Long Memory in Indian Stock Market: An Empirical Study

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By

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DECLARATION

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

Place: Taleigao Plateau.
Date: Naik Ramashanti Anand

CERTIFICATE

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

Prof. Y. V. Reddy

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List of Abbreviations

Abbreviations	Full form
ALSI 40	All Share Index 40
APARCH	Asymmetric Power Autoregressive Conditional Heteroscedasticity
ARFIMA	Autoregressive Fractionally Integrated Moving Average
ARMA	Autoregressive Moving Average
ASE	Amman Stock exchange
BSE	Bombay Stock Exchange
CO_2	Carbon dioxide
COVID-19	Coronavirus Disease 2019
DAX	Deutscher Aktien Index
DCCA	Detrended Cross-Correlation Analysis
DFA	Detrended Fluctuation Analysis
DJIA	Dow Jones Industrial Average
EMH	Efficient Market Hypothesis
ERS DF-GLS	Elliott Rothenberg Stock Dickey Fuller – Generalised Least Square
FIAPARCH	Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroskedasticity
FIGARCH	Fractionally Integrated Generalised Autoregressive Conditional Heteroscedasticity
FTS	Fuzzy Time Series
GPH	Geweke and Porter-Hudak
GST	Goods and Service Tax
KOSPI	Korean Composite Stock Price Indexes
LM	Lagrange Multiplier
LN	Natural Logarithm
MAI	Market for Alternative Investment
MIB30	Milano Indice di Borsa 30
MMI	Major Market Index
MRS-ARFIMA	Markov Regime-Switching Autoregressive Fractionally Integrated Moving Average
NSE	National Stock Exchange, India

OLS	Ordinary Least Square
R/S	Rescaled Range
RJMCMC	Reversible Jump Markow Chain Monte Carlo
S&P	Standard & Poor’s
SET	Stock Exchange of Thailand
US	United States
WAEMU	West African Economic and Monetary Union
WOLS	Wavelet Ordinary Least squares

Abstract

Long memory is a phenomenon that arises in the modelling and analysis of time series data. The long memory indicates that the decay of the autocorrelation function is slower than exponential decay. One of the ways to test market efficiency in stock market returns is by examining long memory. In this study, first, we examine the long memory in returns, liquidity, and volatility in the broader stock market index and investigate if the interdependencies among returns, liquidity, and volatility have any significant impact on the long memory behaviour and forecasting ability of models. Next, we investigate the presence of long memory in the Indian stock market considering sectoral indices of the National Stock Exchange (NSE) of India. Finally, we investigate the long memory in returns, liquidity, and volatility for various stock categories. The study attempt to investigate the role of stock characteristics in the examination of long-memory behaviour in the Indian stock market. The stock characteristics included are Stock Price, Stock Liquidity and Stock Volatility. That is, the study examines if high-priced, moderately priced, or low-priced stocks exhibits long memory. Also, the study examines whether the high-liquid, moderately liquid, and low-liquid stocks exhibits long memory. Further, the study examines if a stock with high volatility, moderate volatility, and low volatility exhibits long memory. The long memory is examined in returns, liquidity and volatility of stock categories representing the individual companies with said stock characteristics. To examine the presence of long memory, the study uses Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a parametric and parsimonious model. The study reveals the evidence of long memory in Stock Index Returns and Stock Index Volatility. The study concludes that interdependencies among the variables do affect the behaviour of long memory. Also, consideration of the effect of interdependencies improves the forecasting ability of the models. Further, the study noticed persistence in the daily return series and anti-persistence in the monthly and quarterly return series. The study concludes that the frequency of data does have a significant effect on the behaviour of long memory patterns. Finally, the study evidences the presence of long memory in the case of high-priced stock returns, moderate to high liquid stock returns and high volatile stock returns. Overall, the results reveal strong evidence of long memory in stock liquidity and stock volatility for various stock categories. The presence of long memory is an indication of an inefficient market, and it suggests that past price information is useful in predicting future returns, which leads to superior returns. Policy inertia can be one of the reasons for inefficiency in the Indian stock market. The results will assist the academicians in providing better clarity about the significant implications of long memory on the Efficient Market Hypothesis and stock market analysis with new sectoral evidence. The application of ARFIMA results to broader indices, sectoral indices, and variables based on various stock categories adds to the existing stock of knowledge, strengthening the applicability of ARFIMA models to financial time series.

Keywords: Long Memory, Stock Market Returns, Stock Market Liquidity, Stock Market Volatility, ARFIMA

Chapter 1

Introduction

This chapter introduces the main research themes of the thesis, elaborates on the need for this study and outlines the scope of this research work. This chapter explains why this study is important in the present context. Also, this chapter presents a literature review of previous studies in the context of the current research area. For the purpose of identification of research gaps for each objective, the literature has been reviewed objective-wise. Also, it incorporates Research Questions derived from research gaps, which is followed by Research Objectives. Finally, the chapter concludes by highlighting the organization of the study, which provides a guide for further chapters of the thesis.

1.1 Introduction

Stock market participants are more concerned about future returns than the present benefits of their earnings (Liu et al., 2017). The reasons behind this worry are future contingencies. In recent years, many expected and unexpected events have affected the Indian stock market returns, such as Coronavirus Disease (COVID-19), Bank Frauds, Financial Crisis, Announcement of Demonetization, Implementation of Goods and Service Tax (GST), etc. (Bhatia & Gupta, 2020; Parab et al., 2020; Gupta et al., 2021). One way to deal with future contingencies is to model time series data to predict future returns. The stock market is sensitive to future expectations (Sultana & Reddy, 2017).

Long memory, which is also referred to as long-range dependence or long-range persistence, is a phenomenon that arises in the modelling and analysis of time series data. The long memory indicates that the decay of the autocorrelation function is slower than exponential decay. The phenomenon where there is exponential decay is called a short memory (Granger & Joyeux, 1980). One of the ways to test market efficiency in stock market returns is an examination of long memory (Lo, 1991).

Hurst (1951) is considered a pioneer in long-range dependence modelling who developed a rescaled range statistic in a study related to examining the long-term stock capacity of reservoirs. Further, Mandelbrot (1972) provided a comparative analysis of statistical techniques investigating long memory and suggested modifications to Hurst's classical Rescaled Range analysis. Geweke and Porter-Hudak (1983) proposed an estimator of a long memory parameter based on a simple linear regression of log periodograms on a non-stochastic regressor. The estimator in the regression was an OLS estimator of the slope parameter. Lo (1991) developed a long memory test robust to short-range dependence, an extension of the classical Rescaled Range Analysis. Jacobsen (1994) showed that the modified rescaled range statistic suggested by Lo (1991) involves unnecessary complications, which can be avoided by correcting the time series for its idiosyncratic short-term dependence and then applying the classical rescaled range test provided by Hurst (1951). The said two methods were illustrated by applying them to an index of the Amsterdam Stock Exchange. A comparison was performed using the Monte Carlo simulation. Robinson (1995) discussed the multiple time series model estimation that allowed spectral density matrix elements to tend to zero or infinity at zero frequency. A log periodogram regression estimate of differencing and scale parameters were proposed that provided modest efficiency improvements over prior methods. The asymptotic normality of the parameter estimates was established, assuming the Gaussianity and additional conditions. Phillips (1999) examined the Discrete Fourier transforms of fractional processes with the representation given in the form of component data. The new representation was found to be useful in analyzing the asymptotic behaviour of the Discrete Fourier transforms and periodogram in nonstationary cases. The study discussed the Local Whittle estimation of memory parameters and applying theory to log periodogram regression and suggested modified versions of these procedures. Ellis (1999) derived Autoregressive Fractionally Integrated Moving Average (ARFIMA) specification as indicated by Granger and Joyeux (1980) from the general autoregressive moving average class of short-term dependent models to model the long-term dependence in time series data. The application of classical rescaled adjusted range to the estimation of ARFIMA fractional differencing parameter was examined and found the ARFIMA to have an advantage which allows separate parameterization of short-term influences.

In financial markets, Long Memory refers to a phenomenon where the present stock returns remain significantly correlated with their values in the distant past (Al-Shboul & Anwar, 2016). The Efficient Market Hypothesis (EMH) proposed by Fama (1965) states that asset prices reflect all the available information, and thus it is challenging to earn abnormal returns. The Efficient Market Hypothesis is associated with random walk indicating that prices are independent and unpredictable. Fama (1965) and Samuelson (1965) concluded that the random character of stock prices results from a rational market. The extensive research on Efficient Market Hypothesis led to Fractal Market Hypothesis (Peters, 1994), Behavioural Finance Theory (Thaler, 1999; Shiller, 2003), Adaptive Market Hypothesis (Lo, 2004), Chaos Theory (Mandelbrot, 2005), and Heterogeneous Market Hypothesis Theory (Corsi, 2009). Long memory has significant implications for these theories. The presence of long memory is an indication of an inefficient market, and it suggests that past price information is useful in predicting future returns, which leads to superior returns (Tripathy 2015). If the stock markets are efficient, there are minimal chances to make profits above the normal profit as stocks are traded at fair prices (Al-Shboul & Anwar, 2016).

1.2 Need for the Study

The ultimate objective of trading or investment is to earn superior profits over inflation. If the stock markets are efficient, there are minimal chances to make profits above the normal profit. The long memory or long-range dependence makes the market inefficient. Thus, in the Indian context, from the perspective of broader indices, sectoral indices and large-cap, mid-cap and small-cap companies, it is important to understand the dynamic nature of long memory. Thus, the present study will examine the presence of long memory in stock market broader indices returns, sectoral stock market indices returns and returns from large-cap, mid-cap and small-cap companies.

Further, a stock market investor is interested in stock market components such as returns, volatility, and liquidity. The investment objective that remained to focus on is higher returns at a given level of risk and stock marketability, which is technically known as liquidity. The investor is also interested to know whether the market is efficient or not. And one of the ways to test market efficiency is an examination of long memory or persistence. Long memory has an important implication in terms of asset allocations and portfolio risk management. Long-range memory indicates market inefficiency and predictability of future prices (Mensi et al., 2019). Long memory remained to be in focus amongst several researchers and investors over many decades. Long memory is such a phenomenon that attracts not only investors but also stock traders. If there is long-range dependence, the forecasting accuracy increases, making the market informational inefficient, thus providing scope to earn significant returns.

1.3 Scope of the Study

In this study, first, we examine the long memory in returns, liquidity, and volatility in the broader stock market index and investigate if the interdependencies among returns, liquidity, and volatility have any significant impact on the long memory behaviour and forecasting ability of models. Next, we investigate the presence of long memory in the Indian stock market considering sectoral indices of the National Stock Exchange (NSE) of India. The sectoral study is important from two aspects. Firstly, the industry analysis is a crucial element of Fundamental Analysis, a prime tool for value investors to analyze the performance of the economy, industry, and companies. And secondly, sectoral study assists in portfolio construction, portfolio analysis, and portfolio revision. Finally, we investigate the long memory in returns, liquidity, and volatility for various stock categories. The study attempts to investigate the role of stock characteristics in the examination of long-memory behaviour in the Indian stock market. The stock characteristics include Stock Price, Stock Liquidity and Stock Volatility. That is, the study examines if high-priced, moderately priced, or low-priced stocks exhibit long memory. Also, the study examines whether the high-liquid, moderately liquid, and low-liquid stocks exhibit long memory. Finally, the study examines if a stock with high volatility, moderate volatility, and low volatility exhibit long memory. The long memory is examined in returns, liquidity and volatility of stock categories representing the individual companies with said stock characteristics.

1.4 Significance of the Study

The stock market, which accumulates a large pool of funds, acts as a barometer of a country's economy. It is expected to make a significant contribution to the country's economic growth and development. The stock market participants channelize their corpus to the stock market in order to earn financial benefits arising out of economic, industrial and company-related situations, which get reflected through stock prices. Among the economy, industry and company-specific factors, one of the crucial factors for the market participants is the company-specific factors. Various aspects determining the investment in equity stocks include the availability of funds, expected returns, risk aptitude, liquidity, time horizon, taxation, legal and regulatory framework & unique characteristics associated with specific industries and companies. The selection of the right equity stocks and the correct strategy increases the possibility of earning excess returns, which arise due to market inefficiency.

The presence of long memory in the broader indices, sectoral indices, or company stocks can have many practical implications as it can assist in investment and policy decisions and construction, diversification, and revision of portfolios. Therefore, this study is aimed to apply the parametric model Autoregressive Fractionally Integrated Moving Average (ARFIMA) to examine the presence of long memory in the Indian stock market. The study is novel due to its application of Autoregressive Fractionally Integrated Moving Average (ARFIMA) models to a broader range of sectoral indices, examination of persistence and anti-persistence at different frequencies of sectoral indices returns, considering the effect of interdependencies among returns, liquidity and volatility in the examination of long memory, and investigating the role of stock characteristics in long memory examination. The research will be of significant use to traders and investors to frame various trading and investment strategies.

1.5 Literature Review

Long-range dependence, which is also known as long memory or long-range persistence, is a highly debatable topic among researchers of various fields of study. This section provides insights into existing literature related to the main themes of this study, i.e. Interdependencies and Long Memory, Sectoral Juxtaposition and Long Memory, and Stock Characteristics and Long Memory. Finally, this section focuses on prominent literature in the Indian context.

1.5.1 Interdependencies and Long Memory

Granger and Joyeux (1980) and Hosking (1981) introduced the Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. The specification of the ARFIMA model is parsimonious and thus allows for different modifications. Since the introduction of ARFIMA, we see many changes to the base model for its better application time series analysis. Chow et al. (1995) concluded that the random walk hypothesis remains a valid description of stock market return performance.

We see Lieberman et al. (2000) estimated a small-sample likelihood-based inference in the ARFIMA model. The Akaike Information Criterion (Akaike, 1973), Bayesian Information Criterion (Akaike, 1979), and Hannan-Quinn Criterion (Hannan, 1980) were used for model specification and selection in ARFIMA models. Eğrïoğlu and Günay (2010) proposed one and two-stage methods using the Reversible Jump Markow Chain Monte Carlo (RJMCMC) method as model selection criteria. Mayoral (2007) introduced a parametric minimum distance time-domain estimator for ARFIMA processes. Chung (2001) examined the vector fractionally integrated autoregressive moving average models' impulse responses using a technique of finite-order generating functions. Ellis (1999) extended the application of classical rescaled adjusted range to ARFIMA and showed that the estimates of fractional differencing parameter 'd' may also be obtained by the Hurst exponent. Deuker and Startz (1998) estimated a multivariate ARFIMA model that illustrated a cointegration testing methodology based on fractional-order estimates of the integration of a co-integrating vector. Hwang (2000) investigated the effects of varying sampling intervals on long memory characteristics using the ARFIMA model. Sadaei et al. (2016) introduced a hybrid method combining ARFIMA and Fuzzy Time Series (FTS) to forecast long-range dependence. Cao and Shi (2017) performed a simulation analysis of multifractal detrended methods based on the ARFIMA process. Zevallos and Palma (2013) proposed a minimum distance methodology to estimate ARFIMA processes with Gaussian and Non-Gaussian errors. Shi and Ho (2015) proposed a Markov Regime-Switching Autoregressive Fractionally Integrated Moving Average (MRS-ARFIMA) model to examine the long memory and regime switching in stock index returns. Kang and Yoon (2007) examined the long memory properties in stock index returns and volatility using the ARFIMA-FIGARCH model. In another study, Lux and Kaizoji (2007) found the pooled estimates for FIGARCH and ARFIMA to provide better results than individually estimated models.

Also, ARFIMA has its application in non-financial market time-series data. We see Baillie et al. (1996) analyzed the inflation by a fractionally integrated ARFIMA-GARCH model. Ambach and Schmid (2015) utilized ARFIMA-APARCH in high-frequency wind speed data comprised of autoregressive fractionally integrated moving average errors in Mean part and asymmetric power generalized autoregressive conditional heteroscedasticity within conditional variance. Arouri et al. (2012) employed the ARFIMA-FIGARCH model to investigate the structural changes and long-memory properties in the volatility and returns of precious metal commodities. We also see the application of ARFIMA in global CO_2 emissions from fuel consumption (Belbute & Pereira, 2015), application in predicting macroeconomic time series (Bharadwaj & Swonson, 2006), estimation of ARFIMA models for unemployment (Gil-Alana, 2001; Lahiani & Scaillet, 2009), application in the examination of long-range dependence in bitcoin market (Zargar & Kumar, 2019).

The daily stock returns are long-term dependent was claimed by Greene and Fielitz (1977). Also, we see Cheung (1993) found evidence of long memory in foreign exchange rates. Cajueiro and Tabak (2004) found long memory in Hong Kong, Singapore, and China's financial markets, to name a few researchers among several others who provided notable contributions in this study domain. Also, the presence of long memory has been declined by many researchers, such as Lo (1991), Aydogan and Booth (1988), Lobato and Savin (1998), and Beine and Laurent (2003), to name a few. Thus, it shows the phenomenon of long memory has been widely debated across global financial markets.

1.5.2 Sectoral Juxtaposition and Long Memory

This section provides insights into the prior studies that compared the long memory tests and prominent studies that utilized various tests. The comparison of long memory testing procedures in past literature is elaborated as follows. Hauser (1997) investigated the finite sample properties of multiple versions of the Modified Rescaled Range and three versions of the Hurst Estimator. The size and power to test long memory under heteroscedasticity, short-run effects, combined long and short-run effects, and t-distributions were performed using Monte Carlo methods. With the limitation of relatively small power, the Modified Rescaled Range with the Bartlett window was robust. Except for large short-run effects, the trimmed Whittle likelihood with high power was found to be robust. Harris et al. (2008) developed a new test statistic and compared the finite sample properties of the procedures with the well-known tests in long memory literature using Monte Carlo simulations. Under the alternatives of long memory, the researchers established the consistency of the test statistic. The test statistic's empirical size properties were found to be robust compared to existing tests. Boutahar (2009) presented the long memory estimation methods and considered semi-parametric and non-parametric methods. The study performed Monte Carlo simulations to analyze the power of proposed tests and size distortion and revealed the non-parametric tests to be better for a small sample size. However, for a large sample size, the two classes of tests were found to be equivalent. Based on the ratios of two scaled variance statistics, Lavancier et al. (2010) constructed a two-sample test to compare the long memory parameters. The two samples were of the same length, which could be mutually dependent or independent. The study modified the test statistic to make it asymptotically free, and an adaptive formula for parameter bandwidth was derived from reducing the test's sensitivity. The simulation study showed the better size of the comparison test lead by the select bandwidth. Sadaei et al. (2016) introduced a hybrid method of combining Fuzzy Time Series (FTS) and Autoregressive Fractionally Integrated Moving Average (ARFIMA) models to forecast long memory and found the proposed hybrid method superior as compared to classical Autoregressive Fractionally Integrated Moving Average models.

Next, we provide insights about studies in long memory testing which utilized various tests and their heterogeneous results. Cheung and Lai (1995) explored the evidence of long memory in Morgan Stanley Capital International Stock Index considering data from 18 countries and employed fractional differencing test and modified rescaled range test. The results suggested minor evidence of long memory in international stock returns. In a similar study, Koong et al. (1997) examined the stock returns behaviour among four Pacific Basin markets. The researchers employed Modified Rescaled Range Test and fractional differencing tests and found minor evidence of long memory in stock returns from the Pacific Basin region. Grau-Carles (2000) utilized Rescaled Range analysis, Modified Rescaled Range analysis, Geweke and Porter-Hudak test, Detrended Fluctuation Analysis (DFA), and Autoregressive Fractionally Integrated Moving Average (ARFIMA) maximum likelihood estimation and provided evidence of long-range behaviour of various speculative returns. However, the persistence in volatility was evidenced to be higher than long memory in returns themselves. Kang and Yoon (2008) applied the Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroskedasticity (FIAPARCH) model using high-frequency data from the Korea Composite Stock Price Index (KOSPI 200 Index) and examined the long memory properties. The results indicated the asymmetry and long memory as captured by the Fractionally Integrated Asymmetric Power Autoregressive Conditional Heteroskedasticity (FIAPARCH) model. The study also concluded that the phenomenon of long memory is not a result of structural breaks but is an inherent characteristic of the data generation process.

Tan et al. (2012) tested the long memory in returns at the market, industry, and firm-level using a wavelet-based maximum likelihood fractional integration estimator. Except for approximately 20% of 175 stocks, there was no evidence of long memory. The absence of long memory was due to contemporaneous stock returns aggregation. The study also found the large firm returns possess a long memory feature than small firm returns using the logistic regression model. Bhattacharya and Bhattacharya (2012) investigated the presence of long memory in ten developed stock markets across the world using Geweke and Porter-Hudak (GPH) statistic, Hurst-Mandelbrot's Classical Rescaled Range statistic, and Lo's statistic. The study evidenced the presence of long memory in volatility and random walk for log return series. Zevallos and Palma (2013) proposed a minimum distance methodology for the Autoregressive Fractionally Integrated Moving Average (ARFIMA) process estimation and found the proposed estimator to perform well for small sample sizes. Lahmiri (2015) used Rescaled Range Analysis and Detrended Fluctuation Analysis to examine the long memory in international financial markets and found the price and return trend to be persistent and their short variations to be anti-persistent. Sensoy and Tabak (2015) examined the time-varying long-range dependence in European Union stock markets by proposing an efficiency index to model the stock market's time-varying inefficiency. The study found the adverse effects of the 2008 financial crisis on European Union stock markets. Li et al. (2016) proposed a model to predict stock market trends using the Hurst exponent and examined the market anomaly of persisting long memory considering 30 stock markets. The study took transaction cost into account to justify why market inefficiency has not been arbitraged away. The results indicated that most markets are efficient under the no-arbitrage assumption and with certain transaction costs. The study also displayed an efficient frontier of Hurst exponent with various transaction costs using Monte Carlo simulation. Sukpitak and Hengpunya (2016) investigated the Hurst exponent of the Stock Exchange of Thailand (SET) index compared to the Market for Alternative Investment (MAI) index. The study found evidence that the Stock Exchange of Thailand (SET) index is more efficient than the Market for Alternative Investment (MAI) index. Behfar (2016) examined the behaviour of long memory of returns after intraday financial jumps. The results indicated long memory after the intraday financial jump with a power-law distribution of return. Ferreira and Dionísio (2016) applied a Detrended Cross-Correlation Analysis (DCCA) to examine the long memory of the United States (US) Stock Markets and found evidence of long memory for about seven months.

Chen et al. (2018) related the domestic excess stock returns to world downside risk. The study evidenced the downside tail risk, a multiplier of volatility to have long memory cointegration properties. The results were based on G7 countries, which indicated the investors are averse to downside risk. Ferreira (2018) investigated the long-range dependence in Eastern European stock markets using Detrended Fluctuation Analysis and found the Czech, Hungarian and Polish indices to have lower dependency levels. In a similar study, Ferreira et al. (2018) examined the long-range dependence in African stock markets using Detrended Fluctuation Analysis and Hurst Exponent. Caporale et al. (2019) investigated the financial time series persistence at different frequencies considering stock markets, foreign exchange, and commodity markets using Rescaled Range analysis and fractional integration. The results showed higher persistence at lower frequencies for both volatility and returns. Ferreira (2019) utilized the Detrended Fluctuation Analysis with a sliding windows approach to examine the dynamic dependence of shares and considered the effects of trading volume on the dynamic dependence. The study found evidence of negative correlations for the firms listed on the main index and similar results for non-listed firms. The study concluded that a lack of liquidity might be related to increased dependence.

Zargar and Kumar (2019) examined the long memory characteristics of Bitcoin volatilities using the Exact Local Whittle estimator, Local Whittle estimator, and Autoregressive Fractionally Integrated Moving Average (ARFIMA) model. The results indicated the long memory to be significant and stable for conditional and unconditional realized volatilities.

