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Stock Return Prediction using ARIMA Model: Evidence from South Asian Markets

by

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I dedicate my thesis work to my family and friends. A special feeling of gratitude to my loving parents and my wife whose words of encouragement and push for tenacity ring in my ears. I also dedicate this thesis to my friends and teachers who have supported me throughout the process. I will always appreciate all what they have done, especially Sir, Dr. Arshad Hassan for helping me developing and polishing my financial empirical skills and special thanks for putting many hours of proofreading.

CERTIFICATE OF APPROVAL

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Abstract

Stock markets are complex and prone to many factors including economic situations, financial, and other factors such as government policies, market behaviors expectations, and political stability. As a result of these considerations, financial markets are difficult to forecast. The goal of this research is to forecast stock returns in South Asian Markets using ARIMA Models as it is crucial in assisting investors in making investment decisions. This research examines the stock markets of South Asia i.e. Pakistan, India, Bangladesh, and Sri Lanka. The nature of the data is secondary. The data for this was obtained from the respective stock exchange markets. The period of this secondary information is for the past 10 years that starts from 1 July 2012 to 30 June 2022. Daily data is utilized in this research to make sure a larger sample size.

The ARIMA model is used to examine daily stock returns for all indices in a time series, and the results show that the mean returns for all indices are positive but close to zero. In the long run, this indicates a regressive trend. The representative indices of the markets have anticipated values that are nearly identical to their actual values, with only minor differences. As a result, the ARIMA model can predict stock returns using the historical values of all the indexes. SARIMA is used to determine seasonality. It's an extension of ARIMA that allows you to directly model the seasonal component of the series. The seasonality is observed in the markets of Pakistan, India, Bangladesh and Sri Lanka. Whereas seasonal shock also influence return in all markets. This study will help investors, investment institutions, Portfolio managers, policymakers to make the better investment selections.

Keywords: Autoregressive Integrated Moving Average (ARIMA), Financial markets, South Asian stock markets, Seasonal Autoregressive Integrated Moving Average (SARIMA), Stock market returns, Dynamic & Static model

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Abbreviations

ACF	Autocorrelation Function
ADF	Augmented Dickey Filler
AIC	Akaike Information Criteria
AR	Autoregressive
ARIMA	Autoregressive Integrated Moving Average
ARMA	Autoregressive Moving Average
ASE	Amman Stock Exchange
BIC	Bayesian Information Criteria
BSE	Bombay Stock Exchange
CSE	Colombo Stock Exchange
DSE	Dhaka Stock Exchange
ERW	Exponential Random walk
ES	Exponential Smoothing
FTSC	Financial Time Stock Exchange (100 index)
GDP	Gross Domestic Product
GNP	Gross National Product
KSE	Karachi Stock Exchange
LSTM	Long Short-Term Memory
MA	Moving averages
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MASE	Mean Absolute Squared Error
NSE	National Stock Exchange of India
NYSE	New York Stock Exchange
OGDCL	Oil and Gas Development Company Limited

PACF	Partial Autocorrelation Function
PP	Phillips-Perron
RMSE	Root Mean Squared Error
ROI	Return on Investment
RW	Random walk
RWH	Exponential Random walk
RWI	Random walk innovation
S&P	Standard and Poor
SARIMA	Seasonal ARIMA
SIC	Schwarz information criterion
SVM	Support Vector Machine
TSF	Time Series Forecasting
URT	Unit Root Test
VR	Variance Ratio Test
WMA	Weighted moving averages

Chapter 1

Introduction

1.1 Back Ground of the Study

Stock market return projections are one of the main challenges faced by investors and other parties. It is difficult and problematic due to the complexities of the stock market and how it is represented in current financial research. It's an interesting topic that keep researchers motivated to improve existing techniques and create new predictive models. The stock market growth and its impacts on economic expansion are two of the most crucial topics of financial research. Academic and technical research aims to determine the best effective forecasting techniques and procedures for making quick and accurate stock market predictions (Contreras et al., 2003). According to theoretical research, the stock market tries to promote long-term economic growth through channels of consumption and investment.

Forecasting is a dynamic and ongoing activity (Golden et al., 1994). Based on inputs, it makes educated assumptions about the course of future trends. It estimates various important factors using both historical and recent data. "Reliability and Accuracy of Forecasting Model is Difficult and Under a Big Question Mark," claim Cao et al. (2019).

By predicting market direction using a forecasting model or approach, it is possible to reduce investment risk and uncertainty. By increasing investment in stock markets, it may also be useful to decision-makers and regulators in obtaining the better conclusions and taking remedial action.

There are three different categories of forecasting approaches: time series analysis, projection models, and qualitative techniques. The most effective of technique is time series analysis. Although there are many time series forecasting strategies, no single strategy is used to predict the whole stock market returns.

According to the different studies, researchers disagree on how to forecast stock market returns. The time series method employs historical data to forecast future outcomes. The assumption is that past demand accurately predicts future demand.

Forecasting methods include Moving Averages, Exponential Smoothing, Auto Regressive Moving Averages, Weighted Moving Averages, and Auto-Regressive Integrated Moving Averages.

Stock market forecasting determines the future movement of the stock price. There are multiple techniques for forecasting stock market price movement. As a result, it is divided into two categories: fundamental & technical analysis. Fundamental analysis is used to determine a stock's essential worth. It is based on financial assessments of businesses or sectors. "Technical analysis is a method of analyzing historical market data, and forecasting future prices based on the assumptions that stock prices are determined by market forces & that history tends to repeat itself" (Levy, 1966).

These techniques have been used to make investment decisions for decades, in 1960 the theory of random walk put them to test, also known as the EMH Fama (1970), put them to the test, contending that future stock price changes cannot be predicted based on historical price changes. There have been extensive empirical studies have found a "random walk" in the stock price (Tong, 2012; Konak and Şeker, 2014). However, Stock prices are easy to predict, according to some empirical investigations (Darrat and Zhong, 2000; Al-Tabbakh et al., 2018; Lo and MacKinlay, 1989; Owido et al., 2013; Radikoko, 2014). Due to stock markets fluctuate on a daily basis, they are referred to as moving averages. Because these markets are so difficult to predict due to the number of independent factors related to the environment and the uncertainty of future movement, this type of market can help to reduce investor risks. As a result, forecasting techniques can help investors make more informed decisions. A growing economy inspires investor confidence, which can lead to higher prices. People invest more in equity markets to increase their wealth when the value of a stock increases.

Analysts of the stock markets are continuously trying to develop successful techniques for predicting the price indexes.

The main goal is to make a lot of money by employing the best investment planning and successful stock market forecasting to achieve the best results while reducing incorrect forecast stock prices. Investors' goal is to develop and implement any predicting strategy that will help them benefit from investment risk in the stock market. "Prediction should be possible from two perspectives: statistical and artificial intelligence techniques," by Wang et al. (2018).

Investors and institutions obtain the capability to make the best investment decisions, for achieving more success, and plan to create efficient strategies for their future and current activities by improving models. Investors are eager to acquire any forecasting method that ensures instant profit while lowering stock market investment risk. The stock market's role is to direct the flow of money from savers to investors. Stock market return is defined by the predicting of the stock movements. Decision making of investment is affected because they guide effective investment toward economic development and growth. The main question is how to forecast a stock's future market price. Generally, stock price forecasting is based on factors affecting value and profitability. The stock market's return is determined by the predictability of stock movements. Returns prediction of stock market is best way to manage risk and diversify your portfolio. "Don't put all your eggs in one basket," as one famous saying goes. Economic growth and financial markets having a positive relation, according to theoretical and empirical research.

Stock markets and economic growth have been found to have a positive relationship in both empirical and theoretical research. Investment decisions are critical in achieving the expected returns from stock market projections. Financial markets, on the other hand, are distinguished by their vibrant, complicated, and risky nature. As a result, predicting stock prices and returns is a difficult assignment. Stock and capital growth determined by a variety of variables, the most important of which is the forecast of stock movement patterns.

The forecasting and prediction of stock market returns in a specific stock market takes place on an everyday basis. Given the significance of predicting the stock prices & returns, studies have concentrated their efforts on increasing model accuracy when predicting movement of stock prices returns. The fundamental explanation in this regard is that to increase the returns of their investments, stock holders, decision makers, and lending companies must be dynamic and perform better in their planning process. If a forecasting techniques can accurately predict the stock price movements, the uncertainty & associated risk in the investment decision can be reduced. As a result, it would be advantageous for stockholders and decision-makers to specify suitable financial decisions and appropriate steps to enhance the flow of investment opportunities in stock markets. To predicted the stock market, several approaches have been utilized. Forecasting primary goal is to help in investment strategies, improve stakeholder reliability, and improve effective operation.

The future direction of the stock price is predicted by market returns. Macroeconomic conditions, international events, and human psychology has an influence on stock market prices. Factors of Macroeconomic such as inflation, interest rates, unemployment, market regulation, and supervision explain changes in premium. Some other factors to consider like size of the market, cash flow, liquidity, intensity, incorporation with the world market, and the regulatory system. Because nobody is able to foresee the market, that's why the stock markets are troubleshooters.

