the Planning Commission shifted to the MRP estimates. Three flaws were noted by the Tendulkar committee as far as the Lakdawala poverty lines are concerned. Firstly, the poverty line baskets of goods and services were defined on the basis of the consumption patterns in 1973–1974, but this does not remain the same decades later even for the poor. Secondly, the consumer price index for agricultural workers understates the true price rise. The upward adjustment in the rural poverty lines was less than necessary thus rural poverty was understated. The Lakdawala committee assumed lines that health and education would be provided by the government. This was not true. Private expenditures on these services had gone up considerably, also for the poor. To correct these flaws, the Tendulkar Committee also shifted to MRP monthly per-capita expenditures while calculating poverty (Ghosal, 2012; Panagariya & Mukim, 2014).

In light of this, and notwithstanding the problems, it would be useful to see if there are clear evidences of both σ and β convergence in all the three indicators considered.

8.3 β and σ Convergence in Well- being Indicators

We take three indicators of well-being- a) Literacy rate (Grlit), b) decline in poverty rates (Dpov) and c) reduction in IMR (DIMR). β convergence is a necessary but not a sufficient condition for σ convergence. Alternatively, even σ convergence is sufficient but not a necessary condition for β convergence (Sala-i-Martin, 1996). Therefore, in order to test for both these conditions, both σ convergence along with β convergence is estimated. In this section we test if there has been β and σ convergence among the states in these indicators. To investigate the spatial variation across the Indian states over time, we employ the conventional measures of regional disparities such as standard deviation and coefficient of variation. This would give us a measure of σ convergence across the Indian states. The trends in coefficient of variation help us to measure convergence relative to the mean. If there is an identical absolute increase in an indicator, the standard deviation would remain unchanged, but the decrease in the percent difference would have been overlooked. Besides the size of the CV does not depend on the chosen unit of measurement. On the other hand, SD is a preferred measure if absolute differences are considered as most relevant. The CV is more relevant if the relative or percentage changes are examined (Sab & Smith, 2001).

For calculating coefficient of variation we employ the following measure;

(8.1) $$CV_t = \sigma_t / \mu_t$$

σ is the standard deviation at time t and μ is thecross regional mean of the variable at time t. Convergence in these variables would be indicative of a more equitable distribution among the states and a balanced regional growth. We begin with a for unconditional convergence, a change in the indicators (IMR, Literacy and Poverty rate) are regressed on their initial value. The absolute β-convergence hypothesis rests on the assumption that there is a negative correlation between the initial level and the growth rate. If there is a negative relationship, then states with higher initial values are experiencing faster decline than the states with lower initial values and catch up in the long run. We can expect convergence as a result of law of diminishing returns wherein there are upper bounds of many development indicators as well as due to diminishing returns of inputs like health expenditures, efforts in education and economic development(Gachter & Theurl, 2011). We assess the IMR convergence first.

8.3.1 Regression Equations for IMR

A cross-section model is used to test the beta-convergence hypothesis. We run a regression with DIMR (decline in IMR) over combinations of time periods as the dependent variable and initial IMR as an explanatory variable for the pre and the post reform period. We thus have three equations spanning the period 1981-91, 1991-2001 and 2001-11, that would capture the relationship between the decline in IMR among the states and the initial IMR. To measure absolute β convergence in a cross section of states, we employ the following models. Accordingly for pre and post reform period we have the following equations. Decline in Infant Mortality rate (Dimr) isdecline in the IMR over particular period say the period 1981-90, 1991-2000 and 2001-11

$$Dimr8190_i = \alpha_i + \beta_1\, imr81_i + \varepsilon_i \tag{8.2}$$

where Dimr8190iis the change in mortality rate in state "i" over the 1981-90, and imr81 is the level of mortality in the starting period. "i" corresponds to the state as the cross sectional unit and β is the convergence coefficient, while ε_i represents an error term.

$$Dimr9100_i = \alpha_i + \beta_1\, imr91_i + \varepsilon_i \tag{8.3}$$

$Dimr9100_i$ is the decline in infant mortality rate over the interval between 1991 and 2000,

$imr91_i$ - Infant mortality rate in 1991

$$Dimr0110_i = \alpha_i + \beta_1\, imr01_i + \varepsilon_i \tag{8.4}$$

With $Dimr0110_i$as thedecline in infant mortality rate, 2001-10 and $imr01_i$ is theInfant mortality rate in 2001.

We next discuss the convergence model for literacy rates. The data on IMR is obtained from EPWRF and Compendium of India's Fertility and Mortality Indicators 1971-2007 based on SRS Office of the Registrar General & Census Commissioner India, Ministry of Home Affairs. New Delhi, India.

8.3.2 Regression Equations for Literacy Rate

The Adult literacy rate (7+ literacy rate) is considered as an ideal variable for quality of opportunity (Census of India, 2011). The data on literacy rate is obtained from EPWRF and Sample Registration System- Office of Registrar General, India. The data on literacy rate has been considered for four periods – 1981, 1991, 2001 and 2011, which is from the Population Census. With unconditional convergence, change in the education indicator is regressed only on its initial value. Our hypothesis is that education (literacy rate) will grow faster in the states with low levels of initial literacy. σ convergence is seen if there is decline in standard deviation and coefficient of variation as in the case of IMR (see equation 8.2).

The regression equations employed for literacy convergence are as follows;

(8.5) $$Grlit8190_i = \alpha_i + \beta_1\, lit81_i + \varepsilon_i$$

Where, $Grlit8191_i$ is the rate of growth of literacy between 1981 and 1990 and $lit81_i$ is theliteracy rate in 1981. For the post reforms period we have the following equations

(8.6) $$Grlit9100_i = \alpha_i + \beta_1\, lit91_i + \varepsilon_i$$

Grlit9101 $_i$ is rate of growth of literacy between 1991 and 2000 and $lit91_{it}$ is the literacy rate in 1991.

(8.7) $$Grlit0110_i = \alpha_i + \beta_1\, lit2001_i + \varepsilon_i$$

$Grlit0110_i$ is the rate of growth of literacy between 2001and 2010 and $lit01_i$ is theliteracy rate in 2001.

In the next sub section we discuss the poverty convergence.

8.3.3 Regression Equations for Poverty Rate

As in the case of reduction in infant mortality rates and rise in literacy, we test if there has been unconditional convergence in poverty rates. While analysing the incidence of poverty both at the national and at the cross-state level, we have used the head -count ratio of poverty as is estimated by the Planning Commission based on the NSSO rounds [38th (1983), 43rd (1987–1988), 50th (1993–1994), 55th (1999–2000), 61st (2004–2005), 66th (2009-10) and 68th (2011–2012)]. The regression models tested are;

(8.7) $D\text{pov83-93}_i = \alpha_i + \beta_1 pov83_i + \varepsilon_i$

Dpov83-93$_i$ is the rate of decline in poverty between 1983 and 199 and $pov83_i$ is the poverty rate in 1983.

(8.8) $Dpov93\text{-}04_i = \alpha_i + \beta_1 pov93_i + \varepsilon_i$

$Dpov\ 93\text{-}04_i$ is rate of decline in poverty between 1991 and 2004 and $pov93_i$ is the poverty rate in 1993.

(8.9) $Dpov0411_i = \alpha_i + \beta_1 pov04_i + \varepsilon_i$

$Dpov\ 0409_i$ is the rate of decline in poverty between 2004 and 2011 while, $pov04_{it}$ is the povertyrate in 2004

(8.10) $Dpov9311_i = \alpha_i + \beta_1 pov04_i + \varepsilon_i$

$Dpov\ 9311_i$ is the rate of decline in poverty between 1993 and 2011, while $pov04_i$ is thepovertyrate in 2004.

As we consider both the 66th and the 68th NSSO rounds for which poverty measures are available, we have the two additional regression equations.

(8.11) $$Dpov0409_i = \alpha_i + \beta_1 pov04_i + \varepsilon_i$$

$Dpov\ 0409_i$ is rate of decline in poverty between 2004and 2009and $pov04_i$ is the povertyrate in 2004

(8.12) $Dpov9309_i = \alpha_i + \beta_1 pov93_i + \varepsilon_i$

$Dpov\ 9309_i$ is therate of decline in poverty between 1993 and 2009and $pov93_i$ povertyrate in 2004.

In the next section we present the results of our analysis.

8.4 Empirical results: β and σ Convergence

We now discuss the patterns of cross regional dispersion or inequality by calculating the standard deviations and the coefficient of variation for IMR, Literacy rate and the Poverty ratios. Then we examine the cross section regression across the states and see if there is β convergence (equation 8.2 to equation 8.12)

8.4.1 Infant Mortality Rate and Convergence

Table 30shows the summary statistics of both the dependent as well as explanatory variable for all the period concerned. From the descriptive data for infant mortality rates over time and across the states in India, we find that there has been a gradual decline of this variable in all states. (see row e - h)

Table 30: Summary Statistics of Infant Mortality Rate (State Level)

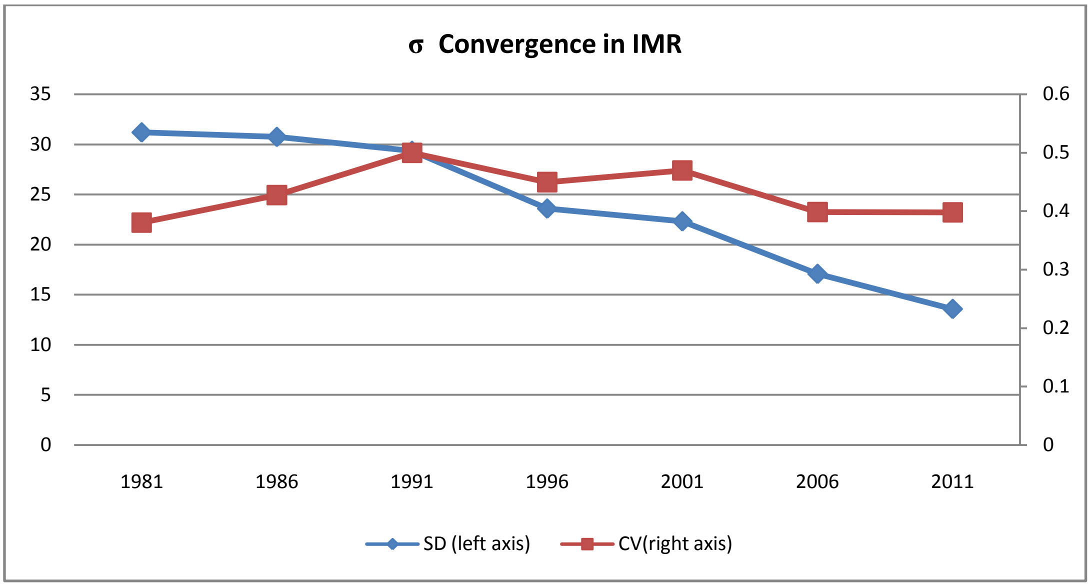
	Variable	Mean	Standard Deviation	Min	Max	Coefficient of Variation
1	2	3	4	5	6	7
a	imr81	82	31.1781	28	150	0.380

b	imr91	58.71429	29.33442	7	124	0.499
c	imr01	47.53571	22.31173	11	91	0.469
d	imr11	34.14286	13.57753	11	57	0.397
e	Dimr8191	-2.32857	1.598809	-5.3	0.8	-0.68
f	Dimr9101	-1.11786	1.131716	-3.5	0.6	-1.0
g	Dimr0111	-1.325	1.196794	-3.4	1.5	-0.90
h	Dimr9111	-1.22857	0.984174	-3.35	0.95	-0.80

Source: Raw data from EPWRF, Compendium of India's Fertility and Mortality Indicators 1971-2007, based on Sample Registration System(SRS), Office of the Registrar General & Census Commissioner and Author's calculations. N=28

Two aggregated indicators of between-state inequality are computed to measure σ convergence in above Table 30 These measures help us to track the course of inequality in health and to test the existence of "σ"convergence or divergence, respectively. The two indicators used are the standard deviation (SD), the coefficient of variation (CV). We find a steady decline in the infant mortality rates as depicted by the decline in standard deviation and the coefficient of variation, which suggests that there has been reduction on average in dispersion levels in IMR.

Figure 32: Sigma Convergence across the States from 1981 to 2011



Source: Raw data from EPWRF, Compendium of India's Fertility and Mortality Indicators 1971-2007, based on Sample Registration System(SRS), Office of the Registrar General & Census Commissioner and Author's calculations

While the concept of sigma-convergence focuses on the overall spread of the mortality distribution, the concept of (absolute) β convergence focuses on the change in mortality rates to the initial level, implying an inverse correlation between the initial values and the rates of change over the period. Table 31 below gives the OLS estimation results for β-convergence.

Table 31: Cross Section Regression Results for IMR - Unconditional β Convergence

	Dependent Variables			
Independent Variables ↓	Dimr8190	Dimr9100	Dimr0111	Dimr9111
imr81	-0.018* (.009)			
imr91		-0.029*** (.005)		-.03*** (.002)
imr01			-0.046*** (.005)	
Constant	-0.78 (.81)	0.556 (.33)	0.856*** (.28)	.58*** (.16)
R-squared	0.14	0.55	0.73	0.84
Adj R-Squared	0.10	0.53	0.72	0.84
Speed of convergence	0.0018	0.0029	0.0046	0.0015

No of observations: 28, Absolute value of coefficients in parentheses,* Significant at 10%; ** significant at 5% ,*** significant at 1%
Source: Raw data from EPWRF, (SRS- various years) and Author's calculations

Columns 2-4 reportsunconditional β-convergence, as specified in equations (8.2-8.4) above. With the exception of the period 1981-90, for all other periods, we find highly significant coefficients for unconditional β-convergence. Thus this analysis suggests that the states exhibit convergence with respect to the reduction in IMR. The coefficient on the reduction in IMR and the initial IMR has been negative and is highly significant in the post reforms period and more particularly in the decade of 2001-11.

Figure 33: Scatter Plots for Change In IMR and the Initial IMR

Source: Raw data from EPWRF, (SRS- various years) and Author's calculations
Note : an-Andhra Pradesh, ap- Arunachal Pradesh, as-Assam, b-Bihar, d-Delhi, go- Goa, gu-Gujarat, h-Haryana, hp-Himachal Pradesh, , jk-Jammu & Kashmir, k-Karnataka, ke-Kerala, mp-Madhya Pradesh, mh-Maharashtra, mr-Manipur, mg-Meghalaya, mz- Mizoram, n- Nagaland, o-Odisha, pb-Punjab, r-Rajasthan, s-Sikkim, t-Tamil Nadu, tr- Tripura, u-Uttar Pradesh, w-West Bengal, pd- Puducherry, AN- Andaman and Nicobar Islands.

Figure 32 presents change in IMR during the different periods under observation given their initial IMR. We find that states which have greater initial IMR have shown greater improvement in IMR vis-à-vis those states which had lower levels of initial IMR. Such a pattern demonstrates evidence of catching-up process in IMR across the states of India. Uttar Pradesh which had the highest IMR in 1981 has been overtaken by Odisha which had high IMR in 1991, 2001 and 2011.

8.4.2 Literacy Rates and Convergence

In this section we see if the educational indicators are converging or diverging across the states India. As in the case of IMR convergence, the rate or the speed of convergence in literacy is examined to see how quickly education indicator approaches its steady state levels. Steady state is the situation where each variable grows at a constant rate. The descriptive statistics given in (Table 32), presents both the measures, standard deviation as well as the coefficient of variation. The steep decline in standard deviation and the coefficient of variation offer strong evidences of convergence in education attainment (literacy rate).

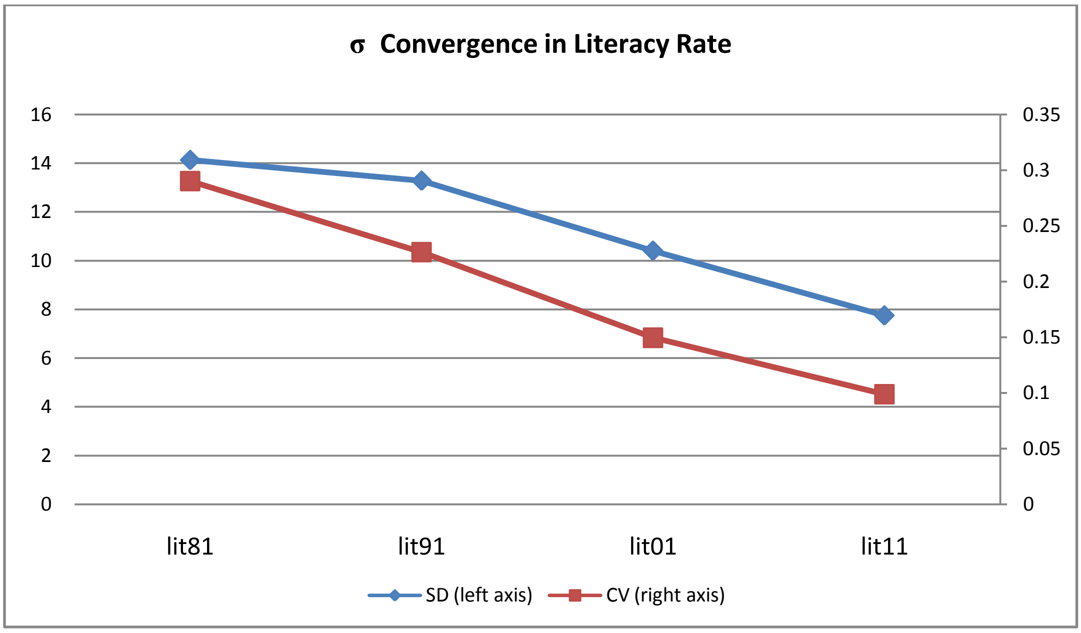
Table 32: Summary Statistics of Literacy Rates (State Level)

	Variable	Mean	Standard Deviation	Min	Max	CV
1	2	3	4	5	6	7
a	lit81	48.69	14.13	25.54	81.56	0.29
b	lit91	58.69	13.28	38	90	0.22
c	lit01	69.63	10.41	47.53	90.92	0.14
d	lit11	78.51	7.75	65.7	93.9	0.09
e	grlit8190	0.999	0.31	0.307	1.882	0.31
f	grlit9100	1.093	0.47	0.092	2.203	0.43
g	grlit0111	0.887	0.40	0.299	1.817	0.45

Source: Raw data from EPWRF, (SRS- various years) and Author's calculations

In examining the absolute convergence using regression analysis, only one variable, the initial literacy rate is used as an explanatory factor in the Figure 33 given below.All the coefficients on the initial literacy levels in the regression in column 2-5 have negative signs.