Further, we elaborate on the studies focused on sectoral indices. Kumar (2014) studied long-range dependence before and after the subprime crisis in eight sectoral indices in India from 2000 to 2011. The study concluded that the sectoral indices Infra, Services, and Information Technology are long-range persistent; however, Bank, Pharma, and Energy indices are anti-persistent. Bala and Gupta (2019) examined the presence of long memory in sectoral indices of the National Stock Exchange (NSE) of India from 2010 to 2018 by using Rescaled Range analysis and concluded that sectoral indices show a long memory effect except for the Nifty Private Bank index. Saleem (2014) performed a similar study in the Russian stock market that examined the long memory in stock market volatility of seven sectoral indices using the Fractionally Integrated Generalized Autoregressive Conditional Heteroscedasticity (FIGARCH) model for the period 2004 to 2013. The results revealed the presence of long memory in the volatility of all the sectoral indices. Rajagopal (2018) tested market efficiency by analyzing long memory in return series of sectoral indices of the Bombay Stock Exchange (BSE) and National Stock Exchange (NSE) by utilizing Classical Rescaled Range Analysis, Wavelets, and Roughness-Length relationship methods and concluded that 50% of select indices exhibit long-range dependence in returns. Hiremath and Kumari (2015) examined long memory by employing the Geweke and Porter-Hudak (GPH) test, the Gaussian Semiparametric Test of Robinson, and the Andrews and Guggenberger test. The study concluded that sectoral indices such as Auto, Consumer Durables, Capital Goods, Health Care, Metal, and Realty show long memory in the returns. The study's findings also suggested the significant presence of long memory in mean returns of the medium and small-sized indices and weaker evidence for large-cap indices. Diallo et al. (2021) examined the structure & efficiency of seven WAEMU (West African Economic and Monetary Union) sectoral indices. The results of wavelet analysis revealed evidence of multi-fractality features for all seven indices. Barkoulas and Baum (1996) tested long memory in the United States (US) stock returns and found no evidence of long memory in composite and sectoral stock indices but noticed such evidence in firm returns. Al-Shboul and Anwar (2016) examined the fractional integration in returns and their volatility measures of five sectoral indices of Jordan's Amman Stock exchange (ASE) using Autoregressive Fractionally Integrated Moving Average (ARFIMA). The results suggested that all sectoral returns exhibit short memory, and volatility exhibits long memory. Bektaş et al. (2007)

examined long memory in returns and absolute returns series of sectoral indices of the Turkish stock market. The long-term dependence was not observed in 76% of sectoral index returns. However, for the absolute return series, long-term dependence was evidenced in all indices' returns.

For analyzing the long-range dependence, past studies used non-parametric, semi-parametric, and parametric tests concerning financial data, communications network traffic data, hydrology data sets, etc. However, the results are mixed. We see minor evidence of long-range dependence in return series examined using non-parametric tests (Cheung & Lai, 1995; Nawrocki, 1995; Jacobsen, 1994; Lux, 1996; Hiemstra & Jones, 1997; Koong et al., 1997; Corazza et al., 1997; Willinger et al., 1999; Huang & Yang, 1999; Grau-Carles, 2000; Sadique & Silvapulle, 2001; Shieh, 2006; Hays et al., 2010; Bhattacharya & Bhattacharya, 2012; Assaf, 2015; Ngene et al., 2018; Mensi et al., 2019; Tebyaniyan et al., 2020). Long-range dependence was noticed using semi-parametric tests (Fang et al., 1994; Barkoulas et al., 2000; Panas, 2001; Granger & Hyung, 2004; Kasman et al., 2009). In contrast, Fung et al. (1994), Cheung & Lai (1995), Koong et al. (1997), and Ngene et al. (2018) did not evidence the presence of long-range dependence. Using parametric tests, evidence of long-range dependence was noticed (Panas, 2001; Floros et al., 2007; Erfani & Samimi, 2009; Aye et al., 2014; Lamouchi, 2020; Dias et al., 2021). In comparison, Henry (2002), Shieh (2006), and Alfred & Sivarajasingham (2020) did not provide evidence of the long memory in return series.

1.5.3 Company Characteristics and Long Memory

The stock characteristics are attributes of stocks such as volume, volatility, liquidity, efficiency, and bid-ask spreads (Naidu & Rozeff, 1994). The characteristics of stocks taken into consideration by market participants include stock prices, risk, and marketability of stocks. These characteristics of stock trading are linked to the expected rate of return on common stock. Illiquid markets tend to be more volatile (Naidu & Rozeff, 1994). The ultimate objective of the investment is to earn superior returns for which the price information is requisite. Prices of scrip can be high or low. The reasons for retail investors prefer low-price stocks in comparison to high-price stocks are price affordability, the benefit of getting more shares, and high liquidity. Another stock characteristic is the risk (also referred to as volatility) indicates price fluctuations and is often associated with price swings in either direction. This stock characteristic is very important for stock traders performing the trades utilizing technical analysis. Also, the marketability of shares (also referred to as liquidity) is vital for market participants. Stock market liquidity indicates the situation in which buying and selling of shares happen quickly with minimal impact on the prices of stocks. Liquidity is the ability of market participants to quickly buy or sell a given quantity of an asset at any time (Xu et al., 2019). The dimensions of liquidity include tightness, immediacy, depth, breadth and resiliency (Bhattacharya et al., 2019).

We see, Barkoulas and Baum (1996) applied the spectral regression method to test for fractal structure for the companies included in the Dow Jones Industrial Index and found strong evidence of long memory for Boeing and Eastman Kodak, while weaker evidence for Merck, Sears and Woolworth stocks. Lux (1996) examined long memory in the returns, squared returns and absolute returns of the DAX, as well as the range of values obtained for the 29 individual share price records and observed that there was an almost complete lack of evidence of long-term memory in returns. The only significant case out of 29 stock is one of anti-persistence. The long memory property was more pronounced in absolute values of returns than in the squares of returns (both used as proxies for volatility). Hiemstra and Jones (1997) applied the modified rescaled range test to the return series of 1952 common stocks, and results revealed that there is some evidence consistent with persistent long memory in the returns of a small proportion of stocks. Lobato and Savin (1998) examined the long memory in stock market returns of 30 stocks of the Dow jones industrial Average index. The results did not provide evidence of long memory in the returns, but there was strong evidence in the squared returns.

Lobato and Velasco (2000) examined long memory in the frequency domain by tapering data of the trading volume of 30 stocks of the DJIA index and found strong evidence of long memory. Ray and Tsay (2000) classified daily stock returns of S&P 500 companies on the basis of the company's size and its business or industrial sector and estimated the strength of long-range dependence in the stock volatilities and results evidenced that almost all of the companies analysed exhibit strong persistence in volatility. So (2000) applied a modified R/S test and GPH test to detect the existence of long-term dependence in volatility for the S&P 500 index, Dow Jones Industrial Average index and its constituent stocks and found Strong evidence of long-term dependence in volatility in nearly all cases and suggested that it is important to incorporate the long memory feature in the modelling of volatility in order to produce good volatility forecasts and derivative pricing formulas. Chandra Babu et al. (2003) studied five popular stock indices, and the stock prices of 26 companies from different industries and concluded that the series of stock prices and stock indices have persistent behaviour. Nearly 18% to 23% of the stock data was found to be influenced by the past. Tolvi (2003) found evidence of long memory in the returns of nearly two-thirds of the 40 individual stocks by the LM testing method. Sibbertsen (2004) examined the volatilities of seven German stocks and the results indicated evidence of long memory in all selected stocks. Andreano (2005) indicated that in the case of stocks in the MIB30 index, the trading volume exhibits long memory and that it shares the same long-memory parameter of the volatility process for most of the stocks considered. Verma (2008) results suggested that the daily returns of only three companies out of 60 companies traded on BSE exhibit long-range dependence. Morris et al. (2009) tested the efficiency of selected shares and ALSI 40 data of the South African stock market. The results of Wavelet analysis indicated that most of the individual share prices and the share index time series are mean reverting over the long run and follow a long memory process, offering evidence against the weak-form efficient market hypothesis.

Fleming and Kirby (2010) examined long-range dependence in daily realized volatilities, and trading volumes for the 20 firms in the MMI, and results indicate that volume and volatility both display long memory but rejected the hypothesis that the two series share a common order of fractional integration for a fifth of the firms in the sample. Moreover, the study found a strong correlation between the innovations to volume and volatility, which suggested that trading volume can be used to obtain more precise estimates of daily volatility for cases in which high-frequency returns are unavailable. Mu et al. (2010) found that non-universal long memory exhibits size dependence on the trading volume, while multifractal nature is independent of the trading volume of 22 liquid stocks traded on the Shenzhen Stock exchange. The study concluded that both long memory and probability distribution of trading volume has an important influences on the multifractal nature. Festić et al. (2012) applied Lo's (1991) modified rescaled range (R/S) test and the Wavelet Ordinary Least Squares (WOLS) estimator of Jensen (1999) and found that both the Croatian stock index Crobex and individual stocks in this index exhibit long memory. Zhao et al. (2013) constructed two portfolios of US equities, i.e., neglected and popular stocks, to measure the degrees of persistence in daily returns. The results indicated that all stocks except one display anti-persistence in the neglect portfolio while the popular portfolio stocks uniformly display random-walk returns.

1.5.4 Overview of Literature in Indian Context

The past literature suggests mixed results of long memory in the Indian stock market. Tripathy (2015) concluded that the Indian stock market exhibits a high degree of positive long-term persistence leading to arbitrage opportunities for the international investors to earn abnormal profits. Goudarzi (2010) found evidence of long rang dependence in the Indian stock market as seen in developed and some emerging stock markets. Whereas Bhattacharya et al. (2018) found an absence of long memory in returns but supported the presence of long memory in absolute returns and volatility. Overall findings of the study did not suggest any significant difference in returns from developed markets and emerging markets in terms of memory, as the presence of long memory could not be established in the return series of both the groups. Mukherjee et al. (2011) rejected the evidence of long memory in raw returns but found evidence of long memory in absolute and squared returns of the Indian stock market. Hiremath and Narayan (2016) examined the adaptive market hypothesis and concluded that the Indian stock market is moving towards efficiency.

Hiremath and Kumari (2015) suggested the significant presence of long memory in mean returns of the medium- and small-sized indices and weaker evidence for large-cap indices of the Indian stock market. Bala and Gupta (2020) observed that long memory persists in the returns of BSE indices during the full sample period; pre and post-subprime crisis period and year-wise analysis and observed that although various regulatory, market micro structure, technological, and structural changes have taken place in Indian stock market from last two decades have not brought any significant change in information observation speeds, and price discovery in the equity market is not efficient yet. Bala and Gupta (2020) studied long memory in stock liquidity and returns of NSE broad indices and concluded that the liquidity series of Nifty midcap 50, Nifty 100, and Nifty 200 show persistent nature.

1.6 Research Gap

Past studies in India and in the world have extensively examined long-memory behaviour for various broader indices. However, studies are inadequate in investigating the role of interdependencies among returns, liquidity and volatility in the examination of long-memory behaviour. Also, past studies did not focus on examining whether consideration of the interdependencies effect can improve the forecasting ability of the models. Present studies bridge these gaps and investigate these issues in the Indian context.

Next, in the Indian context, we see an examination of long memory in sectoral indices (Kumar, 2014; Hiremath & Kumari, 2015; Rajagopal, 2018; Bala & Gupta, 2019), but these studies did not focus on examining the persistence and anti-persistence at different frequencies. This study extends the past research by investigating whether the frequency of returns plays any significant role in the long-memory behaviour of Indian sectoral indices returns.

Further, we see the past literature focused on examining the long memory and anti-persistence in individual stock returns. The results are mixed. Further, studies have been performed on indices which represent predefined groups (Say, Large Cap, Mid Cap, Small Cap, Sectoral, Thematic, etc.). But studies are not adequate to convey stock characteristics such as price affordability, high-mid-low volatility, high-mid-low liquidity aspects, etc. This study identifies this gap and examines the long-memory behaviour of stocks after taking into consideration the various stock characteristics.

1.7 Research Questions

The present study frames the following research questions based on the research gaps identified from the existing literature:

- Does Broader Stock Index reveal evidence of long memory in returns, volatility or liquidity?
- Do interdependencies between returns, liquidity and volatility affect long-memory behaviour?
- Does consideration of the interdependencies effect improve the forecasting ability of the models?
- Do sectoral indices reveal evidence of long memory in returns?
- Does the frequency of data play any significant role in the examination of long memory in sectoral indices returns?
- Do stocks classified based on price levels reveal long memory in stock returns, liquidity, and volatility?
- Do stocks classified based on liquidity reveal long memory in stock returns, liquidity, and volatility?
- Do stocks classified based on volatility reveal long memory in stock returns, liquidity, and volatility?

1.8 Objectives of the Study

Based on the research questions, the study frames the following objectives.

1.8.1 Objective I

To examine the long memory in stock market returns, volatility and liquidity.

Sub-Objectives:

- To analyze the long memory in broader index returns, volatility or liquidity.
- To examine the effect of interdependencies between returns, liquidity and volatility on long memory behaviour.
- To investigate the effect of interdependencies on the forecasting ability of the models.

1.8.2 Objective II

To examine the long memory in stock market returns at Industry Level.

Sub-Objectives:

- To analyze the long memory in sectoral indices returns.
- To examine the effect of data frequency on long memory behaviour.

1.8.3 Objective III

To examine the long memory in stock market returns, volatility and liquidity at Company Level.

Sub-Objectives:

- To examine the long memory in stock returns, liquidity, and volatility of stocks classified based on price levels.
- To examine the long memory in stock returns, liquidity, and volatility of stocks classified based on liquidity.
- To examine the long memory in stock returns, liquidity, and volatility of stocks classified based on volatility.

1.9 Research Methodology

The methodology adopted in this study is elaborated objective-wise as follows.

1.9.1 Research Methodology for Objective I

1.9.1.1 Period of Study

The study considers the data of the Indian stock market index Nifty 50 for the period from January 1997 to December 2020 to examine the long memory in broader stock index returns, stock index liquidity and stock index volatility.

1.9.1.2 Sample Design

For the purpose of the study, the Nifty 50 index of the National Stock Exchange, India, has been considered as a proxy for the Indian stock market.

1.9.1.3 Data Variables and Sources

The natural log returns are computed in the study using the formula as depicted in Equation (1).

$$Rt = LN\left(\frac{Pt}{Pt-1}\right) \qquad (1)$$

Where,

R_t symbolizes natural log returns on the stock index for the day t.

P_t is the closing share price of the stock index for the day t.

P_{t-1} is the closing share price of the stock index for the day t-1.

And the computed daily natural log returns are transferred to monthly natural log returns for analysis purposes. The study use natural log returns instead of simple return or excess return as the natural log returns are time addition, and they can be interpreted as continuously compounded returns.

Further, to represent stock liquidity, we use Amihud Ratio given by Amihud (2002) computed using the following equation.

$$Lt = \frac{Rt}{Vt} \qquad (2)$$

Where,

L_t symbolises Amihud Ratio for the stock index on the day t.

R_t is the stock returns computed in equation (1).

V_t is the volume of the stock index for the day t.

It is important to note that the Amihud ratio, as computed in equation (2), is a measure of illiquidity. As such, on high Amihud Ratio will represent stock illiquidity, and a low Amihud ratio will indicate high stock liquidity.

Various measures of liquidity are (a) tightness, which represents the cost of executing a transaction, (b) Resiliency, which shows the speed of price reversion to eat normally after the shock, (c)Depth which signifies the traded quantity of stock Structured as three dimensions of liquidity by Kyle (1985), (d) Breath, which is the price impact caused by the volume of trade and (e) Immediacy, which signifies a speed of which the trade can be executed as mentioned by Sarr and Lybek (2002). The rationale behind Amihud Ratio as a proxy to Stock liquidity is due to its edge over other liquidity measures.

The comparison between different liquidity measures was performed by Bedowskq-Sojka (2018), who concluded that the Amihud Ratio is a better transactional cost measure of liquidity than others. The computed daily Amihud ratios are transferred into monthly Amihud ratios for analysis purposes. In the case of examination of long memory in stock liquidity, the analysis relates to the examination of long memory of one of the dimensions of long memory that is represented by the Amihud Ratio and not stock liquidity in general.

The study uses Standard Deviation as a proxy to Stock Market Volatility computed month-wise based on daily log returns as depicted in equation (3). Stock volatility considered here represent historical volatility.

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}} \qquad (3)$$

Where,

σ symbolises the monthly standard deviation computed based on daily log returns.

The required data related to the Nifty 50 Index has been extracted from the official website of the National Stock Exchange, India.

1.9.1.4 Statistical and Econometric Techniques

To understand the nature of data, the study utilizes Summary Statistics, which include Mean, Standard Deviation, Skewness, and Kurtosis. Further, the Elliott-Rothenberg-Stock DF-GLS test developed by Elliott et al. (1996) is used to examine the stationarity of the data, which is an essential criterion for long memory examination. The required analyses are performed using E-views Software.

The main limitation of the non-parametric and semi-parametric tests is that it does not reflect the presence of long memory and short memory in a parsimonious model. Thus, to examine the presence of long memory in sectoral indices returns, the study uses Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a parametric model developed by Granger and Joyeux (1980), and Hosking (1981) as expressed in the following Equation (4):

$$\Phi(L)(1-L)^d Y_t = \Theta(L)\varepsilon_t \qquad \varepsilon_t \sim i.i.d(0, \sigma_u^2) \tag{4}$$

Where,

L is the backward-shift operator

$(1-L)^d$ is the fractional differencing operator

AR and MA polynomials are represented as Φ(L) and Θ(L) respectively

Considering the differencing parameter's non-integer values, the Autoregressive Integrated Moving Average (ARIMA) models are generalized by Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. The ARFIMA models are useful for the present study as these models capture the long-range persistence, which stationary ARMA models cannot illustrate. We utilize the above Equation and simulate various models of ARFIMA to find the most appropriate model for the analysis. The models are rejected if the corresponding Autoregressive term, or Moving Average term, or both are insignificant and also if the residuals are serially correlated. From the models which met the criteria of significant Autoregressive and Moving Average terms and white noise residuals, we select the best model using Akaike Information Criterion (Akaike, 1973) and Schwarz Information Criterion (Schwarz, 1978).

In the case of ARFIMA, d=0 is a null hypothesis that signifies a short-term memory process. The series is considered long-range dependent if the estimated significant ‘d’ value lies between 0 and 0.5, and anti-persistent if the estimated significant ‘d’ value lies between -0.5 and 0.

Finally, we check the robustness of the developed ARFIMA models. The residuals from such developed ARFIMA models should be white noise, i.e., there should not be any serial correlation present in the residuals. We test the presence of serial correlation using the Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978., & Godfrey, 1978).

The forecasting ability of the models is examined using Root Mean Squared Error, Theil Inequality Coefficient, and Bias Proportion. Models are utilized to forecast for 3 Months, 6 Months, 9 Months, and 12 Months and compared with actual data.

1.9.2 Research Methodology for Objective II

1.9.2.1 Period of Study

The present study investigates the presence of long memory in the Indian stock market considering 13 sectoral indices of the National Stock Exchange (NSE) of India for the period shown in Table 1.

Table 1: Definition of Variables and Study Period

Variable	Meaning	Study Data Period
LNAUTO	LNAUTO refers to the Natural Log of Nifty Auto Index Returns. Nifty Auto Index is a sectoral index of the National Stock Exchange, India, which reflects the performance of the Automobile sector that includes manufacturers of motorcycles, cars, auto ancillaries, heavy vehicles, tyres, etc. It was incepted on 1st January 2004 and comprises of 15 stocks.	1st January 2004 – 31st December 2020
LNBANK	LNBANK refers to the Natural Log of Nifty Bank Index Returns. Nifty Bank Index is a sectoral index of the National Stock Exchange, India, which reflects the performance of most liquid and large capitalized Indian Banking stocks. It was incepted on 1st January 2000 and comprises of 12 stocks.	1st January 2000 – 31st December 2020

LNCD	LNCD refers to the Natural Log of Nifty Consumer Durables Index Returns. Nifty Consumer Durables Index is a sectoral index of the National Stock Exchange, India, which reflects the performance of stocks belonging to the Consumer Durables industry. It was incepted on 1st April 2005 and comprises of 15 stocks.	1st April 2005 – 31st December 2020
LNFS	LNFS refers to the Natural Log of Nifty Financial Services Index Returns. Nifty Financial Services Index is a sectoral index of the National Stock Exchange, India, which reflects the performance of the Indian financial market, which includes banks, financial institutions, housing finance, insurance companies and other financial services companies. It was incepted on 1st January 2004 and comprises of 20 stocks.	1st January 2004 – 31st December 2020
LNFMCG	LNFMCG refers to the Natural Log of Nifty FMCG (Fast Moving Consumer Goods) Index Returns. Nifty FMCG is a sectoral index of the National Stock Exchange, India, which comprises companies which manufacture goods and products which are non-durable and mass consumption products. It was incepted on 1st January 1996 and comprises of 15 stocks.	1st January 1999 – 31st December 2020
LNIT	LNIT refers to the Natural Log of Nifty IT (Information Technology) Index Returns. Nifty IT is a sectoral index of the National Stock Exchange, India, reflects the performance of companies which have more than 50% of their turnover from IT-related activities. It was incepted on 1st January 1996 and comprises of 10 stocks.	1st January 1999 – 31st December 2020

LNMEDIA	LNMEDIA refers to the Natural Log of Nifty Media Index Returns. Nifty Media Index is a sectoral index of the National Stock Exchange, India, reflects the performance of the Media & Entertainment sector, including printing and publishing. It was incepted on 30th December 2005 and comprises of 10 stocks.	30th December 2005 – 31st December 2020
LNMETAL	LNMETAL refers to the Natural Log of Nifty Metal Index Returns. Nifty Metal Index is a sectoral index of the National Stock Exchange, India, reflects the performance of the metals sector, including mining. It was incepted on 1st January 2004 and comprises of a maximum of 15 stocks.	12th July 2011 – 31st December 2020
LNOG	LNOG refers to the Natural Log of Nifty Oil & Gas Index Returns. Nifty Oil & Gas Index is a sectoral index of the National Stock Exchange, India, reflects the performance of the stocks belonging to the Oil, Gas and Petroleum industry. It was incepted on 1st April 2005 and comprises of 15 stocks.	1st April 2005 – 31st December 2020
LNPHARMA	LNPHARMA refers to the Natural Log of Nifty Pharma Index Returns. Nifty Pharma Index is a sectoral index of the National Stock Exchange, India, reflects the performance of the companies in the Pharma sector. It was incepted on 1st January 2001 and comprises of 10 stocks.	1st January 2001 – 31st December 2020
LNPVTB	LNPVTB refers to the Natural Log of Nifty Private Bank Index Returns. Nifty Private Bank Index is a sectoral index of the National Stock Exchange, India, reflects the performance of the banks from the private sector. It was incepted on 1st April 2005 and comprises of 10 stocks.	1st April 2005 – 31st December 2020
LNPSUB	LNPSUB refers to the Natural Log of Nifty PSU (Public Sector Undertaking) Bank Index Returns. Nifty PSU Bank Index is a sectoral index of the	1st January 2004 – 31st December 2020

	National Stock Exchange, India, reflects the performance of the public sector banks in India. It was incepted on 1st January 2004 and comprises of 13 stocks.	
LNREALTY	LNREALTY refers to the Natural Log of Nifty Realty Index Returns. Nifty Realty Index is a sectoral index of the National Stock Exchange, India, reflects the performance of companies in the real estate industry. It was incepted on 29th December 2006 and comprises of 10 stocks.	29th December 2006– 31st December 2020

Source: Compiled based on information available on https://www.nseindia.com/

Note: For those indices where data is not available since inception, data is considered from the period since it is available.

1.9.2.2 Sample Design

The sectoral indices considered for the analysis include Nifty Auto Index, Nifty Bank Index, Nifty Consumer Durables Index, Nifty Financial Services Index, Nifty FMCG Index, Nifty IT Index, Nifty Media Index, Nifty Metal Index, Nifty Oil & Gas Index, Nifty Pharma Index, Nifty Private Bank Index, Nifty PSU Bank Index, and Nifty Realty Index. These sectoral indices include companies with similar business lines and depict the behaviour and performance of the sectors. The sectoral study is important from two aspects. Firstly, the industry analysis is a crucial element of Fundamental Analysis, a prime tool for value investors to analyze the performance of the economy, industry, and companies. And secondly, sectoral study assists in portfolio construction, portfolio analysis, and portfolio revision. Table 1 also provides the details of variables created for research with their definitions.

1.9.2.3 Data Variables and Sources

The study computes the daily, monthly, and quarterly natural log-returns of sectoral indices using the formula as depicted in Equation 1.

$$Rt = LN\left(\frac{Pt}{Pt-1}\right) \tag{5}$$

Where,

R_t symbolizes natural log returns on sectoral indices for the day, month, and quarter t.

P_t is the closing share price of sectoral indices for the day, month, and quarter t.

P_{t-1} is the closing share price of the sectoral indices for the day, month, and quarter t-1. The required data related to sectoral indices have been extracted from the official website of the National Stock Exchange, India. The daily data have been transformed to monthly and quarterly suing MS Excel.

1.9.2.4 Statistical and Econometric Techniques

The Summary Statistics, which include Mean, Standard Deviation, Skewness, and Kurtosis, are computed to understand the nature of the data. Further, the Elliott-Rothenberg-Stock DF-GLS test developed by Elliott et al. (1996) is used to examine the stationarity of the data, which is an essential criterion for long memory examination. The Elliott-Rothenberg-Stock DF-GLS test has $I(1)$ as the null hypothesis. To verify the results with a stationarity test with $I(0)$ as the null hypothesis, we use the Kwiatkowski-Phillips-Schmidt-Shin test developed by Kwiatkowski et al. (1992). The required analyses are performed using E-views Software.