The stock markets are known for their volatility, complexity & dynamism (Johnson and Soenen, 2003; Cristelli and Cristelli, 2014). The stock market is volatile and exhibits high variability because of shrinking as well as growth, emotional and over-reactions, and because they do not follow a pattern. "Volatility is a simple and sensitive concept that refers to the unexpected return as a result of unexpected events, resulting in massive price movement with non-constant variance." This means that market ups and downs impact share price and demand. One type of risk is volatility. High volatility indicates that the security price can change in any direction in a short time period. This occurs for the variety of reasons, including market factors, the economic environment, political situations, emergencies, and war. As a result of these factors, forecasting is challenging. High volatility is associated with a high probability of a declining market, whereas a high probability of a rising market is associated with low volatility. The good thing is that as high volatility so does the chance to earn more income speedily. The bad thing is that as high volatility also increases risk.

In the financial literature, the reasons for high stock market volatility are currently being debated. As a result, the financial markets exhibit abnormal behavior, which may confuse investors. Stock market volatility, on the other hand, may be a barrier this is especially true in an emerging market where high price volatility causes capital to evacuate the market.

Normally the believe of the general public of the stock market is that it is either extremely risky to invest in or unsuitable for trading in stock market. Despite the fact that investing in the stock market is risky, many people are interested. The most important factor for any investor is to achieve high returns on their investment, and investors are continuously trying to predict or forecast stock prices.

Many intelligent investors use methods such as fundamental and technical analysis to predict the stock prices. Many investors, depends on stock market analysts' and fundamental analysts' viewpoints and suggestions. Some financial investors and analysts use fundamental or technical techniques, as well as prediction algorithms and functions, to forecast the future stock prices and performance.

There are multiple comprehensive studies that can help investors boost their investment returns. The primary focus is on the accuracy of return estimates over various periods of time. It also goes into better detail about their emerging economy portfolio architecture, risk and return, achievement, and trading efficiency. The stock market is extremely significant in the economy. The research of stock market returns in emerging economies is required because big investors seek high volatility and high returns.

The goal is to assist investors who want to invest. As a result, predicting the future is a difficult function, and selecting the best technique is a challenging task. Efficient market hypothesis describes how prices reflect on aggregate information. Also insists that the market follows a random walk. There are various methods for capturing volatility in the financial environment.

Forecasting market returns can be done using a variety of methods. All are used in both developed and emerging markets. These methods are ARMA, ARCH, and GARCH models, but there has been little (if any) work done with the ARIMA model, particularly in South Asian markets, because it is still less explored. There is a need to start investigating the financial markets of an emerging economies like Pakistan, India, Bangladesh, & Sri Lanka, through ARIMA Model to develop investor interest and generate high returns for their investment.

1.2 Theoretical Framework

Different financial theories, models have been proposed in the past to investigate the effects of financial indicators on a country's equity markets. The researchers focused heavily on the stock market's recent efficiency. Efficient market term was introduced by Fama that states "on average the competition will cause the full effects of new information on fundamental value to be represented quickly in real prices". Mainly, it establishes a link between the stock price and related information. According to this, the EMH is related to the above scenario. According to this theory, the efficient market hypothesis states that prices reflect all available information's. It simply means that information is being incorporated into stock prices on a timely and rapid basis. As a result, assessing stock market behavior is significant.

1.3 Motivation of the Study

Stock market is essential in today's economy and has a big impact on it. Prices are a reflection of all the information. The financial environment is quite uncertain and turbulent, hence there are many ways to capture volatility. According to Zhou (1996), these methods have higher correlations but more difficult computing features than non-parametric models, which have superior predictive ability. The ARIMA algorithm is also used to predict the market returns. All models are false, although some are beneficial, according to Box. There are several different ARIMA models, including SVM, PSO, LSTM, VARIMA, SARIMA, and FARIMA.

In the past, several models have used, but essentially no study has used the ARIMA model, particularly for South Asian markets like Pakistan, India, Bangladesh, and Sri Lanka for the forecasting of emerging stock markets returns. Additionally, it shown that the evidence of a series is composed of comprehensive actions for stationary and differencing action for non stationary (Merh et al., 2010).

Forecasting is a difficult process. The suitable method for predicting and comparing the stock prices in developed and emerging markets is difficult to determine. Furthermore, ensuring good long-term forecasting returns through the use of various technologies is always a big topic. It is also critical to provide information on risk and return, trading performance, and efficiency. As explained previously, there are various methods for forecasting market returns. All of these are utilized in both developed and emerging markets.

There have been several studies in recent years that use ARMA type models, but few or almost none of them uses the ARIMA model, especially for the specific regions such as Asia Pacific, Europe, and African stock markets. Many studies presented on forecasting the return of emerging markets using the ARIMA model includes Mexico, Saudi Arabia, and China, but this work is focused on Pakistan, India, Bangladesh, and Sri Lanka markets.

Furthermore, the data set's seasonality must be evaluated. Seasonality is a time series feature in which the data changes on a regular and predictable basis throughout the calendar year. SARIMA is formed by fusing the ARIMA models with the seasonal term. It is an ARIMA extension that directly accepts univariate time series data with a seasonal component.

1.4 Research Questions

This study provides answers to the following questions.

1. Can ARIMA model forecast returns?
2. Does ARIMA model with seasoning effect is better in forecasting return?
3. Does the dynamic model perform better than the static model?

1.5 Research Objectives

The following are the study's objectives:

1. To forecast the returns using ARIMA model.
2. To capture the seasonality in returns through ARIMA model.
3. To identify appropriate model for forecasting returns in each market.

1.6 Significance of the Research

The primary purpose is to help investors for making better decisions about investments and enhance the investor efficiency and accuracy. To get a good return on their investments, investors, governments, and financial institutions must make dynamic decisions. The investment decision has a significant effect on achieving expected returns of stock market. The stock market may fluctuate or disturb its consistency and general unsettled situations. Uncertainty can be overcome by using suitable stock market techniques and appropriate estimation techniques (Zhang et al., 2019b,a). The most difficult aspect is forecasting the stock market accurately and quickly.

A prediction model can accurately predict the movement of stock prices. This method may reduce the risk and uncertainty associated with the investing process. Investors would gain from making informed investment decisions, and government agencies would benefit from making the necessary investments in the stock markets.

The main focus of the research is adjusting the ARIMA is used in such a way that it suitable predicts stock market trends. It also examines whether forecasted values match actual values.

There are numerous methods for forecasting stock market movements. The primary goal of any stock market prediction model is to better correctly estimate the changes in the stock market prices.

An auto-regressive integrated moving average model is a suitable, investors can use statistical modeling techniques to produce accurate and timely return of stock market. Investors are becoming more interested in the emerging countries stock markets as an investment. It stimulates significant investment from many international investors, who predict multiple tasks in this market. As a result of this situation, potential investors must be provided with information about market dynamics in order to make informed decisions. The advanced forecasting tools and techniques are understood by the regulator, institution, and individual investor. This will help regulators and governments in forecasting economic figures and setting an effective course. The efficient price is critical for both investment institutions and individual investors.

The goal of the study is that this forecasting model will be beneficial to evaluate, analyses the market movement. This study not only contributes to the ARIMA model in the context of South Asian countries. Stock market returns have become a popular channel for both investors and academicians. This provides them with a tool that allows them to forecast their market returns more efficiently and reallocate their invested funds for better results.

1.7 Plan of the Research

This research is distributed into five chapters. The first second and third chapters focus on theoretical aspects of the relevant study, while the fourth and fifth chapters contain empirical aspect and interpretations.

The first chapter includes an introduction, theoretical background, motivation, research questions, research objectives, and research significance. The second chapter contains a review of literature on the theory, and forecasting techniques. In Chapter three, the current research study's research methodology is discussed. The fourth chapter explores the data analysis and results. In the fifth chapter the current research study's conclusions, recommendations, and limitations are discussed.

Chapter 2

Literature Review

This chapter discusses the evidence for the theory of returns forecasting in Financial Markets using the different techniques and ARIMA Model.

2.1 Forecasting of Financial Markets

The development of investment policy is highly dependent on stock return forecasting methods. So many methods can be used to forecast the stock market. The ultimate objective is to be able to more accurately forecast stock market price movements. Asymmetric information, insider trading, and other irregularities, on the other hand, may cause market inconsistency or affect the market direction.

Stock returns are the profits generated by a stockholder from stocks owned in the financial market. These earnings can take the form of a dividend or a capital gain for the shareholder. Investors put their money into the stock market in the expectation of profiting from it. Because stock returns show how much an investment has made for the stockholder, investigating stock market returns is a main consideration for market players and portfolio managers. Past studies has shown that the most critical information generated by stock markets are returns, volume, and volatility, which helps in understanding stock market behavior. (Sun, 2003).

Forecasting is an enthralling field of study for scholars and technical agents, and it will continue to fascinate them as they work to enhance the current forecasting model. Predictors are continuously attempting to develop and implement viable methods for predicting price value of index. Several research has used stock return predictability (Rapach et al., 2016; Zhu and Zhu, 2013; Pettenuzzo et al., 2014). Fama (1970, 1991), Lo and MacKinlay (1989), and others have investigated the effectiveness of stock market forecasting. This is because anyone can invest based on their own assessment and potential to plan and implement successful methods for their present and future financial objectives.