Figure 34: Sigma Convergence across the States for Literacy Rate from 1981 to 2011



Source: Raw data from EPWRF, (SRS- various years) and Author's calculations

In all other periods the coefficients are significant at 1 percent level except for the period 1981-91. These results thus provide further evidence of unconditional convergence in literacy rates among the states in India.

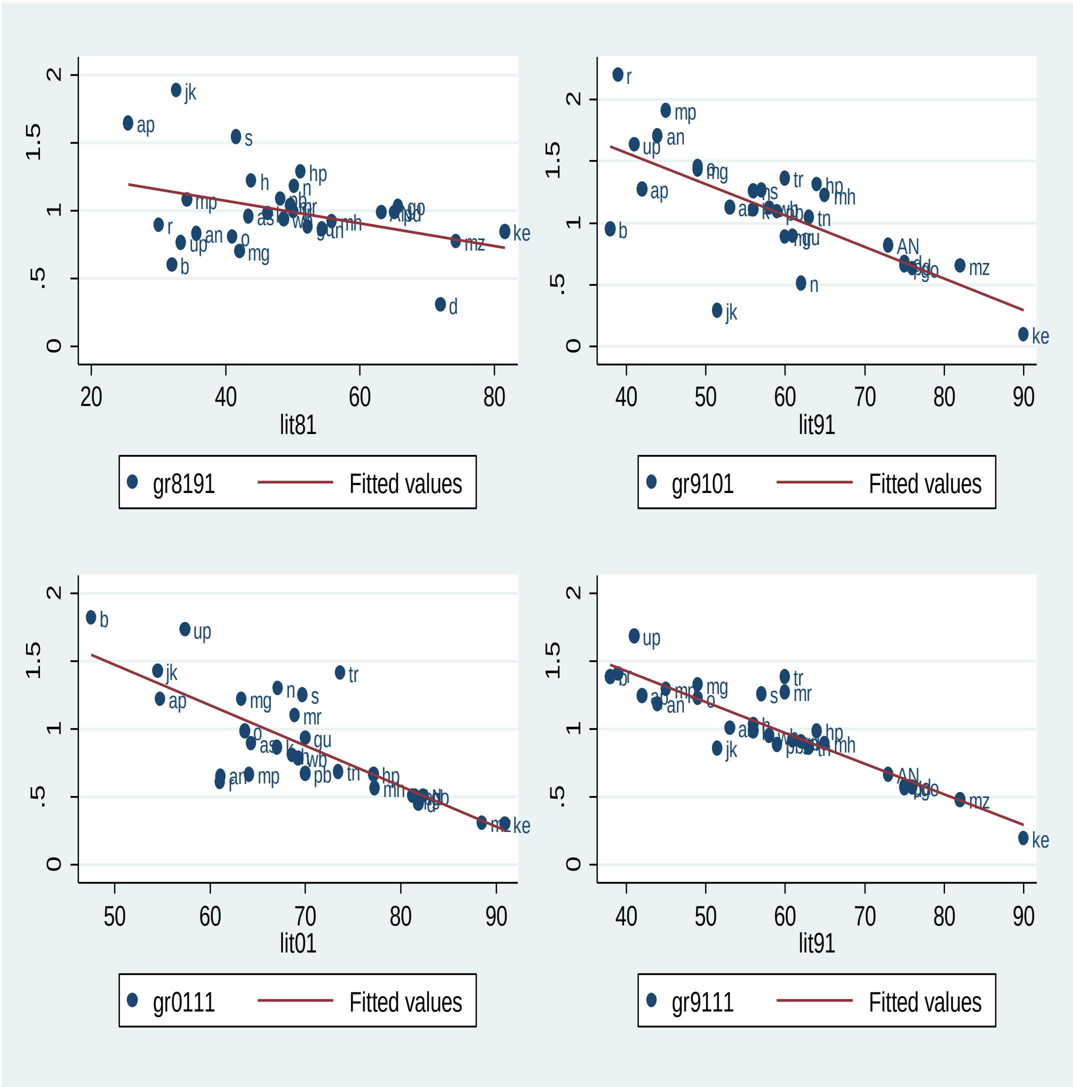
Table 33: Cross Section Regression Results for Literacy Rate - Absolute β Convergence

	Dependent Variables			
1	2	3	4	5
Independent Variables ↓	Grlit8191	Grlit9101	Grlit0111	Gr9111
Lit81	-0.008** (.004)			
Lit91		-0.026*** (.004)		-.022*** (.002)
Lit01			-0.03*** (.004)	
Constant	1.403*** (.20)	2.595*** (.289)	2.969*** (.34)	2.33*** (.13)
R-squared	0.14	0.52	0.59	0.79
Adj R-Squared	0.10	0.50	0.57	0.79
Speed of convergence N=28	-0.0008	-0.0026	-0.003	-0.0011

Standard errors in parentheses,* Significant at 10%; ** significant at 5% *** significant at 1%,
Source: Raw data from Population Census 2011 and Author's calculations

The scatter plot (Figure 34)also shows a negative relationship between the growth rate of literacy and the initial levels of literacy in all four periods. We next examine the convergence in poverty rate.

Figure 35: Scatter plots for Change In Literacy Rate and the Initial Literacy Rate



Source: Raw data from Population Census 2011 and Author's calculations

8.4.3 Poverty Rates and Convergence

The poverty ratios for each of the states for the years 1983, 1987-88, 1993-94, 1999-00, 2004-05 (URP) and 2011-12 (MRP) provided by the Planning Commission has been considered. We have already observed that PCI are diverging in India over the period 1981-2012. States with higher initial PCNSDP show higher rates of economic growth. However, it would be interesting to know if poverty rates following a similar trend. The following section examines if there is convergence in poverty across the states in India. The results are presented by taking into account both the rounds, the 66th quinquennial round as well as the 68th round as discussed earlier.

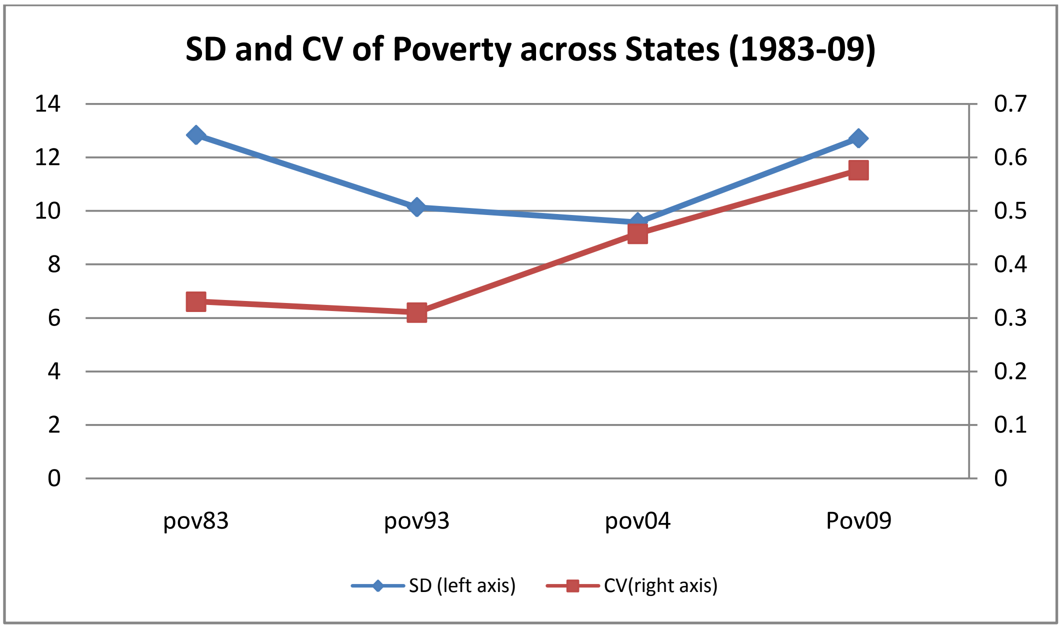
Table 34: Summary Statistics of Poverty Rates (State Level)

	Variable	Mean	Standard Deviation	Min	Max	Coefficient of Variation
1	2	3	4	5	6	7
a	dpov8393	-0.58	0.72	-1.88	1.27	-1.25
b	dpov9304	-1.08	0.59	-1.94	-0.03	-0.54
c	dpov0411	-0.51	1.31	-3.08	2.79	-2.56
d	dpov9311	-0.81	0.49	-1.95	0.03	-0.61
e	dpov0409	0.22	2.06	-4.44	5.96	9.10
f	dpov9309	-0.66	0.66	-2.03	0.5	-1.01
g	pov83	38.81	12.83	16.18	65.29	0.33
h	pov93	32.66	10.13	11.77	54.96	0.31
i	pov04	20.92	9.57	5.4	46.4	0.45
j	Pov09	22.05	12.70	.4	53.5	0.57
k	pov11	17.32	10.37	1	36.89	0.59

Source: Raw data from Planning Commission and Author's calculations. N=28

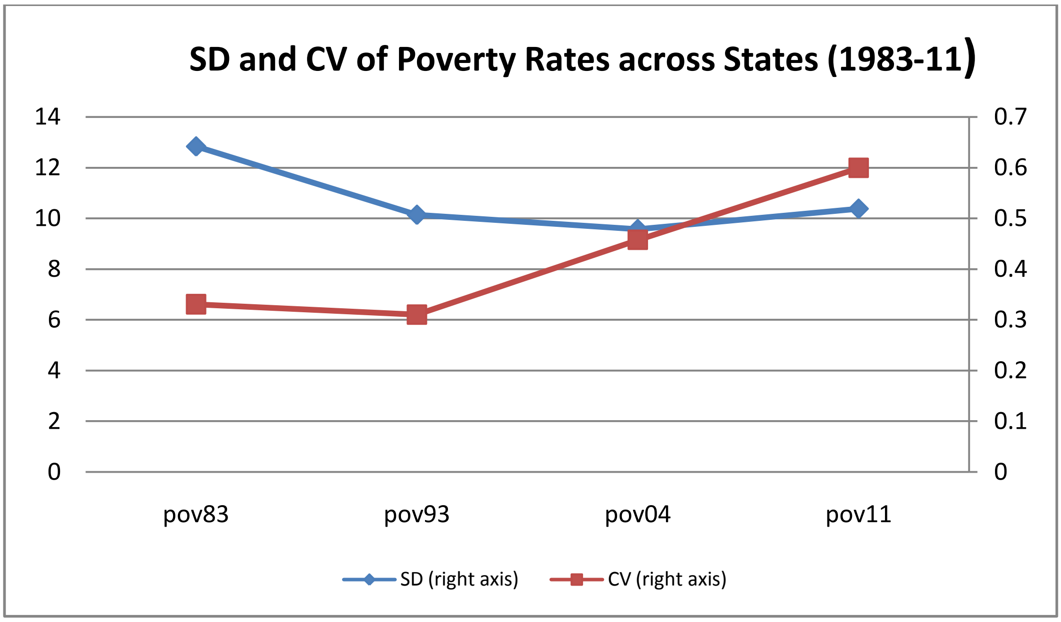
Unlike the IMR and Literacy rate there is a rise in the SD and CV particularly in the post reforms period. This suggests that there are no signs of σ convergence in poverty rates in India.

Figure 36: Standard Deviation and Coefficients of Variation of Poverty across Indian States(1983-09)



Source: Raw data from Planning Commission and Author's calculations

Figure 37: Standard Deviation and Coefficients of Variation of Poverty across Indian States(1983-11)



Source: Raw data from Planning Commission and Author's calculations

With respect to β convergence the results suggest that there has been convergence among the states with respect to the reduction in the poverty ratios from 1983 onwards. In figure 35, we find that states with higher level of poverty in the initial period experience greater absolute reductions in the poverty headcount ratio. These trends are statistically significant in regressions reported below. When we regress the absolute change in the headcount ratio on the initial poverty level, we see a negative and statistically significant coefficient.

Table 35: Decline in the Poverty rate by States and the initial level of poverty(1983-11)

Dependent Variables				
1	2	3	4	5
	Dpov83-93	Dpov93-04	Dpov04-11	Dpov93-11
pov83	-0.034*** (.008)			
pov93		-0.024*** (.01)		-.024*** (.008)
pov04			-0.054** (.024)	
Constant	0.735* (.36)	-0.31 (.35)	0.614 (.57)	-.003 (.284)
R-squared	0.36	0.16	0.15	0.25
Adj R-Squared	0.33	0.12	0.12	0.24

Source: Raw data from Planning Commission (various years) and Author's calculations
N=28 ,standard errors in parentheses,
* Significant at 10%; ** significant at 5% *** significant at 1%

With regard to poverty convergence across the states in India in the pre and the post reforms period, there is a evidence of unconditional poverty convergence. We find that there has been a negative relationship between the initial poverty rate and the rate at which the poverty is declining. For all the years, the value of the coefficient is negative and significant. This suggests a catching up process whereby the states with high poverty rates are experiencing a higher rate of progress and are able to reduce poverty rates faster.

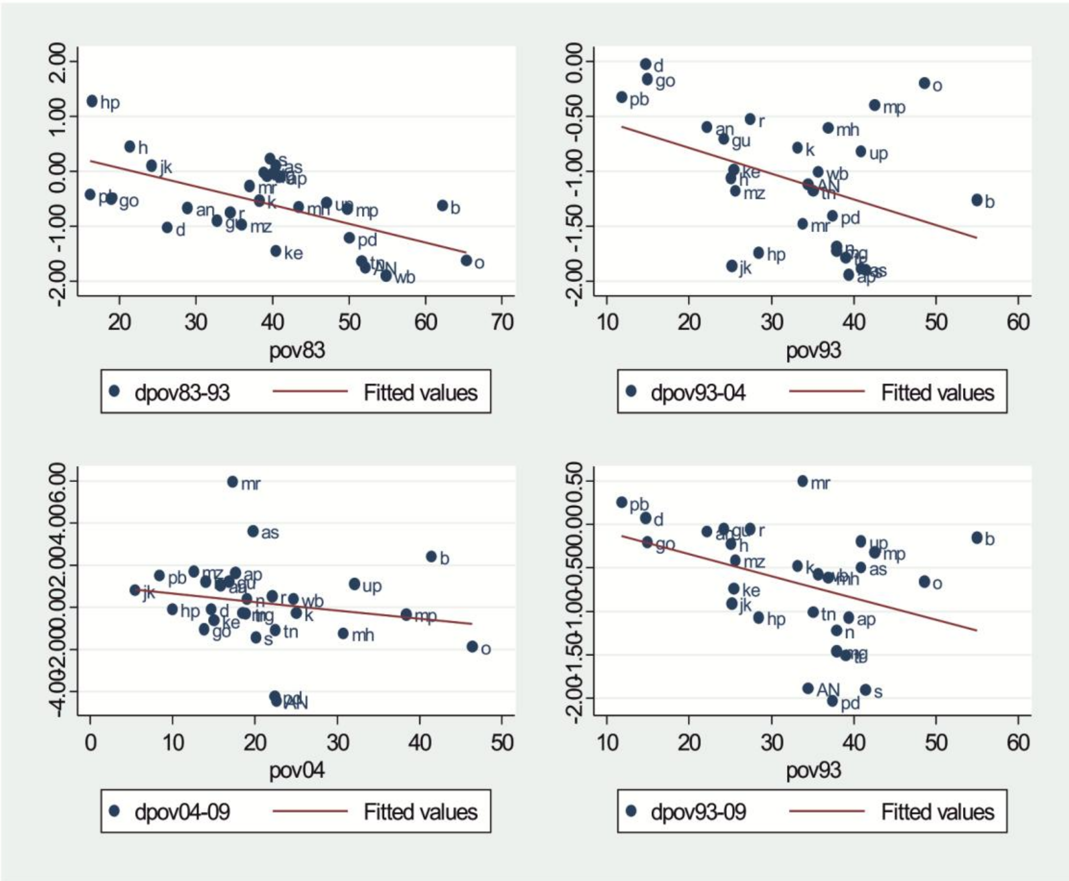
However in the Table 36below, except for the period 2004-09, we find unconditional poverty convergence among the states in reduction in poverty rates.