The methodology for this study have been adopted as illustrated by Baum (2016) as follows. Hurst (1951) introduced Rescaled Range Analysis, which measures the variability of time series data and was modified by Mandelbrot (1972). How the variability of the time-series changes with the time-period length is assessed using the R/S statistic. Hurst (1951) and Mandelbrot (1972), which developed the Classical Rescaled Range statistic, is a range of a partial sum of deviations from its mean in a time series rescaled by its standard deviation, which is expressed for a sample of n values (X_1, X_2, …. X_n) as follows:

$$Q_n = \frac{1}{S_n}\left[Max_{1\le k\le n}\sum_{j=1}^{k}\left(X_j + \bar{X}_n\right) - Min_{1\le k\le n}\sum_{j=1}^{k}\left(X_j + \bar{X}_n\right)\right] \quad (6)$$

Where, the maximum likelihood estimator of the standard deviation is expressed as S_n.

The Classical R/S statistic was sensitive to short-range dependence. Thus, Lo (1991) modified the Classical R/S statistic by applying Newey-West correction using Bartlett Window to account for the short-range dependence effect.

To obtain an estimate of memory parameter ‘d’, Geweke and Porter-Hudak (1983) proposed a semi-parametric procedure involving fractionally integrated process X_t is a model of the form as shown in equation (7).

$$(1-L)^d X_t = \in_t \quad (7)$$

Where continuous spectral density $f_{\in}(\lambda) > 0$ and $\in_t$ is stationary with mean = 0.

Phillips (1999) solved the weakness of the Geweke and Porter-Hudak estimator, wherein the case of d=1 was not addressed. The modification was expressed as follows:

$$\omega_x(\lambda_s) = \frac{\omega_u(\lambda_s)}{1-e^{i\lambda s}} - \frac{e^{i\lambda s}}{1-e^{i\lambda s}} \frac{X_n}{\sqrt{2\pi n}} \quad (8)$$

An alternative Log Periodogram Regression was proposed by Robinson (1995), which provides superior asymptotic efficiency, as claimed in the study. The Robinson Log Periodogram Regression also allows for the formulation of a multivariate model. The periodogram of X_{gt} is expressed as:

$$l_g(\lambda) = (2\pi n)^{-1} \left[\sum_{t=1}^{n} X_{gt} e^{it\lambda}\right]^2 \quad (9)$$

However, the main limitation of the above non-parametric and semi-parametric tests is that it does not reflect the presence of long memory and short memory in a parsimonious model. Thus, to examine the presence of long memory in sectoral indices returns, the study uses Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a parametric model developed by Granger and Joyeux (1980), and Hosking (1981) as expressed in Equation 10.

$$\Phi(L)(1-L)^d Y_t = \Theta(L)\varepsilon_t \qquad \varepsilon_t \sim i.i.d(0, \sigma_u^2) \quad (10)$$

Where,

L is the backward-shift operator

$(1-L)^d$ is the fractional differencing operator

AR and MA polynomials are represented as Φ(L) and Θ(L) respectively

Considering the differencing parameter's non-integer values, the Autoregressive Integrated Moving Average (ARIMA) models are generalized by Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. The ARFIMA models are useful for the present study as these models capture the long-range persistence, which stationary ARMA models cannot illustrate.

We utilize Equation 10 and simulate various models of ARFIMA to find the most appropriate model for the analysis. The models are rejected if the corresponding Autoregressive term, or Moving Average term, or both are insignificant and also if the residuals are serially correlated. From the models which met the criteria of significant Autoregressive and Moving Average terms and white noise residuals, we select the best model using Akaike Information Criterion (Akaike, 1973) and Schwarz Information Criterion (Schwarz, 1978).

In the case of ARFIMA, d=0 is a null hypothesis that signifies a short-term memory process. The series is considered long-range dependent if the estimated significant d value lies between 0 and 0.5, and anti-persistent if the estimated significant d value lies between -0.5 and 0.

As the study has a long data period, we test the presence of structural breaks using the Bai-Perron Multiple Breakpoint Test (Bai, 1997; Bai & Perron, 1998; Bai & Perron, 2003). The null hypothesis for Bai-Perron Multiple Breakpoint Test is H0: No Structural Breaks. Finally, we check the robustness of the developed ARFIMA models. The residuals from such developed ARFIMA models should be white noise, i.e., there should not be any serial correlation present in the residuals. We test the presence of serial correlation using the Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978., & Godfrey, 1978).

1.9.3 Research Methodology for Objective III

1.9.3.1 Period of Study

To examine the long memory at the company level, the study considers stocks listed on the Nifty 50 index for the period January 1999 to December 2020. As the data for the said period is not available for all 50 stocks, we consider the study period for such stocks based on their availability.

1.9.3.2 Sample Design

The study sample consists of Nifty 50 stocks of the National Stock Exchange, India. The rationale behind selecting Nifty 50 stocks is that it represents the listed large-cap stocks. These blue-chip stocks form part of the Nifty 50 Index and are considered financially stable due to their past track records and, as such, form part of the investment portfolio of the risk-averse investors.

Also, the stocks included in the Nifty 50 index represent about 66.8 % of the free-float market capitalization of stocks listed on NSE and total value traded for the last six months is about 53.4 % as of March 2019 as per data available on the official website of NSE, India. The study selects the companies listed on the Nifty 50 index, as reflected in Table 2.

Table 2: List of Nifty 50 Companies

Symbol	Name Of Company
ADANIENT	Adani Enterprises Limited
ASIANPAINT	Asian Paints Limited
AXISBANK	Axis Bank Limited
BAJAJ-AUTO	Bajaj Auto Limited
BAJAJFINSV	Bajaj Finserv Limited
BAJFINANCE	Bajaj Finance Limited
BPCL	Bharat Petroleum Corporation Limited
BHARTIARTL	Bharti Airtel Limited
INFRATEL	Bharti Infratel Limited
BRITANNIA	Britannia Industries Limited
CIPLA	Cipla Limited
COALINDIA	Coal India Limited
DRREDDY	Dr. Reddy's Laboratories Limited
EICHERMOT	Eicher Motors Limited
GAIL	GAIL (India) Limited
GRASIM	Grasim Industries Limited
HCLTECH	HCL Technologies Limited
HDFCBANK	HDFC Bank Limited
HEROMOTOCO	Hero MotoCorp Limited
HINDALCO	Hindalco Industries Limited
HINDUNILVR	Hindustan Unilever Limited
HDFC	Housing Development Finance Corporation Limited
ICICIBANK	ICICI Bank Limited
ITC	ITC Limited
IOC	Indian Oil Corporation Limited
INDUSINDBK	IndusInd Bank Limited
INFY	Infosys Limited
JSWSTEEL	JSW Steel Limited
KOTAKBANK	Kotak Mahindra Bank Limited
LT	Larsen & Toubro Limited

M&M	Mahindra & Mahindra Limited
MARUTI	Maruti Suzuki India Limited
NTPC	NTPC Limited
ONGC	Oil & Natural Gas Corporation Limited
POWERGRID	Power Grid Corporation of India Limited
RELIANCE	Reliance Industries Limited
SBIN	State Bank of India
SHREECEM	Shree Cement Limited
SUNPHARMA	Sun Pharmaceutical Industries Limited
TCS	Tata Consultancy Services Limited
TATAMOTORS	Tata Motors Limited
TATASTEEL	Tata Steel Limited
TECHM	Tech Mahindra Limited
TITAN	Titan Company Limited
UPL	UPL Limited
ULTRACEMCO	UltraTech Cement Limited
VEDL	Vedanta Limited
WIPRO	Wipro Limited
YESBANK	Yes Bank Limited
ZEEL	Zee Entertainment Enterprises Limited

Source: Official website of NSE, India

1.9.3.3 Data Variables and Sources

The data set includes closing prices and total traded quantity, commonly referred to as volume in daily frequency. Data was compiled based on information available on the official website of the National Stock Exchange, India (https://www.nseindia.com/). For those indices where data is not available since inception, data is considered from the period since it is available.
The study computes the natural log-returns using the formula as depicted in Equation.

$$Ri,t = LN\left(\frac{Pi,t}{Pi,t-1}\right) \quad (11)$$

Where,

$R_{i,t}$ symbolizes natural log returns on stock i for the day t.

$P_{i,t}$ is the closing share price of stock i for the day t.

$P_{i,\,t-1}$ is the closing share price of the stock i for the day t -1.

And the computed daily natural log returns are transferred to monthly natural log returns for analysis purposes. We use natural log returns instead of simple returns or excess returns as the log returns are time addition, and they can be interpreted as continuously compounded returns.

Further, to represent stock liquidity, we use Amihud Ratio given by Amihud (2002) computed using equation 12.

$$Li,t = \frac{Ri,t}{Vi.t} \qquad (12)$$

Where,

$L_{i,t}$ symbolises Amihud Ratio for stock I on the day t.

$R_{i,t}$ is the stock returns computed in eq,1

V_{it} is the volume of stock i for the day t.

It is important to note that the Amihud ratio, as computed in equation 12, is a measure of illiquidity. As such, on high Amihud Ratio will represent stock illiquidity, and a low Amihud ratio will indicate high stock liquidity.

In the case of the examination of long memory in stock liquidity, the analysis relates to the examination of long memory of one of the dimensions of long memory that is represented by the Amihud Ratio and not stock liquidity in general.

The study uses Standard Deviation as a proxy for Stock Market Volatility computed based on daily log returns as depicted in the equation (13). Stock volatility considered here represent historical volatility.

$$\sigma = \sqrt{\frac{\sum(x-\bar{x})^2}{n-1}} \qquad (13)$$

Where,

σ symbolises the monthly standard deviation computed based on daily log returns.

Considering the stock characteristics, stock aggregates are developed using quintiles as follows.

Table 3: Creation of Stock Categories based on Quintiles

Stock Categories	For Examination of Long Memory in Returns	For Examination of Long Memory in Liquidity	For Examination of Long Memory in Volatility
High Priced Stocks	C1Q1LR	C1Q1AR	C1Q1SD
Moderate to High Priced Stocks	C1Q2LR	C1Q2AR	C1Q2SD
Moderately Priced Stocks	C1Q3LR	C1Q3AR	C1Q3SD
Moderate to Low Priced Stocks	C1Q4LR	C1Q4AR	C1Q4SD
Low Priced Stocks	C1Q5LR	C1Q5AR	C1Q5SD
High Liquid Stocks	C2Q1LR	C2Q1AR	C2Q1SD
Moderate to High Liquid Stocks	C2Q2LR	C2Q2AR	C2Q2SD
Moderately Liquid Stocks	C2Q3LR	C2Q3AR	C2Q3SD
Moderate to Low Liquid Stocks	C2Q4LR	C2Q4AR	C2Q4SD
Low Liquid Stocks	C2Q5LR	C2Q5AR	C2Q5SD
High Volatile Stocks	C3Q1LR	C3Q1AR	C3Q1SD
Moderate to High Volatile Stocks	C3Q2LR	C3Q2AR	C3Q2SD
Moderately Volatile Stocks	C3Q3LR	C3Q3AR	C3Q3SD
Moderate to Low Volatile Stocks	C3Q4LR	C3Q4AR	C3Q4SD
Low Volatile Stocks	C3Q5LR	C3Q5AR	C3Q5SD

Source: Authors' Compilation

The stocks are classified in quintiles based on their price, liquidity and volatility. Here the focus is on the prices of the stocks and not their value or the returns. When an investor constructs a portfolio, it is implied that if stocks worth less price are bought, the number of shares accumulated will be more, and the stocks with high prices cannot be purchased in large quantities given a limited corpus. Thus, highly-priced stocks may not form part of a small retail investors' portfolios. Now, given the fact that not all investors will be investing in all types of stocks (high-priced, moderate-priced, or low-priced), we suspect an anomaly. Thus, it becomes interesting to investigate whether stocks with a high price, moderate price, or low-price exhibits long memory. Similarly, the study investigates if stocks with high liquidity, moderate liquidity, low liquidity, high volatility, moderate volatility, and low volatility exhibit long memory.

1.9.3.4 Statistical and Econometric Techniques

The Summary Statistics, which include Mean, Standard Deviation, Skewness, and Kurtosis, are computed to understand the nature of the data. Further, the Elliott-Rothenberg-Stock DF-GLS test developed by Elliott et al. (1996) is used to examine the stationarity of the data, which is an essential criterion for long memory examination. The required analyses are performed using E-views Software.

The main limitation of the non-parametric and semi-parametric tests is that it does not reflect the presence of long memory and short memory in a parsimonious model. Thus, to examine the presence of long memory in sectoral indices returns, the study uses Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a parametric model developed by Granger and Joyeux (1980), and Hosking (1981) as expressed in the following Equation 14.

$$\Phi(L)(1-L)^d Y_t = \Theta(L)\varepsilon_t \qquad \varepsilon_t \sim i.i.d(0, \sigma_u^2) \tag{14}$$

Where,

L is the backward-shift operator

$(1-L)^d$ is the fractional differencing operator

AR and MA polynomials are represented as Φ(L) and Θ(L) respectively

Considering the differencing parameter's non-integer values, the Autoregressive Integrated Moving Average (ARIMA) models are generalized by Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. The ARFIMA models are useful for the present study as these models capture the long-range persistence, which stationary ARMA models cannot illustrate.

We utilize equation 14 and simulate various models of ARFIMA to find the most appropriate model for the analysis. The models are rejected if the corresponding Autoregressive term, or Moving Average term, or both are insignificant and also if the residuals are serially correlated. From the models which met the criteria of significant Autoregressive and Moving Average terms and white noise residuals, we select the best model using Akaike Information Criterion (Akaike, 1973) and Schwarz Information Criterion (Schwarz, 1978).

In the case of ARFIMA, d=0 is a null hypothesis that signifies a short-term memory process. The series is considered long-range dependent if the estimated significant d value lies between 0 and 0.5, and anti-persistent if the estimated significant d value lies between -0.5 and 0. Finally, we check the robustness of the developed ARFIMA models. The residuals from such developed ARFIMA models should be white noise, i.e., there should not be any serial correlation present in the residuals. We test the presence of serial correlation using the Breusch-Godfrey Serial Correlation LM Test (Breusch, 1978., & Godfrey, 1978).

1.10 Hypotheses of the Study

The study frames the hypothesis to support the analysis of all the objectives of the study. The null hypotheses are presented as follows:

1.10.1 Hypothesis to examine the presence of unit root in the data

H0a: The variable has a unit root.

1.10.2 Hypothesis to examine the presence of long memory and anti-persistence in the model.

H0b: The fractional differencing parameter ‘d’ is 0. In other words, the fractional differencing parameter is not significant.

1.10.3 Hypothesis to investigate the presence of structural breaks.

H0c: There are no structural breaks in the data.

1.10.4 Hypothesis to examine the presence of serial correlation.

H0d: There is no serial correlation in the developed model.

1.11 Organization of Study

Chapter 1 focuses on the introduction, need for the study, scope of the study, the significance of the study, review of literature, research gaps, research questions, objectives of the study, and provides a detail research methodology utilized for the purpose of this study followed by hypothesis development and organization of the study.

Chapter 2 incorporates results and discussion pertaining to the analysis of Objective I.

Chapter 3 incorporates results and discussion pertaining to the analysis of Objective II.

Chapter 4 incorporates results and discussion pertaining to the analysis of Objective III.

Chapter 5 presents the findings of the study, conclusions of the study, recommendations of the study, policy implications of the study, the contribution of the study, limitations of the study, and scope of further research.

Chapter 2

Interdependencies and Long Memory

This chapter presents the results and discussion relating to the examination of interdependencies among stock index returns, liquidity and volatility, and long memory behaviour. The chapter begins by depicting the trends in Nifty 50 Index Prices and Volume and the trends in Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility. The results incorporated to support the main analysis include Summary Statistics, Unit Root Test, Identification of Outliers, and Model Selection. The study then examines the presence of long memory in Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility using ARFIMA Models. Further, the long memory is examined using ARFIMA Models considering the effect of Interdependencies. In addition, the study also evaluates the forecasting ability of the models and presents the comparison of forecasted values with actual values. Finally, the results of the Model Diagnosis are incorporated.

2.1 Trends in Nifty 50 Index Prices and Volume

Figure 1 depicts the linear trends in Nifty 50 index prices and volume. We can notice that in the case of Nifty 50 index prices, there has been a sharp rise in the prices from 2004 to 2008, followed by a major crash from 2008 to 2009 period. This crash was due to the 2008 US supreme crisis. Also, we notice a significant rise in volume for the same period. Post-crisis, the market recovered, and we see a rising trend from 2010 to 2020, which also includes corrections due to events such as the major depreciation of the Indian currency, the announcement of demonetization, the implementation of Goods and Service Tax (GST), COVID-19 pandemic, etc. (Bhatia & Gupta, 2020; Parab et al., 2020; Gupta et al., 2021).

We also noticed a major fall in prices in March 2020 which was due to the outbreak of the COVID-19 pandemic. Also, during this period, we see a significant rise in the number of shares traded in the market. Although from 2010 to 2020, there has been a linear trend in Nifty 50 prices, the volume has remained stable. The spike in volumes during extreme events like US supreme crisis or the COVID-19 pandemic reveals the panic selling behaviour of market participants during such events. However, visibly, Nifty 50 index has recovered well from these events and continued the uptrend.

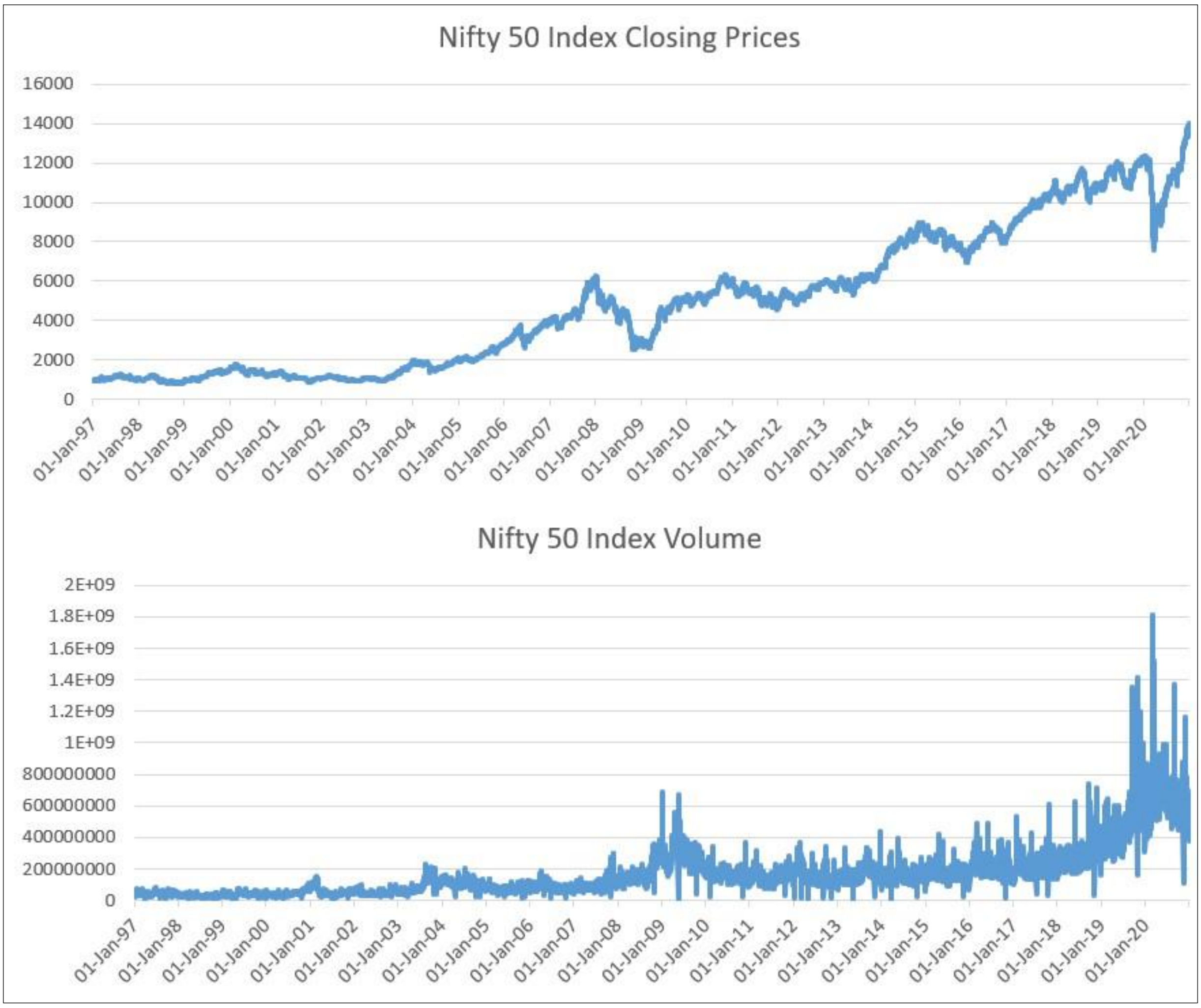

Figure 1: Trends in Nifty 50 Index Closing Prices and Volume

Source: Authors' Compilation

2.2 Trends in Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility

Figure 2 presents the trends in stock index returns, stock index liquidity, and stock index volatility. The purpose of this analysis is to understand the graphical representation of these variables to be used in the study. We can notice that there have been fluctuations in stock index returns over the period of time. However, the data tend to concentrate near the mean to suggest it to be stationary. The liquidity in Figure 2 represents the Amihud Ratio. We can notice the fluctuation in the Ratio to be within the range except for a sharp rise in 2008-2009 on account of the US subprime crisis. This visual representation gives a possibility of an outlier in stock liquidity data. Finally, the volatility also depicts fluctuations for the period, and such fluctuations appear to be more from 2008 to 2009 and March 2020. Overall, the data appear to be stationary, which will be further tested and confirmed using Unit root testing.

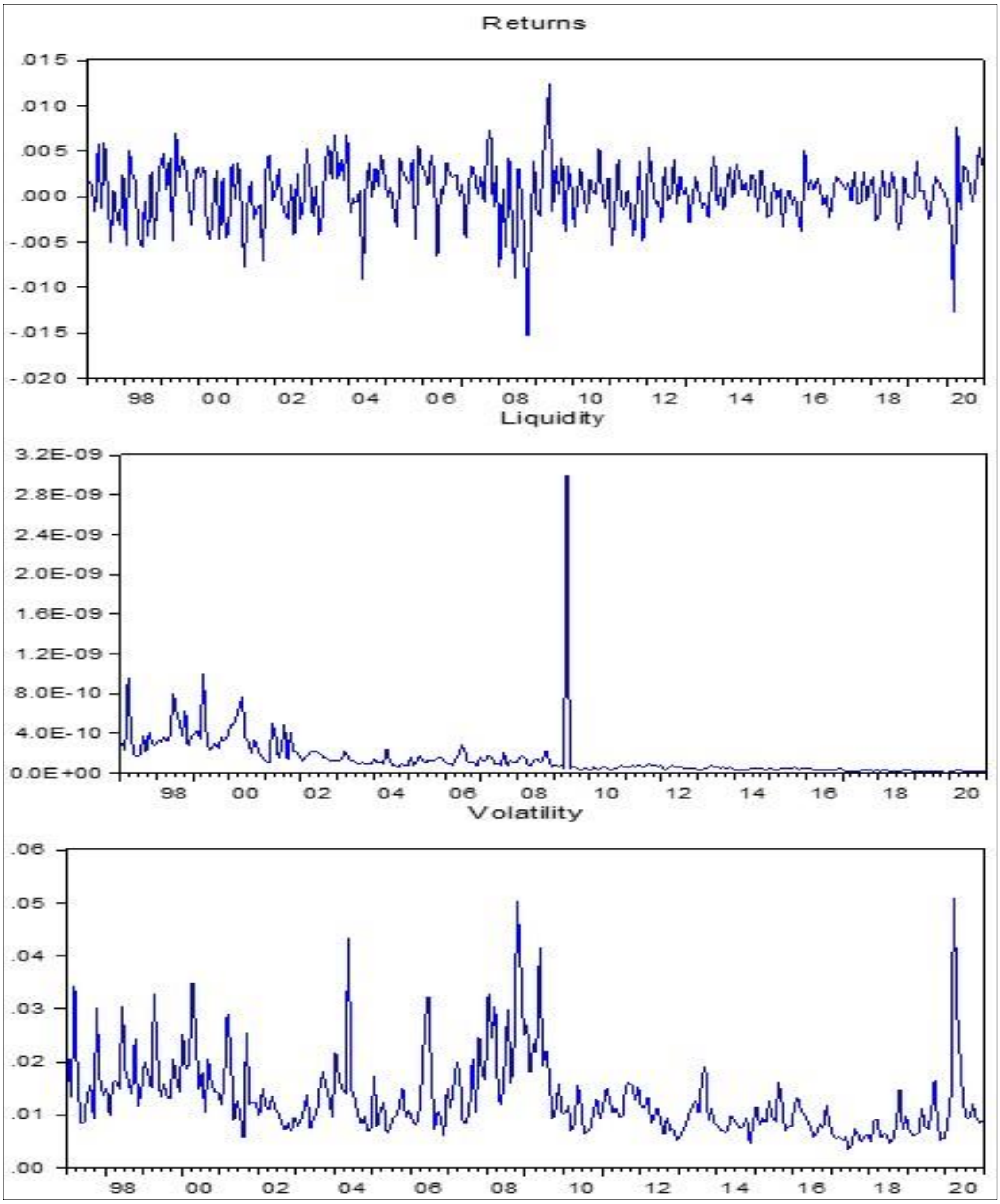

Figure 2: Trends in Nifty 50 Returns, Liquidity, and Volatility

Source: Authors' Compilation

2.3 Summary Statistics

Table 4: Results of Summary Statistics of Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility

Statistic	Stock Index Returns	Stock Index Liquidity	Stock Index Volatility
Mean	0.00044	1.44E-10	0.01319
Median	0.00068	7.69E-11	0.01118
Standard Deviation	0.00333	2.29E-10	0.00748
Skewness	-0.64440	7.51490	2.03749
Kurtosis	5.37324	87.19984	8.48477
Observations	288	288	288
ERS DF-GLS test statistic	-16.02860***	-3.72597***	-9.81271***

Source: Authors' Compilation

Summary statistic results are presented in Table 4 to understand the nature of the data. We notice the average daily return of the Nifty 50 index has been positive, which is also supported by an uptrend in closing prices, as reflected in Figure 1. Also, the Amihud ratio, which represents illiquidity, is low, which shows high liquidity in the Indian stock market. The results of skewness indicate the Nifty index returns to be negatively skewed and the stock index liquidity and stock index volatility to be positively skewed. Also, the data is noticed to be leptokurtic. The results of skewness and kurtosis indicate the data to be not normally distributed. However, for the study, data normality is not a precondition for the analysis used in the study. What is essential is the stationarity of the data, the results of which are presented in Table 5.