The main objective of the investors is to construct any forecasting techniques, that will enable them to profit from the stock market while reducing their investment risk. Investors constantly attempt to forecast the stock prices. Investor biases that can lead to incorrect stock market price predictions include overconfidence and perception of control and trying to herd mindset. As a result, the underlying issues are estimating more exact and current stock price forecasting.

According to Neely et al. (2014), Wang et al. (2018), and Challa et al. (2020), unexpected losses in invested capital can occur for a variety of reasons, including investor mistakes in forecasting their investments or portfolios. The author discusses evidence-based stock return forecasting. Technical indicators was used to estimate stock returns, they are financially and statistically significant, by Neely et al. (2014).

Fundamental analysis includes industrial, firms and economic analyses. Using historical market data, technical analysis helps us to predict future prices. Exact stock price projections would not only minimize stock price uncertainty but would also allow investors to develop expectations and avoid potential huge market cycles. The predicted stock market environment, as well as stock price projections, are critical for determining stock investment time frame and relative investment attractiveness among different market sectors (Pesaran and Timmermann, 1995; Donald and Jordon, 1995).

According to Pai and Lin (2005), stock price projections is the most difficult tasks due to the complicated structure of the equity markets. Suits (1962), Zotteri et al. (2005), and Wen et al. (2019) describe how various econometric methods are used to predict the movement of stock market. Forecasting is the process of predicting the direction of the future market trend based on previous information. It is based on current and historical data, and some significant aspects may be estimated. Using a forecasting model or approach that predicts market direction can assist in reducing investment uncertainty and risk.

Researchers are very interested in stock market efficiency. It establishes a connection between stock price and information set and proposes their timely and rapid incorporation. It is said to be efficient when stock prices completely represent relevant or available information at any given time. The assessment of stock market behavior is important. According to Boehmer and Kelley (2009), security price results come before information because market information assists investment decisions. There are different prediction techniques, but time series analysis is the most efficient.

Time series analysis is thought to be an efficient technique for forecasting trends. Explaining that "time is money" is a critical business tool that relates anywhere time and money are associated. A time series is a collection of statistics-related observations on a phenomenon made at regular intervals of time. Objective of time series analysis is avoiding to make predictions of future values. However, one of the trends chart's major drawbacks is that it does not always accurately represent, foresee, or maintain the market's continuous flow. "Past patterns or flows, seasonal economic expansion, or changes in stock prices all pique the curiosity of investors," as per study of Faisal (2012) and Mallikarjunappa (2009). This comprehensive view of the stock market is required.

Time Series forecasting is a dynamic field of research that has drawn analysts over the last few years. "A suitable approach fitting is necessary for an efficient time series forecasting," writes Tong (2012). Analysts have spent a significant amount of time and effort over the years developing capable approaches that can improve predictive performance. Some many main time series forecasting models have been developed in compliance over time. " Time Series Forecasting is an example of foreseeing the future through comprehension of the past," by Raicharoen et al. (2003). He stated that the most important aspect of showing a time arrangement is to carefully gather and consider carefully prior perceptions of a time arrangement in order to construct a good model that demonstrates the arrangement's essential structure. In order to make forecasts, this model is used to calculate future values for the structure.

"Time Series Forecasting defines that the lines can be called evidence of predicting the future via understanding the past," writes Zhang (2007). Because time series models are so meaningful in so many disciplines, such as business, finance, economics, sciences and engineering, and so on, it is essential to match an appropriate time series model to the required setup.

Time Series Forecasting is the method of estimation that focuses on the dependent variable's historical behavior. TSF models are an alternative method of analyzing and predicting future developments using the previous behavior of the objective. The TSF model, in general, assumes that there is no connection influencing the parameter being forecasted. A prediction can be generated using a simple numerical method, such as linear estimations, or a complicated stochastic model, such as flexible prediction.

"Stationarity is a type of statistical equilibrium," by Hipel and McLeod (1994). A stationary process's mean and variance are not time-dependent. If there are more historical observations, the time series is more likely to be non-stationary, where as we normally are using different methods or transformations in our approach to maintaining it stationary for short time duration.

Time-series forecasting is commonly done using statistical-based approaches such as linear AR models, according to Fang and Xu (2003). The ARMA model is one of these. First-order non-stationarity could be deleted or reduced utilizing methods such as the linear ARIMA, which is based on increment growth.

"The research group is interested in stock market prediction," writes Bagnall and Janacek (2004). Time series analysis includes a variety of prediction models. Researchers have developed several differences on the basic ARIMA model and found that these techniques generate outstanding results.

2.2 ARIMA Model and Forecasting

Box and Jenkins first proposed the ARIMA model in 1970. Another name for it is the Box-Jenkins method. This approach, which was first explained in 1976 by Box and Jenkins (1976), has been further refined in the 1990s for time series forecasting. According to Shumway and Stoffer (2011), "ARIMA is used with fewer liquidity data to create a consistent class of models to handle time correlated modeling and predicting" in Box and Jenkins' 1970 paper. It is a model that defines a time series using observed values and can predict future values. This method consists of a series of steps for detecting, predicting, and identifying ARIMA models with time series data. When applied to any time series, these models reveal non-seasonal patterns free of random white noise.

By comparing the accuracy of an auto ARIMA model with two customized ARIMA models, the objective is to create an accurate stock prediction model. When attempting to make a safe investment, understanding both the present and the future is critical. It also helps in understanding the ARIMA model's significance for time series forecasting as well as the high accuracy of its methodologies.

The significance of creating and refining time-series forecasting models and studying their effectiveness and success, this study aims to improve the accuracy of inventory forecasting by comparing the accuracy results of automated and fitted ARIMA models. The purpose is to obtain a model. Depending on the application, current econometric models have been updated (Zotteri et al., 2005). Used for short-term forecasting of financial time series data, ARIMA is an econometric model that is more efficient and resilient than ordering approaches such as artificial neural networks (ANNs) (Merh et al., 2010; Híl'ovská et al., 2011). ARIMA models can forecast short-term financial time series data with high accuracy. (Schmitz and Watts, 1970; Rajan and Zingales, 1998; Merh et al., 2010; Híl'ovská et al., 2011).

For forecasting financial time series, ARIMA model is considered reliable and effective than most common ANN approaches, especially for short-term forecasting. For predicting short-term stock returns, the ARIMA method is more accurate than for predicting long-term market returns (Sabur and Haque, 1992). In most cases, financial markets are primarily forecasted by other models, so they are not the best models for understanding the past and future forecasting when dealing with financial time series. ARIMA has some effectiveness and can produce good results, especially if the data is non-volatile. ARIMA models have been used in a few studies to predict stock market reversals. (Al-Shiab, 2006; Ojo and Olatayo, 2009; Adebayo et al., 2014). According to several studies, for financial time series data, ARIMA models produce relatively poor forecasts. (Zhang, 2003; Adebayo et al., 2014; Khandewal et al., 2015).

ARIMA predicts a most likely value of our variable of concern based on the dependent variables' historical values as well as the error term. It does an excellent job of forecasting future stock prices. It is also used to determine whether a model is better at short-term forecasting or anticipating stock values over time.

ARIMA beat complex structural models when it came to generating short-term forecasts. The time-consuming process of creating these methods for forecasting of short-term stock prices are defined. The findings gathered from actual data showed that the strength provides investors with short-term predictions that can help them make investment decisions, according to this model. The processes involved in developing an ARIMA predictive model are model identification, parameter estimation, and diagnostic testing. Despite its widespread use, many questions about ARIMA's accuracy remain unanswered.

Stock market return forecasting has been a hot topic for years. Researchers are likely to be most interested in forecasting financial markets. Successful price estimates provide multiple benefits. ARIMA is one of the most popular models. It is used to forecast future stock returns using historical data from the assets in question. One of the most popular financial forecasting models. This demonstrates a high level of efficiency in the generation of short-term forecasts. In short-term forecasting, it consistently outperforms complex structural models. In this model, a variable's future value is a linear mixture of its past data and errors.

There are only a few studies in the field of stock price forecasting that implement alternative approaches like GARCH and ARIMA, and even smaller numbers in emerging stock markets. Moreover, the majority of the study was solely concerned with forecasting movements in stock prices. It also did not compare estimated and actual numbers to ensure that the estimates were correct (Zhang et al., 2019a,b).

The main idea is that it creates a data series by forming a predicted item as a random series over a set amount of time. A relevant statistical method is proposed on autocorrelation analysis could be developed to classify the time series. After establishing the approach construct, future values of time series can be forecasted using past and current values. A variety of methods and theories for predicting stock prices have been developed throughout history. ARIMA models are frequently used in statistical models. According to the research, prediction can be done using two types of techniques: statistical technique and artificial intelligence technique. It has found wide applications in economics and finance.

Some other statistical techniques include regression, smoothing, and generalized autoregressive conditional hetero skedasticity (GARCH). From the point of view of statistical models, ARIMA models are frequently used in economics and finance, as well as stock predicting. Stock market forecasting in time series, on the other hand, is regarded as one of the most complicated issues due to its volatility and noise. Because stock price movements are non-linear and non-stationary, creating precise and trustworthy projections is complicated.