Table 36: Decline in the Poverty rate by States and the initial level of poverty(1983-09)

	dpov83-93	dpov93-04	dpov04-09	Dpov93-09
pov83	-0.034*** (.008)			
pov93		-0.024*** (.01)		-0.025*** (.011)
pov04			-0.04 (0.04)	
Constant	0.73* (0.36)	-0.31 (0.35)	1.06 (0.95)	0.16 (0.40)
R-squared	0.36	0.16	0.03	0.14
Adj R-Squared	0.33	0.12	-0.002	0.11

Source: Raw data from Planning Commission (various years) and Author's calculations
No of observations: 28 ,standard errors in parentheses, * Significant at 10%; ** significant at 5% *** significant at 1%

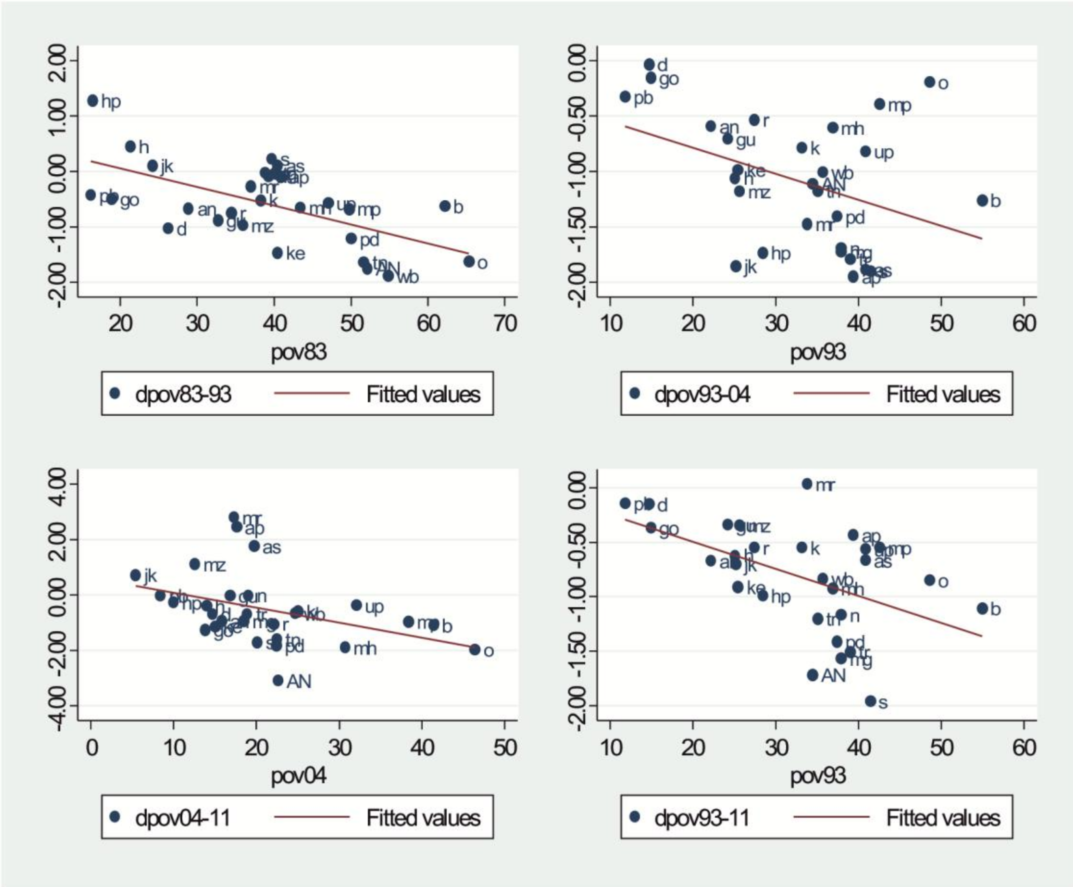
Figure 38: Scatter Plots For Poverty Rates across the States (using 66th Round 2009-10)



Source: Raw data from Planning Commission (various years) and Author's calculations

The scatter plots in Figure 37 and 38 show negative relationship between the reduction in the poverty rates and initial level of poverty both the 66th and 68th NSSO Rounds.

Figure 39: Scatter Plots for Poverty Rates across the States(using 68th Round 2011-12)



Source: Raw data from Planning Commission (various years) and Author's calculations

Interestingly almost all the states have experienced a declining trend in the incidence of poverty in varying degrees during the pre and post period from 1993-94 to 2009-10. We also find that the relative positions of the states regarding their ability to reduce poverty has also varied remarkably at the inter temporal level over the period of our study.

8.5 Summary

This chapter examined if there was convergence in education, health and poverty among the states in India. We find evidences of β convergence in all the three indicators considered. This is despite the fact that there is divergence in the income (PCNSDP). As far as σ convergence is concerned there is a fall in regional inequality in health and education but not in poverty rates. In fact we find that the Standard Deviation in poverty has gone up especially in the post reform period. This indicates that the is no sign of σ convergence when it comes to poverty in India.

In the next chapter focuses on the causes for the differences in the per capita incomes of the states in India and employ an instrumental variable approach for the panel data growth models.

Chapter IX

An Application of Instrumental Variable Approach to Convergence

9.1 Introduction

The empirical debate on economic convergence centres around the inverse relationship between the growth of per capita income and the starting levels of income across countries or across the regions within the countries. Besides the PCI there could be a number of factors that influence the growth rate. Series of contributions in growth empirics have seen convergence of the countries towards the steady state levels (Barro,et al, 1991; Barro, 1991; Sala-i-Martin, 1996), while large many have argued that the economies have diverged from the steady state levels(Kanbur & Zhang, 2005; Laurini et al., 2005; Nayyar, 2008; Raju, 2012; Weiss & Rosenblatt, 2010). However, there are studies which question the existing empirical literature on cross-country growth rates on grounds of using inconsistent estimation procedures (Caselli, et al, 1996; Castineira & Nunes, 1999; Levine & Renelt, 1992). This inconsistency arises because a subset of the explanatory variables could be endogenously determined and so the estimated coefficient of initial income will be biased. If endogeneity is present in growth regressions, the convergence rate and the other growth coefficients obtained could be unreliable.

Endogeneity occurs in multiple regression because of (i) measurement error (we are not able to fully observe all variables all the time), (ii) omitted variable bias (arises as we do not include certain variables that are unobserved) and (iii) simultaneity problem (causality is not uni-directional). In order to avoid these problems that arise out of endogeneity, the instrumental variable estimation approach for the panel data growth models is often employed. This is the proposed approach for this chapter.

Apart from the differences in the national income what are the fundamental causes for the differences in the per capita incomes of the states in India? The international and Indian literature suggests that social stratification, public expenditure policies and the political sources could explain why some countries or states can accumulate more capital (see Alberto & Perotti, 1996; Annett, 2000; Brunetti, et al, 1997; Deshpande & Ramachandran, 2014; Deshpande, 2013).

One of the primary objectives of economic growth in India isto reduce poverty and inequality. However there is a general perception that growth alone cannot bring down poverty, it is the distribution of income that is important(Dreze & Sen, 2002). The inequalities do not allow the benefits of growth to reach the poor; as a result not all regions and states in India have grown at the same pace nor has the decline in poverty rates been uniform.

In the late 1990s the term pro-poor growth became popular as economists began to analyze policy packages that could achieve more rapid poverty reduction through growth and distributional change(Kakwani & Son, 2003).The extent to which growth reduces poverty depends on the degree to which the poor participate in the growth process and share in its proceeds. Thus, both the pace and pattern of growth matter for reducing poverty. High inequality affects the pace and pattern of growth and its effectiveness in reducing economic poverty.

In India, besides economic, religious and linguistic disparities, there are historically established social hierarchies where the caste system still prevails as one of the key drivers of poverty and inequality (Rao, 2010). Since Indian society is segregated into castes, and some of them are economically and socially deprived to a great extent, it is necessary to bridge the caste gaps and ultimately eliminate all forms of social barriers which are discriminatory. Recognizing these caste based inequalities, the

Government of India initiated affirmative action as a remedial measure. The presence of identity based groups has of course political ramifications and in India has impacted on election process as well as political decision making.

There have been some efforts to identify the relationship between political decision making processes and economic growth (Kohli, 2006). Different aspects have been examined in this context. Measures of democracy (Alberto & Perotti, 1996; Barro, 1989; Dasgupta, 1989), Government stability, political violence (Alberto & Perotti, 1996; Barro, 1989,1991), political volatility (Dollar, 1992),and subjective measures of politics (Brunetti, et al, 1997) have been used as explanatory political variables in many studies. In addition to these measures we argue that the centre-state relations play an important role. In the Indian context, development of a state could be expedited if the state receives a larger chunk of federal support. This could happen if the same party ruled in both state and Centre. We use a political variable which counts the number of years the state and centre were political allies. If the state and the centre parties are allies it is expected that the ally state would benefit with favourable grants from centre.

This chapter is divided into two parts:

1) In the first section, the influence of politics and social discrimination (caste system) on economic growth is examined. This is done by making these variables as instruments that determine initial level of income. We know that one of the most challenging problems of growth studies is the presence of endogeneity. If the per capita income across the states is endogenous, then variables such as caste, development expenditures and politics could be considered as instruments. We analyze how these variables influence the

initial per capita incomes of the states in a instrumental variable (IV) framework.

2) Secondly, this chapter documents India's record of economic growth impacting on poverty reduction over the last three decades and sees if there has been poverty convergence among the states in India. The specific measure of poverty here is the poverty rate or headcount ratio (HCR). This is the proportion of the population with income or expenditures below the poverty line. This section mainly highlights the trends in poverty reduction and focuses on how economic growth has affected levels poverty across the states. We look at the redistributive role of the Governments through the pattern of developmental revenue expenditures across the states in implementing the poverty alleviation policies and reducing inequality. Here too we extend the IV framework to control for presence of endogeneity.

9.2 Relevance of Caste, Politics and Expenditure Policies in India

Caste, religion and region are some of the important facets of inequality faced in India. We begin by giving a brief backgroundabout caste and its economic implications in India (we do not enter the large social literature on caste).

9.2.1 Background of Caste System in India

The caste system is one of the key drivers of poverty and inequality in India (see Iversen, et al, 2010; Rao, 2010). The caste system was a way of classifying people into different social classes. According to Deshpande (2011), caste has two different concepts; *Varna and Jati.* The *Varna* system divides the Hindu society into four or five distinct Varnas; Brahmins, Kshatriyas, Vaisyas, Sudras and the Atisudras, the untouchables, also known as Harijans or Dalits, (considered unfit to be given a

Varna) who fall outside of the caste system all together. The *Varna* hierarchy was relatively straightforward, (first three tiers were considered as superior than the next two). As the economy grew more complex, the *Varna* system was referred as the *"Jati"* system, which had the basic characteristics as the *Varna,* but the hierarchy of the *Jati* was much more complex. The *Jatis* are not the exact subset of the *Varna,* evolution of specific *Jati* varies across the regions, as a particular *Jati* could be considered backward in one state but not necessarily in the other state. Besides, if a *Jati* claims a certain *Varna* status, it could be disputed by other *Jatis* and so on (Deshpande, 2000). There are 3,000 Jatis in India with more complex hierarchy and rules of conduct towards each other. In fact *Varna* provides scale of status to which the *Jati* aligns themselves. Thus caste can be referred to as *Jati* (sub-caste) or the more general *Varna.*

Besides, there are more than 50 million Indian who are said to belong to the tribal community - the Adivasis, who are distinct from the Hindu caste system, with lifestyles and languages different from the other communities of India(Deshpande, 2011; GOG, 2013). Tribal groups have a system of hierarchy based on the ecology, ranking, status, etc. The untouchables and the tribe who are economically weakest and subjected to discrimination and deprivation are called as the Schedule Castes (SC) and Schedule Tribes (ST) respectively. Recognizing the caste based inequalities, Government of India initiated affirmative action as a remedial measure with reservations in jobs, education etc. All states in India have quotas for the SCs, STs and the OBCs. The caste system has been widely researched by other social sciences (Sociology, Anthropology) but somehow economists have not ventured into this area much (Deshpande, 2011).

Up to mid-1990s, in the national data sets, population in India was divided into three broad categories; SC, ST and the 'Others' (which meant everyone else). After mid 1990s this classification further divided 'Others' into "Other Backward Classes" and the remaining were labeled 'Others'. The Constitution refers to this additional category of disadvantaged citizens as Other Backward Classes (OBC- a large and heterogeneous category which contains castes close to the SCs in social and economic backwardness).

This issue was first addressed by the Other Backward Class Commission (1955) constituted by Prime Minister Jawaharlal Nehru, and later and more decisively by the Mandal Commission (1978-80). With the Mandal Commission's recommendations, reservation benefits to OBCs were extended, and were declared constitutionally legitimate by the Supreme Court in 1992 (Iversen et al., 2010). There is a large, growing body of literature documenting the changes in the standard of living as well as the economic discrimination faced by the SCs and STs, (Deshpande & Ramachandran, 2014; Prakash, 2009; Zacharias & Vakulabharanam, 2011). However, the discussion and empirical analysis about the living conditions or the economic dominance of the group of castes and communities that belong to the 'Other Backward Classes' is relatively small. The reason for few studies on OBCs was because of the lack of hard data. Until the 2001 census, OBCs were not counted as a separate category, despite the affirmative action(quotas in jobs etc) were targeted towards OBCs at the national level since 1991, and at the state level fromeven earlier (Deshpande & Ramachandran, 2014).

The pre-colonial diversity in India got further complicated on economic and social grounds, as different states had dissimilar social reform movements that shaped the socio cultural institutions of each state. Social reforms impacted the functioning of the caste systems in those states where there was effective mobilization by caste groups. Caste inequalities took state specific characteristics over time. The north eastern states are all ST dominated, with each state having unique ethnic identities. India has states with diverse histories and cultural interrelationships. The specific history of social reforms and the political protests against upper-caste domination particularly in Tamil Nadu, Kerala and Maharashtra have brought about overall higher achievements in the educational outcomes as well as better outcomes for SC's and women. Social reforms have also influenced variables like the access to primary education, occupation, landholdings, asset and livestock for certain states in India (Deshpande, 2011).

9.2.2 India's Affirmative Action Programme

After independence, the Constitution of India adhered to the idea of preferential policies, declared untouchability illegal and was based on the ideal of a casteless society. Affirmative action are the policies used by government and various other institutions with the objectiveof uplifting the historically disadvantaged groups in the society. This preferential treatment was assigned because of the disparities between SCs, STs and OBCs and the forward classes in material standards of living, poverty rates, health status, educational attainment and occupational outcomes (Deshpande, 2013).

Affirmative action programme was initiated because of the following discrimination faced in the society;

a) Social discrimination- which includes various aspects of stigmatization, exclusion, rejection and untouchability (Deshpande, 2013).

b) Economic discrimination- Average wages for SCs and General categories differ across all occupation categories. Besides there are substantial gaps between SCs and Others in access to education and resources that could enhance learning, quality of education (Deshpande, 2013).

c) Compensation for historical wrongs: compensating for the damages caused by the past discrimination that kept untouchables at the very bottom of the social and economic order.

The nature and implementation of affirmative action policies differs across different countries (Prakash, 2009).These policies are broadly classified into two categories.

1) Policy of mandated quota system: in this case certain number or share of jobs or seats is set aside for disadvantaged minorities in public sector enterprise, private sector enterprise, political spheres and educational institutions.

2) Policy of preferential treatment: here members of historically disadvantaged groups receive more favourable consideration for school admission or employment; however no specific slots in the institution are actually set aside for them.

India's affirmative action programme is mainly caste-based, though there is some affirmative action for women also. In India there is caste based quota in government jobs, in higher education and there are political constituencies. There is different quota for the SC, ST and the OBC, which are proportional to their share in the population (though statequotas vary and are not according to the percentage of population).

A question that is often asked is whether the affirmative action in India has had any impact on the inter caste social mobility? How have the states which are dominated by lower caste/tribes performed in terms of per capita income growth?

In India, Scheduled Castes, on average comprise about 18 percent of the Indian population; Scheduled Tribes (ST), about 8 percent of the Indian population; Other Backward Classes (OBCs, a heterogeneous collection of Hindu low castes, some non-Hindu communities and some tribes which are not included in the STs), are not yet counted by the census; however according to the 66th round of the National Sample Survey (2009-10), they constitute 43 percent of the rural and 39 percent of the urban population and the remaining are "Others"-the forward caste (Deshpande, 2013).