2.4 Unit Root Test

Table 5: Results of Unit Root Test of Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility

Statistic	Stock Index Returns	Stock Index Liquidity	Stock Index Volatility
Elliott-Rothenberg-Stock DF-GLS test statistic	-16.02860***	-3.72597***	-9.81271***

Source: Authors' Compilation

Table 5 presents the results of the Elliott-Rothenberg-Stock DF-GLS test. The results indicate the Elliott-Rothenberg-Stock DF-GLS test Statistics in the case of Nifty index returns, Nifty index liquidity, and Nifty index volatility to be less than -3.47 at 1% level of significance, less than -2.91 at 5% level of significance, and less than -2.61 at 10% level of significance, resulting in rejection of null hypothesis at the said level of significances. This indicates the data to be stationary.

2.5 Identification of Outliers

The presence of outliers in the data may hamper the results. The outliers may also result in spurious results. As such, the study identifies the outliers using Box Plot, as highlighted in Figure 3 and neutralizes the significant outliers using the median. The data, after neutralizing the outliers, are considered for further analysis.

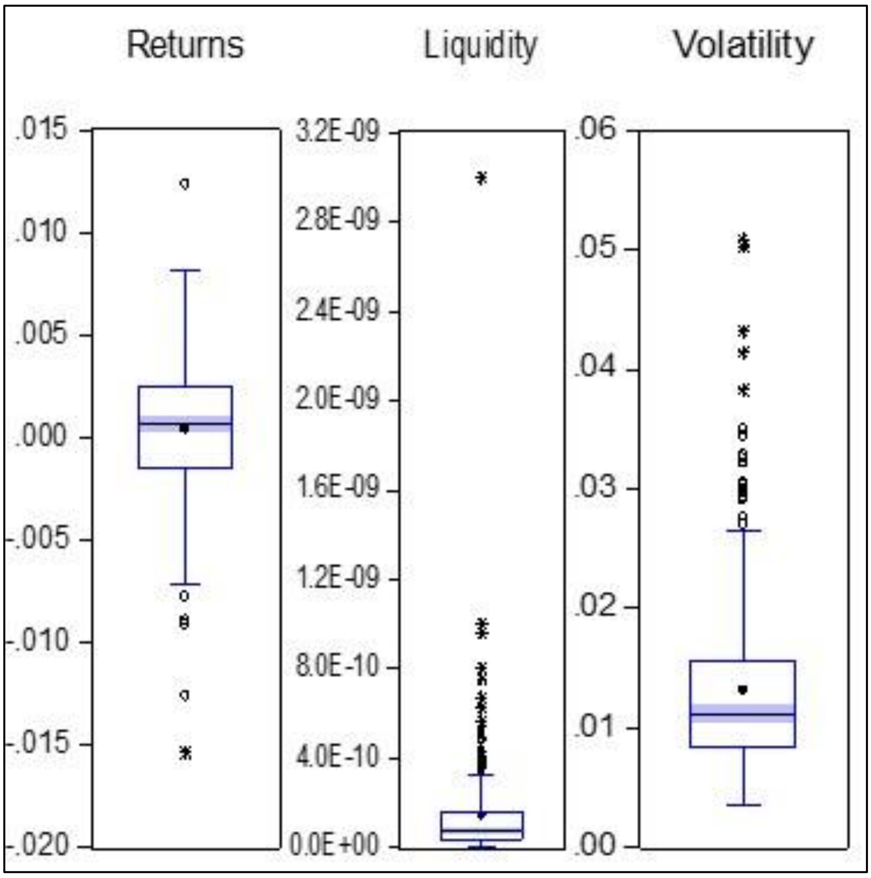

Figure 3: Box Plot of Stock Index Returns, Liquidity and Volatility

Source: Authors' Compilation

2.6 Model Selection

2.6.1 Model selection in the examination of persistence

Table 6: Results of model selection in the examination of persistence

	ARFIMA (p,d,q) Models	AIC	SIC
Yt = LSIR	ARFIMA (0,d,0)	-8.562503*	-8.537066*
Yt = LSIL	ARFIMA (1,d,1)	-43.52573*	-43.47486*
Yt = LSIV	ARFIMA (0,d,0)	-7.306235*	-7.321478*

Source: Authors' Compilation

Note: *indicates the selected models with the lowest AIC and SIC values.

In the case of examination of persistence in stock index returns, stock index liquidity and stock index volatility, the study simulates various ARFIMA(p,d,q) models. The models are rejected if the AR or MA polynomials are insignificant or the residuals of such models indicate the presence of serial correlation. Table 6 presents those models which fulfil the criteria of significant AR or MA polynomials and residuals that are white noise. The best model is selected per AIC and SIC criteria.

2.6.2 Model selection in the examination of persistence and interdependencies

Table 7: Results of model selection in the examination of persistence and interdependencies

	ARFIMA (p,d,q) Models	AIC	SIC
Yt = LSIR X1 = LSIL X2 = LSIV	ARFIMA (0,d,0)	-8.687385*	-8.63651*
Yt = ΔLSIL X1 = LSIR X2 = ΔLSIV	ARFIMA (1,d,1)	-43.82403*	-43.74771*
Yt = ΔLSIV X1 = LSIR X2 = ΔLSIL	ARFIMA (0,d,0)	-7.743073*	-7.692199*

Source: Authors' Compilation

Note: *indicates the selected models with the lowest AIC and SIC values.

In the case of examination of persistence in stock index returns, stock index liquidity and stock index volatility considering the effect of interdependencies among stock index returns, stock index liquidity and stock index volatility, the study simulates various ARFIMA(p,d,q) models. The models are rejected if the AR or MA polynomials are insignificant or the residuals of such models indicate the presence of serial correlation. Table 7 highlights those models which fulfil the criteria of significant AR or MA polynomials and residuals that are white noise. The best model is selected per AIC and SIC criteria.

2.7 ARFIMA Models

Table 8: Results of ARFIMA models

Y	Model	Coefficient	Standard Error	t-Statistic	P-value
Stock Index Returns	ARFIMA (0,d,0)	-0.0010	0.0484	-0.0196	0.9843
Stock Index Liquidity	ARFIMA (1,d,1)	0.2001	0.1567	1.2771	0.2026
Stock Index Volatility	ARFIMA (0,d,0)	0.3914	0.0454	8.6197	0.0000***

Source: Authors' Compilation

Note: ***1% level of significance

Table 8 reflects the results of ARFIMA (p,d,q) models utilized in the examination of long memory in Stock Index Returns, Stock Index Liquidity, and Stock Index Volatility. In the case of Stock Index returns, the t-statistic and corresponding p-value indicate the fractional differencing parameter 'd' to be insignificant. Also, similar results are noticed in the case of Stock Liquidity.

However, in the case of Stock Volatility, the study noticed the fractional differencing parameter 'd' to be significant at 1% level of significance. The value of 'd' in the case of Stock Index Volatility is 0.3914, which is in the range of 0 to 0.5, thus revealing the presence of long memory. In other words, the evidence of long-range dependence in Indian stock market volatility. The above-developed ARFIMA(p,d,q) models do not consider the effects of interdependencies among the variables. Hence the study developed the ARFIMA(p,d,q) models considering the effects of interdependencies. The results of such ARFIMA(p,d,q) models are presented in Table 9.

2.8 ARFIMA Models with Effect of Interdependencies

Table 9: Results of ARFIMA models with effect of interdependencies

Variables	Model	Coefficient	Standard Error	t-Statistic	P-value
Yt = Stock Index Returns X1 = Stock Index Liquidity X2 = Stock Index Volatility	ARFIMA (0,d,0)	0.0929	0.0458	2.0270	0.0436**
Yt = Stock Index Liquidity X1 = Stock Index Returns X2 = Stock Index Volatility	ARFIMA (1,d,1)	0.1755	0.1892	0.9279	0.3543
Yt = Stock Index Volatility X1 = Stock Index Returns X2 = Stock Index Liquidity	ARFIMA (0,d,0)	0.4556	0.0469	9.7187	0.0000***

Source: Authors' Compilation

Note: **5% level of significance, and ***1% level of significance

We notice similar results of ARFIMA (p,d,q) models with the inclusion of the regressors in the case of Stock Index Liquidity and Stock Index Volatility. In the case of Stock Index Liquidity, the t-statistic and corresponding p-value indicate the fractional differencing parameter 'd' to be insignificant. However, the fractional differencing parameter 'd' in the case of Stock Index Volatility is 0.4556, which is significant at 1% level of significance. It indicates the presence of long-range persistence.

Thus it is evident that the inclusion of regressors in ARFIMA (p,d,q) models pertaining to Stock Index Liquidity and Stock Index Volatility does not provide contrasting results. The juxtaposition of the fractional differencing parameter in the case of Stock Index Volatility indicates the strong presence of long memory in models which consider the effect of interdependencies. Further, the study noticed the fractionally integrated parameter 'd' in the case of Stock Index Returns is 0.0929, which is significant at 5% level of significance, thus indicating the presence of long-range persistence. Thus, it is evident that the interdependencies among the variables do affect the behaviour of long memory.

2.9 Model Forecasting and Evaluation

Table 10, Table 11, and Table 12 highlight the results of ARFIMA (p,d,q) models forecasting and evaluation. The various statistics used to examine the forecasting accuracy of the developed ARFIMA (p,d,q) models include Root Mean Squared Error, Theil Inequality Coefficient, and Bias Proportion. The results are presented for 3 months forecast, 6 months forecast, 9 months forecast, and 12 months forecast period. The study noticed the Root Mean Squared Error in the case of developed ARFIMA (p,d,q) models to be close to 0.

Further, the Theil Inequality Coefficient is noticed to be less than 1. This indicates that the forecasting errors in the case of the developed ARFIMA (p,d,q) models are significantly low. The study also noticed that these forecasting errors tend to get further reduced when models incorporate the effect of interdependencies among variables. Thus, it is evident that consideration of the effect of interdependencies improves the forecasting ability of the models.

Table 10: Results showing forecasting accuracy of models relating to Stock Index Returns

		Without Interdependencies				With Interdependencies			
	Forecasts	Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion	Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion
Stock Index Returns	3 Months Forecast	ARFIMA (0,d,0)	0.0034	0.8016	0.7976	ARFIMA (0,d,0)	0.0027	0.5492	0.7193
	6 Months Forecast	ARFIMA (0,d,0)	0.0027	0.7766	0.5205	ARFIMA (0,d,0)	0.0021	0.5051	0.3451
	9 Months Forecast	ARFIMA (0,d,0)	0.0034	0.8217	0.4045	ARFIMA (0,d,0)	0.0042	0.8222	0.3807
	12 Months Forecast	ARFIMA (0,d,0)	0.0049	0.9122	0.0010	ARFIMA (0,d,0)	0.0040	0.5686	0.0328

Source: Authors' Compilation

Table 11: Results showing forecasting accuracy of models relating to Stock Index Liquidity

	Forecasts	Without Interdependencies				With Interdependencies			
		Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion	Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion
Stock Index Liquidity	3 Months Forecast	ARFIMA (1,d,1)	4.55E-11	0.6250	0.9820	ARFIMA (1,d,1)	7.38E-12	0.2273	0.3558
	6 Months Forecast	ARFIMA (1,d,1)	5.83E-11	0.6894	0.9734	ARFIMA (1,d,1)	1.43E-11	0.4821	0.0936
	9 Months Forecast	ARFIMA (1,d,1)	6.47E-11	0.6681	0.9203	ARFIMA (1,d,1)	2.78E-11	0.4632	0.3004
	12 Months Forecast	ARFIMA (1,d,1)	6.56E-11	0.6422	0.8793	ARFIMA (1,d,1)	1.17E-10	0.7427	0.6294

Source: Authors' Compilation

Table 12: Results showing forecasting accuracy of models relating to Stock Index Volatility

	Forecasts	Without Interdependencies				With Interdependencies			
		Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion	Model	Root Mean Squared Error	Theil Inequality Coefficient	Bias Proportion
Stock Index Volatility	3 Months Forecast	ARFIMA (0,d,0)	0.0036	0.1641	0.9797	ARFIMA (0,d,0)	0.0013	0.0657	0.9319
	6 Months Forecast	ARFIMA (0,d,0)	0.0052	0.2132	0.9635	ARFIMA (0,d,0)	0.0038	0.1631	0.9548
	9 Months Forecast	ARFIMA (0,d,0)	0.0059	0.1766	0.6406	ARFIMA (0,d,0)	0.0047	0.1512	0.2922
	12 Months Forecast	ARFIMA (0,d,0)	0.0141	0.4781	0.2363	ARFIMA (0,d,0)	0.0133	0.4660	0.3798

Source: Authors’ Compilation

2.10 Comparison of Forecasted Values with Actual Values

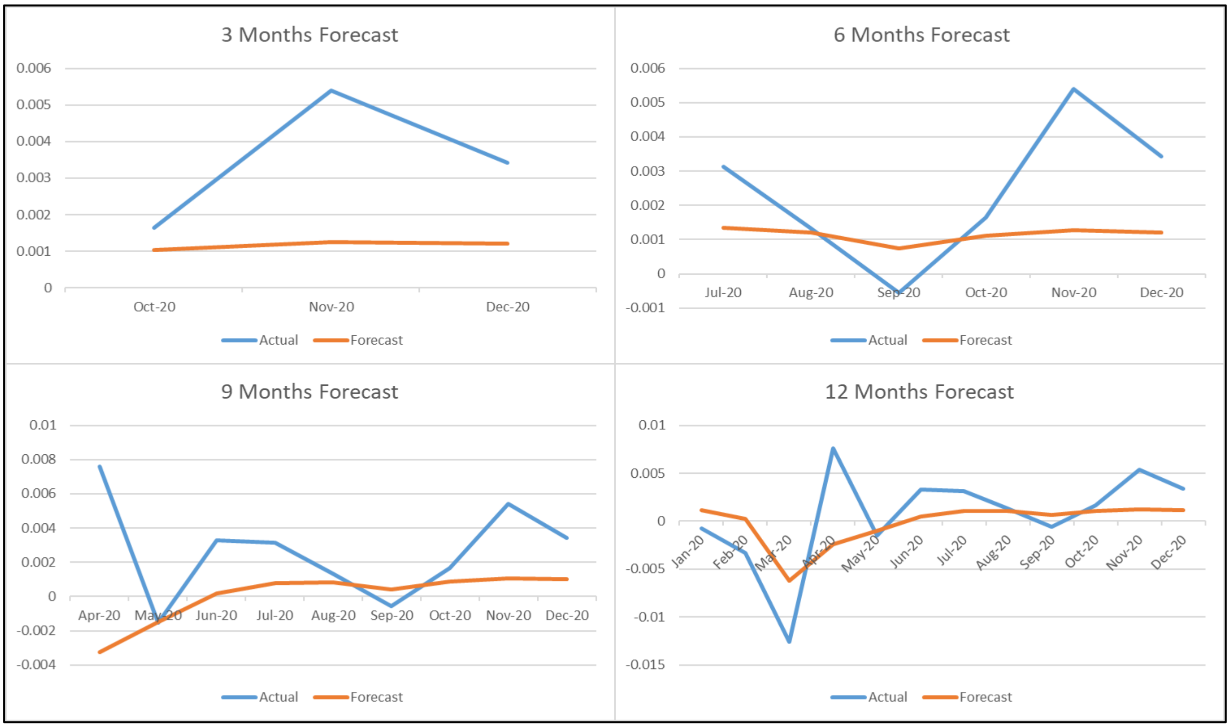

Figure 4: Comparison of Forecasted Stock Index Returns with Actual Stock Index Returns

Source: Authors' Compilation

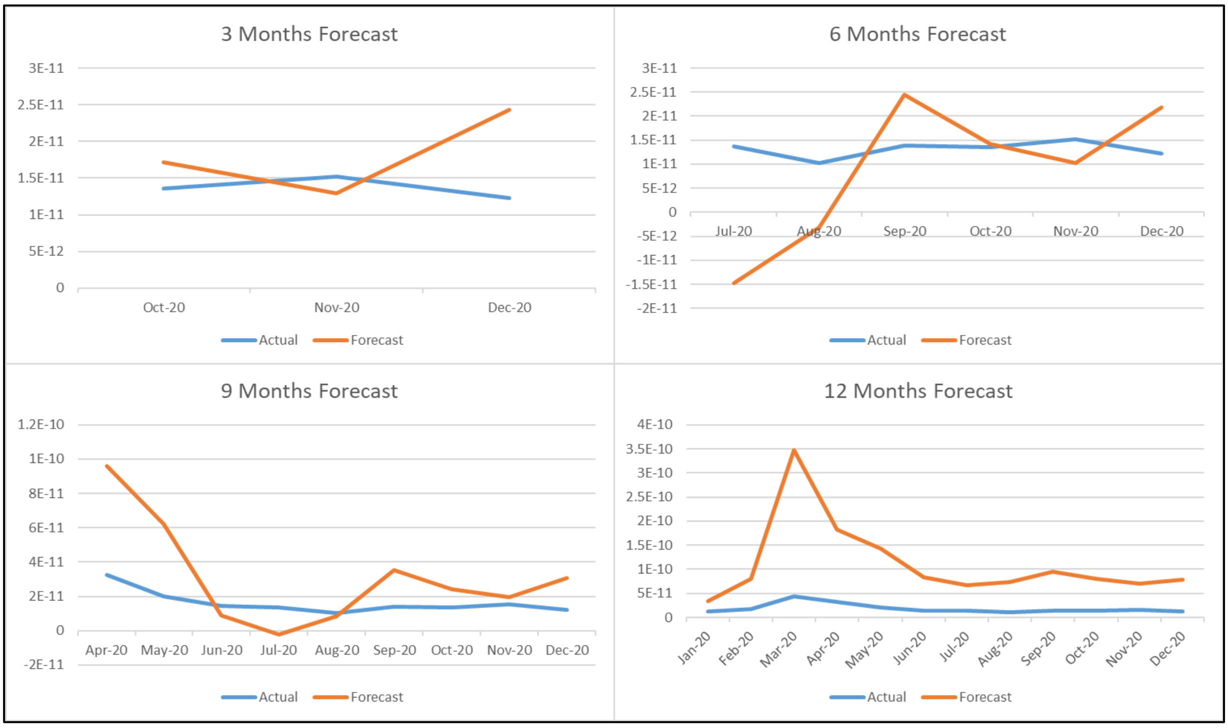

Figure 5: Comparison of Forecasted Stock Index Liquidity with Actual Stock Index Liquidity

Source: Authors' Compilation

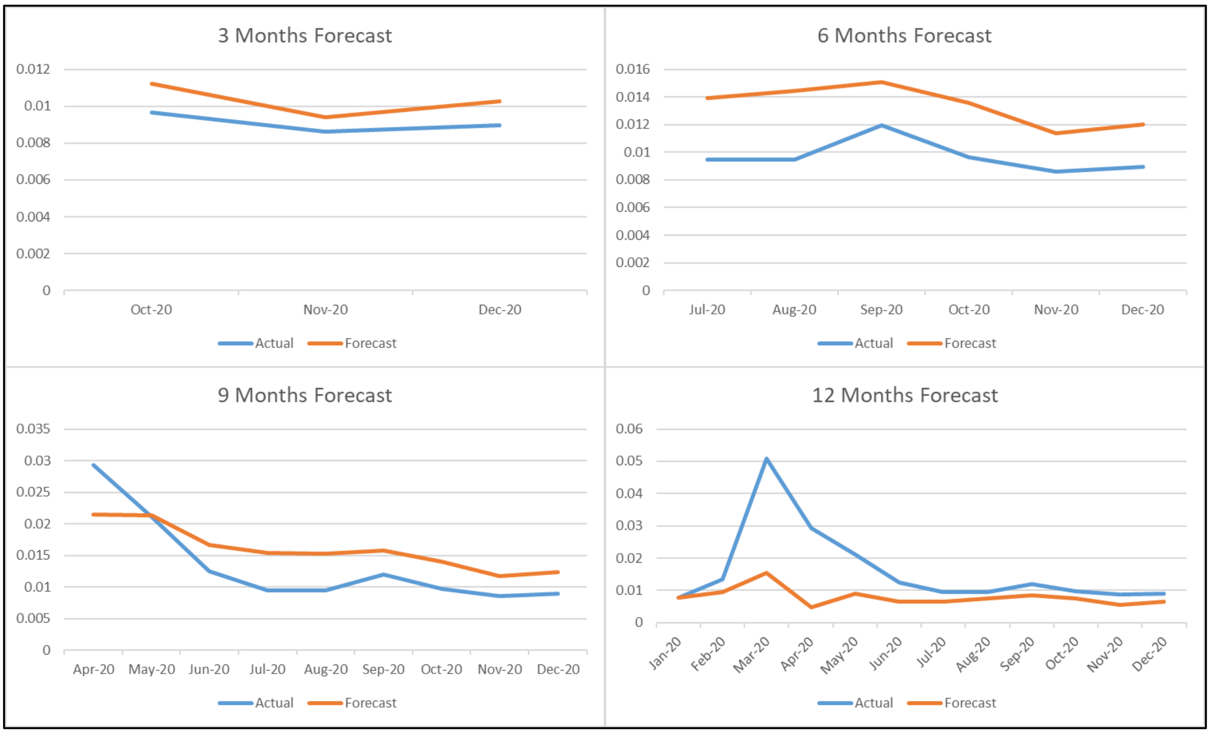

Figure 6: Comparison of Forecasted Stock Index Volatility with Actual Stock Index Volatility

Source: Authors' Compilation

Figure 4, Figure 5, and Figure 6 depict the results of actual values and forecasted values derived using the developed ARFIMA (p,d,q) models. The results are presented for 3 months forecast, 6 months forecast, 9 months forecast, and 12 months forecast period. The results indicate fewer deviations in actual and predicted values, thus further confirming the forecasting accuracy of the developed ARFIMA (p,d,q) models.

2.11 Model Diagnostics

Table 13 presents the results of the Breusch-Godfrey Serial Correlation LM Test results. The study noticed the p-values obtained using the Breusch-Godfrey Serial Correlation LM Test in case of the developed ARFIMA(p,d,q) models is more than 0.01, 0.05, and 0.10 at 1% level of significance, 5% level of significance and 10% level of significance. Thus the results indicate the developed ARFIMA(p,d,q) models to be white noise.