Several researchers used ARIMA methodology to forecast the stock returns. (Khashei et al., 2009; Lee and Ko, 2011; Khashei et al., 2012). It is crucial to choose a method capable of indicating patterns and providing appropriate detail for an investor to make an informed choice. According to Devi et al. (2013), ARIMA is an algorithmic method of modifying the series that is better compared to forecasting directly because it yields more accurate results. According to Al Wadia and Ismail (2011), the ARIMA model has the best technique and was designed specifically for time series data. Their projections are more precise and reliable due to it being a univariate model. As a result, signs and informational factors are inapplicable in this situation.

Nochai and Nochai (2006) apply ARIMA methodology to palm oil price of time series data and find that the expected ARIMA model is effective for forecasting of future returns. The three primary variables in this model are stationary at level, invariability, and similarity, which are used for recognition, assessment, and diagnostic testing, including both (Asteriou and Hall, 2015). Ali et al. (2011) use ARIMA techniques to forecast the stocks of Pakistan's oil, gas companies. Mondal et al. (2014) use the ARIMA model to predict the future rates of return of 56 companies of India from various industries. They found that 85 percent of their projections were accurate. Banerjee (2014) uses the ARIMA technique to forecast the stock market index of India. As per the research, the model's short-run prediction power is the best for achieving the greatest results. Rapach et al. (2016) used vector to decompose an operating cash channel and identify the source of predictive power, use auto regression. Furthermore, evidence of a link between short sellers and traders has been discovered.

On the basis of US stock returns, Wang et al. (2018) discover the volume & returns dynamic relationship. They found that following the volume graph provides no significant return. Zhang et al. (2018) investigate price of oil projections using eighteen macroeconomics & scientific variables. The results suggested correct predictions and trust equal return developments for the investment manager. (Zhang et al., 2019a,b) not only does intraday stock movement trading behavior need to be explained, but so does U-shaped investment curve evidence. They discovered that morning returns can be used to forecast stock prices in the afternoon.

Using the most recent Auto-Regressive Integrated Moving Average Model (ARIMA), these economic projections decline in Europe, Iran as a whole, and especially in France, Italy, and Spain. Mid of the April 2020, the United States will shock everyone by becoming a hotspot for new happenings. To research the accumulated set of statistics for time series analysis, utilize four models. The ARIMA model, which combines the AR (Auto Regression) and MA (Moving Average) models into a single model is included.

On publicly available Netflix stock data, the ARIMA model was tested. The dataset includes daily stock price data from Netflix covering five years, from 7th April 2015 to 7th April 2020. Partial Autocorrelation Functions (PACFs), Autocorrelation Functions (ACFs), and Mean Absolute Percentage Error (MAPE) are employed to contrast accuracy of the model and structure across research. Durham (2002) thinks that the stock market growth in low-income countries is overstated. Because high-income countries are considered in cross-country regression analyses in different studies, the stock market's impact on expansion is overstated.

The index of stock market is a graphical representation of the stock market. It is determined by combining the prices of many stocks. It is a technique used by finance managers and investors to describe the market and make comparisons of investment income (Assaf, 2006). "Pakistan's stock market remains not smart enough to have a meaningful influence on the economy's private sector," write Husain and Mahmood (2001); Husain (2006). Moreover, the Pakistani stock exchange cannot be regarded as a going to lead measure of economic behavior. Stock market fluctuations have an impact on both the economy and people's daily lives. The current economic disaster is more likely to be precipitated by a decrease in the value of a share.

"Stock price forecasting can help investors predict and avoid price risk," writes Emenike Kalu et al. (2014). He predicts the Nigerian Stock Exchange (NSE) using the ARIMA (p, d, q) model on a monthly basis., with a fit sample duration 24 years is 1985 to 2008 and an out-of-sample prediction period ranging from 2009. The methodology forecasts indices and rates of growth that vary from the index values and rates that were noticed. The estimations did not reflect market efficiency during the forecast timeframe. As a result, the model's capacity was tested by making one-period forecasts for the next twelve periods, and statistical data discovered that the model prediction outperformed the naive Model. The world economic disaster demolished the correlation connection between both the NSE All-Share Index as well as its background as a result of the anomalies.

Prediction time series is a crucial subject in macroeconomics, according to Sultana et al. (2013). We analyze time series data using two techniques. Decomposition is one of the most basic technique for predicting time series. Decomposing a time series technique dividing it into its four components: cycle, seasonality, irregularity, and trend. In this research, they predict macroeconomic factors CPI and LSM for the three months of 2013 based on the actual series' decomposition of these factors and the ARIMA model for monthly series from 2008 to 2013. Make a comparison the out of sample projections of two mthods using the mean absolute deviation and the total of the squared errors to decide which method provides the accurate prediction performance for decision makers to use when predicting inflation (CPI) and economic expansion (LSM).

"The predicting time series stock market has stimulated the interest of applied researchers all over the world to the vital role it plays within the economy," according to Adebayo et al. (2014). They choose the ARIMA model for forecasting the stock market in Nigeria and Botswana utilizing common model selection processes such as BIC, AIC, HQC, MAE, and RMSE. According to the empirical research, the ARIMA (1,1,4) and ARIMA (3,1,1) models were discovered to be the most accurate forecast technique for the Nigeria and Botswana stock markets, respectively.

Adebayo et al. (2014) state that stock price projections are essential for finance and economics researchers to improve forecasting models over time. As a result of this inspired study, ARIMA has been observed in publications for time series forecasting. They go through the whole process of creating a predictive model with ARIMA. The New York Stock Exchange and the Nigeria Stock Exchange data were used in this research. The research's findings indicate that the ARIMA model can compete very successfully with more established short-term stock price forecasting methods.

According to Wahyudi (2017), predicting future volatility in stock prices is essential. Because of its ease of use and general acceptance, ARIMA was utilized in this research of Indonesia stock markets. A daily Composite Stock Price Index was used to achieve this objective from 4th January 2010 to 5th December 2014. According to the research, ARIMA could be utilized to predict Indonesian stock prices. The results demonstrated that the model has a high degree of promise for short term forecasting and can fight with other stock price forecasting techniques. The accurate ARIMA model (0,0,1) for forecasting the Indonesia CSPI was recognized using the AIC criterion.

Gay et al. (2016) discuss the well-established (emerging) connection between stock prices and economic factors for the America and other major economies. ARIMA model was used to examine the time series relationship between stock prices and macroeconomic factors such as oil price and exchange rate for the of (BRIC) Brazil, Russia, India, and China, and no meaningful correlation in between the relevant exchange rate and oil price on either BRIC country's index of stocks prices, this could be due to the influence of other macroeconomic indicators at the national and global levels on stock returns, necessitating even farther study. Moreover, no significant correlation was found between old and present stock market results, implying that BRIC markets are ineffective.

According to Ashik and Kannan (2019), the National Stock Exchange is India's biggest and most completely automated trading platform. The Nifty 50 is a stock market investor that includes 50 businesses. ARIMA is a common and important aspect of the Box-Jenkins strategy to time series technique. The stock market of Nifty 50 prices was examined using Box-Jenkins approach, and the trend of future trading day stock market fluctuations was predicted. According to the data, the R-Square value 94% is high, and the Mean Absolute Percentage Error is comparatively low. As a result, forecast of Nifty 50 closing stock price is more precise. As a result, the current study's closing stock price of Nifty 50 shows a moderate falling fluctuation tendency for the next trading days.

According to Wadhawan and Singh (2019), volatility is utilized to predict associated risks with an investment in an indirect way. The research analyzes the accuracy of various volatility estimation methods to that of prediction models. Volatility is estimated using the Close, Garman-Klass, Parkinson, Roger-Satchell, and Yang-Zhang techniques in (1980), while volatility is forecasted using the ARIMA approach. The effectiveness and bias of various volatility estimators were investigated in this study. Comparison evaluates using many error measuring metrics such as MASE, ME, MAE, RMSE, MAPE, MPE, and ACF were used to determine the accuracy of forecasting to use the better volatility estimator. The Parkinson estimator was found to be the most efficient volatility estimator out of five volatility estimators studied over a period of 10 years and tested properly for prediction. The results show that the predicted values were strongly dependent on the RMSE and MAE results. This study was conducted in response to the demand from traders, option professionals, and other stock market people involved for an efficient volatility estimator capable of estimating volatility with high accuracy.

According to Afeef et al. (2018), stock price forecasting has always been and will proceed to be one of the most major investment conjectures confronting investors. In this study, the predicting strategy relied on the variable's prior values. The ARIMA technique was applied to the stock prices of OGDCL, one of Pakistan's big company. The company's daily adjusted closing stock prices were collected from 2004 to 2018. According to the research results, some of the ARIMA models and theories used in the study have a high potential for short-term forecasting. As a result, the ARIMA model performs exceptionally well in forecasting the future in the short term. The findings of the study could help stockholders enhance their results.

Monthly stock price patterns, as per Jarrett* and Kyper (2005), follow predictable patterns. Jarrett and Kyper also explored the consistency of return series for over 50 companies listed on US stock exchanges, concluding that daily differences exist and are easily predicted. In order to achieve stationarity in G7 stock price indexes, Hamori and Takihisa investigated non-seasonal unit roots. Furthermore, several studies examined the Monday effect (as well as other daily effects) in daily stock returns and price index for these stock markets (Cho et al., 2007).