In the previous chapters we have seen that across the states in India there has been growing divergence and the formation of clubs with clear indication of multimodality. The reforms of 1990s has led to the increasing privatization of education and jobs (Kikeri, 1997). There has also been a weakening of affirmative action (Deshpande, 2011). The nature and degree of change in the economic ranking between castes, needs empirical verification. At the same time it is necessary to examine the impact of this social diversity on the economic growth and whether this diversity could be a factor leading to diverging growth rates among the states.

The tables 37, 38 and 39 below represents the transition matrices for the period 1981-12 with each of the matrix depicting the dominance of different caste categories like; 40 %(OBC),18%(SC) and 8%(ST). We analyze the period from 1981-82 to 2012-13 with the 28 states and UTs and observe the mobility of the states in terms of income beyond the category where they started in 1981-82. The states in bold green are the ones which have OBC population of more than 40 percent (as the national average percentage of OBC population is around 40% in India). The movement of the states above the diagonal would indicate an improvement in the performance of the state from where it started. If the states are located below the diagonal it would mean a fall in their relative per capita levels as compared to the initial period (1981-82).

Table 37: Relative Per Capita Income Transition Dynamics, 1981-12 (states with OBC >40 per cent)

		2012				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1981	States with starting level <0 .75	0.333 Bihar, M.P, Odisha	0.556 Meghalaya, Tripura U.P, Mizoram, Rajasthan	0.111 Kerala		9
	States with starting level =or >0 .75 but < 1 or = 1	0.182 Manipur, Assam	0.182 J&K, W.B	0.545 Andhra P. Arunachal P, H.P,Karnataka, Nagaland,Tamil Nadu	0.091 Sikkim	11
	States with starting level >1 but < 2or =2			0.857 Gujarat, Haryana, Maharashtra, Punjab, Puducherry, A&N Islands	0.143 Goa	7
	States with starting level > 2				1 Delhi	1

Source: Author's calculation based on EPWRF data

Kerala, Sikkim, Andhra Pradesh, Tamil Nadu, Karnataka and Rajasthan which are the OBC dominated states have moved above the diagonal. Most of this group except Sikkim are southern states and is in conformity with the literature that social reforms in the southern states have brought about significant social development (Deshpande & Ramachandran, 2014; Deshpande, 2011).

In the Table 38 below, the states in bold blue are the ones which have SC population of more than 18 percent (as the national average percentage of SC population is around 18% in India).

Table 38: Relative Per Capita Income Transition Dynamics, 1981-12 (states with SC >18 per cent)

		2012				Numb er of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1981	States with starting level <0 .75	0.333 Bihar, M.P, Odisha	0.556 Meghalaya, Tripura U.P, Mizoram, Rajasthan	0.111 Kerala		9
	States with starting level =or >0 .75 but < 1 or = 1	0.182 Manipur, Assam	0.182 J&K, West Bengal	0.545 Andhra P. Arunachal P, Himachal P, Karnataka, Nagaland,Tamil Nadu	0.091 Sikkim	11
	States with starting level >1 but < 2or =2			0.857 Gujarat, Haryana, Maharashtra, Punjab, Puducherry, A&N Islands	0.143 Goa	7
	States with starting level > 2				1 Delhi	1

Source: Author's calculation based on EPWRF data

The states with more than the national average of the SC population are on the diagonal of the transition matrix. Though Tripura, U.P and Rajasthan have moved above the diagonal, they are still at the lower end of the income levels. Again, besides the southern states of Andhra Pradesh and Tamil Nadu, Arunachal Pradesh has shown a remarkable improvement.

In the Table 39 below states in bold yellow are the ones which have ST population of more than 8 percent (as the national average percentage of ST population in India is around 8%).The North Eastern states have a high proportion of ST population. Most of these states have moved above the diagonal showing an improvement in their per capita levels. From the above tables we can conclude that some of the OBC, SC and ST dominated states are progressing and have moved above the diagonal. This is more prominent for the Southern states.

Table 39: Relative Per Capita Income Transition Dynamics, 1981-12 (states with ST > 8 percent)

		2012				Number of states
		States with ending level <0.75	States with ending level = or >0 .75 but < 1 or = 1	States with ending level > 1 but < 2or =2	States with ending level > 2	
1981	States with starting level <0 .75	0.333 Bihar, M.P, Odisha	0.556 Meghalaya, TripuraU.P, Mizoram, Rajasthan	0.111 Kerala		9
	States with starting level =or >0 .75 but < 1 or = 1	0.182 Manipur, Assam	0.182 J&K, W.B	0.545 Andhra P. Arunachal P, H.P, Karnataka, Nagaland,Tamil Nadu	0.091 Sikkim	11
	States with starting level >1 but < 2or =2			0.857 Gujarat, Haryana, Maharashtra, Punjab, Puducherry, A&NIslands	0.143 Goa	7
	States with starting level > 2				1 Delhi	1

Source: Author's calculation based on EPWRF data

In the Instrumental Variable (IV) growth regression models, caste is considered as an instrument because it is a given category not influenced by any other factor. The impact of having higher percentage of the SC, ST and OBC population on the growth rates as well is examined later in this chapter.

9.2.3. Political Variables In Growth Analysis

As discussed earlier, a heterogeneous set of political variables are tested in growth regressions in a large number of studies across and within the countries. It has generally been argued that the development transfers to a state would be larger and accelerated if the same party ruled in both the state and the Centre. In India, for most of the years since independence, the federal government has been headed by the Indian National Congress (INC). The two largest political parties have been the INC and the Bharatiya Janata Party (BJP). Although the two parties have dominated the national politics, regional parties have played a significant role too. From 1950 to 1990, barring two brief periods, the INC enjoyed a parliamentary majority (Corbridge, et al, 2013).

States in India have their own elected governments, whereas Union Territories are governed by an administrator appointed by the President. There could be considerable center-state conflict when ruling a political party in a state is different and not an ally of the national ruling party. Besides since the 73rd and 74th constitutional amendments in the early 1990s, the lower castes have become an important force in Indian politics at the- local, state and national levels. The political variable employed in this chapter is the number of years the state party is an ally at the centre. It is a dummy variable, that takes the value one if the state and the centre parties are allies, and is zero otherwise. The Political variable is also treated as an instrument in IV regression.

9.2.4 Public Expenditures across India

Expenditures consist of resources expended by the state governments according to each state government's policies and priorities.We have used revenue (or broadly, current expenditures) of the state governments for the analysis. Within revenue expenditures, there are "development expenditures" and "non- development expenditures". The development expenditures refer to expenditures on various socio-economic development programs in the social sectors and economic sectors.The amount of the public expenditures on various social services includes a) Education, Sports, Art and Culture b) medical and Public Health c) Family Welfare d) Water Supply and Sanitation e) Housing f) Urban Development g) Welfare of SC, ST h) Labour and Labour Welfare i) Social Security and Welfare j) Nutrition k) Relief on account of Natural Calamities. The Economic services undertaken are a) Agriculture and Allied Activities b) Rural Development c) Special Area Programme d) Irrigation and Flood Control e) Energy f) Industry and Minerals g) Transport and Communications h) Science, Technology and Environment. These expenditures are based on the state level as well as the central allocations, as revenues generated by the states generally falls short to cover up the bulk of the capital expenditures and the Central Government makes up for the balance. The amount of these expenditures undertaken would raise the income as well the quality of life of the people. To analyze the impact of the expenditures on the rate of growth of the states, the total development expenditure (expenditure on Social Services and Economic Services) is taken as an instrument in the growth regression because public expenditure is commonly assumed as autonomous in much of the macroeconomic literature.

9.3 Endogeneity and Instrumental Variable Approach

As discussed earlier (section 3.6) an assumption of the OLS regression is that there is no correlation between the explanatory variable and the error termthat is $E(u / x) = 0$. However a multiple regression model would suffer from functional form misspecification if it does not take into account the relationship between the dependent and the observed explanatory variables(Wooldridge, 2009). Thus a regression is said to be inconsistent if there is correlation between the explanatory variables and the error term. One of the major concerns in growth literature is the probable presence of endogeneity of some regressors. Endogeneity is said to occur when one or more independent variables are correlated with the error term. Instrumental variable estimation is therefore used in this chapter to tackle the endogeneity problem. When the error term and regressor are correlated with additional variables or instruments, we obtain consistent estimators of β_0 and β_1. An alternative solution would be using lags of the explanatory variables, thereby ensuring that they are predetermined with respect to the dependent variable.

9.3.1 PCI and Endogeneity

In the growth equation (9.1), we suspect the explanatory variable- initial PCNSDP to be correlated with the error term, thus being endogenous.

(9.1) $$Y_{it} = \beta_0 + \beta_1 lnpcnsdp_{it-\tau} + u_{it}$$

Where, "Y_{it}" is the growth rate of PCI, while the "$lnpcnsdp_{it}$" is the initial PCI. We used the Hausman test to compare random vs. fixed effect finding that random effect are not consistent. The analysis thus uses the fixed effects model After having tested the regressor lnpcnsdp, it was found the explanatory variable lnpcnsdp is endogenous, with highly significant p-value (0.002). We thus use exogenous variation in percentage of SC, ST and OBC population of the states, per capita development expenditures and the political variable that are correlated with the per capita income of the states as instrumental variables for initial PCI in the first stage equation;

(9.2) $$\mathrm{lnpcnsdp_{it}} = \alpha_0 + \alpha_1 \mathrm{SC}_{i,t-\tau} + \alpha_2 \mathrm{ST}_{i,t-\tau} + \alpha_3 \mathrm{OBC}_{i,t-\tau} + \alpha_4\, \mathrm{pcdevexp}_{i,t-\tau} + \alpha_5 \mathrm{pol\_l1}_{i,t-\tau} + \alpha_6 \mathrm{sq\_pol\_l1}_{i,t-\tau} + \varepsilon_{it}$$

"$\mathrm{lnpcnsdp_{it}}$" is regressed on the above instruments, where, " $\mathrm{SC}_{i,t-\tau}$"," $\mathrm{ST}_{i,t-\tau}$" and "$\mathrm{OBC}_{i,t-\tau}$" is the percentage of SC, ST and OBC population in the states. " $pcdevexp_{it-\tau}$" is the per capita development expenditures, " $pol\_l1_{i,t-\tau}$ " is the political variable (lagged by one period) and " $sq\_pol\_l1_{i,t-\tau}$" is the square of political variable. We then take the predicted value of initial PCI (lnpcnsdp) back to the original structural equation (9.1). The two-stage-least-square (2SLS) estimation to test theimpact of initial PCI on growth ofPCI is given as under;

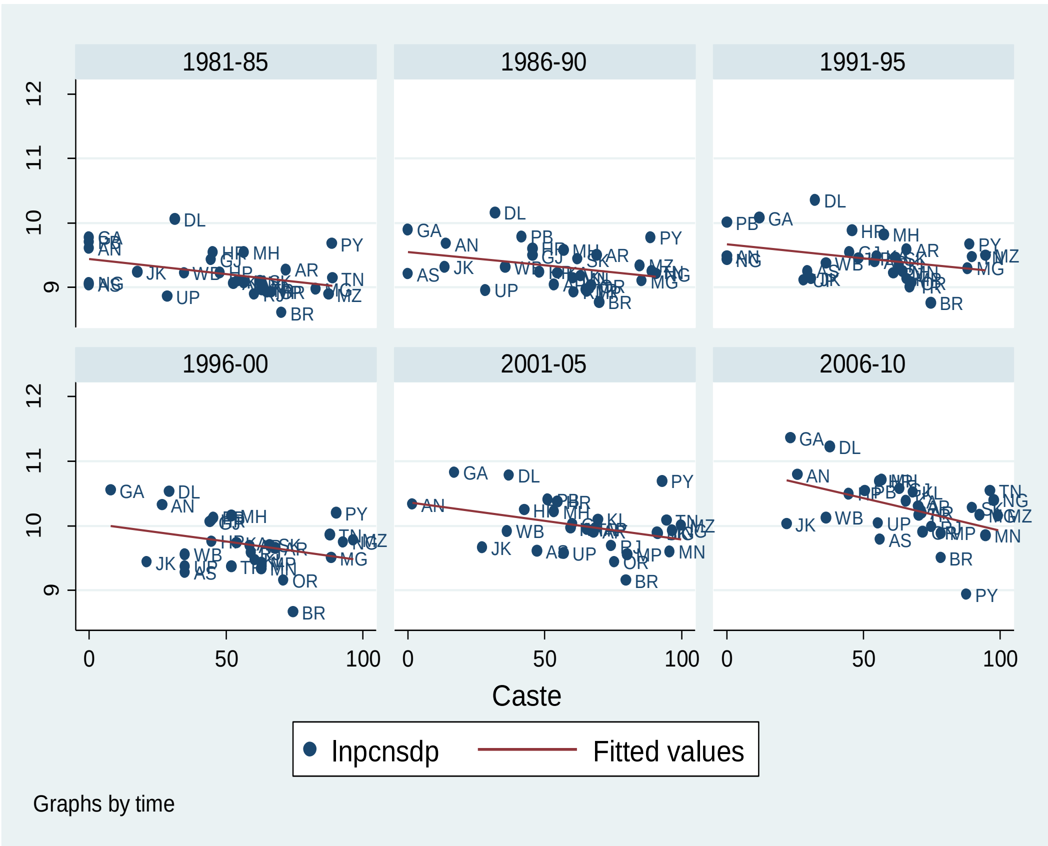
(9.3) $$Y_{it} = \beta_0 + \beta_1 \widehat{lnpcnsdp}_{i,t-\tau} + u_{it}$$

Where $\widehat{lnpcsdp}_{it}$ is the predicted value of initial PCI that is derived from the first stage leat square equation (9.2). In the next section we present the empirical results.

9.3.2 Empirical Results

To see the relation between the per capita income and the percentage of the lower caste (summation of SC, ST and OBC) population, we present the scatter plots for the 6 time periods from 1981-2010, each of 5 year span. On the y-axis we have the "lnpcnsdp", while on the x-axis we have, the percentage of caste.

Figure 40: Scatter Plots for LNPCSNDP and Caste across Time



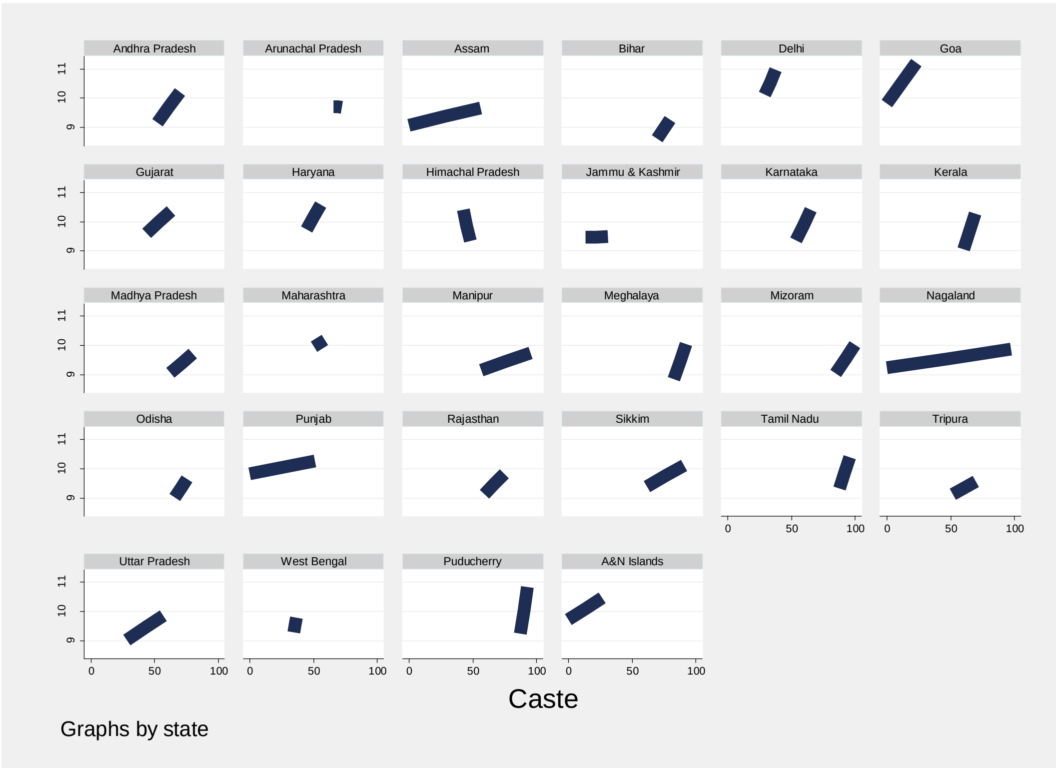
Source: EPWRF data and Author's calculations

In the scatter plots above we notice that there is a negative relationship between the PCI of the states and the percentage of caste across different time periods. The states with higher percentage of SC, ST and OBC population (caste) are the states with low PCI.

This confirms to the general argument with respect to caste - higher the percentage of SC, ST and OBC population in a particular state, lower would be the PCI.

However when we look at the PCI- Caste relationship at the state level we find a positive relation between the two. This reflects that over time as PCI has grown, so has the proportion of caste in the population.