Table 13: Results of Serial Correlation LM Test of the ARFIMA Models

	Without Interdependencies			With Interdependencies		
	Model	F-statistic	P-value	Model	F-statistic	P-value
Stock Index Returns	ARFIMA (0,d,0)	0.2977	0.5857	ARFIMA (0,d,0)	1.1831	0.2777
Stock Index Liquidity	ARFIMA (1,d,1)	0.7032	0.4024	ARFIMA (1,d,1)	0.1801	0.6716
Stock Index Volatility	ARFIMA (0,d,0)	1.4479	0.2299	ARFIMA (0,d,0)	1.7630	0.1853

Source: Authors' Compilation

Chapter 3

Long Memory and Sectoral Juxtaposition

This chapter presents the results relating to the examination of long memory in sectoral indices returns and investigating the role of frequency of sectoral indices returns in long memory behaviour. Firstly, the chapter highlights the trends in sectoral indices prices and returns and provides an overview of summary statistics, unit root test, and identification of structural breaks. Further, the chapter focuses on model selection using AIC and SIC. The results of ARFIMA are presented to support the examination of long memory in sectoral indices returns. Finally, the chapter presents the model diagnostics.

3.1 Trends in Prices and Returns of Sectoral Indices

The trends in sectoral indices closing prices and log returns are presented in Figure 7 and Figure 8. We can notice a rising trend in the case of the sectoral indices since their inception, except in the case of the Nifty Realty index and Nifty Metal index. In the case of such indices, we notice the fluctuations to be higher than the other indices. The trend in the Nifty Realty index was severely affected due to the 2008 US subprime crisis. And the significant price fall in the case of the Nifty Metal index was due to the major depreciation of the Indian Rupee in 2013, the meltdown of the Chinese stock market in 2015, and the Brexit Referendum in 2016.

The sectoral indices also witnessed price correction during these periods. Also, we notice a price fall in March 2020 in all sectoral indices, resulting from the COVID-19 crisis. For analysis of the study, we consider the log returns of these indices to eliminate the effect of trends and unit root. As indicated in Figure 8, we notice the fluctuations in sectoral indices returns. However, the mean-variance and covariance of these data appear to be stable over time, indicating the data to be stationary by visual observation. We confirm this using Summary Statistics as reflected in Table 14, Table 15, and Table 16.

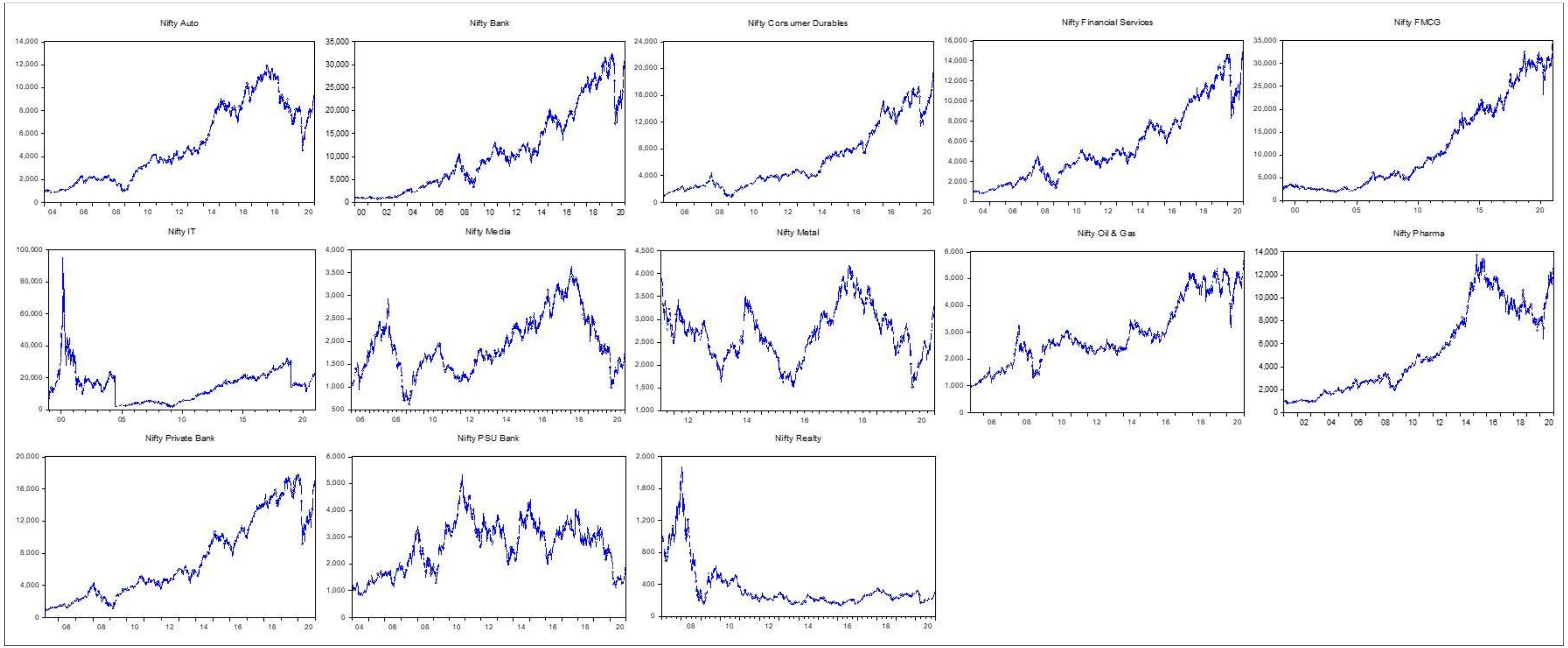

Figure 7: Trends in Sectoral Indices Prices

Source: Authors' Compilation

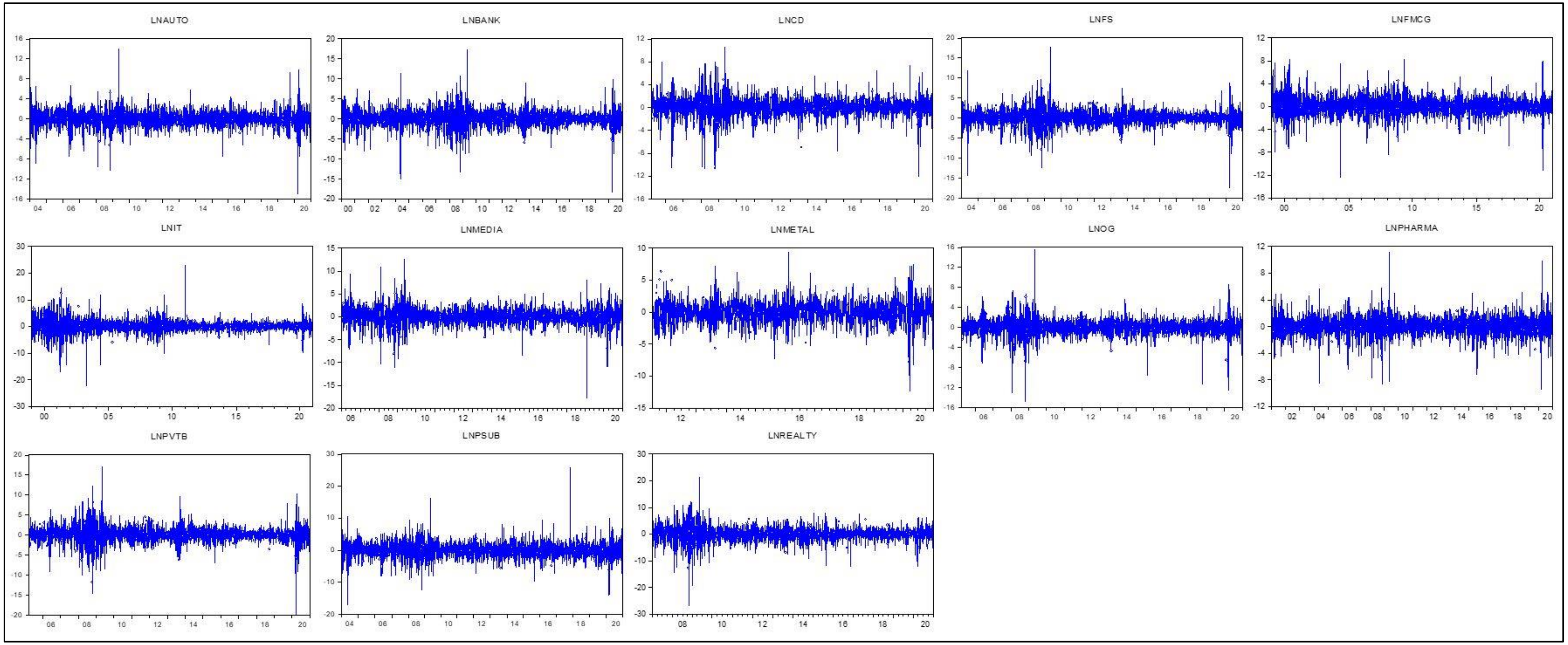

Figure 8: Trends in Sectoral Indices Returns

Source: Authors' Compilation

3.2 Summary Statistics

We notice the average daily returns generated by the Nifty IT index to be the highest, followed by the Nifty Consumer Durable index and Nifty Private Bank index, which is 0.079, 0.077, and 0.073, respectively, as indicated in Table 14. The average monthly return was highest in the Nifty Consumer Durable index, Nifty Private Bank index, and Nifty IT index, as reflected in Table 15. And for the quarterly return series, Nifty Private Bank Index, Nifty Consumer Durable Index, and Nifty Bank index returns were higher than other indices, as shown in Table 16.

Although we notice the returns of the Nifty FS Index to be higher as compared to the Nifty PSU Bank index returns, the Nifty Private Bank index returns have been higher than both of these indices. This phenomenon was driven mainly by the HDFC bank stock. Also, this signifies the growth potential of the private banking sector. The returns generated by the Nifty Metal index and Nifty Realty index were noticed to be negative for daily, monthly, and quarterly return series, which indicates the failure in the recovery of these indices.

Table 14: Summary Statistics of Daily Return Series

	Mean	Standard Deviation	Skewness	Kurtosis	Observations
LNAUTO	0.05257	1.53775	-0.34406	10.37839	4220
LNBANK	0.06589	1.89786	-0.32461	10.23836	5225
LNCD	0.07668	1.60908	-0.59487	10.04807	3903
LNFS	0.06433	1.84528	-0.32537	11.75422	4220
LNFMCG	0.04853	1.38716	-0.19955	9.14379	5478
LNIT	0.07946	2.18988	-0.21331	12.91892	5474
LNMEDIA	0.01345	1.79174	-0.52991	9.87481	3718
LNMETAL	-0.00656	1.77004	-0.27219	6.05387	2347
LNOG	0.04378	1.58847	-0.60816	13.63861	3904
LNPHARMA	0.05145	1.30123	-0.31041	8.47880	4973
LNPVTB	0.07289	1.93044	-0.32523	11.83486	3907
LNPSUB	0.01333	2.25172	0.17308	10.99494	4210
LNREALTY	-0.03342	2.66979	-0.51728	10.38605	3468

Source: Authors' Compilation

Table 15: Summary Statistics of Monthly Return Series

	Mean	Standard Deviation	Skewness	Kurtosis	Observations
LNAUTOM	1.08725	6.49419	-0.99452	5.95256	203
LNBANKM	1.33533	7.45948	-0.42633	4.85585	251
LNCDM	1.54819	7.96379	-1.21507	7.99113	188
LNFSM	1.30275	7.23295	-0.54831	5.41478	203
LNFMCGM	0.98143	4.85442	-0.54328	3.88327	263
LNITM	1.45845	9.64838	-0.35197	9.84193	263
LNMEDIAM	0.27393	7.96441	-1.14722	7.38764	180
LNMETALM	-0.17436	7.70515	-0.45958	5.48373	113
LNOGM	0.91844	6.32875	-0.95618	7.39171	188
LNPHARMAM	1.06850	5.33540	-0.38261	5.16911	239
LNPVTBM	1.51352	7.84589	-0.48364	6.49829	188
LNPSUBM	0.22305	9.39767	-0.28901	3.66526	203
LNREALTYM	-0.72974	12.03601	-0.54052	5.77240	168

Source: Authors' Compilation

Table 16: Summary Statistics of Quarterly Return Series

	Mean	Standard Deviation	Skewness	Kurtosis	Observations
LNAUTOQ	3.17066	12.09473	0.21852	4.49498	67
LNBANKQ	3.88256	12.72748	-0.16290	3.54823	83
LNCDQ	4.34917	14.40152	-1.29646	8.33387	62
LNFSQ	3.83789	12.71847	-0.15273	4.02610	67
LNFMCGQ	2.78135	7.59262	-0.24452	2.87511	87
LNITQ	2.35971	16.27114	-0.70686	4.82773	87
LNMEDIAQ	0.71390	13.93270	-0.94267	5.53820	60
LNMETALQ	-0.59806	13.05179	0.14721	2.23740	37
LNOGQ	2.63586	10.60026	0.23361	7.14557	62
LNPHARMAQ	3.18808	8.95568	-0.13767	4.69523	79
LNPVTBQ	4.38105	13.91485	-0.21109	4.70903	62
LNPSUBQ	0.47837	15.36550	-0.18395	3.64079	67
LNREALTYQ	-2.45075	22.16393	-0.47891	5.44771	56

Source: Authors' Compilation

The standard deviation, which reflects the variation in returns of these sectoral indices, was highest in the Nifty Realty index for daily, monthly, and quarterly return series, as reflected in Table 14, Table 15 and Table 16. The results indicate negative skewness and leptokurtic nature of the distribution in the majority of the sectoral indices. The results of skewness and kurtosis together indicate the data to be not normally distributed. This is supported by the past literature, which shows that the Indian stock market data are not normally distributed (Kumar & Maheswaran, 2013). Also, the normality of data is not a necessary precondition for the analysis of the study. More critical is the stationarity of data revealed by ERS DF-GLS test statistic and KPSS test statistic in Table 17, Table 18, and Table 19.

3.3 Unit Root Test

Table 17, Table 18 and Table 19 present the results of the Elliott-Rothenberg-Stock DF-GLS test and KPSS test for the daily return series, monthly return series, and quarterly return series. The results indicate the data to be stationary.

Table 17: Unit Root Test of Daily Return Series

	ERS DF-GLS test statistic	KPSS test statistic
LNAUTO	-59.25509	0.12568
LNBANK	-50.49911	0.06732
LNCD	-55.17884	0.04692
LNFS	-45.79283	0.03497
LNFMCG	-72.64620	0.08604
LNIT	-67.92201	0.06054
LNMEDIA	-56.33062	0.14734
LNMETAL	-48.18311	0.14527
LNOG	-59.47653	0.05591
LNPHARMA	-65.83236	0.07480
LNPVTB	-56.23829	0.07299
LNPSUB	-59.00944	0.21008
LNREALTY	-53.18107	0.16144

Source: Authors’ Compilation

Note: The critical values for ERS DF-GLS test are -2.574, -1.94, and -1.616 at 1%, 5%, and 10% level of significance respectively. The critical values for KPSS test are 0.739, 0.463, and 0.347 at 1%, 5%, and 10% level of significance.

Table 18: Unit Root Test of Monthly Return Series

	ERS DF-GLS test statistic	KPSS test statistic
LNAUTOM	-8.50470	0.10144
LNBANKM	-5.32341	0.07491
LNCDM	-2.24917	0.03796
LNFSM	-9.01109	0.03646
LNFMCGM	-1.81914	0.13627
LNITM	-0.79203	0.04125
LNMEDIAM	-8.50179	0.11271
LNMETALM	-3.85246	0.14614
LNOGM	-10.07141	0.07091
LNPHARMAM	-11.89645	0.09947
LNPVTBM	-9.96878	0.08154
LNPSUBM	-9.90697	0.20769
LNREALTYM	-5.88879	0.13302

Source: Authors' Compilation

Note: The critical values for ERS DF-GLS test are -2.574, -1.94, and -1.616 at 1%, 5%, and 10% level of significance respectively. The critical values for KPSS test are 0.739, 0.463, and 0.347 at 1%, 5%, and 10% level of significance.

Table 19: Unit Root Test of Quarterly Return Series

	ERS DF-GLS test statistic	KPSS test statistic
LNAUTOQ	-5.02730	0.12154
LNBANKQ	-6.48807	0.09802
LNCDQ	-3.55607	0.04947
LNFSQ	-5.84986	0.06518
LNFMCGQ	-5.36269	0.17494
LNITQ	-4.13941	0.19621

LNMEDIAQ	-4.41894	0.11731
LNMETALQ	-4.11684	0.08914
LNOGQ	-2.82322	0.11616
LNPHARMAQ	-3.96785	0.15096
LNPVTBQ	-4.53285	0.10409
LNPSUBQ	-6.83609	0.37035
LNREALTYQ	-5.06730	0.28368

Source: Authors' Compilation

Note: The critical values for ERS DF-GLS test are -2.574, -1.94, and -1.616 at 1%, 5%, and 10% level of significance respectively. The critical values for KPSS test are 0.739, 0.463, and 0.347 at 1%, 5%, and 10% level of significance.

3.4 Identification of Structural Breaks

Table 20: Results of Bai-Perron Multiple Breakpoint Test for Daily Return Series

	Sequential F-statistic determined breaks	Break Test	F-statistic
LNAUTO	0	0 vs. 1	2.471
LNBANK	0	0 vs. 1	2.416
LNCD	0	0 vs. 1	5.636
LNFS	0	0 vs. 1	2.835
LNFMCG	0	0 vs. 1	2.764
LNIT	0	0 vs. 1	1.164
LNMEDIA	0	0 vs. 1	3.428
LNMETAL	0	0 vs. 1	5.595
LNOG	0	0 vs. 1	5.652
LNPHARMA	0	0 vs. 1	3.401
LNPVTB	0	0 vs. 1	5.306
LNPSUB	0	0 vs. 1	3.919
LNREALTY	0	0 vs. 1	3.929

Source: Authors' Compilation

Note: Critical value for the Bai-Perron Multiple Breakpoint Test at 5% level of significance is 8.58.

The results of structural breaks obtained using the Bai-Perron Multiple Breakpoint Test (Bai, 1997; Bai & Perron, 1998; Bai & Perron, 2003) are depicted in Table 20, Table 21, and Table 22. For the daily return series, the study notice the F-statistic to be less than the Critical Value at 5% level of significance, which results in non-rejection of the null hypothesis (H0: No Structural Break). Thus, it is evident that there are no structural breaks present in the daily frequency data utilized for analysis in the present study.

Table 21: Results of Bai-Perron Multiple Breakpoint Test for Monthly Return Series

	Sequential F-statistic determined breaks	Break Test	F-statistic
LNAUTO	0	0 vs. 1	2.492474
LNBANK	0	0 vs. 1	2.799492
LNCD	0	0 vs. 1	4.183734
LNFS	0	0 vs. 1	3.346498
LNFMCG	0	0 vs. 1	5.570403
LNIT	0	0 vs. 1	1.718954
LNMEDIA	0	0 vs. 1	3.697921
LNMETAL	0	0 vs. 1	5.608179
LNOG	0	0 vs. 1	5.465352
LNPHARMA	0	0 vs. 1	4.072441
LNPVTB	0	0 vs. 1	6.34079
LNPSUB	0	0 vs. 1	4.06847
LNREALTY	0	0 vs. 1	3.521674

Source: Authors' Compilation

Note: Critical value for the Bai-Perron Multiple Breakpoint Test at 5% level of significance is 8.58.

For the monthly return series, the study found the F-statistic to be less than the Critical Value at 5% level of significance, which results in non-rejection of the null hypothesis (H0: No Structural Break). Thus, it is evident that there are no structural breaks present in the monthly frequency data utilized for analysis in the present study.

Table 22: Results of Bai-Perron Multiple Breakpoint Test for Quarterly Return Series

	Sequential F-statistic determined breaks	Break Test	F-statistic
LNAUTO	0	0 vs. 1	2.929796
LNBANK	0	0 vs. 1	2.723327
LNCD	0	0 vs. 1	1.499727
LNFS	0	0 vs. 1	3.456068
LNFMCG	0	0 vs. 1	7.928321
LNIT	0	0 vs. 1	5.74252
LNMEDIA	0	0 vs. 1	5.352267
LNMETAL	0	0 vs. 1	4.214768
LNOG	0	0 vs. 1	5.935091
LNPHARMA	0	0 vs. 1	5.351311
LNPVTB	0	0 vs. 1	7.471247
LNPSUB	0	0 vs. 1	5.065709
LNREALTY	0	0 vs. 1	2.60755

Source: Authors' Compilation

Note: Critical value for the Bai-Perron Multiple Breakpoint Test at 5% level of significance is 8.58.

For the quarterly return series, the study noticed the F-statistic to be less than Critical Value at 5% level of significance, which results in non-rejection of the null hypothesis (H0: No Structural Break). Thus, it is evident that there are no structural breaks present in the data utilized for analysis in the present study.

The results in Table 20, Table 21, and Table 22 are justified as we consider the log returns of sectoral indices instead of the original closing prices. The log returns that signify the daily percentage changes in data eliminate the trends to a maximum extent, making the data stationary.

3.5 Model Selection

Table 23: Selection of Models in case of Daily Return Series

Indices	Model	AIC	SIC
LNAUTO	ARFIMA(0,d,1)	3.69138*	3.69589*
	ARFIMA(1,d,0)	3.69145	3.69596
LNBANK	ARFIMA(0,d,1)	4.10725*	4.11102*
LNCD	ARFIMA(0,d,1)	3.77316	3.77798
	ARFIMA(1,d,0)	3.77320	3.77802
	ARFIMA(1,d,1)	3.77127*	3.77770*
LNFS	ARFIMA(0,d,1)	4.05150	4.05601
	ARFIMA(1,d,1)	4.05137*	4.05347*
LNFMCG	ARFIMA(0,d,1)	3.49216*	3.49578*
LNFMCG	ARFIMA(1,d,0)	3.49218	3.49580
LNIT	ARFIMA(0,d,1)	4.39899*	4.40260*
	ARFIMA(1,d,0)	4.39900	4.40262
LNMEDIA	ARFIMA(0,d,0)	3.99876*	4.00210*
LNMETAL	ARFIMA(0,d,1)	3.97923	3.98660
	ARFIMA(1,d,0)	3.97914*	3.98651*
LNOG	ARFIMA(0,d,0)	3.76256	3.76577*
	ARFIMA(1,d,0)	3.76236*	3.76718
LNPHARMA	ARFIMA(0,d,1)	3.36073	3.36466
	ARFIMA(1,d,0)	3.36059	3.36321*
	ARFIMA(1,d,1)	3.36039*	3.36432
LNPVTB	ARFIMA(0,d,1)	4.14307*	4.14788
	ARFIMA(1,d,0)	4.14355	4.14836
LNPSUB	ARFIMA(0,d,1)	4.45330*	4.45782*
	ARFIMA(1,d,0)	4.45340	4.45792
LNREALTY	ARFIMA(0,d,1)	4.79196	4.79729
	ARFIMA(1,d,0)	4.79195*	4.79727*

Source: Authors' Compilation.

Note: *Indicates the selected models with the lowest AIC and SIC values.

Table 24: Selection of Models in case of Monthly Return Series

Indices	Model	AIC	SIC
LNAUTO	ARFIMA(0,d,1)	6.41877*	6.46773*
	ARFIMA(1,d,0)	6.44197	6.49093
LNBANK	ARFIMA(0,d,1)	6.71784*	6.75998*
LNCD	ARFIMA(0,d,1)	6.82969	6.88133
	ARFIMA(1,d,1)	6.80970*	6.87856*
LNFS	ARFIMA(0,d,1)	6.61683	6.66580
	ARFIMA(1,d,1)	6.59455*	6.65984*
LNFMCG	ARFIMA(0,d,1)	5.98896*	6.02970*
	ARFIMA(1,d,0)	5.99250	6.03325
	ARFIMA(1,d,1)	5.99161	6.04594
LNIT	ARFIMA(0,d,1)	7.29142	7.33216
	ARFIMA(1,d,1)	7.27626*	7.33059*
LNMEDIA	ARFIMA(0,d,1)	6.89456*	6.94778*
	ARFIMA(1,d,0)	6.91327	6.96648
LNMETAL	ARFIMA(0,d,1)	6.84257	6.91498
	ARFIMA(1,d,0)	6.84046	6.91287*
	ARFIMA(1,d,1)	6.83691*	6.93345
LNOG	ARFIMA(0,d,1)	6.43340	6.48505*
	ARFIMA(1,d,1)	6.42662*	6.49548
LNPHARMA	ARFIMA(0,d,1)	6.16594	6.20958
	ARFIMA(1,d,0)	6.16588*	6.20951*
LNPVTB	ARFIMA(0,d,1)	6.76022	6.81187*
	ARFIMA(1,d,1)	6.74389*	6.81276
LNPSUB	ARFIMA(0,d,1)	7.15627*	7.20523*
LNREALTY	ARFIMA(0,d,1)	7.67205*	7.72784*
	ARFIMA(1,d,0)	7.70769	7.76347

Source: Authors’ Compilation

Note: *Indicates the selected models with the lowest AIC and SIC values.