The forecast S&P Bombay Stock Exchange (BSE) Sensex index return values are discussed by Latha et al. (2018). The BSE Sensex has the top 30 companies were listed on the stock market or 30 blue-chip corporate bodies. The financial econometric technique Auto ARIMA algorithm is used to estimate future returns. ARIMA is used to forecast future return values from 2017 to 2019 by fitting ten decades of historical data from 2007 to 2017. The AIC value was utilized to evaluate different models. Validation was performed by comparing expected and actual data values over a 2 different period from 2015 to 2017. Both the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) used to assess accuracy (MAE). The approach may be used by different investors to select firms based on their future returns.

According to Wadi et al. (2018), closed price forecasting is a standard procedure in economics and finance, so scholars created a fit model to improve prediction performance. ARIMA has been used to develop and launch numerous applications. This study's model forecasts closed time series data of eight years from Amman Stock Exchange (ASE) between 2010 and 2018. The results are the ARIMA model provides significant short-term future performance and it will be suitable for investments. According to Dash et al. (2019), RWH is the result of two GBM and EMH. The research looks at the RWH for 20 major stocks in the banking sector of India. This study examines the RWH for 20 significant stocks in the banking sector of India. The data was gathered from NSE between 2017 and 2018 using the ARIMA techniques. ADF, URT, and ARIMA are also used in the research. In this case, the ADF supports RWH while auto ARIMA provides proof against RWH.

According to Pandey and Bajpai (2019), the ARIMA (p,d,q) model & artificial neural networks (ANN) both have been used to predict time series data, with the evidence that ANN is better compared. A few ARIMA (p, d, q) and ANN mixtures were utilized to compare expected accuracy. Using daily data collected over a ten years period, this study aims to enhance ARIMA and ANN combinations for forecasting the Indian stock market, particularly the NSE Nifty 50. ARIMA (p,d,q) and ANN model predictive performance was investigated simultaneously using AAE, RMSE, MAPE, and MSPE statistical techniques. The findings show ARIMA (2,1,2) & ANN (4,10,1) with train features GDX and BFG are the most accurate predictors, with the ANN being the most accurate predictor.

According to Dinardi (2020), forecasting stock returns is important in economics, Finance, and academic fields such as time series analysis. He analyzes listed firms on the S. Pauflo Stock Exchange based on such data and estimates future stock return behavior using a wide range of predicting techniques. ARIMA models are frequently used in time series analysis and generate satisfactory performance in the majority of cases. In view of the high volatility data, other techniques, especially those in the ARCH family, must be examined. These techniques are primarily utilized to forecast data from international stock markets. Exact projections can gain the both institutions that create them and the decision makers directly because they provide enough information to make positive future decisions.

According to Siami-Namini et al. (2019), prediction of time series challenges is being explained using machine and strong training methodologies. These methodologies have been shown to generate more precise results than classical regression based modeling. ARIMA has been shown to be significantly outperformed by artificial RNNs with memory, such as the LSTM.

Deka and Resatoglu (2019) said "The significant portion of uncertainty in the international foreign exchange market create warning among players in the market, dealers, and decision-makers". To forecast future values and eliminate risk, it is required to create a reliable and sophisticated prediction model for foreign exchange rates and their operators. In this study, the Methodology is used to predict Turkey's foreign exchange rate, with inflation playing an important role. ARIMA (3,1,3) is the accurate ARIMA model for predicting Turkey foreign exchange rate, while the best ARIMA model is for predicting inflation (1,1,4). However, over time, the suggested technique for forecasting Turkey's foreign exchange rate & inflation should be updated to reflect new statistics. AIC, ACF, BIC and PACF statistics, as well as performance measures of forecasting like MAPE, MAE, RMSE, and Theil U statistics, are extremely beneficial in the process of choosing the accurate model.

According to Dong et al. (2020), there is no observable criteria for choosing a time series window to fit an ARIMA method. Moreover, no convincing decisions have been made on whether the older data from the data set should be disposed. As a result, assessing the ARIMA model's prediction accuracy is unrealistic. The goal of this project is to close this information gap. It gathers approximately two million ARIMA forecasts of future daily returns from 1996 to 2017. In projections, different model variables are used. They assert that the 5 years moving resolved window best represents USA equity market asset prices, with a yearly over-optimistic error of 2.656%. However, when negative and positive return scenarios kept separate, the ARIMA models generate prediction errors of 0.0009% and 0.011%, respectively, and both understate loss and profit. The discrepancies are lower for low volatility stocks. They conclude that the lack of non-linearity in the ARIMA model is not a main concern and that the model's validity is not compromised if the information is carefully selected.

Boye et al. (2020) create a short-term stock exchange prediction model using the Box-Jenkins technique. They examined monthly data from the Ghana Stock Exchange market for the period of March 2013 to February 2018. The data from the Bayesian Information Criterion (BIC) is made to fit to the ARIMA (0, 2, 1) model (BIC). Diagnostic testing revealed that the residuals of the fitted model were uncorrelated. This technique is used to predict for the next 6 months. According to the forecasted figures, the Ghana Stock Exchange's performance will increase significantly over the next 6 months.

According to Challa et al. (2020). His study forecasts the volatility features and return of the Indian Bombay Stock Exchange S&P BSE-Sensex and S&P BSE-IT indexes. They use statistical analysis such as variance ratio, ADF, PP, and KPSS and ARIMA to examine daily stock returns. The results indicate that mean returns of both indexes are positive, but near zero. This appears to indicate a regressive trend in the long run. With only a few exceptions, the expected and actual numbers are nearly identical. As a result, using historical values of both indexes, ARIMA model can forecast medium and long-term perspectives.

According to Khan and Alghulaiakh (2020), Auto ARIMA is used in this investigation due to the increasing accessibility of historical information and the need to predict, which includes making financial decisions, developing strategies and plans for future projects, and the difficulty of forecasting the stock market because of its complicated factors. ARIMA (p, d, q) is used to generate a precise stock prediction models using Netflix stock history data for 5 years. In terms of MAPE calculation and holdout testing, ARIMA (1, 1, 3) outperformed the other two models, showing the ARIMA model's utility in stock prediction.

Securities, bonds, Shares, & currencies are all trade on a daily basis in the stock market, making the sets of data time-series information according to Dhyani et al. (2020). ARIMA is an analysis of a time series tool that extracts significant data to help in forecasting stock prices. It also helps in the knowledge of what has happened in the past and forecasting future data behavior. Time series is a unique characteristic that demands a distinct set of forecasting models. The element of time series data has been described and applied for collected daily data of NIFTY 50 index, with the goal of predicting future stock value, using the ARIMA model.

According to Meher et al. (2021), many investors use various strategies to forecast stock prices, such as basic research and technical analysis. At times, they also rely on the comments of different stock market analysts. ARIMA is the time series analysis method used in forecasting algorithms, and the objective of this research is to predict the stock prices of selected Indian pharmaceutical listed companies on the NIFTY 100 using the ARIMA model. The sample size for each company begins on 2017 to 2019. The ADF test is used to determine whether the data is stationary or not.

The top 5 models were then chosen using the Volatility Adjusted R-squared and Akaike Information Criterion, and the necessary inculcation of multiple AR and MA terms was made to modify the approaches and decide the best fitted ARIMA technique for each company. The findings could be used to study stock prices and forecasts in greater depth in future ongoing research. Every day, the stock exchange index changes frequently. Because of politically and economically unstable situations, stock indexes frequently fall or rise. As a result, extensive financial research has been conducted to investigate the necessary aspects of the stock index.

ARIMA models, according to Adebiyi Ayodele et al. (2014), can participate fairly very well in emerging prediction models in short-term forecasting. Adebiyi Ayodele et al. (2014) developed a price forecasting models for stock predicting based on publicly available information collected from the New York Stock Exchange and the Nigeria Stock Exchange. According to performance comparisons based on their own Duane model & ARIMA models, the ARIMA model is a suitable option that produces acceptable forecasts.

2.3 Hypothesis of the Study

H1: *Past returns and past shocks has influence on current returns.*

H2: *The seasonality influences return in South Asian Markets.*

H3: *The dynamic models are better than static models in forecasting returns.*

Chapter 3

Research Methodology

In this Chapter, the data description, population, empirical test of forecasting models, and econometric model are discussed briefly.

3.1 Methodology

Stock price projections have become an attractive activity for investors seeking the best stock market outcomes. As a result, a variety of techniques and methods for stock price prediction have been created over the past decade. Information in time series is mentioned as discrete-time sequences that are consistently randomly distributed in time, and prediction is completed by analyzing studied points within the series to predict the future.

Financial market prediction is likely to draw the most interest from researchers. Forecasts have obvious advantages. Many studies in this perspective are focused on return predictability approaches, but by including ARIMA models, an attempt has been made to predict stock prices. The ARIMA model is used, which has not been frequently appropriate in the majority of previous research studies. This technique is appropriate for predicting stock returns market. It is used to forecast the future stock return using historical data from the investments in question.

ARIMA comes in a variety of forms. To forecast market index returns, the ARIMA model is used. Both SVM and LSTM are hybrid models used to forecast the returns of stocks. To detect a number of time series matrices, the VARIMA model is used. To identify seasonal effects, the SARIMA model can be used. It is based on an error-correcting approach, and it also improves the order of the AR and MA model parts.