Figure 41: Scatter Plots for PCNSDP and Caste Across States



Source: Authors calculation based on EPWRF and Planning Commission Data.

In economic growth literature, only economic factors are considered to be influencing the per capita income and growth rates of the countries or states, while the social and political factors are ignored. But our findings suggests that both social factors (as represented by the percentage of SC, ST and OBC population) and political factors (State and Central political parties being allies) do influence the per capita incomes.

Table 40 below shows the two stage least square (2SLS) coefficient estimates along with the fixed effects results (equation 2) . By using the fixed effect model, the results show evidences of divergence, as there is a positive relationship between the initial PCI and the growth of PCI.

Table 40: Instrumental Variable Estimation

Independent Variable	Dependent variable – Growth rate		
	Fixed Effect Model	First stage (dep variable- lnpcnsdp)	IV regression (2SLS) Second stage (dependent variable - Growth Rate)
1	2	3	4
lnpcnsdp	0.027*** (0.007)		0.051*** (.018)
SC (instrument)		0.03* (0.017)	
ST (instrument)		0.009 (0.01)	
OBC (instrument)		0.02*** (0.005)	
Pcdevexp (instrument)		0.00005* (0.00002)	
pol_l1(instrument)		0.13* (0.072)	
sq_pol_l1(instrument)		-0.03** (0.013)	
Constant	-0.21 (0 .077)		
Obs/ No of states	168/28	127/27	127/27
R-squared	0.06		
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.			

Source: Data from EPWRF, Census, NSSO and Authors' calculations

We now employ the instrumental variable estimation technique in which lnpcnsdp (initial PCI) is treated as endogenous, with percentage of ST,SC and OBC population, per capita development expenditures and political variables as instruments. We notice that the first stage (column 3) relationship between the PCI and the instruments is positive and significant (except for the ST population which is negative but insignificant). There is a positive relationship between the initial per capita incomes and percentage of SC, ST and OBC population. Which means as the percentage of SC, ST and OBC population increases per capita incomes also increases. In the two stage least square equation (equation 3), there is a positive relationship of per capita income with growth rate of PCI confirming divergence among the states in India. Generally poor states are the ones with higher percentage of ST, SC and OBC population. These states with higher percentage are indicating a positive impact on per capita incomes. It is not evident why caste is driving per capita incomes in India, it must be working through political factors and high development expenditures.

We find that the per capita development expenditures and political variable have a positive relationship with the initial PCI. This indicates higher the development expenditures in states higher the PCI. Our finding is in line with studies that have looked at the impact of public investment on economic growth. Barro (1991) found that the average share of public investment in GDP had a positive, but statistically insignificant, impact on economic growth.

Similarly, PCI is also affected by the political and square of political variable. The original political variable is positive; while the square is negative (inverted U-shaped curve). Thus the above results clearly highlight the importance of social and political factors in the growth of per capita incomes among the states in India. In the next section we document India's economic growth and its role in poverty reduction.

9.4 Economic Growth and Poverty Reduction

In this section, economic growth is discussed in the larger context of reduction in poverty and inequality. There exists large amount of economic literature that has emphasized the role of higher economic growth to tackle the problem of poverty.Some have argued that the nineties have been a period of an improvement in living standards. Agrawal (2015)provide evidences of higher growth rates leading to a faster decline in poverty. Growth has helped increase in employment and real wages that has contributed to poverty reduction.Bhalla (2002; 2000) has argued that growth process in the last twenty years of globalization has been highly pro-poor. Poverty has fallen far more rapidly in the 1990s than previously. Others have claimed that nineties has been a time of widespread impoverishment.Datt &Ravallion (2002)emphasized the considerable diversity in performance across states, with important clues for understanding why economic growth has not done more for India's poor. For Deaton & Drèze (2002) regional disparities increased in the 1990s, with the southern (except Andhra Pradesh) and western regions doing much better than the northern and eastern regions. This is a matter of concern, since the northern and eastern regions were poorer to start with. Economic inequality also increased within states, especially within urban areas, and between urban and rural areas. The relative positions of the states regarding their ability to reduce poverty varied remarkably. Temporal variations in the social sector expenditure and growth rate of per capita NSDP and the growth rate of per capita NSDP from service sector are the crucial explanatory factors for the cross state temporal variations in the incidence of poverty(Ghosal, 2012).

Firstly we look at the transition dynamics of economic growth and the poverty reduction among the states and secondly, see the influence of caste domination in the states on public expenditure policies which in turn could bring down the incidence of poverty. The relationship between growth and poverty is complex and is significantly determined by the level and changes in inequality (Kakwani & Son, 2003). Besides focusing on the India's economic growth against poverty reduction over the last three decades this section examines if there has been poverty convergence among the states in India. The poverty rates of the states are normalized using the national poverty rate. In the transition probability matrices presented below, for the poverty dynamics, the four categories of relative poverty rates are- greater than 1.25 of the average national poverty rate, between 1 and less than 1.25, greater than 0.5 and less than 0.5. In the Table 41and 42below, the inter- state poverty estimates based on the Tendulkar Methodology for the 66th and the 68th Round is analyzed.

Table 41: Relative Poverty Transition Dynamics (66th NSSO Round, 1983-09)

		2009-10				Numbe r of states
		States with ending level > 1.25	States with ending level > or= 1 but < =1.25	States with ending level > or = .5 but < 1	States with ending level < .5	
1983	States with starting level > 1.25	0.50 Bihar	0.50 Odisha			2
	States with starting level > or= 1 but <=1.25	0.167 Uttar Pradesh	0.167 Madhya Pradesh	0.33 Tamil Nadu, West Bengal	0.33 Andaman & Nicobar, Puducherry	6
	States with starting level > or = .5 but < 1	0.125 Assam, Manipur		0.625 Andhra P, Arunachal P, Gujarat, Karnataka, Maharashtra, Meghalaya, Mizoram, Nagaland, Rajasthan, Tripura	0.25 Delhi, Kerala, Jammu & Kashmir, Sikkim	16
	States with starting level < .5			0.50 Punjab, Haryana	0.50 Goa, Himachal Pradesh	4

Source: raw data from Census, NSSO and Authors' calculations.

In 2000, three new states, Chhattisgarh, Jharkhand and Uttarakhand were carved from their parent states, Madhya Pradesh (M.P), Bihar and Uttar Pradesh (U.P). But the data on poverty ratio for the newly carved states, is available only from 61st round (2004-05). These new states are thus not considered in our analysis. For the period 1983-2005, we use the data of the undivided states (M.P, Bihar and U.P) and from 2004-05 to 2011-12, only the data of parent states of M.P, Bihar and U.P leaving out the newly created states from this analysis.

Interestingly, most of the states in India have experienced declining trend in the incidence of poverty at different rates during the pre and the post reform period (as shown in Table 41 and 42).

Table 42: Relative Poverty Transition Dynamics(68th NSSO Round, 1983-2011)

		2011-12				Number of states
		States with ending level > 1.25	States with ending level > or= 1 but < =1.25	States with ending level > or = .5 but < 1	States with ending level < .5	
1983	States with starting level > 1.25	1 Bihar, Odisha				2
	States with starting level > or= 1 but <=1.25	0.16 Madhya Pradesh		0.5 Tamil Nadu, Uttar Pradesh, West Bengal	0.33 Puducherry, Andaman & Nicobar	6
	States with starting level > or = .5 but < 1	0.187 Arunachal P, Assam, Manipur		0.5 Gujarat, Karnataka, Maharashtra, Meghalaya, Mizoram, Nagaland, Rajasthan, Tripura	0.31 Andhra Pradesh, Delhi, Jammu & Kashmir, Kerala, Sikkim	16
	States with starting level < .5			0.25 Haryana	0.75 Goa, Himachal Pradesh , Punjab	4

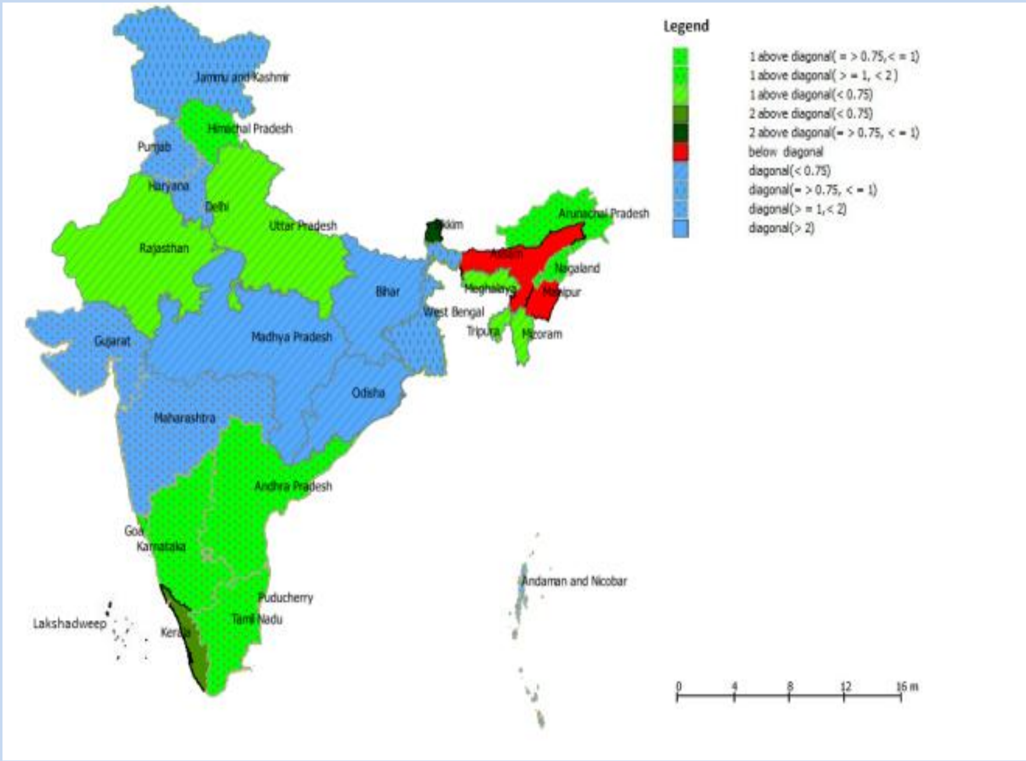
Source: raw data from Census, NSSO and Authors' calculations

If the states are on the diagonal of the matrix then it shows that there has been persistence, they started with a particular poverty rate in the initial period and have been at the same rate in the end period. Movement on the right side of the diagonal means the states were in a position to reduce their poverty rates, while mobility towards the left side of the diagonal is not a good sign as it implies that the poverty rates of the states have actually gone up. We find that the relative positions of the states regarding their ability to reduce poverty vary remarkably. For the period from 1983 to 2011, there has been mobility for many states towards the right side of the diagonal. Besides Tamil Nadu, West Bengal, Delhi, Kerala J&K, Andhra Pradesh and Sikkim which have jumped a step ahead, Andaman and Nicobar Islands and Puducherry have shown a tremendous reduction in poverty. In contrast, poverty has worsened in Uttar Pradesh, Assam, Madhya Pradesh, Arunachal Pradesh and Manipur and its incidence continues to be high in Bihar and Odisha. Some states that have had high rates of economic growth and enjoy higher income per capita also have low levels of poverty compared to the other states which are lagging behind. What is interesting in the matrix is that there have been a couple of states that have low rates of economic growth but have shown higher reduction in the levels of poverty. Except for Arunachal Pradesh, Manipur and Assam, most of the other North Eastern states like Meghalaya, Nagaland, Tripura and Mizoram have had lower incidence of poverty in 1983 as well as in 2011-12. Sikkim with lower levels of poverty has moved a step ahead in reducing poverty rates.

The growth and the poverty dynamics are mapped geographically in the figures below. In the figure 41, the southern and the western states have shown movements towards higher levels of per capita incomes. Almost all the states have shown improvements in their growth rates except the north eastern states of Assam and Manipur which have moved down from their initial levels. Even in Deaton & Drèze (2002) growth patterns in the nineties were characterised by regional imbalances.

The low-growth states, were in the north and east. This is a matter of concern, since the northern and eastern regions were poorer to start with.

Figure 42: Spatial Spread of Growth Rates (28 regions between 1981-2012)

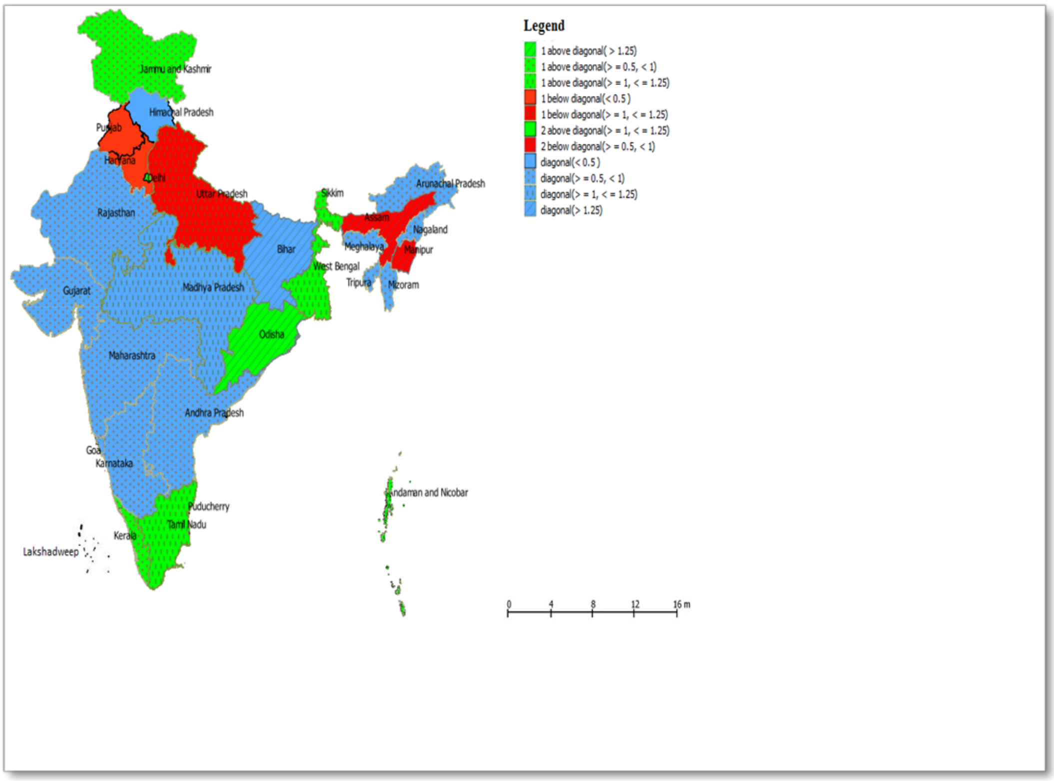


Source: Author's calculations based on QGIS data

With regard to the transition dynamics of the poverty rates, to compare both, the data from the quinquennial 66th Round (2009-10) and 68th Round (2011-12),two maps are shown (Figure 42 and 43).

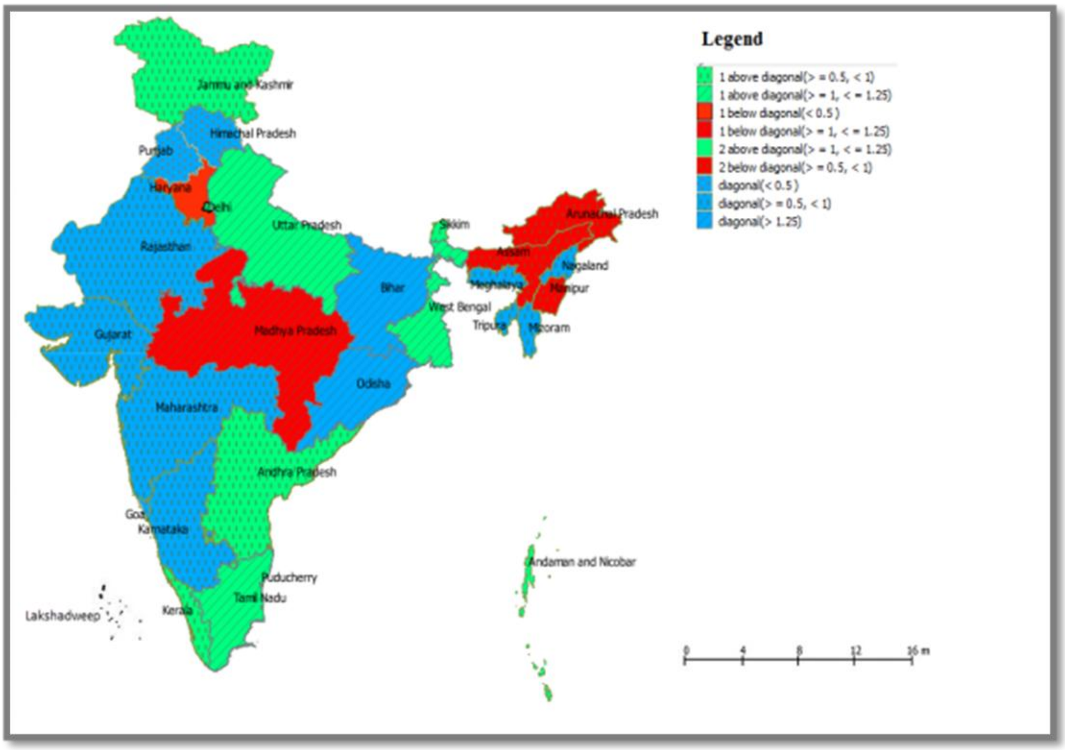
Both these rounds give differing view. With respect to the poverty rates based on the 66th round, Uttar Pradesh, Assam, Manipur were the states where there is a rise in the poverty rates in 2009. Even in Punjab and Haryana the poverty increased form their previous levels.