Table 25: Selection of Models in case of Quarterly Return Series

Indices	Model	AIC	SIC
LNAUTO	ARFIMA(0,d,1)	7.66029*	7.75901*
	ARFIMA(1,d,1)	7.66878	7.80040
LNBANK	ARFIMA(0,d,1)	7.90311*	7.99054*
	ARFIMA(1,d,1)	7.91584	8.03241
LNCD	ARFIMA(0,d,1)	7.94781	8.05073
	ARFIMA(1,d,1)	7.91043*	8.04766*
LNFS	ARFIMA(0,d,1)	7.83415*	7.93286*
LNFMCG	ARFIMA(0,d,0)	6.89808	6.95477*
	ARFIMA(1,d,0)	6.88825*	6.97328
LNIT	ARFIMA(0,d,1)	8.23170*	8.31673*
LNMEDIA	ARFIMA(0,d,1)	7.98242*	8.08713*
LNMETAL	ARFIMA(0,d,0)	8.05151	8.13859*
	ARFIMA(0,d,1)	8.05134*	8.18195
LNOG	ARFIMA(0,d,1)	7.51805*	7.62097*
	ARFIMA(1,d,1)	7.53272	7.66996
LNPHARMA	ARFIMA(0,d,1)	7.19515	7.28513
	ARFIMA(1,d,0)	7.18142*	7.27140*
LNPVTB	ARFIMA(0,d,1)	8.02755*	8.13047*
LNPSUB	ARFIMA(0,d,0)	8.34223*	8.40804*
LNREALTY	ARFIMA(0,d,1)	8.83765*	8.94615*

Source: Authors' Compilation

Note: *Indicates the selected models with the lowest AIC and SIC values.

We select the Autoregressive Fractionally Integrated Moving Average (ARFIMA) models using Akaike Information Criterion (Akaike, 1973) and Schwarz Information Criterion (Schwarz, 1978), as reflected in Table 4. First, we simulated different orders of Autoregressive and Moving Average Terms in Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. Next, the models which had insignificant Autoregressive terms or Moving Average terms or both were rejected. Also, we rejected the models wherein the residuals were serially correlated. Finally, once we obtained the appropriate models which met the criteria of significant Autoregressive and Moving Average terms and white noise residuals, we selected the best model, as indicated in Table 23, Table 24, and Table 25. If there was a conflict between the results of both criteria, we considered the Schwarz Information Criterion as it is more parsimonious (Schwarz, 1978).

3.6 Examination of Long Memory

Table 26, Table 27, and Table 28 highlight the results of Autoregressive Fractionally Integrated Moving Average (ARFIMA) models. These models met the criteria as per Table 23, Table 24, and Table 25. Autoregressive Fractionally Integrated Moving Average (ARFIMA) generalizes the Autoregressive Integrated Moving Average (ARIMA). Table 26, Table 27, and Table 28 depict the values of the variable 'd', a fractional differencing parameter obtained from ARFIMA(p,d,q) models used to describe the presence of long memory, anti-persistence, or absence of such behaviour. We notice the fractional differencing parameter for daily return series to be significant in Nifty Consumer Durable Index Returns, Nifty Media Index Returns, and Nifty Metal Index Returns at 1% level of significance as reflected in Table 26. Also, in the case of Nifty Oil & Gas Index Returns and Nifty Realty Index Returns, the fractional differencing parameter is significant at 5% significance level. At the same time, the fractional differencing parameter is significant at 10% level of significance in the case of Nifty IT Index Returns. The significant fractional differencing parameter in such cases lies between 0 to 0.5, thus revealing the presence of long memory.

Table 26: Results of ARFIMA in case of Daily Return Series

Indices	Variable	Coefficient	Standard Error	t-Statistic	P-value
LNAUTO	C	0.053	0.028	1.878	0.060
	D	0.012	0.018	0.670	0.503
	MA(1)	0.079	0.023	3.424	0.001
LNBANK	C	0.066	0.022	2.928	0.003
	D	-0.035	0.015	-2.289	0.022**
	MA(1)	0.148	0.020	7.497	0.000
LNCD	C	0.081	0.051	1.581	0.114
	D	0.086	0.013	6.428	0.000***
	AR(1)	-0.892	0.050	-17.998	0.000
	MA(1)	0.919	0.043	21.481	0.000

LNFS	C	0.064	0.026	2.422	0.016
	D	-0.021	0.019	-1.070	0.285
	AR(1)	-0.234	0.135	-1.727	0.084
	MA(1)	0.362	0.121	2.991	0.003
LNFMCG	C	0.048	0.015	3.299	0.001
	D	-0.036	0.016	-2.239	0.025**
	MA(1)	0.054	0.021	2.578	0.010
LNIT	C	0.082	0.039	2.084	0.037
	D	0.028	0.016	1.740	0.082*
	MA(1)	0.055	0.021	2.669	0.008
LNMEDIA	C	0.015	0.047	0.319	0.750
	D	0.061	0.013	4.720	0.000***
LNMETAL	C	-0.006	0.056	-0.109	0.913
	D	0.065	0.025	2.610	0.009***
	AR(1)	-0.062	0.032	-1.971	0.049
LNOG	C	0.044	0.033	1.352	0.177
	D	0.032	0.013	2.542	0.011**
LNPHARMA	C	0.051	0.023	2.208	0.027
	D	0.024	0.019	1.261	0.207
	AR(1)	0.042	0.024	1.792	0.073
LNPVTB	C	0.073	0.030	2.386	0.017
	D	-0.016	0.018	-0.888	0.375
	MA(1)	0.124	0.023	5.364	0.000
LNPSUB	C	0.013	0.036	0.367	0.713
	D	-0.007	0.018	-0.416	0.677
	MA(1)	0.103	0.023	4.535	0.000
LNREALTY	C	-0.032	0.067	-0.479	0.632
	D	0.044	0.022	1.967	0.049**
	AR(1)	0.054	0.029	1.901	0.057

Source: Authors' Compilation

Note:***1% level of significance, **5% level of significance, and *10% level of significance.

Table 27: Results of ARFIMA in case of Monthly Return Series

Indices	Variable	Coefficient	Standard Error	t-Statistic	P-value
LNAUTO	C	1.116	0.582	1.917	0.057
	D	-0.010	0.070	-0.148	0.882
	MA(1)	0.470	0.077	6.110	0.000
LNBANK	C	1.366	0.330	4.142	0.000
	D	-0.143	0.061	-2.345	0.020**
	MA(1)	0.532	0.064	8.278	0.000
LNCD	C	1.423	0.139	10.253	0.000
	D	-0.957	0.167	-5.719	0.000***
	AR(1)	0.896	0.078	11.415	0.000
	MA(1)	0.472	0.096	4.917	0.000
LNFS	C	1.244	0.089	13.998	0.000
	D	-0.986	0.175	-5.633	0.000***
	AR(1)	0.877	0.090	9.787	0.000
	MA(1)	0.507	0.090	5.660	0.000
LNFMCG	C	0.990	0.278	3.561	0.000
	D	-0.052	0.068	-0.762	0.447
	MA(1)	0.222	0.084	2.632	0.009
LNIT	C	1.340	0.165	8.106	0.000
	D	-0.886	0.148	-6.003	0.000***
	AR(1)	0.922	0.056	16.387	0.000
	MA(1)	0.261	0.106	2.454	0.015
LNMEDIA	C	0.295	0.711	0.414	0.679
	D	-0.018	0.078	-0.228	0.820
	MA(1)	0.378	0.090	4.219	0.000
LNMETAL	C	-0.103	0.434	-0.237	0.813
	D	-0.423	0.367	-1.151	0.252
	AR(1)	0.703	0.316	2.222	0.028
LNOG	C	0.864	0.296	2.922	0.004
	D	-0.165	0.075	-2.191	0.030**
	MA(1)	0.454	0.082	5.558	0.000
LNPHARMA	C	1.079	0.301	3.588	0.000

	D	-0.096	0.118	-0.814	0.417
	AR(1)	0.298	0.141	2.107	0.036
LNPVTB	C	1.465	0.452	3.242	0.001
	D	-0.125	0.071	-1.759	0.080*
	MA(1)	0.579	0.071	8.214	0.000
LNPSUB	C	-0.716	0.863	-0.829	0.408
	D	-0.089	0.079	-1.122	0.263
	MA(1)	0.507	0.082	6.168	0.000
LNREALTY	C	0.336	0.436	0.772	0.441
	D	-0.150	0.070	-2.139	0.034**
	MA(1)	0.465	0.077	6.023	0.000

Source: Authors' Compilation

Note:***1% level of significance, **5% level of significance, and *10% level of significance

Table 28: Results of ARFIMA in case of Quarterly Return Series

Indices	Variable	Coefficient	Standard Error	t-Statistic	P-value
LNAUTO	C	3.186	1.152	2.765	0.007
	D	-0.181	0.122	-1.481	0.144
	MA(1)	0.653	0.112	5.828	0.000
LNBANK	C	4.062	0.796	5.106	0.000
	D	-0.238	0.121	-1.964	0.053*
	MA(1)	0.416	0.131	3.185	0.002
LNCD	C	4.168	0.330	12.631	0.000
	D	-1.136	0.568	-2.000	0.050*
	AR(1)	0.733	0.412	1.778	0.081
	MA(1)	0.718	0.124	5.788	0.000
LNFS	C	3.776	0.459	8.225	0.000
	D	-0.489	0.133	-3.683	0.001***
	MA(1)	0.608	0.119	5.114	0.000
LNFMCG	C	2.680	1.542	1.738	0.086
	D	0.150	0.087	1.719	0.089*
LNIT	C	2.332	1.533	1.522	0.132
	D	-0.120	0.109	-1.104	0.273

	MA(1)	0.566	0.109	5.206	0.000
LNMEDIA	C	0.556	1.400	0.397	0.693
	D	-0.202	0.133	-1.522	0.133
	MA(1)	0.710	0.127	5.604	0.000
LNMETAL	C	-0.635	3.005	-0.211	0.834
	D	0.094	0.149	0.630	0.533
LNOG	C	2.328	0.424	5.494	0.000
	D	-0.490	0.135	-3.620	0.001***
	MA(1)	0.626	0.119	5.253	0.000
LNPHARMA	C	3.239	0.583	5.560	0.000
	D	-0.508	0.455	-1.115	0.268
	AR(1)	0.718	0.375	1.915	0.059
LNPVTB	C	4.291	0.694	6.182	0.000
	D	-0.399	0.144	-2.781	0.007***
	MA(1)	0.572	0.131	4.365	0.000
LNPSUB	C	0.417	2.485	0.168	0.867
	D	0.068	0.105	0.642	0.523
LNREALTY	C	-2.544	1.378	-1.845	0.071
	D	-0.362	0.137	-2.632	0.011**
	MA(1)	0.713	0.117	6.100	0.000

Source: Authors' Compilation

Note:***1% level of significance, **5% level of significance, and *10% level of significance.

Further, in Table 26, we also notice the fractional differencing parameter to be significant at 5% level of significance in the case of Nifty Bank Index Returns and Nifty FMCG Index Returns. But, the corresponding value of the fractional differencing parameter in the case of said indices lies between -0.5 to 0, thus indicating anti-persistence. However, in the case of monthly and quarterly return series, as reflected in Table 27 and Table 28, we notice evidence of anti-persistence in the case of Nifty Bank Index Returns, Nifty Oil & Gas Index Returns, Nifty Private Bank Index Returns and Nifty Realty Index Returns. The findings support the evidence provided by Kumar (2014) and Hiremath & Kumari (2015) in the Indian context.

Overall, the results indicate evidence of persistence in the daily return series and evidence of anti-persistence in the monthly and quarterly return series. This proves that the frequency of data does have a significant effect on the behaviour of long memory patterns. The evidence of persistence and anti-persistence have significant implications for the Efficient Market Hypothesis theory. The results support the evidence of the weak form of market efficiency in the Indian stock market noticed by Kalsie (2012). If the markets are inefficient, it provides an opportunity for traders and investors to earn abnormal returns after systematic fundamental and technical analysis. In the Indian stock market, we see active Futures & Options (F&O) derivatives products such as Nifty 50 F&O, Nifty Bank F&O, Nifty Financial Services F&O, and a few F&O stocks. The evidence of anti-persistence in the Nifty Bank Index (daily, monthly, and quarterly return series) and Nifty Financial Services Index (quarterly return series), which are underlying assets for Nifty Bank F&O, and Nifty Financial Services F&O, is justified due to its large volumes of trade. The further evidence of persistence and anti-persistence in other sectoral indices can be a motivating factor to the stock exchanges to activate derivative products based on other sectoral indices, which also can attract larger volumes of trade due to such evidence.

3.7 Model Diagnostics

Table 29. Results of Breusch-Godfrey Serial Correlation LM Test in case of Daily Return Series

Indices	F-Statistic	P-value
LNAUTO	0.024	0.878
LNBANK	1.668	0.197
LNCD	0.539	0.463
LNFS	0.052	0.820
LNFMCG	0.018	0.892
LNIT	0.003	0.958
LNMEDIA	2.524	0.112
LNMETAL	0.450	0.502
LNOG	2.631	0.105
LNPHARMA	0.593	0.441
LNPVTB	0.718	0.397
LNPSUB	0.014	0.905
LNREALTY	0.056	0.813

Source: Authors’ Compilation

Table 30. Results of Breusch-Godfrey Serial Correlation LM Test in case of Monthly Return Series

Indices	F-Statistic	P-value
LNAUTO	0.044	0.834
LNBANK	0.019	0.889
LNCD	0.615	0.434
LNFS	0.143	0.706
LNFMCG	0.325	0.569
LNIT	0.399	0.528
LNMEDIA	0.002	0.963
LNMETAL	1.579	0.212
LNOG	0.947	0.332
LNPHARMA	0.014	0.907
LNPVTB	0.628	0.429
LNPSUB	0.200	0.655
LNREALTY	0.068	0.794

Source: Authors' Compilation

Table 31. Results of Breusch-Godfrey Serial Correlation LM Test in case of Quarterly Return Series

Indices	F-Statistic	P-value
LNAUTO	0.100	0.752
LNBANK	0.593	0.444
LNCD	0.573	0.452
LNFS	1.313	0.256
LNFMCG	1.114	0.294
LNIT	1.513	0.222
LNMEDIA	0.086	0.770
LNMETAL	1.950	0.172
LNOG	0.078	0.781
LNPHARMA	0.778	0.381
LNPVTB	2.320	0.133
LNPSUB	2.441	0.123
LNREALTY	0.647	0.425

Source: Authors' Compilation

Further, we examine the presence of serial correlation in the developed ARFIMA models, as reflected in Table 29, Table 30, and Table 31. The results of the F-statistic and its corresponding p-values obtained using Breusch-Godfrey Serial Correlation LM Test indicate failure in rejection of the null hypothesis (H0: No Serial Correlation). The results signify the absence of serial correlation in the said models, and thus the residuals are white noise.

Chapter 4

Stock Characteristics and Long Memory

This chapter focuses on results and discussions relating to objective III, that is, examining the long memory in stock returns, stock liquidity and stock volatility for various stock categories. To support the analysis, the results incorporated include summary statistics of stock returns, summary statistics of stock liquidity, summary statistics of stock volatility, unit root test of stock returns, unit root test of stock liquidity, unit root test of stock volatility, Identification of outliers in case of stock returns, stock liquidity and stock volatility, model selection in case of examination of long memory in stock returns, model selection in case of examination of long memory in stock liquidity, model selection in the examination of long memory in stock volatility, Results of ARFIMA Models in case of stock returns, results of ARFIMA models in case of stock liquidity, and results of ARFIMA Models in case of stock volatility. Finally, the results of model diagnostics of developed models are incorporated.

4.1 Summary Statistics

4.1.1 Summary Statistics of Stock Returns

Table 32: Results of Summary Statistics of Stock Returns

Variables	Mean	Median	Standard Deviation	Skewness	Kurtosis	Observations
C1Q1LR	0.00067	0.00081	0.00401	-0.63928	5.03694	264
C1Q2LR	0.00034	0.00069	0.00382	-1.22441	7.37517	264
C1Q3LR	0.00019	0.00056	0.00446	-1.04637	5.51351	264
C1Q4LR	0.00013	0.00049	0.00509	-0.72098	6.41880	264
C1Q5LR	1.03E-05	0.00020	0.00458	-0.86556	6.31891	264
C2Q1LR	0.00023	0.00042	0.00381	-0.66995	5.11673	264
C2Q2LR	0.00025	0.00065	0.00478	-0.96669	7.79986	264
C2Q3LR	0.00016	0.00062	0.00401	-0.69726	4.78452	264
C2Q4LR	0.00029	0.00079	0.00461	-1.59409	9.19559	264

C2Q5LR	0.00038	0.00068	0.00441	-0.84299	5.24258	264
C3Q1LR	0.00023	0.00057	0.00535	-0.73438	5.94534	264
C3Q2LR	0.00025	0.00086	0.00494	-0.86802	6.45108	264
C3Q3LR	0.00012	0.00074	0.00404	-0.97738	5.64421	264
C3Q4LR	0.00044	0.00072	0.00379	-1.75119	10.95548	264
C3Q5LR	0.00022	0.00059	0.00363	-3.67720	34.37040	264

Source: Authors' Compilation

Table 32 highlights the results of summary statistics of log returns for various stock categories. The study noticed the average returns, which are represented by the mean, are highest in the case of high-priced stocks, moderate to low volatile stocks and low liquidity stocks. However, the average returns have been lowest in the case of low-priced stocks, followed by moderately volatile stocks and moderate to low-priced stocks. This indicates the superior average returns generated by high-priced stocks as compared to low-priced stocks. The study also notices the returns generated by high volatile stocks and high liquid stocks to be approximately the same. However, these returns are less as compared to high-priced stocks and low-liquid stocks.

The standard deviation in the Table 32 represents the variations in returns. The study notices the variation to be highest in the case of highly volatile stocks, followed by moderate to low-priced stocks and moderate to high-volatile stocks. Although the moderate to low volatile stocks generated higher average returns, the variation in such stocks has been comparatively low. And justifying the nature of the stock category, the lowest variation has been noticed in the case of low-volatile stocks. The results of skewness indicate the data pertaining to returns to be negatively skewed across all the stock categories.

In addition, the results of kurtosis reveal the stock returns to be leptokurtic. The results of skewness and kurtosis indicate the data to be not normally distributed. However, data normality is not an essential condition for the analysis focused on in this study. The results are incorporated primarily to understand the nature of data utilised for analysis.

4.1.2 Summary Statistics of Stock Liquidity

Table 33: Results of Summary Statistics of Stock Liquidity

Variables	Mean	Median	Standard Deviation	Skewness	Kurtosis	Observations
C1Q1AR	1.00E-06	4.01E-07	3.59E-06	9.73219	105.69710	264
C1Q2AR	1.87E-06	3.64E-07	6.99E-06	8.15996	76.14667	264
C1Q3AR	2.63E-07	3.43E-08	6.71E-07	4.30661	25.10707	264
C1Q4AR	2.07E-07	1.32E-08	8.00E-07	12.35587	179.91170	264
C1Q5AR	2.73E-07	2.34E-08	8.51E-07	5.70650	41.59757	264
C2Q1AR	1.08E-08	5.76E-09	1.62E-08	6.70701	68.05535	264
C2Q2AR	4.58E-08	1.70E-08	8.13E-08	3.71954	19.57979	264
C2Q3AR	1.32E-07	2.72E-08	3.33E-07	5.31610	38.60713	264
C2Q4AR	3.90E-07	8.80E-08	9.93E-07	6.67449	59.04564	264
C2Q5AR	2.41E-06	7.47E-07	7.58E-06	7.93339	76.20131	264
C3Q1AR	6.29E-07	1.56E-07	2.05E-06	8.79327	98.05762	264
C3Q2AR	2.12E-07	2.08E-08	6.45E-07	7.98688	87.87510	264
C3Q3AR	2.17E-07	4.26E-08	6.34E-07	8.46233	98.70778	264
C3Q4AR	4.43E-07	1.99E-07	1.35E-06	12.23652	173.02960	264
C3Q5AR	6.62E-07	3.26E-07	1.00E-06	3.86037	30.20442	264

Source: Authors' Compilation

The summary statistics results of the stock liquidity are presented in Table 33. The stock liquidity here is presented by the Amihud Ratio, which is a measure of stock illiquidity. This means that stocks with a higher Amihud Ratio signify illiquidity, and stocks with a low Amihud Ratio indicate high liquidity. As the focus is on stock liquidity, it is obvious to notice high liquidity in the case of high liquid stocks and low liquidity in the case of low-liquid stocks. In addition, the study noticed liquidity to be high in the case of moderate to low-priced stocks and moderate to high-volatile stocks. Also, the liquidity of moderately priced stocks and low-priced stocks has been moderate. The study also noticed the stock liquidity to be comparatively low in the case of high-priced stocks and moderate to high-priced stocks. This indicates that low-priced stocks and moderate to low-priced stocks offer better liquidity as compared to high-priced stocks.

The variation in stock liquidity is presented in Table 33 as reflected by the standard deviation. Although the low liquid stock offer low liquidity, the variations in such stocks have been highest. This indicates infrequent large purchase and sell orders making such large variations in stock liquidity. Similarly, the high-liquid stocks reveal low variations in stock liquidity. The stocks which are highly liquid are frequently traded, resulting in less variations in stock liquidity. The results of skewness indicate the data relating to stock liquidity to be positively skewed. And the results of Kurtosis indicate the data to be leptokurtic, suggesting the non-normality of the data. Also, data normality is not an essential condition for the analysis of this study; hence these results are incorporated to understand the nature of the data.

4.1.3 Summary Statistics of Stock Volatility

Table 34: Results of Summary Statistics of Stock Volatility

Variables	Mean	Median	Standard Deviation	Skewness	Kurtosis	Observations
C1Q1SD	0.02393	0.01993	0.01140	1.87274	6.92444	264
C1Q2SD	0.02224	0.01885	0.01097	2.53678	11.06955	264
C1Q3SD	0.02614	0.02211	0.01352	2.22788	9.57262	264
C1Q4SD	0.02714	0.02375	0.01227	2.89201	15.94363	264
C1Q5SD	0.02578	0.02157	0.01366	4.30197	32.18058	264
C2Q1SD	0.02282	0.01942	0.01002	2.42386	11.44228	264
C2Q2SD	0.02576	0.02212	0.01414	3.91746	25.83764	264
C2Q3SD	0.02539	0.02139	0.01214	2.30915	11.18192	264
C2Q4SD	0.02461	0.02043	0.01295	2.84752	13.67010	264
C2Q5SD	0.02613	0.02258	0.01156	2.21449	9.26507	264
C3Q1SD	0.03033	0.02673	0.01365	2.26579	10.25564	264
C3Q2SD	0.02702	0.02333	0.01251	2.04883	8.48051	264
C3Q3SD	0.02418	0.02017	0.01164	2.52689	11.75529	264
C3Q4SD	0.02216	0.01868	0.01114	3.06224	15.64797	264
C3Q5SD	0.01939	0.01619	0.01272	7.80424	90.99227	264

Source: Authors' Compilation

The results of summary statistics of stock volatility for various stock categories are presented in Table 34. The stock volatility here represents the monthly standard deviation computed using daily returns of the month. As such, we find the stock volatility to be highest in the case of high-volatile stocks and stock volatility to be low in the case of low-volatile stocks. In addition, the study noticed the volatility to be high in the case of moderate to low-priced stocks and moderately priced stocks, followed by low-liquid stocks and low-priced stocks. On the other hand, the volatility of moderate to high-price stocks has been low, followed by high-liquid stocks and high-priced stocks. The standard deviation in Table 34 represents the variation in the stock volatility across various stock categories. The study noticed such variation to be highest in the case of moderate to high liquid stocks followed by low-priced stocks and high volatile stocks. Thus, it means that although the volatility in high-volatile stocks is more, the variations in such volatility are low as compared to moderate to high-liquid stocks and low-priced stocks. The study also noticed such variations to be least in the case of high liquid stocks followed by moderate to high-priced stocks, moderate to low volatile stocks, and high-priced stocks. The results of skewness indicate the data to be positively skewed. Also, the results of kurtosis signify the data to be leptokurtic. As such, the data is not normally distributed, as indicated by the results of skewness and kurtosis. Also, as mentioned before, data normality is not an essential condition for the analysis of this study, what is essential is the stationarity of data, as reflected in Table 35, Table 36, and Table 37.