Investment institutions and individuals make decisions on making an investment and create a plan or strategies for their future endeavors. As a result, the researchers' current forecasting areas have been attempting to enhance approaches over time. Especially when the making of decision process is perceived to be unavailable in general due to the need to accumulate and obtain information from large amounts of data.

Autoregressive Integrated Moving Average models (ARIMA models) based on the methodology proposed by Box & Jenkins in the 1970. Linear models of the ARIMA family are capable of representing both stationary and non-stationary time series. Independent variables are not incorporated into the construction of ARIMA models. To make predictions, they make use of the data in the series itself.

ARIMA models depend a lot on data auto-correlation patterns. ARIMA predicting future technique differs from most methodologies in that it does not presume any particular pattern in the historical information of the sequence to be predicted. It employs an appropriate methodology to select an appropriate model from a large group of models. The strategies are especially then validated against old data to ensure that it perfectly represents the set.

Auto Regressive Integrated Moving Average (ARIMA) is a model that explains a time series utilizing observed data values which can be utilized to forecast future values. When applied to any time series, an ARIMA model produces a non-seasonal pattern with no random noise. For making short-term forecasts, ARIMA models have been shown to outperform complex structural models in their efficiency. In the ARIMA model, the prospective price of variable is a linear function of the previous price and the error.

Autoregressive (AR) models could be a combination of moving average (MA) models to form the Autoregressive Moving Average (ARMA) group of time series forecasting. When the information is stationary, it can be utlized. This category of models can be advanced to non-stationary set by having allowed data series differencing. These models are known as Autoregressive Integrated Moving Average (ARIMA). It is essential to be aware of both the present and future projections, especially when looking for a secure investment. Understanding the function of time series forecasting is also helpful ARIMA model and the efficiency of the technique. ARIMA is most frequently used with information that is limited in volatility. Box and Jenk- ins (1970) developed a systematic class to negotiate with time-correlated modeling and prediction (Shumway and Stoffer, 2011). Regardless of its widespread use, ARIMA's accuracy remains a concern. For example, what window length should be utilized to generate regression variables and thus forecast the future, and whether the window must be placed width moving or begin increasing. To estimate the future value of the stocks using the ARIMA model, test the auto ARIMA values in addition to creating customized ARIMA (p, d, q) models to obtain an effective forecasting strategy.

The core concept of ARIMA Model is that a forecasting element is developed as a random collection to take a set of data over a specified time period. A relevant statistical technique for explaining the series may be developed based on autocorrelation analysis of the time series. Once the approach is established, future values can be predicted using the past and current values of time series. An ARIMA (p, d, q) model is an I (d) process with an integer difference from a stationary ARMA (p, q) process. The technique used in this research to establish the ARIMA model for forecasting stock prices is detailed in the subsections that follow. The data of stock markets used in this research are daily stock price obtained from the relevant stock markets of selected countries. Time series forecasting has grown in popularity as historical information becomes more easily accessible and forecasting becomes more necessary. TSF offers a method of future value projections that overcomes the constraints of conventional prediction such as uncertainty and duration. TSF forecasts future system behavior using historical and current information.

3.2 Data Description

Emerging economies are still not fully integrated with developed economies, but they are appealing to foreign investors due to high returns. South Asian stock markets are classified as developing markets. In May 2017, it was categorized; MSCI categorized it as an emerging market, while FTSE categorized it as a secondary developing market.

The stock markets of South Asian countries are limited and have limited liquidity. This limits the function of stimulating the economy. Due to speculators and the noise trade, it appears to be quite volatile. It also appears to generate a profit to reimburse for increased market volatility.

Four countries are discussed in this study. Pakistan, India, Bangladesh, and Sri Lanka are the countries involved. Among other things, all of these stock markets are emerging with significant volatility, good returns, high market concentration, and difficulty mobilizing new investments.

These markets are categorized and less sensitive to foreign shocks, enabling for global trade. These markets also offer significant improvements to stockholders, which compensate for market volatility.

3.3 Population and Sample of the Study

This research look, at using the ARIMA model to forecast the stock returns of Pakistan, India, Bangladesh, and Sri Lanka. The purpose of this study is to determine whether ARIMA model is best, accurate, and reliable for forecasting in all markets. For this purpose, the study looks into the historical stock exchange prices of Pakistan, India, Bangladesh, and Sri Lanka.

For Pakistan Karachi Stock Exchange, For India Bombay Stock Exchange, For Bangladesh Dhaka Stock Exchange, and Sri Lanka Colombo Stock Exchange provided information used in this research.

The nature of the data is secondary. The data for this was obtained from the respective stock exchange markets. The period of this secondary information is for the past 10 years that starts from 1 July 2012 to 30 June 2022 (the start date is used to integrate all four countries of the research). Daily data is utilized in this research to make sure a larger sample size.

3.3.1 Karachi Stock Exchange (Pakistan)

Karachi Stock Exchange is the most well-known and oldest stock market of Pakistan. On March 10, 1949, KSE was established as Karachi Stock Exchange. The KSE began with 5 listed companies and a net worth of Rs. 37 Million. The KSE has assisted capital formation for over 60 years, serving a diverse range of participants, including institutional and individual investors. In November 1991, the KSE 100 index was formed. This market capitalization-weighted index of equities includes the biggest companies from each of the 34 industry sectors, while the remaining 66 companies are chosen based on market capitalization, regardless of industry sector. Total Free float market capitalization 13,950 Million. In Pakistan there are 6 markets, but KSE-100 is representative index.

3.3.2 Bombay Stock Exchange (India)

Bombay Stock Exchange is an Indian stock exchange. It is It is located on Dalal Street in Mumbai. It is the oldest stock exchange market in Asia and the 10th oldest market in the world, it was established in 1875. As of January 2022, the BSE is the 8th largest stock exchange in the world, having a total market worth of 276.713 lakh crore. In India there are 21 markets, but BSE Sensex 30 is representative index. There are 30 companies are listed in BSE Sensex30.

3.3.3 Dhaka Stock Exchange (Bangladesh)

Dhaka Stock Exchange Limited is an important stock market in Bangladesh. On April 28, 1954, the Dhaka Stock Exchange was founded as the East Pakistan Stock Exchange Association Ltd., and in 1956 sale purchase was started. On July 23, 1962, it was changed its name East Pakistan Stock Exchange Ltd. The Stock Exchange's name was changed once more to Dhaka Stock Exchange Ltd. On May 13, 1964. There are 2 stock markets in Bangladesh, but Dhaka Stock Exchange is main stock market. The majority of the listed companies on the DSE 30 are based in Bangladesh. As of October 13, 2021, the DSE's stock value in US dollars was $67.11 billion.

3.3.4 Colombo Stock Exchange (Sri Lanka)

The Colombo Stock Exchange (CSE) was established in 1982 under Companies Act No.17. It is the only approved stock market in Sri Lanka, and it is registered with the Securities and Exchange Commission of Sri Lanka. The Board of Directors is the Exchange's main decision makers. The Colombo Stock Exchange (CSE) was formally founded in 1985, taking over the Stock Market from the Colombo Share Brokers Association.

There are 2 stock markets in Sri Lanka, but Colombo Stock Exchange All-Share Index is a representative stock market index that follows the achievement of all listed companies on Sri Lanka's Colombo Stock Exchange. The Colombo Stock Exchange (CSE) has 290 companies representing 19 GICS industry groups as at 30th December 2022, with a market capitalization of Rs. 3,847.15 Bn.

3.4 Descriptions of Variables

The only variable in this forecasting is return. It is calculated using the formula shown below.

$$R_{i,t} = \ln\left(\frac{p_t}{p_{t-i}}\right) \tag{1}$$

describes the return of an index at time t and where:

Ri,t represents the index's return at time t.

ln represents the logarithm of the returns in natural logarithms.

pt represents the closing price of the index at time t.

pt-i represents the closing price of the index at time t-i.

3.4.1 Econometric Model

This research is conducted on the ARIMA forecasting tool. This is a form of linear approach that can predict both stationary & non-stationary time series information and does not necessitate the presence of independent variables in the data series. It is applied to stationary data, but it can also be applied to non-stationary data by having allowed the data series to be distinguished. It is based on data auto - correlation trends. This model is distinct in that no specific pattern in the series' historic information is assumed.

This technique, according to Pankratz (2009), combines Autoregressive (AR) and Moving Average (MA) models to forecast future returns. The term AR refers to the present value of a time series that is estimated from previous values of that same series., whereas MA term refers to the current value of a series estimated from a linear combination of past errors. In standard non-seasonal ARIMA model (p, d, q), "p" is the number of auto regressive terms, "d" is the number of differences, and "q" is the number of moving average terms.