Figure 43: Spatial Spread of Poverty Rates (28 regions,1983-2009)



Source: Author's calculations based on QGIS data

Figure 44: Spatial Spread of Poverty Rates (28 regions, 1983-2011)



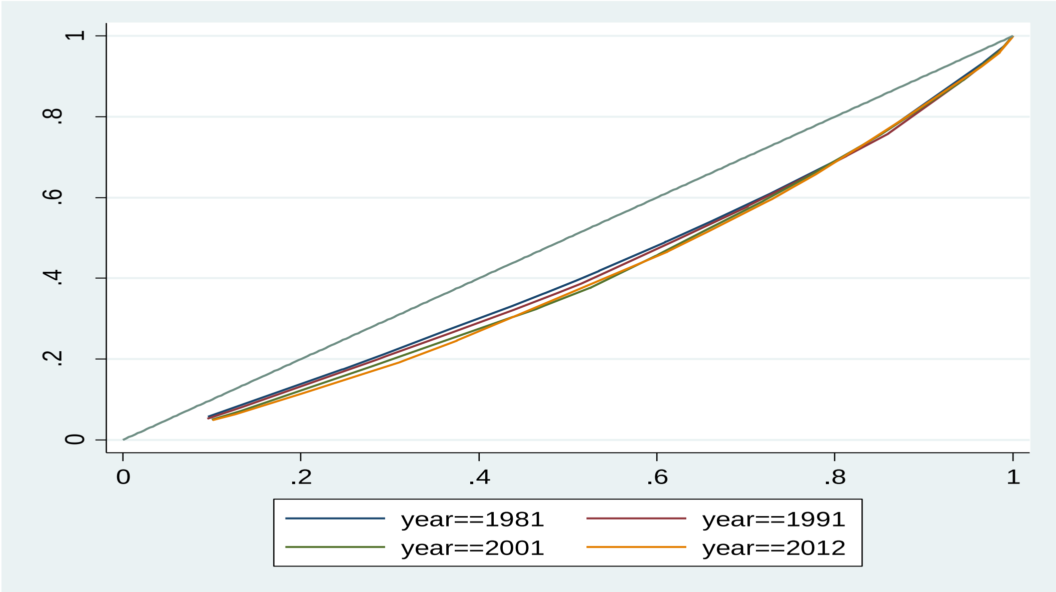
Source: Author's calculations based on QGIS data

The 68th round of NSSO gives different results. Five states, Assam, Manipur, Arunachal Pradesh, Haryana and Madhya Pradesh experienced rise in the rate of poverty as compared to their initial levels. Arunachal Pradesh has seen a rise in PCI as well as rise in poverty rate. This finding suggeststhat though the states have been able to improve their per capita income, they have not been doing so in terms of the reduction in their poverty levels. Kerala, Andhra Pradesh, Jammu and Kashmir and Sikkim have performed very well in poverty reduction. The western states of Goa, Andhra Pradesh, Gujarat and the Northern states of Rajasthan, Punjab, Himachal Pradesh had low levels of poverty in the initial period and they have remained so in end period.

9.4.1 Increasing Inequalities

To capture the extent of inter-state disparity among the Indian states, the Lorenz Curve is been adopted as it is of the most popular tool of representing income distributions (Bellu & Liberati, 2005). In constructing a Lorenz curve, the numbers of income recipients (population) are plotted on the horizontal axis, not in absolute terms but in cumulative percentages. The diagonal line is representative of “perfect equality” in size distribution of income. The further away the Lorenz curve is from the diagonal (perfect equality), the greater the degree of inequality. Several inequality indices can be derived from the Lorenz diagram. The Lorenz Curve construction also gives us a rough measure of the amount of inequality in the income distribution called the Gini Coefficients. India's Gini coefficient rose slightly from 0.192 in 1981 to 0.194 in 1991, but in post 90's there has been a steady rise from 0.221 in 2001 to 0.261 in 2012 indicating rising inequality.

Figure 45: Lorenz Curve And Income Inequality Across The Indian States(1981-12)



Source: Author's calculations based on EPWRF data

Though India has experienced relatively high rates of economic growth particularly after the reforms period, we realize that such growth had brought little by way of benefits to their poor. From the above analysis we can infer that there exists income disparities among the states. What is of concern is that these disparities have continued to persist over the decades. The gap in performance between India's rich and poor states has widened dramatically in the post reforms period, more particularly in the decade of 2001-12 (see Figure 38).

9.4.2 Empirical Results: Poverty rates and Public Expenditures

In order to further analyze the relationship between poverty rates and growth rates, we use an econometric model. However instead of using a simple OLS regression model, we use the panel (fixed effect) framework to see the relationship between incidence of poverty and set of explanatory variables from 1983 onwards. While analyzing the incidence of poverty both at the national and at the state level, we have used the head count ratio of poverty as estimated by the Planning Commission based on the NSSO Rounds [38th (1983), 43rd (1987-1988), 50th (1993-1994), 55th (1999-2000), 61st (2004-2005), 66th (2009-2010) and 68th (2011-2012)]. We accordingly have the following equations;

(9.4) $POV_{it} = \beta_0 + \beta_1 GRavpc_{i,t-\tau} + \beta_2 pcavsoc_{i,t-\tau} + \beta_3\, pcaveco_{i,t-\tau} + \beta_4\, pcaveco\_sq_{i,t-\tau} + \beta_5 pol\_l1_{i,t-\tau} + \beta_6\, sq\_pol\_l1_{i,t-\tau} + \beta_7\, SC_{i,t-\tau} + \beta_8\, ST_{i,t-\tau} + u_{it}$

"POV_{it}" is the poverty rate in the states, " GRavpc " is the five yearly annual compound growth rate of NSDP per capita among the states .Since the poverty data is from 1983, all the variables considered in the model are from 1983 onwards. To capture the impact of the policy variables across time and across states on the incidence of poverty, we have used the political "$pol\_l1_{i,t-\tau}$" (lagged by one period) and the square of the political variable "$sq\_pol\_l1_{i,t-\tau}$" along with expenditures made by the state governments (average of 5 years from 1983 onwards) viz: the social (per capita average social expenditure,) "pcavsoc" and the economic (per capita average economic expenditures) " pcaveco" along with the square of economic expenditures " pcaveco_sq ".

In the next equation (9.5), instead of taking a break up of public expenditures into social and economic we have taken per capita development expenditures "pcdevexp" (sum of pcavsoc and pcaveco). The rest of the variables are the same as equation (9.4).

We thus have;

(9.5) $POV_{it} = \beta_0 + \beta_1 GRavpc_{i,t-\tau} + \beta_2 pcdevexp_{it-\tau} + \beta_3 pol_{l1_{it-\tau}} + \beta_4 sq\_pol\_l1_{it-\tau} + \beta_5\, SC_{it-\tau} + \beta_6\, ST_{it-\tau} + u_{it}$

Table 43: Empirical Results of Fixed Effects Panel and Instrumental Variable Model

Independent Variable	Dependent variable – poverty rate					
	FE	FE	IV- First stage (dep var => pcavsoc)	Second Stage (2SLS)	IV-First stage (dep var => pcdevexp)	Second Stage (2SLS)
1	2	3	4	5	6	7
GRavpc	-0.492*** (0.157)	-.576*** (0.201)	85.66*** (35.83)	-0.541*** (0.201)	132.12*** (64.42)	-0.576*** (.201)
pcavsoc	-0.003*** (0.001)			-0.003*** (.001)		
pcaveco	-0.0037*** (0.0021)					
pcaveco_sq	7.27e-07*** (1.61e-07)					
pcdevexp		-.001*** (0.0005)				-0.001*** (.0005)
pol_l1 (Instrument)	-.28 (1.28)		748.85*** (296.95)		1299.0*** (533.95)	
sq_pol_l1 (Instrument)	.01 (.23)		-145.58*** (54.34)		-257.48*** (97.72)	
SC (Instrument)	0.086 (0.212)		147.8*** (47.71)		271.0*** (85.8)	
ST (Instrument)	-.072 (.14)		111.1*** (33.10)		197.7*** (59.53)	
Constant	36.8*** (5.13)	33.55*** (1.04)	-3598.1*** (1163.13)	33.43*** (1.41)	-6321.3*** (2091.4)	33.55*** (1.49)
Obs/ No of states	152/27	152/27	128/27	128/27	128/27	128/27
R-squared within	0.56	0.39	0.25	0.43	0.24	0.37
Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1.						

Source: Data from EPWRF, Census, NSSO and Authors' calculations

It is evident in equation 1, that there is a negative relationship between the poverty rates and average rate of growth of the NSDP per capita (Table 43). States with higher PCI have low rates of poverty. Similarly, coefficients of the social and economic expenditures among the states are highly significant and negative. Equation 2 shows the effect of development expenditures on poverty which is again significant and negative. States with higher development expenditures have lowerpoverty rates.Different studies in India have also shown the effectiveness of public expenditure in reducing poverty in India. For 14 Indian states India using 13th to 53rd rounds of NSSO, Shariff (2002)confirms that development and health expenditures help reduce poverty. Precisely,expenditure on higher, university, technical, adult and vocational educations as opposed to elementary and secondary education more effective in poverty reduction(Jha & Biswal, 2001). Similarly for Sasmal & Sasmal (2016) economic growth is important for poverty alleviation and development of infrastructure is necessary for growth.

However, the percentage of SC and ST population and the political variable seems to have no impact on the poverty rates. We suspect that some of the coefficients are likely to be affected by endogeneity bias. To control for this, we apply a fixed-effects instrumental variable model.

In equation (9.4), the variable " pcavsoc " is tested for endogeneity and the results confirms that the " pcavsoc " variable is endogenous (0.09 p-value). The variable " pcavsoc " is thus instrumented by the variables - percentage of SC and ST population in the states, political and political square variable (lagged by one period).The first stage equation is given as under;

(9.6) $\mathrm{pcavsoc}_{\mathrm{it}} = \alpha_0 + \alpha_1\, \mathrm{SC}_{it-\tau} + \alpha_2 \mathrm{ST}_{\,it-\tau} + \alpha_3 \mathrm{pol\_l1}_{\,it-\tau} + \alpha_4\, \mathrm{sq\_pol\_l1}_{it-\tau} + \varepsilon_{it}$

We then take the predicted value of initial pcavsoc in reduced form of equation (9.6) back to the original structural equation (9.4). The two-stage-least-square (2SLS) estimation to test theimpact of "pcavsoc" on poverty rate is given as under;

(9.7) $$POV_{it} = \beta_0 + \beta_1 p\widehat{cavso}c_{i,t-\tau} + \beta_2 GRavpc_{i,t-\tau} + u_{it}$$

The columns 4 &5 show the first and the second stage of the IV estimates.The first stage of the IV shows statistically significant coefficients between the instruments and the proposed endogenous regressor, with "$GRavpc$"as the exogenous variable. The second stage estimation results show that the predicted value of "pcavsoc" in turn significantly negatively influences the poverty rates. This implies that higher the amount of social expenditures in the states greater would be the reduction in the poverty rates.

In columns 6 & 7 in table 40, we have taken the per capita development expenditure as the endogenous variable, while we retain the other variables from the earlier model - percentage of SC and ST population in the states, political and political square variable (lagged by one period) are employed as instruments. The first stage equationis given as under;

(9.8) $pcdevexp_{it} = \alpha_0 + \alpha_1 SC_{it-\tau} + \alpha_2 ST_{\ it-\tau} + \alpha_3 pol1_{1_{it-\tau}} + \alpha_4 sq\_pol\_l1_{it-\tau} + \varepsilon_{it}$

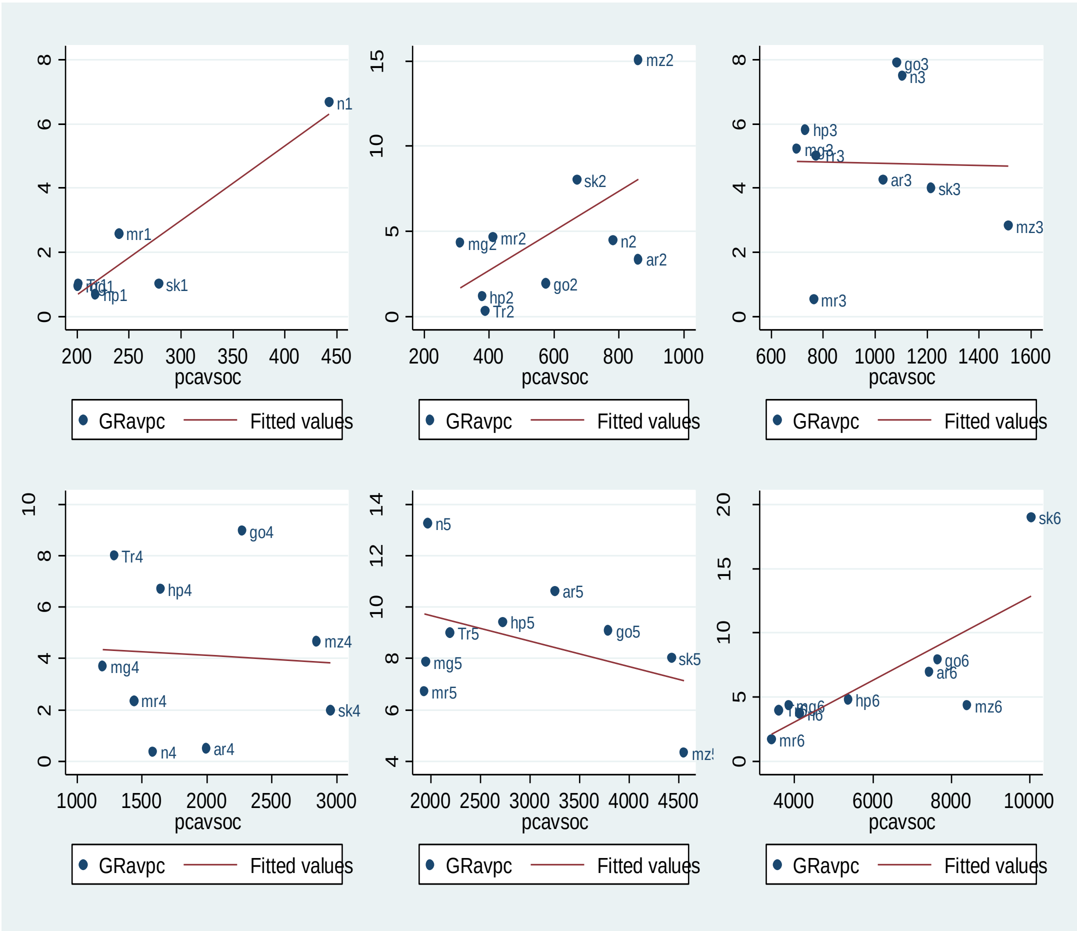
We then take the predicted value of initial "pcdevexp"from equation (9.8) and regress this in the equation (9.5). The two-stage-least-square (2SLS) estimation to test theimpact of pcdevexp on poverty rate is given as under;

(9.9) $$POV_{it} = \beta_0 + \beta_1 pc\widehat{deve}xp_{it-\tau} + \beta_2 GRavpc_{it-\tau} + u_{it}$$

The results in (Table 40) thereby confirm that states with higher percentage of population of SC and ST category as well as if the state and centre ruling parties are allies, are able to exert more pressure on the government to increase the spending on development expenditures and this is helpsin bringing down the level of poverty.

In Figures 45and 46 below we consider the influence of the expenditures on social services made by the state on the growth rates of per capita NSDP. The states are divided on the basis of the size of the population in those states. We accordingly have Arunachal Pradesh, Goa, Himachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, Tripura, Andaman and Nicobar Islands and Puducherry belonging to the category of small states. Due to the unavailability of data on per capita social expenditures for Andaman and Nicobar Islands and Puducherry for all the years, these UT are not considered in our analysis.