4.2 Unit Root Test

4.2.1 Unit Root Test of Stock Returns

Table 35: Results of Unit Root Test of Stock Returns

Variables	Elliott-Rothenberg-Stock DF-GLS test statistic
C1Q1LR	-3.58882
C1Q2LR	-13.20774
C1Q3LR	-3.94424
C1Q4LR	-14.52551
C1Q5LR	-14.90764
C2Q1LR	-13.86154
C2Q2LR	-6.39978
C2Q3LR	-6.36043
C2Q4LR	-14.22083
C2Q5LR	-12.56293

C3Q1LR	-13.52208
C3Q2LR	-4.66679
C3Q3LR	-13.98231
C3Q4LR	-4.86003
C3Q5LR	-3.62725

Source: Authors' Compilation

Table 35 highlights the results of the Elliot-Rothenberg-stock-DF-GLS test. In the case of stock returns, the results indicate the Elliot-Rothenberg-stock-DF-GLS test statistics to be less than -3.47, -2.92 and -2.62 at 1% level of significance, 5% level of significance and 10 % level of significance, respectively. Thus, the study rejects the null hypothesis of unit root at the said level of significances. Therefore, the results indicate the data to be stationary, which is favourable in the context of analysis of the present study.

4.2.2 Unit Root Test of Stock Liquidity

Table 36: Results of Unit Root Test of Stock Liquidity

Variables	Elliott-Rothenberg-Stock DF-GLS test statistic
C1Q1AR	-12.26362
C1Q2AR	-4.37495
C1Q3AR	-3.80454
C1Q4AR	-6.63115
C1Q5AR	-9.31349
C2Q1AR	-5.46640
C2Q2AR	-4.31519
C2Q3AR	-3.39103
C2Q4AR	-4.23554
C2Q5AR	-5.84273
C3Q1AR	-3.64924
C3Q2AR	-3.34459
C3Q3AR	-3.83205
C3Q4AR	-15.44117
C3Q5AR	-5.62932

Source: Authors' Compilation

Table 36 highlights the results of the Elliot-Rothenberg-stock-DF-GLS test. In the case of stock liquidity, the results indicate the Elliot-Rothenberg-stock-DF-GLS test statistics to be less than -3.47, -2.92 and -2.62 at 1% level of significance, 5% level of significance and 10 % level of significance, respectively. Thus, the study rejects the null hypothesis of unit root at the said level of significances. Therefore, the results indicate the data to be stationary, which is favourable in the context of analysis of the present study.

4.2.3 Unit Root Test of Stock Volatility

Table 37: Results of Unit Root Test of Stock Volatility

Variables	Elliott-Rothenberg-Stock DF-GLS test statistic
C1Q1SD	-6.34168
C1Q2SD	-11.80147
C1Q3SD	-12.59693
C1Q4SD	-8.05312
C1Q5SD	-8.25297
C2Q1SD	-11.11923
C2Q2SD	-3.05654
C2Q3SD	-12.27434
C2Q4SD	-12.67201
C2Q5SD	-8.35448
C3Q1SD	-8.15492
C3Q2SD	-11.10389
C3Q3SD	-6.35306
C3Q4SD	-12.34287
C3Q5SD	-12.51322

Source: Authors' Compilation

Table 37 highlights the results of the Elliot-Rothenberg-stock-DF-GLS test. In the case of stock volatility, the results indicate the Elliot-Rothenberg-stock-DF-GLS test statistics to be less than - 3.47, -2.92 and -2.62 at 1% level of significance, 5% level of significance and 10 % level of significance, respectively. Thus, the study rejects the null hypothesis of unit root at the said level of significances. Therefore, the results indicate the data to be stationary, which is favourable in the context of analysis of the present study.

4.3 Identification of Outliers

4.3.1 Box Plot of Stock Returns

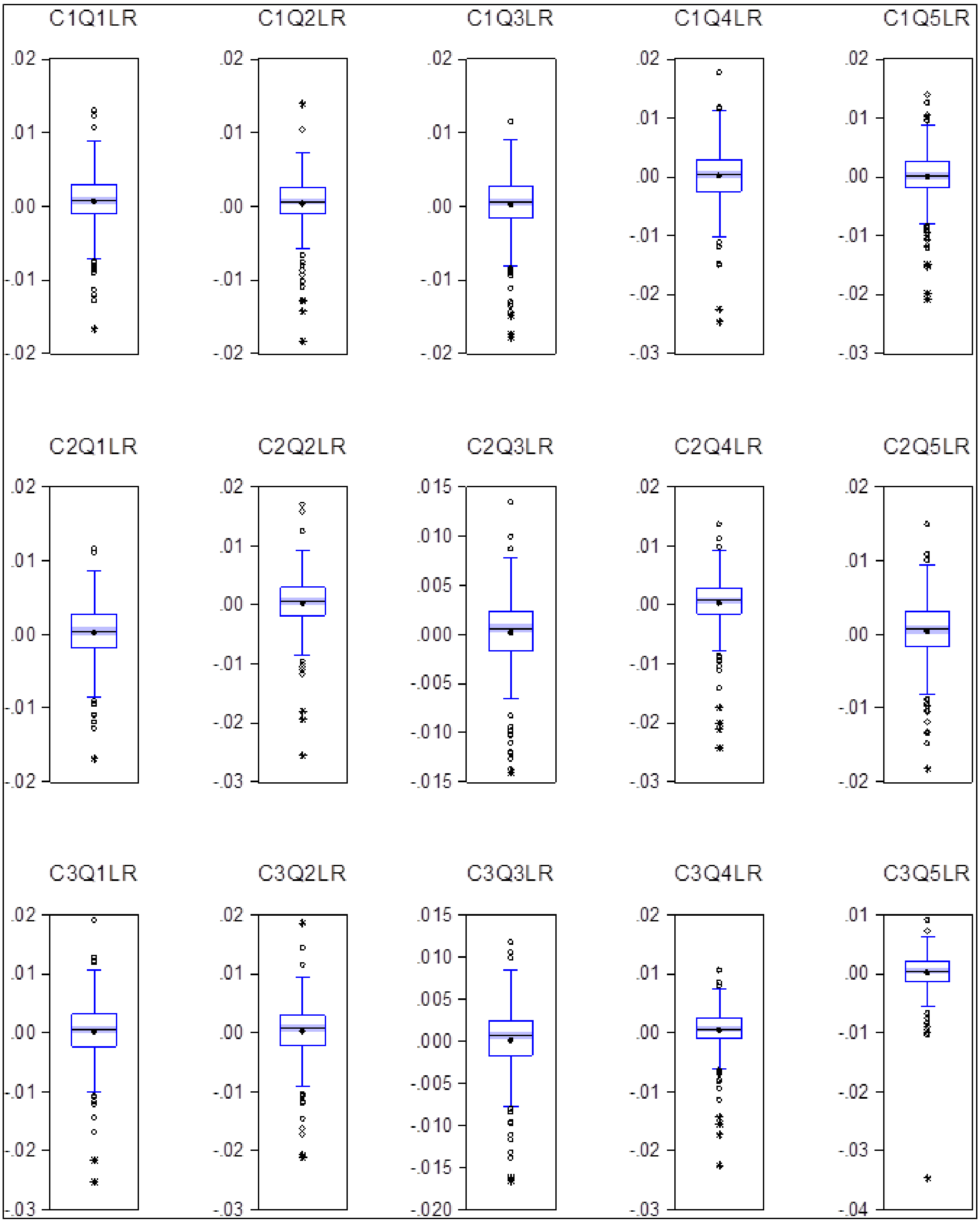

Figure 9: Box Plot of Stock Returns

Source: Authors' Compilation

Figure 9 depicts the results of the box pilot in the case of stock returns for the various stock categories. The purpose of the box plot is to identify the outlier. We can notice in Figure 9 near and far outliers, which are neutralised using the median, and such data of stock returns for various stock categories has been utilised for developing ARFIMA models.

4.3.2 Box Plot of Stock Liquidity

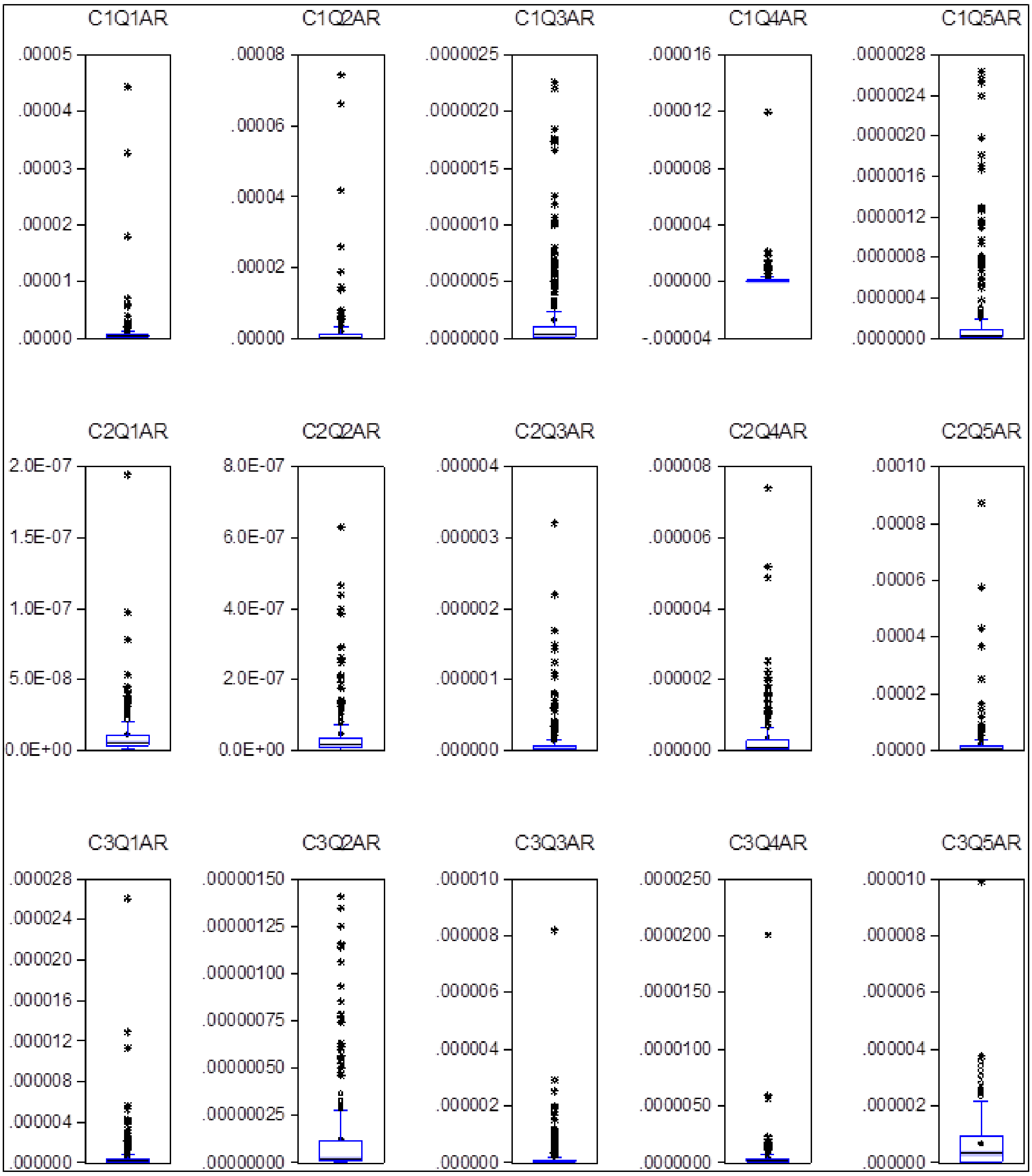

Figure 10: Box Plot of Stock Liquidity

Source: Authors' Compilation

Figure 10 depicts the results of the box pilot in the case of stock liquidity for the various stock categories. The purpose of the box plot is to identify the outlier. We can notice in Figure 10 near and far outliers which are neutralized using the median, and such data of stock liquidity for various stock categories has been utilized for developing ARFIMA models.

4.3.3 Box Plot of Stock Volatility

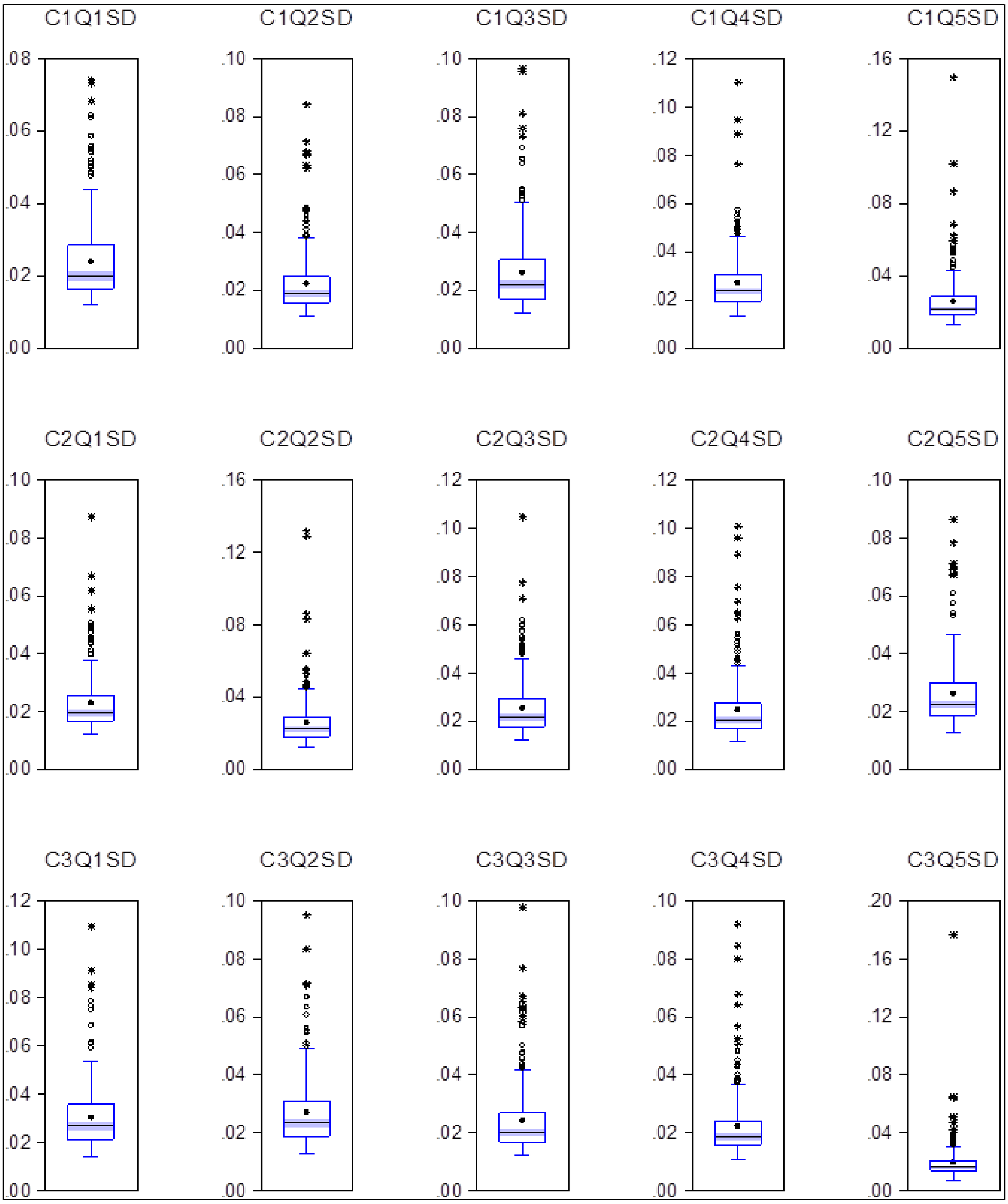

Figure 11: Box Plot of Stock Volatility

Source: Authors' Compilation

Figure 11 depicts the results of the box pilot in case of stock volatility for the various stock categories. The purpose of the box plot is to identify the outlier. We can notice in Figure 11 near and far outliers which are neutralised using the median, and such data of stock volatility for various stock categories has been utilised for developing ARFIMA models.

4.4 Model Selection

4.4.1 Model Selection in Examination of Long Memory in Stock Returns

Table 38: Results of Model Selection in Examination of Long Memory in Stock Returns

Variables	Model	AIC	SIC
C1Q1LR	ARFIMA(0,d,0)	-8.1980	-8.1709
C1Q2LR	ARFIMA(1,d,0)	-8.2904	-8.2498
C1Q3LR	ARFIMA(1,d,0)	-8.0133	-7.9727
C1Q4LR	ARFIMA(0,d,0)	-7.7163	-7.6892
C1Q5LR	ARFIMA(0,d,0)	-7.9269	-7.8998
C2Q1LR	ARFIMA(0,d,0)	-8.2889	-8.2618
C2Q2LR	ARFIMA(0,d,0)	-7.8501	-7.8231
C2Q3LR	ARFIMA(0,d,0)	-8.1889	-8.1619
C2Q4LR	ARFIMA(1,d,0)	-7.9453	-7.9047
C2Q5LR	ARFIMA(1,d,0)	-8.0382	-7.9976
C3Q1LR	ARFIMA(0,d,0)	-7.6368	-7.6097
C3Q2LR	ARFIMA(1,d,0)	-7.8180	-7.7774
C3Q3LR	ARFIMA(0,d,1)	-8.1825	-8.1419
C3Q4LR	ARFIMA(1,d,0)	-8.3383	-8.2977
C3Q5LR	ARFIMA(0,d,0)	-8.3963	-8.3692

Source: Authors’ Compilation

The present study simulated various ARFIMA models of stock returns for various stock categories. The models were rejected if the AR or MA polynomials were insignificant. Also, the study rejected the models if the residuals of such models were severally correlated. In case there were multiple models which fulfilled the above two conditions, the best model was selected based on AIC and SIC criteria. The results of such criteria of the selected ARFIMA models are presented in Table 38.

4.4.2 Model Selection in Examination of Long Memory in Stock Liquidity

Table 39: Results of Model Selection in Examination of Long Memory in Stock Liquidity

Variables	Model	AIC	SIC
C1Q1AR	ARFIMA(0,d,0)	-22.3015	-22.2744
C1Q2AR	ARFIMA(0,d,0)	-21.3181	-21.2910
C1Q3AR	ARFIMA(0,d,0)	-27.2991	-27.2720
C1Q4AR	ARFIMA(1,d,0)	-25.3781	-25.3375
C1Q5AR	ARFIMA(0,d,0)	-27.1559	-27.1288
C2Q1AR	ARFIMA(0,d,1)	-33.2853	-33.2447
C2Q2AR	ARFIMA(0,d,0)	-30.5092	-30.4821
C2Q3AR	ARFIMA(0,d,0)	-27.4714	-27.4443
C2Q4AR	ARFIMA(1,d,1)	-25.8494	-25.7952
C2Q5AR	ARFIMA(0,d,0)	-21.0546	-21.0275
C3Q1AR	ARFIMA(0,d,0)	-23.4528	-23.4257
C3Q2AR	ARFIMA(0,d,0)	-27.9310	-27.9040
C3Q3AR	ARFIMA(1,d,0)	-25.9633	-25.9227
C3Q4AR	ARFIMA(0,d,0)	-24.1954	-24.1683
C3Q5AR	ARFIMA(1,d,1)	-25.3463	-25.2922

Source: Authors' Compilation

The present study simulated various ARFIMA models of stock liquidity for various stock categories. The models were rejected if the AR or MA polynomials were insignificant. Also, the study rejected the models if the residuals of such models were severally correlated. In case there were multiple models which fulfilled the above two conditions, the best model was selected based on AIC and SIC criteria. The results of such criteria of the selected ARFIMA models are presented in Table 39.

4.4.3 Model Selection in Examination of Long Memory in Stock Volatility

Table 40: Results of Model Selection in Examination of Long Memory in Stock Volatility

Variables	Model	AIC	SIC
C1Q1SD	ARFIMA(0,d,0)	-6.6314	-6.6043
C1Q2SD	ARFIMA(0,d,0)	-6.2946	-6.2675

C1Q3SD	ARFIMA(0,d,0)	-6.0499	-6.0228
C1Q4SD	ARFIMA(1,d,1)	-6.0998	-6.0456
C1Q5SD	ARFIMA(0,d,0)	-5.9158	-5.8887
C2Q1SD	ARFIMA(0,d,0)	-6.5698	-6.5427
C2Q2SD	ARFIMA(1,d,0)	-5.8867	-5.8461
C2Q3SD	ARFIMA(0,d,0)	-6.2393	-6.2123
C2Q4SD	ARFIMA(0,d,0)	-6.0389	-6.0118
C2Q5SD	ARFIMA(0,d,0)	-6.1940	-6.1669
C3Q1SD	ARFIMA(0,d,1)	-5.9270	-5.8864
C3Q2SD	ARFIMA(0,d,0)	-6.1954	-6.1683
C3Q3SD	ARFIMA(0,d,0)	-6.2476	-6.2205
C3Q4SD	ARFIMA(0,d,0)	-6.3435	-6.3164
C3Q5SD	ARFIMA(0,d,0)	-5.9837	-5.9566

Source: Authors' Compilation

The present study simulated various ARFIMA models of stock volatility for various stock categories. The models were rejected if the AR or MA polynomials were insignificant. Also, the study rejected the models if the residuals of such models were severally correlated. In case there were multiple models which fulfilled the above two conditions, the best model was selected based on AIC and SIC criteria. The results of such criteria of the selected ARFIMA models are presented in Table 40.

4.5 Examination of Long Memory

4.5.1 Examination of Long Memory in Stock Returns

Table 41: Results of ARFIMA in case of Stock Returns

Variables	Model	Coefficient	Standard Error	t-Statistic	P-value
C1Q1LR	ARFIMA(0,d,0)	0.0829	0.0501	1.6559	0.0989*
C1Q2LR	ARFIMA(1,d,0)	-0.1171	0.1012	-1.1565	0.2485
C1Q3LR	ARFIMA(1,d,0)	-0.7967	0.1074	-7.4184	0.0000
C1Q4LR	ARFIMA(0,d,0)	0.0577	0.0505	1.1409	0.2550
C1Q5LR	ARFIMA(0,d,0)	0.0446	0.0501	0.8903	0.3741

C2Q1LR	ARFIMA(0,d,0)	0.0020	0.0499	0.0404	0.9678
C2Q2LR	ARFIMA(0,d,0)	0.0957	0.0497	1.9263	0.0551*
C2Q3LR	ARFIMA(0,d,0)	-0.0301	0.0512	-0.5882	0.5569
C2Q4LR	ARFIMA(1,d,0)	-0.8210	0.1180	-6.9597	0.0000
C2Q5LR	ARFIMA(1,d,0)	-0.7787	0.0971	-8.0164	0.0000
C3Q1LR	ARFIMA(0,d,0)	0.1347	0.0503	2.6802	0.0078***
C3Q2LR	ARFIMA(1,d,0)	-0.8313	0.1286	-6.4671	0.0000
C3Q3LR	ARFIMA(0,d,1)	-0.0648	0.0683	-0.9488	0.3436
C3Q4LR	ARFIMA(1,d,0)	-0.8717	0.1237	-7.0475	0.0000
C3Q5LR	ARFIMA(0,d,0)	0.0782	0.0500	1.5635	0.1192

Source: Authors' Compilation

Note: ***1% level of significance, **10% level of significance

Table 41 presents the results of ARFIMA models developed for examining the long memory in stock returns for various categories of stocks. The value of the fractionally differencing parameter is depicted in Table 41. In the case of high-priced stock returns, the study noticed the fractionally differencing parameter to be significant at 10% level of significance. Further, in the case of moderate to high liquid stock returns, the study noticed the fractionally differencing parameter to be significant at 10% level of significance and the fractional differencing parameter in the case of high volatile stocks to be significant at 1% level of significance.

To consider the series persistent, the fractional differencing parameter should be in the range of 0 to 0.5. Therefore, even when we notice the fractional differencing parameter in the case of other stock categories to be significant, we cannot say it possesses long memory characteristics as the fractional differencing parameter is either less than 0 or more than 0.5. Thus, the study noticed fractional differencing parameters to be in the range of 0 to 0.5 only in the case of high priced stocks returns, moderate to high liquid stocks returns and high volatile stock returns. Thus, the study found the presence of long memory in the case of high-priced stock returns, moderate to high liquid stock returns and high volatile stock returns.