The mathematical formula for the model is given below to check the error term.

$$\begin{aligned} R_t = b_0 + b_1 R_{t-1} + b_2 R_{t-2} + b_3 R_{t-3} + \cdots + b_p R_{t-p} + \lambda_{t-1}\mu_{t-1} + \lambda_{t-2}\mu_{t-2} \\ + \lambda_{t-3}\mu_{t-3} + \cdots + \lambda_{t-q}\mu_{t-q} + \text{error term} \end{aligned} \tag{2}$$

The mathematical model given below to forecasting the seasonality of ARIMA Model

$$\begin{aligned} R_t = b_0 + b_1 R_{t-1} + b_2 R_{t-2} + b_3 R_{t-3} + \cdots + b_p R_{t-p} + \lambda_{t-1}\mu_{t-1} + \lambda_{t-2}\mu_{t-2} \\ + \lambda_{t-3}\mu_{t-3} + \cdots + \lambda_{t-q}\mu_{t-q} + \nu_t SAR_t + \Upsilon_t SMA_t + Error \end{aligned} \tag{3}$$

SAR is the seasonal auto regressive terms

SMA is the seasonal moving average terms

The Box-Jenkins approach asserts that time series is stationary if the first-level difference is not used. The ARIMA model (p, d, q) is applied in this situation, with d representing the degree of difference selection. If time series data is already stationary position, ARIMA becomes an ARMA model.

"Researchers feel that the GARCH and EGARCH models, when compared to ARIMA models, cannot produce the most accurate results because ARIMA is the right model for predicting and modeling stock prices. Furthermore, by assuming both symmetric and asymmetric effects, many combined models, such as ARIMA GARCH, EGARCH, TGARCH, and GJR, can be utilized to forecast the volatility of the stock returns.

The ARIMA model is constructed in four steps.

FIGURE 3.1: ARIMA model

The first step is to identify the effective values of p, d, and q using the correlogram & partial correlogram techniques. ADF tests is also used to determine whether the data is stationary. In the second step, which is an estimation, the parameters of the proposed solution are predicted using the least squares estimation technique.

In the third step entails performing an analytic test to determine whether the residuals from the estimated model contain white noise. If the specified model already exists, accept it; otherwise, start over. As a result, this approach is iterative in nature. In the fourth stage, predicting future efficiency, the suitable ARIMA model from third step.

3.5 Application of ARIMA Method

The ARIMA method is split into two phases: the progress of the ARIMA model, and the correlation of actual and expected outcomes. According to the publications, a holdback time is required to verify correct projections. The analytic and factor importance tests are used to see whether residuals values are white noise.

3.5.1 Determine the Appropriate Values of p, d, and q

The auto correlation function and Partial autocorrelation function correlogram are two types of correlation coefficients. The ACF shows the connection among both current initial 1st differences and lags. PACF (partial autocorrelation function) shows the connection between each of the data collected for the study and their corresponding middle interruptions. To determine the ARMA model and the required p & q variables, ACF and PACF methods are used.

3.5.2 Unit Root Tests

The unit root test used for the check for series stationarity. In this research, the presence of unit roots is tested using three tests like ADF, PP, & KPSS. Because the p-values were less than 5%, the stock returns series. The unit root analysis is performed under these parameters.

With an intercept

With a trend and an intercept, without intercept.

3.5.3 ARIMA Model Estimations

ARIMA is formed by combining the abbreviations AR and MA. A linear regression model is used to calculate the best-fit values. Once established, the ARIMA could be used to forecast future returns. This can be completed through the use of either static or dynamic forecasting methods. Dynamic forecasting used previously anticipated values, whereas static forecasting used current and delayed values. AIC and SIC (both) comparisons are used in the ARIMA model estimate to determine the best appropriateness of the time series data for future forecasting. The verification stage is critical for determining the correctness of the expected values. In the ARIMA process, a static forecasting instrument could be used to accomplish this. The researchers attempted to forecast future returns after completing the predicting stage by comparing predicted returns to actual returns. The descriptive statistics reveal the mean returns, types of tendencies, return probability and mean value of returns.

Chapter 4

Results and Discussion

This chapter demonstrates the empirical analysis of the econometric models. There are several tests includes such as descriptive statistics, unit root analysis, and check correlogram for model selection, ARIMA and SARIMA are applied to examine the phenomena under discussion, and analyses the results obtained.

4.1 Data Analysis and Result Discussion

In this chapter, discuss the different steps, First, examine data is stationarity or not, and the graphical representations of time series data based on historical data of four South Asian Countries' stock indices is presented. The test of descriptive statistics is included in the second stage of the results. The third section discusses unit root analysis, is used to evaluate data stationarity. ADF is tested at level and first difference with combinations of none, intercept, and trend intercept, as well as AIC and SIC. PP is tested at the level and first difference with none, intercept, and trend intercept combinations, as well as AIC and SIC. KPSS are examined at the level and first difference using a combination of intercept and trend intercept along AIC and SIC. Then apply the ARIMA model for forecasting returns of four indices. For this, first, check the correlogram of the selected data at level & 1st difference.

Once the model is developed, run the equation with the chosen model. The fourth step is the econometric model auto-regressive integrated moving averages (ARIMA) to examine the efficiency of all selected stock markets indices, such as the Karachi Stock Exchange, Bombay Stock Exchange, Dhaka Stock Exchange, and Colombo Stock Exchange indices. The fifth step is to select the best of a dynamic and static model.

The first step in the explanation is to examine the data's behavior. In other words, the data from the indices of all four countries must be checked for stationarity. For further predicting future assessments, it must be stationary.

4.2 Karachi Stock Exchange (Pakistan)

4.2.1 Graphical Representations

Figure 4.1 and 4.2 shows the trend of the KSE index and return respectively. Mix trends are shown in these graphs. Index has growing trend in 2012 to 2016, and then downfall started in 2017 to 2019 due the COVID 19 pandemic. After 2020 the growing trend was again started. First graph of KSE index shows that the data of time series is non stationary. While the returns of KSE Index are replaced in the second graph as stationarized.

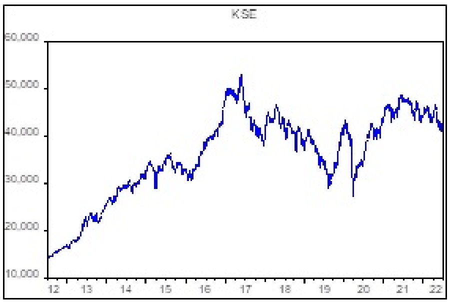

FIGURE 4.1: KSE Index

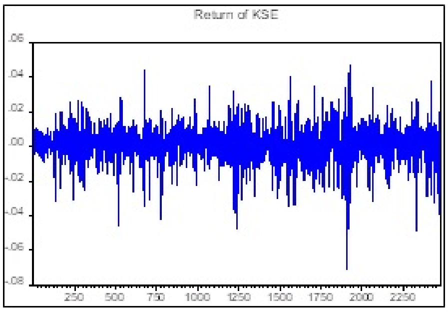

FIGURE 4.2: KSE Return

4.2.2 Descriptive Statistics of KSE

The next step is to examine the data's behavior using descriptive statistics for the index. Descriptive statistics are employed to summarize a set of data by using simple descriptive coefficients that can capture the entire data set. This is divided into two categories: measures of central tendency and measures of variability.

In other words, it is an overview of key statistics or moments such as mean, median, variance, standard deviation, skewness, kurtosis, and Jarque-bera values that can be used to investigate and ensure that the data is natural. Mean values display the average index values points for the time period selected. The median value is the point at which the sample data is divided in half. Essentially, it is the data's middle value. Similarly, standard deviations explain data deviance from the mean. The skewness and kurtosis figures are commonly used to examine the location of data. Skewness is a test of the asymmetry of the probability distribution of a real-valued random variable around its mean.

Figure 4.3 covers the descriptive statistics for the KSE index with 2474 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

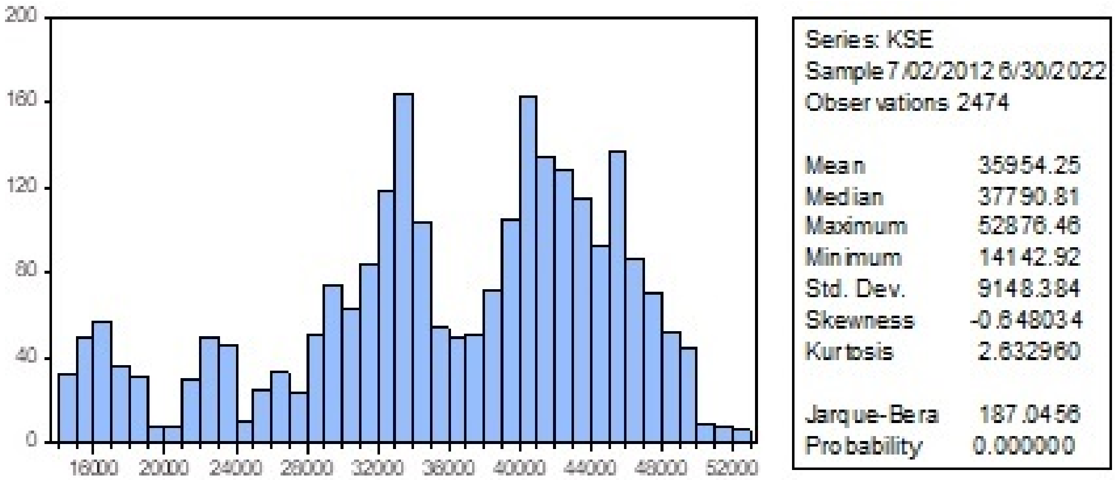

Figure 4.3: Descriptive Statistics of KSE

The mean value of the KSE Index is 35954.25. So, the mean value is positive. It also shows the mean average returns of the indices in this time period is positive, which indicates a long-term regressive trend. The median value of the KSE Index is 37790.81. The maximum value of KSE Index is 52876.46. The minimum value of the KSE Index is 14142.92. The standard deviation value of KSE Index is 9148.384. The skewness value of the KSE Index is -0.648034. So, it's easy to predict that they are negatively skewed at left and represents as asymmetric tail. The kurtosis value of the KSE Index is 2.632960. The value of Jarque-bera KSE Index is 187.0456.