Figure 46: Expenditures on Social Services by Small states

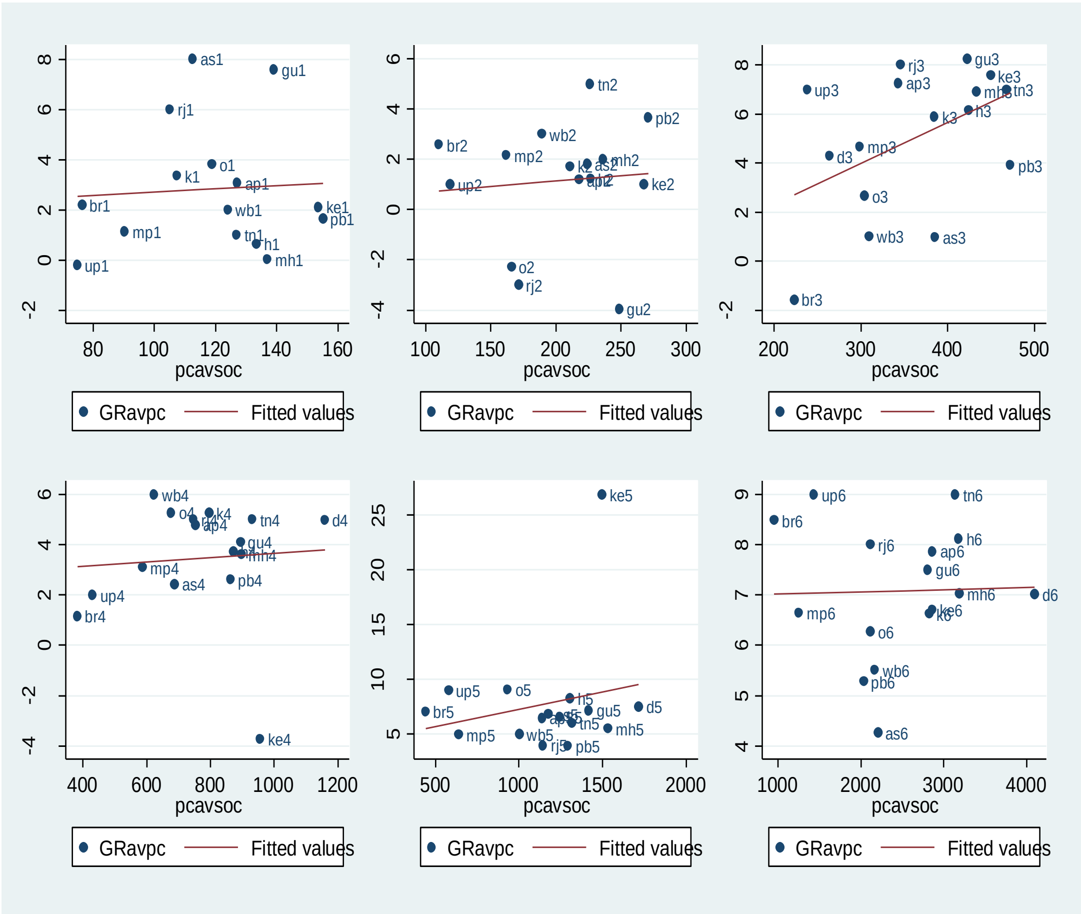


Source: Author's calculations based on EPWRF data

There is a positive relationship between the growth rate of per capita NSDP and the spending on social services in the pre reform period and the period after 2005.

Similarly, the Figure 45 shows the relationship between the growth rate per capita and the expenditures for the large states (Andhra Pradesh, Assam, Bihar, Delhi, Gujarat, Haryana, J&K, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal). For all the periods we find a positive relationship between the growth rates and the expenditures.

Figure 47: Expenditures on Social Services by large states



Source: Author's calculations based on EPWRF data

9.5 Summary

In econometric analysis, the use of instrumental variables has been popularized to tackle the problem of endogeneity. In this chapter, the instruments employed are caste, political variable and the public expenditures. In the first part of this chapter, the influence of political variable, development expenditures and social stratification (caste) on economic growth is highlighted. In the second part, India's economic growth and its relation to poverty reduction is examined. Here again, the caste and political variables are used as instruments. These influence the expenditures by the states and thereby are responsible for bringing down the incidence of poverty rates in the states.

Our results confirm that the per capita development expenditures and the growth rate of per capita NSDP are the major factors explaining the differences in the poverty rates among the states in India. The caste dynamics and politics across the states have been positively influencing the expenditures which in turn is instrumental in bringing down the level of poverty. Thus there seems to be an urgent need for the positive role of per capita developmental expenditure (PCDE) in reducing the magnitude of poverty in India.

Chapter X

Conclusion

The key economic issue in empirical growth economics is whether rich nations will remain rich and the poor remain poor in the long run or whether the initial laggards will grow faster and catch up with the rich ones. An important prediction of the neo classical growth theories was, regions having unequal growth rates in the short run, would converge to a common steady state growth rate in the long run. The convergence hypothesis, based on the standard neo classical production function, focused on the diminishing returns to reproducible capital. The process of catching up envisaged two related concepts of convergence: a) The β convergence, states that poor regions tend to grow at a faster rate than the richer regions, thus catching up with the rich ones; and b) The σ convergence, focused on decrease in cross regional dispersion (inequalities). Economies were said to converge (in terms of “σ”) if the dispersion in per capita levels of GDP decreased over time. The β convergence focused on a strong notion of convergence called "absolute" or "unconditional" convergence, where the parameters like the saving rate, technological progress, depreciation and the rate of growth of population were the same across the regions and countries. However in reality, as it was unlikely for these parameters to be same across countries, the notion of "conditional" convergence emerged. In this case each country need not converge to one common steady state but move towards different steady state levels determined by the parameters of each country.

It was in the 1980s the convergence debate caught the attention of macroeconomists for two reasons: firstly, to judge whether the modern theories of growth are valid as the existence of convergence across the economies had to be tested and secondly because of availability of data sets for international comparisons of GDP levels for many countries from the mid-1980s. With these data sets it was possible to see the evolution and compare the GDP levels across a large number of economies over time (Sala-i-Martin, 1996). Further, the emergence of new econometric methods and the development of the new growth theories led to the investigation of the pattern of convergence in different national and regional samples using a cross section, pooled or panel regressions. Interestingly some studies did report convergence; while others showed divergence across economies with different initial conditions.

Economic planning in India focused on reducing inequalities – both inter and intra regionally. A system of Five Year plans articulated the Indian government's strategies in which two organizations played a crucial role – the Planning Commission (now in a new avatar called the NITI Aayog) and the Finance Commission. They had different mandates – the Finance Commission had a Constitutional mandate to evolve a mechanism for raising and sharing of tax revenues between the Centre and States. The Planning Commission was tasked with estimating the funds requirement for implementing programmes and distributing Plan funds from the Centre to the states in a manner that would best serve the targets set out in each plan.

India's growth performance, both at the national level as well as its spatial distribution (across the states), has been the subject of considerable research interest. From a closed economic set-up, India moved to a liberalized and a globalised economy from the mid-1980s but more rapidly after the early 1990s economic crisis. Many had expected that the market forces in the post-liberalization period would free the economy from the shackles of licensing to promote growth and in turn reduce regional inequality and poverty in the Indian economy. The high growth story of

India however is conflicting with the poor performance on the HDI front. This raises the question whether the benefits are reaching all the sections of the society or not. In order to explore and assess how rapid economic growth in India has been and how this has shaped regional income inequalities, the performance of all the regions in India in the post reform period was compared with the performance in the previous decade.

Again the Indian economy is socially diverse with different religions, languages, castes and cultures which have added to inter - state economic differentiation. Even though India has much to learn from its international counterparts, more importantly it can learn from the diverse nature of growth within the economy itself. Issues of economic growth in India have been seen in the larger context of reduction in poverty and inequality, as there are instances of rise in inequality, even though the incomes have gone up, both at the top and the bottom levels.

While reviewing the literature on convergence in the Indian context, it was found that a number of issues remained to be satisfactorily understood. Therefore this study proposed to address the following research questions;

1) Is there evidence of convergence in per capita incomes over the last thirty years?
2) Is there validity in the claim that the growth convergence process in India exhibits twin peak (bimodal) behaviour?
3) Why are different states showing differences in inequality and poverty reduction?
4) How does social heterogeneity influence growth outcomes?
5) Are the neighbourhood spill-over effects important in the Indian context?

Thus applying the classical convergence analysis, in this study we proposed to investigate the growth performance across states in India for the period 1981-2013.

We used the Net State Domestic Product (NSDP) per capita series at current prices for the period 1981–2013 provided by Economic and Political Weekly Research Foundation (EPWRF Domestic Products of States India module). We also used the Net Domestic Product (NDP) series for both current prices and constant prices from the same database (EPWRF-National Accounts Statistics of India module). The per capita income data was made comparable not only across states (cross section) but also over time. To control for price variability NSDP at constant price series was generated. The per capita income data was made comparable not only across states (cross section) but also over time. The NDP deflator was generated by taking the ratio of NDP at current prices to NDP at constant prices. By dividing the NSDP (at current prices) of each state by the corresponding value in this index we derived the NSDP at constant prices (base 2004–5 prices) of each state.

Most of the earlier studies have mainly focused on the major states of India, while ignoring the smaller states and the special category states. Choosing only the major states has its advantages—the data availability is for a longer period. However, choosing states on the basis of their size may lead to problems of selection bias. We would have a limited understanding of regional inequality and miss a lot of the action in terms of mobility evident in the smaller as well as special category states.

In India, in the last 30 years not only has income and population grown, the number of states also have grown due to their administrative and political re-organisation. This poses problems for long term analysis where sub-national entities are the units of observation. In order to overcome this problem in our study, we have used data for

25 states and 3 Union Territories (UT) till 2000–2001. The 3 UTs included in our study are Delhi, Andaman and Nicobar Islands and Puducherry. In 2000 by a constitutional amendment three new states were created (Chhattisgarh bifurcated from Madhya Pradesh, Jharkhand bifurcated from Bihar and Uttarakhand bifurcated from Uttar Pradesh). So, from 2001 to 2012 we have considered 31 states and UTs.

Apart from the data on per capita income, socio indicators like quality of life and quality of opportunity was analyzed in different states of India. The data on literacy rate, gender ratio and percentage of urban population was obtained from the Population Census of India, while the data on IMR was obtained from EPWRF and Sample Registration System- Office of Registrar General, India. Besides, the data on Expenditure on Education and Health was also taken from the EPWRF. For the political variable, data from the Election Commission of India was used. In our analysis we have used the gender ratio and the percentage of population in urban areas as the explanatory variables.

Variability in growth across states was analyzed from various methodological perspectives. To investigate the convergence hypothesis, growth regressions were used, where the initial income per capita was the main explanatory variable, while literacy rate- proxy to human capital, political variable, components of public expenditures, urbanization, gender ratio were the conditioning variables employed. The pattern of convergence in India was investigated using a cross section, pooled and panel regressions. In the panel model, the time series information is derived by splitting the time-period of analysis into three, ten-year sub-periods, namely 1981-90, 1991-00 and 2001-10 and six, five-year sub periods namely, 1981- 85, 1986–90, 1991-95, 1996-00, 2001-05 and 2006-10.

Various econometric methods offering improvements over the classical convergence model were discussed in each chapter that included; a) quantile regression techniques to address the issue of income convergence and regional heterogeneity (Chapter 5), b) a nonparametric approach that uses the kernel plots, Markov process and transition matrices focusing on the multimodality that arises in the distribution (Chapter 6), c) different procedures to test for spatial associations among observations (Chapter 7) and d) the instrumental variable approach to study the likelihood of endogeneity (Chapter 9).

Our study attempts to make the following contributions to the growth literature in India;

a) We find presence ofmulti-modality in the income distribution and lack of evidence of bi-modality (twin peaks) for the years under consideration (1981-2012). While the claim of divergence is validated, we find more than twin peaks in the distribution of income especially in the period post-liberalisation.

b) This study contributes to the quantile regression literature by applying panel quantile regressions to β-convergence across the states in India. The panel versions of the quantile regressions are used to control for parameter heterogeneity and unobserved state specific or country effects.

c) Most of the empirical studies that have used the spatial econometric framework to test for regional convergence have relied on cross section regressions, with very few focusing on the panel estimation. This study is one of the first attempts to contribute to the spatial literature by adopting the panel data fixed effect approach to see the spatial dependence among the states in India from 1981-2010.

d) This is one of the few studies focusing on convergence in social indicators and adds to current literature of convergence.

e) Another contribution lies in the application of instrumental variable estimation for regional convergence with caste, politics and social expenditures as instruments. This shows how these variables have influenced the initial per capita incomes of the states and how economic growth has influenced poverty reduction over time.

Our analysis suggests that economic divergence among the states could be attributed to social heterogeneity. Though the economic growth in India has increased significantly, certain sections of society have remained excluded, especially in terms of improvements in human capabilities and entitlement.

The summary of chapters and main findings of the thesis that explain the research questions are given as under;

In the Introduction chapter 1, we provide an overview of economic growth and regional convergence across the different countries and regions. This chapter then outlines the research gaps, the main objectives, the research questions of the study. The different data sources and methodology adopted in the study are highlighted here.

In chapter 2, a review of theoretical and empirical literature on convergence is provided. Empirical research has used different growth models to investigate the process of convergence. Beginning with Solow's (1956) growth model using two covariates to understand why some countries flourished while the others lagged behind is discussed. The on-going discussion on the validity of the convergence models and the various flaws that have been identified in these models has led to the development of alternative theories. This chapter also discusses the relevant academic debates that have come up with respect to different notions of convergence. In India, some have claimed convergence (Bajpai, & Sachs, 1996; Cashin & Sahay, 1996; Dholakia, 1994), in certain sub periods or groups of states, while others have found divergence (Ahluwalia, 2000; Bajpai, & Sachs, 1996; Cherodian & Thirlwall, 2015; Dasgupta et al., 2000; Ghosh et al., 1998; Kurian, 2000; Mitra & Marjit, 1996; Raju, 2012)especially when comparing the pre- and the post-reform period.

The analytical framework adopted in the study is elaborated in chapter 3 along with the details of the data and variables employed to test for the existence of convergence in per capita NSDP across the Indian states. Along with the dominant methods of σ and β convergence, various econometric methods offering improvements over the classical convergence model are discussed in details. These methods form the basis for the empirical analysis in the subsequent chapters. In order to address the issue of income convergence by taking into account regional heterogeneity we employ the quantile regression techniques (Koenker & Bassett, 1978; Koenker, 2004). A nonparametric approach (Quah, 1997) that uses the kernel plots, Markov process and transition matrices is also explored. We attempt to address the issue of endogeneity by using the instrumental variable approach. While discussing convergence, regions are viewed as independent entities. The dependence that may exist between the regions is not accounted for in the classical models. Spatial dependence among the observations if ignored could give rise to model misspecification. Recent developments in spatial econometrics have offered different procedures to test for spatial associations which may occur in three forms, dependence in the dependent variable, the explanatory variables or the error terms. Testing procedures for spatial dependence are also discussed in this chapter.

To investigate the convergence process for the Indian states from 1981-2012, the β and σ convergence is tested in chapter 4. The variability in growth across states has been analyzed from various theoretical perspectives using the cross section, pooled and panel data estimation techniques. It was evident that there are substantial variations in the per capita NSDP as well as the average annual growth rate among the states and the U.Ts in India. The results obtained from single cross section regressions are significantly different from the panel estimation in the study. The panel data takes into account the differences in technology and preferences which are unobserved and immeasurable. The statistical analysis of unconditional β convergence reveals that there has been unconditional divergence under the fixed effect panel data estimation both for the periods of five years and the ten years. The states are not converging to identical levels of per capita income in the steady-state; rather the richer states have been growing significantly faster than poorer states. We find that the coefficient on the initial income is highly significant but has a positive sign.

New growth theory suggests that even if there is no unconditional convergence, there may be conditional convergence. Each state may converge to its own steady-state level of income, once the factors that affect steady-state levels of income are controlled for. The poor states would grow faster on average than the rich ones. Interestingly, the inclusion of literacy as an explanatory variable, makes the state’s per capita growth rate to be inversely related to its initial level of income. By holding constant the measure of initial human capital-literacy rate and the social expenditures, there is evidence that states with lower per capita NSDP tend to grow faster. This is indicative of Indian states converging to increasingly divergent steady-states.

There is an increase in the dispersion of per capita incomes across states over time which, again is logically consistent with our finding of absolute β-divergence, i.e, states are not converging in levels of per capita income over time. We can thus conclude that inequality in per capita income levels between Indian states is rising over time and this is more pronounced with respect to the special category states.

For analysing growth or the economic inequality among the states, what is of interest is the backward state (lower tail) and the forward state (upper tail). When the distribution is highly skewed the median can be very informative. Knowing the magnitude of the effects of the explanatory variables at the tails of the conditional growth distribution could more interesting and useful than finding the magnitude of such effects at the conditional mean. Thus to address these problems, Quantile regression, is applied in chapter 5. The quantile regression estimation procedure yields quantile coefficients; one for each sample quantile, thus providing a complete picture of the relationship between the dependent and the independent variables.

We apply the quantile regression technique for the cross section, pooled and panel data estimation.The cross section regression reveals interesting results at different quantiles. Though the coefficient on initial per capita income is not significant across the entire conditional distribution, there has been a negative relationship between the growth rate of PCI in 1981-90 and the initial PCI in 1981. These results provides strong evidence of unconditional convergence at the lower most quantile (10^{th}) as well as the upper quantiles (95^{th} and 99^{th}). However, for the consolidated periods 1991-13 and 1981-13, we do not find evidence of convergence for any of the quantiles. In case of pooled regression, for unconditional convergence the coefficients of the initial per capita income variables are positive and significant for the median quantiles as well as the lower quantiles (10^{th} and 25^{th}), reflecting the diverging growth of the low income states. Our results confirm that the initial level of per capita income has different impact on the growth rate of per capita NSDP. Though there has been unconditional divergence among the states in India, it depends on whether the states are in the upper or the lower quantile of the distribution.