4.5.2 Examination of Long Memory in Stock Liquidity

Table 42: Results of ARFIMA in case of Stock Liquidity

Variables	Model	Coefficient	Standard Error	t-Statistic	P-value
C1Q1AR	ARFIMA(0,d,0)	0.2134	0.0491	4.3485	0.0000***
C1Q2AR	ARFIMA(0,d,0)	0.4451	0.0479	9.2939	0.0000***
C1Q3AR	ARFIMA(0,d,0)	0.3493	0.0403	8.6610	0.0000***
C1Q4AR	ARFIMA(1,d,0)	0.3319	0.0615	5.3970	0.0000***
C1Q5AR	ARFIMA(0,d,0)	0.4778	0.0364	13.1431	0.0000***
C2Q1AR	ARFIMA(0,d,1)	0.3900	0.0826	4.7198	0.0000***
C2Q2AR	ARFIMA(0,d,0)	0.4251	0.0378	11.2548	0.0000***
C2Q3AR	ARFIMA(0,d,0)	0.3915	0.0354	11.0679	0.0000***
C2Q4AR	ARFIMA(1,d,1)	-0.2453	0.2419	-1.0141	0.3115
C2Q5AR	ARFIMA(0,d,0)	0.3810	0.0475	8.0233	0.0000***
C3Q1AR	ARFIMA(0,d,0)	0.2191	0.0457	4.7893	0.0000***
C3Q2AR	ARFIMA(0,d,0)	0.2738	0.0431	6.3522	0.0000***
C3Q3AR	ARFIMA(1,d,0)	0.4107	0.0491	8.3676	0.0000***
C3Q4AR	ARFIMA(0,d,0)	0.0853	0.0474	1.8011	0.0728*
C3Q5AR	ARFIMA(1,d,1)	-0.0532	0.2068	-0.2575	0.7970

Source: Authors' Compilation

Note: ***1% level of significance, **10% level of significance

The results of ARFIMA models developed for examining the long memory in stock liquidity for various stock categories are reflected in Table 42. The values in Table 42 pertain to the fractional differencing parameters, which signifies the presence of long memory of such significant value, i.e., within the range of 0 to 0.5. The results indicate that the fractional differencing parameter in the case of Amihud Ratios of high-priced stocks, moderate to high-priced stocks, moderately priced stocks, moderate to low-priced stocks and low-priced stocks are significant at 1% level of significance. Also, the significant fractional differencing parameters being in the range of 0 to 0.5, suggest the presence of long memory. The study also noticed the fractional differencing parameter to be significant at 1 % level of significance in the case of liquidity of highly liquid stocks, moderate to high liquid stocks, moderately liquid stocks and low liquid stocks. The significant fractional differencing parameter is within the range of 0 to 0.5, which indicates the presence of long memory for said category of stocks. Similarly, in the case of stock liquidity of high volatile stocks, moderate to high volatile stocks and moderately volatile stocks, the study noticed the fractional differencing parameter to be significant at 1% level of significance and 10% level of significance in the case of moderate to low volatile stocks. This indicates the presence of long memory for such categories of stocks as the significant fractional differencing parameter lies within the range of 0 to 0.5. Overall the results reveal strong evidence of long memory in stock liquidity. The stock liquidity here is represented by Amihud Ratio, which actually depicts stock illiquidity. Thus the results suggest the presence of long memory in one of the dimensions of stock liquidity that is represented by the Amihud Ratio and not the presence of long memory in stock liquidity in general. Previously, Bala and Gupta (2020) have found evidence of persistence in stock liquidity in the Indian stock market.

4.5.3 Examination of Long Memory in Stock Volatility

Table 43: Results of ARFIMA in case of Stock Volatility

Variables	Model	Coefficient	Standard Error	t-Statistic	P-value
C1Q1SD	ARFIMA(0,d,0)	0.4064	0.0406	10.0095	0.0000***
C1Q2SD	ARFIMA(0,d,0)	0.2346	0.0467	5.0260	0.0000***
C1Q3SD	ARFIMA(0,d,0)	0.2969	0.0440	6.7399	0.0000***
C1Q4SD	ARFIMA(1,d,1)	0.1698	0.1261	1.3474	0.1790
C1Q5SD	ARFIMA(0,d,0)	0.2669	0.0461	5.7943	0.0000***
C2Q1SD	ARFIMA(0,d,0)	0.2988	0.0466	6.4113	0.0000***
C2Q2SD	ARFIMA(1,d,0)	0.3732	0.0615	6.0672	0.0000***
C2Q3SD	ARFIMA(0,d,0)	0.2936	0.0439	6.6942	0.0000***
C2Q4SD	ARFIMA(0,d,0)	0.2642	0.0453	5.8375	0.0000***
C2Q5SD	ARFIMA(0,d,0)	0.2263	0.0458	4.9366	0.0000***
C3Q1SD	ARFIMA(0,d,1)	0.3806	0.0831	4.5805	0.0000***
C3Q2SD	ARFIMA(0,d,0)	0.3305	0.0462	7.1536	0.0000***
C3Q3SD	ARFIMA(0,d,0)	0.2771	0.0453	6.1179	0.0000***
C3Q4SD	ARFIMA(0,d,0)	0.2691	0.0455	5.9153	0.0000***
C3Q5SD	ARFIMA(0,d,0)	0.2224	0.0470	4.7290	0.0000***

Source: Authors' Compilation

Note: ***1% level of significance

Table 43 depicts the results of ARFIMA models developed for examining the long memory in stock volatility for various stock categories. The table incorporates the values of fractional differencing parameters. In the case of stock volatility of high-priced stocks, moderate to high-priced stocks, moderately priced stocks, low priced stocks, the study noticed the fractional differencing parameter to be significant at 1% level of significance. As such significant fractional differencing parameter values lie within the range of 0 to 0.5, it indicates the presence of long memory. Further, we notice the fractional differencing parameter in case of volatility of high liquid stocks, moderate to high liquid stocks, moderately liquid stocks, moderate to low liquid stocks, and low liquid stocks to be significant at 1% level of significance. Also, the value of the fractional parameter being within the range of 0 to 0.5 indicates the presence of long memory in stock volatility. Similarly, in the case of volatility of high volatile stocks, moderate to high volatile stocks, moderately volatile stocks, moderate to low volatile stocks and low volatile stocks, the study noticed the fractional differencing parameters to be significant at 1% level of significance. This also suggests the presence of long memory in stock volatility as the fractional differencing parameters lie within the range of 0 to 0.5. Overall, the results indicate strong evidence of long memory in stock volatility.

4.6 Model Diagnostics

4.6.1 Model Diagnostics for ARFIMA Models in case of Stock Returns

Table 44: Results of Breusch-Godfrey Serial Correlation LM test of ARFIMA models in case of Stock Returns

Variables	Model	F-statistic	P-value
C1Q1LR	ARFIMA(0,d,0)	0.4745	0.4915
C1Q2LR	ARFIMA(1,d,0)	0.2075	0.6491
C1Q3LR	ARFIMA(1,d,0)	0.1572	0.6920
C1Q4LR	ARFIMA(0,d,0)	0.4296	0.5127
C1Q5LR	ARFIMA(0,d,0)	0.1226	0.7265
C2Q1LR	ARFIMA(0,d,0)	0.9641	0.3271
C2Q2LR	ARFIMA(0,d,0)	0.0159	0.8998
C2Q3LR	ARFIMA(0,d,0)	0.1184	0.7311

C2Q4LR	ARFIMA(1,d,0)	0.7523	0.3865
C2Q5LR	ARFIMA(1,d,0)	0.0166	0.8976
C3Q1LR	ARFIMA(0,d,0)	0.2996	0.5846
C3Q2LR	ARFIMA(1,d,0)	0.2340	0.6290
C3Q3LR	ARFIMA(0,d,1)	0.5431	0.4618
C3Q4LR	ARFIMA(1,d,0)	1.7743	0.1840
C3Q5LR	ARFIMA(0,d,0)	1.7780	0.1836

Source: Authors' Compilation

Table 44 highlights the results of the Breusch-Godfrey Serial Correlation LM test for the models examining the long memory in stock volatility for various stock categories. The p-values as indicated in Table 44 are more than 0.01, 0.05 and 0.10 at 1% level of significance, 5 % level of significance and 10 % level of significance respectively. Thus, the study fails to reject the null hypothesis of no serial correlation at the respective levels of significances. Therefore, the ARFIMA models developed for the purpose of examining long memory in stock volatility do not contain serial correlation. In other words, the residuals of such models are white noise.

4.6.2 Model Diagnostics for ARFIMA Models in case of Stock Liquidity

Table 45: Results of Breusch-Godfrey Serial Correlation LM test of ARFIMA models in case of Stock Liquidity

Variables	Model	F-statistic	P-value
C1Q1AR	ARFIMA(0,d,0)	1.4176	0.2349
C1Q2AR	ARFIMA(0,d,0)	0.1343	0.7144
C1Q3AR	ARFIMA(0,d,0)	1.2420	0.2661
C1Q4AR	ARFIMA(1,d,0)	0.7267	0.3948
C1Q5AR	ARFIMA(0,d,0)	1.2253	0.2693
C2Q1AR	ARFIMA(0,d,1)	0.1003	0.7517
C2Q2AR	ARFIMA(0,d,0)	2.1113	0.1232
C2Q3AR	ARFIMA(0,d,0)	2.3221	0.1001
C2Q4AR	ARFIMA(1,d,1)	0.7783	0.3785
C2Q5AR	ARFIMA(0,d,0)	0.1540	0.6950
C3Q1AR	ARFIMA(0,d,0)	0.3062	0.5805
C3Q2AR	ARFIMA(0,d,0)	2.2943	0.1311

C3Q3AR	ARFIMA(1,d,0)	1.2487	0.2648
C3Q4AR	ARFIMA(0,d,0)	0.5023	0.4791
C3Q5AR	ARFIMA(1,d,1)	0.7355	0.3919

Source: Authors' Compilation

Table 45 highlights the results of the Breusch-Godfrey Serial Correlation LM test for the models examining the long memory in stock liquidity for various stock categories. The p-values as indicated in Table 45 are more than 0.01, 0.05 and 0.10 at 1% level of significance, 5 % level of significance and 10 % level of significance. Thus, the study fails to reject the null hypothesis of no serial correlation at the respective levels of significances. Therefore, the ARFIMA models developed for the purpose of examining long memory in stock liquidity do not contain serial correlation. In other words, the residuals of such models are white noise.

4.6.3 Model Diagnostics for ARFIMA Models in case of Stock Volatility

Table 46: Results of Breusch-Godfrey Serial Correlation LM test of ARFIMA models in case of Stock Volatility

Variables	Model	F-statistic	P-value
C1Q1SD	ARFIMA(0,d,0)	0.6603	0.4172
C1Q2SD	ARFIMA(0,d,0)	0.0143	0.9048
C1Q3SD	ARFIMA(0,d,0)	1.6862	0.1952
C1Q4SD	ARFIMA(1,d,1)	0.5864	0.4445
C1Q5SD	ARFIMA(0,d,0)	0.2063	0.6501
C2Q1SD	ARFIMA(0,d,0)	0.0405	0.8407
C2Q2SD	ARFIMA(1,d,0)	0.9150	0.3397
C2Q3SD	ARFIMA(0,d,0)	1.2636	0.2620
C2Q4SD	ARFIMA(0,d,0)	0.1940	0.6599
C2Q5SD	ARFIMA(0,d,0)	0.9570	0.3289
C3Q1SD	ARFIMA(0,d,1)	0.0703	0.7911
C3Q2SD	ARFIMA(0,d,0)	0.0970	0.7557
C3Q3SD	ARFIMA(0,d,0)	0.4400	0.5077
C3Q4SD	ARFIMA(0,d,0)	0.0928	0.7609
C3Q5SD	ARFIMA(0,d,0)	0.1044	0.7469

Source: Authors' Compilation

Table 46 highlights the results of the Breusch-Godfrey Serial Correlation LM test for the models examining the long memory in stock volatility for various stock categories. The p- values as indicated in Table 46, are more than 0.01, 0.05 and 0.10 at 1% level of significance, 5 % level of significance and 10 % level of significance. Thus, the study fails to reject the null hypothesis of no serial correlation at the respective levels of significances. Therefore, the ARFIMA models developed for the purpose of examining long memory in stock volatility do not contain serial correlation. In other words, the residuals of such models are white noise.

Chapter 5

Findings and Conclusions

This section focuses on highlighting the key findings from the study and conclusions drawn based on the findings. Also, this section incorporates policy implications of the study, contribution of the study, limitations of the study, and scope for further research.

5.1 Findings of the Study

The main findings of the study are summarized as follows.

5.1.1 Findings from Objective I

- The study found that in the case of Nifty 50 index prices, there had been a sharp rise in the prices from 2004 to 2008, followed by a major crash from 2008 to 2009 period due to the 2008 US supreme crisis. Also, the number of shares traded significantly rose for the same period.
- The market recovered from the post-2008 subprime crisis, and there was a rising trend from 2010 to 2020, which also included corrections due to various economic events.
- The study noticed a major fall in Nifty 50 index prices in March 2020, which was due to the outbreak of Covid 19 pandemic. During this period, there was a significant rise in the number of shares traded in the market.
- For the period 2010 to 2020, there had been a linear trend in Nifty 50 prices, but the volume was noticed to be stable.
- The study noticed the fluctuations in Stock Index Returns over the period of time. The fluctuations in Stock Index Liquidity were stable over the period of time except for a sharp rise in 2008-2009 on account of the US subprime crisis. The Stock Index Volatility also depicted fluctuations for the period, and such fluctuations appeared to be more from 2008 to 2009 and March 2020 due to the 2008 subprime crisis and the outbreak of Covid 19 pandemic, respectively.

- The study noticed the average daily returns of the Nifty 50 Index to be positive for the period. Amihud Ratio, which represents illiquidity, was found to be low, which represents high liquidity in the Indian stock market for the study period.
- In the case of Stock Index returns and Stock Index Liquidity, the study did not evidence the presence of long memory. However, the study found evidence of long-range dependence in Stock Index Volatility.
- After considering the effect of interdependencies among returns, liquidity and volatility, the study noticed the presence of long memory in the case of Stock Index Returns and Stock Index Volatility but the absence of such behaviour in Stock Index Liquidity.
- It was evident that the inclusion of regressors in ARFIMA (p,d,q) models pertaining to Stock Index Liquidity and Stock Index Volatility did not provide contrasting results. However, the Juxtaposition of the fractional differencing parameter in the case of Stock Index Volatility indicated the strong presence of long memory in models, which considered the effect of interdependencies.
- The study found the forecasting errors in the case of the developed ARFIMA (p,d,q) models to be significantly low. Also, the forecasting errors were noticed to get further reduced when models incorporated the effect of interdependencies among variables.
- The study found fewer deviations in actual and predicted values for 3 months forecast, 6 months forecast, 9 months forecast, and 12 months forecast period, which confirmed the forecasting accuracy of the developed ARFIMA (p,d,q) models.

5.1.2 Findings from Objective II

- The study noticed a rising trend in the case of the sectoral indices since their inception, except in the case of the Nifty Realty index and Nifty Metal index. In the case of such indices, the study noticed the fluctuations to be higher than the other indices.
- The trend in the Nifty Realty index was found to be severely affected due to the 2008 US subprime crisis.

- The study noticed that the fall in prices of the Nifty Metal index prices was due to the major depreciation of the Indian Rupee in 2013, the meltdown of the Chinese stock market in 2015, and the Brexit Referendum in 2016.
- The study noticed a sharp decline in all sectoral indices during March 2020 due to the COVID-19 crisis.
- The study noticed the average daily return generated by the Nifty IT index to be the highest, followed by the Nifty Consumer Durable index and Nifty Private Bank index for the study period.
- The average monthly return was highest in the Nifty Consumer Durable index, Nifty Private Bank index, and Nifty IT index.
- For the quarterly return series, Nifty Private Bank Index, Nifty Consumer Durable Index, and Nifty Bank index returns were higher than other sectoral indices.
- The Nifty Private Bank index returns were noticed to be higher than the Nifty FS Index returns and Nifty PSU Bank index returns.
- The returns generated by the Nifty Metal index and Nifty Realty index were noticed to be negative for daily, monthly, and quarterly return series, which indicated the failure in the recovery of these indices.
- The variation in returns of sectoral indices was highest in the Nifty Realty index for daily, monthly, and quarterly return series.
- The study did not find any structural breaks in the data utilized for analysis.
- For daily return series, the study noticed the presence of long memory in the case of Nifty Consumer Durable Index Returns, Nifty Media Index Returns, Nifty Metal Index Returns, Nifty Oil & Gas Index Returns and Nifty Realty Index Returns, and Nifty IT Index Returns.
- The study noticed anti-persistence in the case of Nifty Bank Index Returns and Nifty FMCG Index Returns for daily return series.
- In the case of monthly and quarterly return series, the study evidenced anti-persistence in the case of Nifty Bank Index Returns, Nifty Oil & Gas Index Returns, Nifty Private Bank Index Returns and Nifty Realty Index Returns.

- Overall, the study found evidence of persistence in the daily return series and evidence of anti-persistence in the monthly and quarterly return series.

5.1.3 Findings from Objective III

- The study found the average returns to be highest in the case of high-priced stocks, moderate to low volatile stocks, and low liquidity stocks. However, the average returns were found to be lowest in the case of low-priced stocks, followed by moderately volatile stocks and moderate to low-priced stocks.
- The study noticed the returns generated by high volatile stocks and high liquid stocks to be approximately the same. However, these returns were less as compared to high-priced stocks and low-liquid stocks.
- The study noticed the variation to be highest in the case of high volatile stocks, followed by moderate to low-priced stocks and moderate to high-volatile stocks. Although the moderate to low volatile stocks generated higher average returns, the variation in such stocks was comparatively low.
- The study noticed liquidity to be high in the case of moderate to low-priced stocks and moderate to high-volatile stocks. The liquidity of moderately priced stocks and low-priced stocks was found to be moderate. However, in the case of high-priced stocks and moderate to high-priced stocks, the stock liquidity was found to be comparatively low.
- The study found that, although the low liquid stock offer low liquidity, the variations in such stocks have been highest.
- The study noticed the volatility to be high in the case of moderate to low-priced stocks and moderately priced stocks, followed by low-liquid stocks and low-priced stocks. But, the volatility of moderate to high-price stocks was found to be low, followed by high-liquid stocks and high-priced stocks.
- The study found the presence of long memory in returns in the case of high-priced stocks, moderate to high liquid stocks and high volatile stocks.
- The study found the presence of long memory in one of the dimensions of liquidity (Amihid Ratio) in the case of high-priced stocks, moderate to high-priced stocks,

moderately priced stocks, moderate to low-priced stocks, low-priced stocks, high liquid stocks, moderate to high liquid stocks, moderately liquid stocks, and low liquid stocks.

- The study also found the presence of long memory in the dimension of liquidity (Amihud Ratio) in the case of high volatile stocks, moderate to high volatile stocks, moderately volatile stocks, and low volatile stocks.
- The study noticed long memory in volatility of high-priced stocks, moderate to high-priced stocks, moderately priced stocks, low-priced stocks, high liquid stocks, moderate to high liquid stocks, moderately liquid stocks, moderate to low liquid stocks, low liquid stocks, high volatile stocks, moderate to high volatile stocks, moderately volatile stock, moderate to low volatile stock and low volatile stocks.

5.2 Conclusions of the Study

Long memory is a phenomenon that arises in the modelling and analysis of time series data. The long memory indicates that the decay of the autocorrelation function is slower than exponential decay. One of the ways to test market efficiency in stock market returns is by examining long memory (Lo, 1991). Hurst (1951) is considered a pioneer in long-range dependence modelling who developed a rescaled range statistic. In financial markets, Long Memory refers to a phenomenon where the present stock returns remain significantly correlated with their values in the distant past (Al-Shboul & Anwar, 2016).

In this study, first, we examined the long memory in returns, liquidity, and volatility in the broader stock market index and investigated if the interdependencies among returns, liquidity, and volatility have any significant impact on the long memory behaviour and forecasting ability of models. Next, we investigated the presence of long memory in the Indian stock market considering sectoral indices of the National Stock Exchange (NSE) of India. Finally, we investigated the long memory in returns, liquidity, and volatility for various stock categories. The study attempted to investigate the role of stock characteristics in the examination of long-memory behaviour in the Indian stock market. The stock characteristics included were Stock Price, Stock Liquidity and Stock Volatility. That is, the study examined if high-priced, moderately priced, or low-priced stocks exhibited long memory. Also, the study examined whether the high-liquid, moderately liquid, and low-liquid stocks exhibited long memory. Finally, the study examined if a stock with high volatility, moderate volatility, and low volatility exhibited long memory. The long memory was examined in returns, liquidity and volatility of stock categories representing the individual companies with said stock characteristics. To examine the presence of long memory, the study uses Autoregressive Fractionally Integrated Moving Average (ARFIMA), which is a parametric and parsimonious model developed by Granger and Joyeux (1980).

The present study revealed evidence of long memory in Stock Index Returns and Stock Index Volatility. The study concludes that interdependencies among the variables do affect the behaviour of long memory. Also, consideration of the effect of interdependencies improves the forecasting ability of the models. Further, the study noticed persistence in the daily return series and anti-persistence in the monthly and quarterly return series. The study concludes that the frequency of data does have a significant effect on the behaviour of long memory patterns. The findings support the evidence provided by Kumar (2014) and Hiremath & Kumari (2015) and the weak form of market efficiency in the Indian stock market noticed by Kalsie (2012). Finally, the study evidenced the presence of long memory in the case of high-priced stock returns, moderate to high liquid stock returns and high volatile stock returns. Overall, the results reveal strong evidence of long memory in stock liquidity and stock volatility for various stock categories. The presence of long memory is an indication of an inefficient market, and it suggests that past price information is useful in predicting future returns, which leads to superior returns (Tripathy 2015). If the stock markets are efficient, there are minimal chances to make profits above the normal profit as stocks are traded at fair prices (Al-Shboul & Anwar, 2016). Policy inertia can be one of the reasons for inefficiency in the Indian stock market (Hiremath & Narayan, 2016).

5.3 Policy Implications of Study

The present study has implications for present and potential investors, institutional investors, portfolio managers, and policymakers. The current investors can make use of the results while performing fundamental analysis and rebalancing the portfolios. Results of long memory can act as a motivating factor for potential investors to tap profit opportunities after systematic fundamental and technical analysis. The short, medium, and long-run analyses are significant in technical analysis. The results of long memory at different frequencies will assist the technical analysts in performing analysis at different trading horizons. Also, domestic and foreign institutional investors may find the results helpful in making investment decisions in the Indian stock market. We see the Futures and Options Segment of the National Stock Exchange (NSE) of India is restricted to a few sectoral indices. The active Futures & Options (F&O) products are Nifty 50 F&O, Nifty Bank F&O, Nifty Financial F&O, Nifty Midcap F&O, and select stocks.

The sectoral evidence from the present study can motivate the stock exchanges to activate derivative products based on other sectoral indices, which can attract larger volumes of trade due to such evidence. This will provide traders and investors with more comprehensive trading or investment opportunities. The results are also helpful for portfolio managers while examining the sectors of the Indian stock market during the construction of mutual fund portfolios and subsequent rebalancing of portfolios. The evidence of long memory in sectoral indices implies market inefficiency. The findings will assist the regulators in bringing out measures to facilitate the quick dissemination of information, which will make the markets efficient.

5.4 Contribution of the Study

The findings of the study contribute significantly to academics and research. The results will assist the academicians in providing better clarity about the significant implications of long memory on the Efficient Market Hypothesis and stock market analysis with new sectoral evidence. The application of ARFIMA results to broader indices, sectoral indices, and variables based on various stock categories adds to the existing stock of knowledge, strengthening the applicability of ARFIMA models to financial time series.

5.5 Limitations of the Study

The present study faces the limitation that: Study examines only one broader stock market index in the Indian context. In the case of sectors, the study examines the long memory in stock index returns but not in stock index liquidity and stock index volatility. This was due to the unavailability of data for most sectoral indices. Also, stock categories are based on a few characteristics, such as Price, Volume and Volatility.

5.6 Scope for Future Research

An examination of long memory in stock market returns, liquidity and volatility, can be undertaken in the future considering broader indices of various stock markets and juxtaposition of the same with the Indian stock market. Besides the stock characteristics such as Price, Volume and Volatility, various other stock characteristics can be examined. Also, the long memory can be examined using other techniques such as Detrended Fluctuation Analysis (DFA), Multifractal Detrended Fluctuation Analysis (MF-DFA), and Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroskedastic (FIEGARCH) to examine other aspects of long memory which were beyond the scope of the present study.

Research Paper Publication

1. Naik, R., & Reddy, Y. V. (2021). Examination of Long Memory in Indian Stock Market: A Sectoral Juxtaposition. FIIB Business Review. Sage Publisher. doi:10.1177/23197145211040274 [SCOPUS Q2]

Research Paper Presentations

1. Presented a research paper on the topic “Long Memory and Stock Returns" in the seminar on Current Issues and Policy Options in Financial Markets jointly organized by NISM and TIES on 26th August – 27th August 2020.
2. Amity Award for Best Research Paper Presentation for the paper titled “Persistence, Anti-persistence and Interdependencies in Indian Stock Market Returns, Liquidity and Volatility: An ARFIMA Approach” presented at 21st International Business Horizon INBUSH ERA World Summit 2021 organized by Amity University on 17th – 19th February 2021.
3. Presented a research paper and secured Best Paper Presenter Award on the topic “Stock Price Affordability and Long Memory in Stock Returns: Evidence from India” in International Conference on Financial Perspective organized by Rajkiya Engineering College, UP, India on 24th March – 25th March 2022.

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