The major findings from the above chapters answer our first research question; whether there is evidence of convergence in per capita incomes over the last thirty years.

The evolution of relative income distribution for Indian states was modelled using the 'distribution dynamics' methodology proposed Quah (1996c, 1997,1993a)in chapter 6. The stochastic kernels (continuous) and transition probability matrices (discrete)- the two main empirical models were used to estimate distributional mobility of countries or regions. With the kernel-based approach that estimates the probability density function (PDF) of a continuous random variable, we identified the empirics of catch-up more accurately. We tracked the distribution of per capita income in Indian states over four time-periods i.e. (1981, 1991, 2001 and 2012). The conclusion of 'twin peak' formation in the distribution of PCI among the Indian states in the earlier studies seemed to be premature since the kernel density plots had an inherent flaw—the unweighted kernel density estimates that treated each observation with equal weight. When we compared the weighted kernel density estimates with the un-weighted estimates we found the possibility of multiple modes in the distribution. This implied that stratification has increased in the middle income states in all the sub periods – an outcome not so clearly demonstrated in the un-weighted smoothed kernel analysis. These results suggest that the hypothesis of bimodality of PCI can be rejected for the years under consideration.

Our second research question was whether the growth convergence process in India exhibits twin peak (bimodal) behavior.

Our findings provide evidence that the claim of the existing literature on bi-modality is not valid. The growth distribution is multi-modal especially in the last two decades.

Recognising the importance of geographical distribution, the spatial models were incorporated in our analysis (Chapter 7). Most of the studies on spatial dependence carried out at the regional level(see Rey & Montouri, 1999; Elias and Rey 2011; Baumont, et al, 2002; Fischer and Stumpner 2008; Ertur, et al, 2007) have used the cross section regression and have tried to show how the unconditional regression model is mis-specified as a result of ignoring the spatial dependence. In recent years, some studies (Arbia, et al, 2005; Elhorst, 2014; Piras & Arbia, 2007) have also taken into account the spatial panel data models. However, estimation of the convergence in per-capita NSDP across Indian states based on the spatial panel data models has been not attempted yet.

Firstly, the exploratory spatial data analysis (ESDA) was applied to test for spatial autocorrelation and spatial heterogeneity among the Indian states. To test for spatial autocorrelation the Global Moran's I and Local Moran's I (LISA – Local Indicators of Spatial Autocorrelation) tests were used. This preliminary analysis based on the contiguity and distance based matrix confirmed the presence of spatial dependence, suggesting that the evolution of state income distribution is clustered in nature. Two strong regional clusters seemed to have persisted for above 30 years in India. The first one is the western, southern and some northern cluster of high income states. The second is the North eastern and Eastern cluster of low income states. Originally the main focus of spatial econometrics had been on the Spatial Lag and the Spatial

Error Model. In this chapter, along with these two models, the Spatial Autocorrelation Model and the Spatial Durbin Model using both the contiguity and distance based matrices were estimated. Over the years, the main focus of the spatial econometrics literature was on the causal relationships in a cross-sectional setting. However, only in the last decade, models estimating the econometric relationships based on spatial panels have emerged. The performance of the different spatial models in cross section as well as in empirical panel setting has been demonstrated.

The literature on convergence in India by a large majority has established that there is divergence in the growth rates. In this chapter we find confirmation of these findings. However, our results above suggest that the OLS and panel data estimates on convergence in earlier studies suffer from bias, inconsistency and inefficiency due to misspecification caused by the omitted spatial component in their analysis. Our estimates from the fixed effect spatial panel confirm that the process of growth in India is spatially dependent. Further, the impact of initial income on growth is much smaller than earlier anticipated once we control for spatial dependence. Our analysis suggests that neighbourhood effects play a significant role in determining growth outcomes of Indian states. We believe that this is the first attempt to demonstrate this in the Indian context and has important implications for policy making. Areas of low incomes could benefit from growth spill over effects from richer neighbours and be able to break the vicious circle of poverty. This chapter examined our research question on the importance of neighbourhood spill-over effects in the Indian context.

As the high growth story of India is conflicting with the poor performance on the HDI front, we needed to study whether the benefits of high growth are reaching all sections of the society. We know that income is only one dimension of economic well-being. In analyzing convergence, other dimensions also have to be taken into consideration. To measure inequality in non-income dimensions there are two approaches; one views inequality as variation of an outcome indicator across individuals while the other views inequality as disparities across socioeconomic groups (Chakraborty, 2002). Thus along with the income convergence, we analyse if there exists convergence in development indicators in (chapter 8). Convergence hypothesis for non-income indicators across Indian states, using both β and σ convergence techniques was tested. The focus was on how different states have fared in terms of reduction in IMR, reduction in the poverty ratios and improvements in literacy rates over the years. Interestingly, the results suggested clear evidences of β convergence in all the three indicators despite the fact that there is divergence in the income variable such as real NSDP per capita. However in terms of σ convergence, we have found a fall in regional inequality in terms of state-wise dispersion of health and education index, we cannot draw the same conclusion for the decline in poverty rates. In fact we find that the standard deviation with regard to poverty has gone up especially in the post reform period.

The empirical debate on economic convergence centres around the inverse relationship between the growth of per capita income and the starting levels of income across countries or across the regions within the countries. However, there are studies which question the existing empirical literature on cross-country growth rates as it is relies on inconsistent estimation procedures (Caselli, et al, 1996; Castineira & Nunes, 1999; Levine & Renelt, 1992). This inconsistency arises whena subset of the explanatory variables could be endogenously determined. In order to avoid the problems that arise out of endogeneity, the instrumental variable estimation approach for the panel data growth models was employed in (chapter 9).

The extent to which growth reduces poverty depends on the degree to which the poor participate in the growth process and share in its proceeds. Thus, both the pace and pattern of growth matter for reducing poverty.

In India, besides economic, religious and linguistic disparities, there are historically established social hierarchies where the caste system still prevails as one of the key drivers of poverty and inequality (Rao, 2010). Since Indian society is segregated into castes, and some of them are economically and socially deprived to a great extent, it is necessary to bridge the caste gaps and ultimately eliminate all forms of social barriers which are discriminatory. Recognizing these caste based inequalities, the Government of India initiated affirmative action as a remedial measure. The presence of identity based groups has of course political ramifications and in India has impacted on the election process as well as political decision making.

There have been some efforts to identify the relationship between political decision making process and the economic growth (Kohli, 2006). Different aspects have been examined in this context like measures of democracy (Alberto & Perotti, 1996; Barro, 1989; Dasgupta, 1989), Government stability, political violence (Alberto & Perotti, 1996; Barro, 1989, 1991), political volatility (Dollar, 1992),and subjective measures of politics (Brunetti, et al, 1997) have been used as explanatory political variables in many studies.

In addition to these measures we argue that the Centre-state relations play an important role. In the Indian context, development of a state could be expedited if the same party ruled in both state and Centre. We use a political variable which counts the number of years the state and Centre were political allies. If the state and the Centre parties are allies it is expected that the ally state would benefit more by favourable grants from Centre. Therefore to see what are the fundamental causes for the differences in the per capita incomes of the states in India, social diversity, public expenditure policies and the political sources were considered in this chapter. In the first section of this chapter the influence of politics and social stratification (caste system) on economic growth was examined. As one of the most challenging problems of growth studies is the presence of endogeneity. As the per capita income across the states was found to be endogenous, we used caste, development expenditures and politics as instruments. We analyzed how these variables influence the initial per capita incomes of the states in an instrumental variable (IV) framework. Secondly, this chapter also documented India's economic growth against poverty reduction over the last three decades to see if there has been poverty convergence among the states in India. The specific measure of poverty used in this study is the official Planning Commission poverty rate or headcount ratio (HCR). We examined the role of developmental revenue expenditures across the states in implementing the poverty alleviation policies and reducing inequality. Here too we extended the IV framework to control for presence of endogeneity. Our results confirmed that the per capita development expenditures and the growth rate of per capita NSDP are the major explanatory factors explaining the differences in the poverty among the states in India. The caste dynamics and politics across the states have been positively influencing the expenditures which in turn is instrumental in bringing down the level of poverty. We also found that the per capita development expenditures and political variable have a positive relationship with the initial PCI. This indicates higher development expenditures takes place in states with higher the PCI. Similarly, PCI is also affected by the political and square of political variable. Generally we find that poor states have higher percentage of ST, SC and OBC population. These states with higher percentage are indicating a positive impact of caste on per capita incomes. It is not self-evident why caste is driving per capita incomes in India. Probably it may be working through political factors and high development expenditures.

In terms of reduction in IMR, poverty rates and improvements in the rate of literacy, it has been noticed that most of the southern states are experiencing a faster decline in IMR as compared to the Northern states of India. The gap between the states for IMR has also narrowed substantially, which was greater during the pre-reform period compared with the post reforms. However, substantial gap still exists between the demographically advanced states like Kerala, Goa, Puducherry and demographically weaker states like Bihar, Madhya Pradesh, Odisha, Rajasthan and Uttar Pradesh. Different parts of India have disparate records as far as literacy is concerned. Again the southern states and the UTs, especially Kerala, Tamil Nadu, A &N Islands and Puducherry, have achieved considerable amount of success in driving up their literacy rates. Similarly the North eastern states like Mizoram, Tripura, Sikkim have shown considerable improvements, with Mizoram ranking second among all the states in India in the last two decades.

As a final note, as rates of economic growth vary substantially across states, policy makers would be interested in knowing how many years it would take for these states to double their per capita incomes. To obtain from growth rates the number of years it takes for incomes to double, a convenient rule of thumb is used. According to this rule a state growing at "g" percent per year will double its per capita income every $\frac{70}{g}$ years (Jones, 2002; Lucas, 1988).If $y(t)$ is the per capita income at time "t"and $y(o)$ is initial value of per capita income, then $y(t) = y_0 e^{gt}$. The time it takes for per capita income to double is given by the time "td" at which $y(t) = 2y_0$(Jones, 2002). Thus, (10.1) $$2y_0 = y_0 e^{gtd}$$

(10.2) $$\ln(2y_0) = lny_0 + gtd\,.lne$$

(10.3) $$ln2 + lny_0 = lny_0 + gtd$$

(10.4) $$ln2 = gtd$$

(10.5) $$td = \frac{ln2}{g},$$ where,

"g" is the growth rate.

The average annual change in the (natural) log of NSDP per capita for each states from 1981-90, 1991-2000 and 2001-10 respectively are reported in columns 2-4 (Table 44). If we use the most recent decadal growth rate of the states (2001-10) we can predict the number of years taken by the states to double their PCI (Column 5). Manipur (21), Assam (18), Tripura (16) would take maximum years to double their per capita incomes, while Sikkim (5), Goa (7), Tamil Nadu (7) would be the quickest to double their per capita incomes.

We also estimated how many years it would take for the different states to catch up with the highest current level of PCI state (Goa). The equation below informs us on how many years this gap will be covered;

(10.6) $$\frac{\ln y_r - \ln y_l}{g}$$

Where, "y_r " is the state with highest per capita income, while "y_l " is the state with lower income and "g" is the growth rate.

Table 44: Growth Rates of the States

states	Average annual growth rate			Number of years to double PCI	Number of years to catch up with Goa
	1981-1990	1991-2000	2001-2010		
1	2	3	4	5	6
Andaman & Nicobar	-0.002	0.075	0.073	9	10

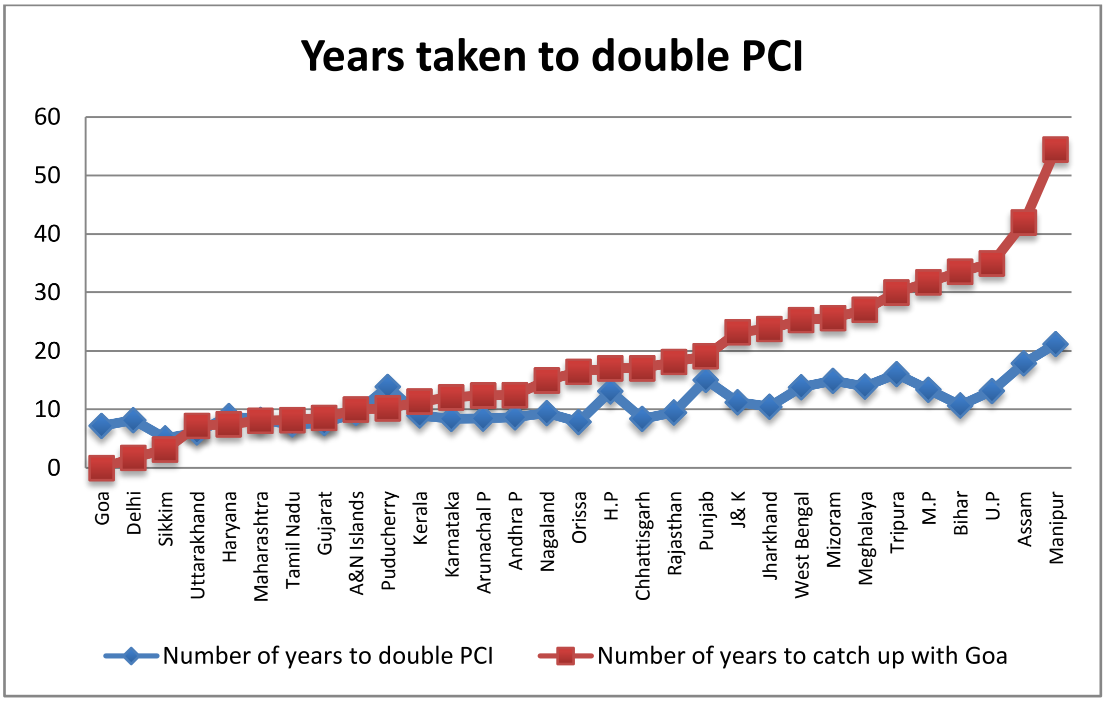
Andhra Pradesh	0.033	0.054	0.079	8	12
Arunachal Pradesh	0.025	0.013	0.081	8	12
Assam	0.022	0.027	0.038	17	41
Bihar	0.024	0.014	0.064	10	33
Delhi	0.025	0.047	0.084	8	1
Goa	0.022	0.090	0.096	7	0
Gujarat	0.020	0.045	0.090	7	8
Haryana	0.032	0.043	0.078	8	7
Himachal P	0.027	0.063	0.052	13	17
J & K	-0.007	0.058	0.061	11	23
Karnataka	0.029	0.055	0.082	8	12
Kerala	0.023	0.028	0.077	8	11
Madhya Pradesh	0.031	0.051	0.051	13	31
Maharashtra	0.035	0.038	0.084	8	8
Manipur	0.024	0.035	0.032	21	54
Meghalaya	0.038	0.050	0.049	13	27
Mizoram	0.067	0.045	0.046	14	25
Nagaland	0.041	0.032	0.073	9	14
Odisha	0.012	0.039	0.088	7	16
Puducherry	0.009	0.123	0.049	13	10
Punjab	0.033	0.034	0.046	15	19
Rajasthan	0.032	0.050	0.073	9	18
Sikkim	0.049	0.045	0.136	5	3
Tamil Nadu	0.042	0.066	0.093	7	8
Tripura	0.013	0.091	0.043	16	29
Uttar Pradesh	0.026	0.030	0.052	13	34
West Bengal	0.017	0.059	0.050	13	25
Chhattisgarh			0.082	8	17
Jharkhand			0.066	10	23
Uttarakhand			0.113	6	7

Source: Author’s calculations based on EPWRF data

Goa had the highest per capita income in 2010. We estimate the number of years taken by all the states to catch up with Goa's per capita income (Column 6).

In the figure 48, we see the number of years taken by the states to double their per capita incomes. It also shows the number of years taken by the states to catch up with the growth of Goa.Manipur with the lowest PCI in 2010 and with a growth rate of 0.03 will require the longest (54 years) as per our estimates to catch up with Goa.

Figure 48: Years Taken to Double PCI



Source: Author's calculations based on EPWRF data

To conclude, our study confirms unconditional divergence among the states and Union Territories in India. The richer states have been growing significantly faster than poorer states. However, once factors that affect steady-state levels of income are controlled for there is conditional convergence. There has also been an increase in the dispersion of per capita incomes over time. Though there is evidence of divergence in per capita incomes, the nature of divergence is not bi-modal but multi-modal especially in the last two decades. The OLS and panel data estimates on convergence in earlier studies suffer from bias, inconsistency and inefficiency due to misspecification caused by the omitted spatial component in their analysis. The impact of initial income on growth is much smaller than earlier anticipated once we control for spatial dependence. By using the instrumental variable regressions, the study also addresses the problems of selection bias and unobserved heterogeneity.

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