4.2.3 Descriptive Statistics of KSE Return

Figure 4.4 covers the descriptive statistics for the KSE Return with 2473 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

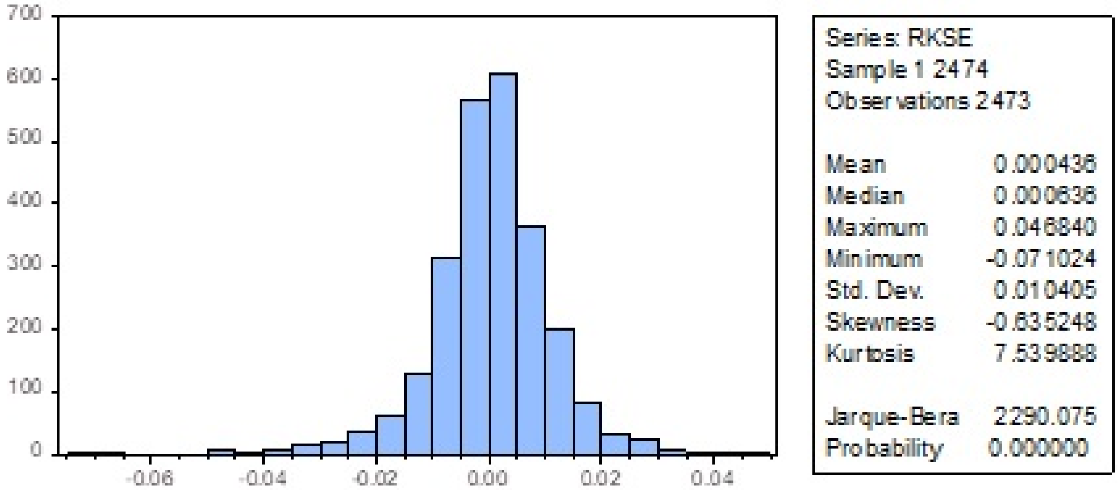

FIGURE 4.4: Descriptive Statistics of KSE Return

The mean value of the KSE return is 0.000436. So, the mean value is positive. It also shows the mean average returns of the indices in this time period is positive, which indicates a long-term regressive trend. The median value of the KSE return is 0.000636. The maximum value of KSE return is 0.046840. The minimum value of the KSE return is -0.071024. The standard deviation value of KSE return is 0.010405. The skewness value of the KSE return is -0.635248. So, it's easy to predict that they are negatively skewed at left and represents as asymmetric tail. The kurtosis value of the KSE index is 7.539888. The value of Jarque-bera KSE Index is 2290.075.

4.2.4 Unit Root Test (KSE)

Because time series data isn't distributed normally in most cases, stationarity may not exist. Because several previous research reports that it is critical to check the stationarity of data before trying to apply the statistical method, the stationarity of the series is checked using unit root tests. This is also required for data trending and seasonality estimation.

In the present investigation of the Index, three techniques have been used to check stationarity via unit root tests.

TABLE 4.1: Unit Root Test (KSE)

Unit Root Test of KSE				
Test Type			T-stats	Prob.
ADF	Level	None	1.7121	0.9794
		Intercept	-3.1001	0.0267
		T&I	-2.3821	0.3889
	1st diff	None	-43.1512	0.0001
		Intercept	-43.2084	0.0000
		T&I	-43.2851	0.0000
PP	Level	None	1.651191	0.9764
		Intercept	-3.086401	0.0277
		T&I	-2.412728	0.3727
	1st diff	None	-43.5041	0.0001
		Intercept	-43.4928	0.0000
		T&I	-43.4737	0.0000
KPSS	Level	Intercept	3.8369	0
		T&I	1.0588	0
	1st diff	Intercept	0.4402	0
		T&I	0.0634	0

ADF test use to test the stationarity of data. It assumed that data is i. i. d. However, there may be week dependence in data so PP, and KPSS are also used the Unite root test. The Unite Root analysis is done with the assumption of no intercept and no trend, intercept and trend and intercept only.

The results show that the data is nonstationary at the level and stationary at the first difference which is shown in the table 4.1.

4.2.5 Correlogram

The correlogram is a tool that used to checking the randomness in a data set. Auto-correlation Function (ACF) and Partial Auto-correlation Function (PACF) are the two forms of correlation coefficients used in correlogram. ACF measures the average correlation in a time series data and previous values of the series measured for different lag lengths. PACF indicates the correlation between the total observations.

4.2.6 ACF and PACF Through Correlogram

TABLE 4.2: ACF and PACF (KSE)

ACF and PACF at Level						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—******	—******	1	0.998	0.998	2464.9	0
—******	— —	2	0.995	-0.031	4918.1	0
—******	— —	3	0.992	-0.005	7359.4	0
—******	— —	4	0.99	-0.006	9788.7	0
—******	— —	5	0.987	0.005	12206	0
—******	— —	6	0.984	-0.016	14612	0
—******	— —	7	0.982	-0.007	17005	0
—******	— —	8	0.979	-0.004	19386	0
—*******	— —	9	0.976	0.005	21755	0

—*******	— —	10	0.974	-0.007	24112	0

ACF and PACF at 1st Difference

Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—* —	—* —	1	0.139	0.139	47.838	0
— —	— —	2	0.004	-0.016	47.878	0
— —	— —	3	0.014	0.016	48.368	0
— —	— —	4	0.019	0.015	49.229	0
— —	— —	5	0.045	0.041	54.183	0
— —	— —	6	0.029	0.018	56.309	0
— —	— —	7	0.013	0.007	56.736	0
— —	— —	8	-0.009	-0.013	56.953	0
— —	— —	9	-0.001	0.001	56.956	0
— —	— —	10	0.011	0.009	57.261	0

The correlogram in this study is an image that describes the correlation statistics of the data set at the level and first-differencing with 36 lags. But only 10 lags are selected. This method is used to calculate the proper p, d, q parameters for the ARIMA model.

The first table shows that the data is not stationary. So, the next step is the Correlegram test at 1st difference level. Table 4.2 of correlogram of the KSE index.

The results of the correlograms for identifying the model using ACF and PACF for the KSE index show that lag 1 is sufficient for running the ARMA model.

After deciding on a model, the parameters must be calculated. This model is built using the least squares approach. As per the correlogram finding, using the best fitted ARMA model (p, q) as (1, 1) for the KSE Index.

4.2.7 ARMA Model Estimation

ARMA is an abbreviation for AR and MA. The linear regression model was used to estimate the best-fit values. The best fit estimate for the KSE index The ARMA model is built with lags 1,2,6, and 8. The AR & MA terms 1,1 are significant in the KSE Index.

The Akaike Information Criterion and the Schwarz Criterion are the most commonly used measurements for selecting the best model. Both best-fit models' residuals were tested for ADF, revealing that the residual data from this methodology is stationary.

According to the result, the values of all parameters are used for making of model. The significance value is based on the number of variables less than 5% confidence intervals. The result shows that the significant number of variables is zero. The Sigma Q value is 0.0001 for the index is the lowest.

According to the rules, the adjusted R-squared value must be higher i.e, 0.9988. AIC value -6.3056 and SBC value -6.2962, both values are minimum.

4.2.8 Forecasting the Return by using ARIMA Model

Once ARMA model is fitted, it could be used to forecast future returns. This is possible with two forecasting methods: dynamic and static. The previously forecasted values are used in dynamic forecasting. In static forecasting, the actual present and lagged values were used.

According to result, the values of all parameters are used for making of model. The significance value is based on the number of variables less than 5% confidence intervals. The result shows that the significant number of variables is zero. The Sigma Q value is 0.0001 for the return is the lowest. According to the rules, the adjusted R-squared value must be higher i.e, 0.0184. AIC value -6.3100 and SBC value -6.3006, both values are minimum.

ARIMA technique is used to forecast the future stock returns. This can be accomplished by utilizing dynamic and static forecasting methods, which employ dynamic and static forecasting methods.

4.2.9 ARIMA Model Through Dynamic and Static Models

Figure 4.5 and 4.6 show the ARIMA Model through dynamic and static models.

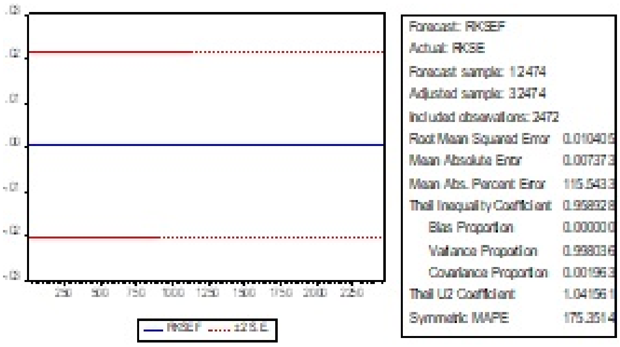

FIGURE 4.5: Dynamic Model (KSE Return)

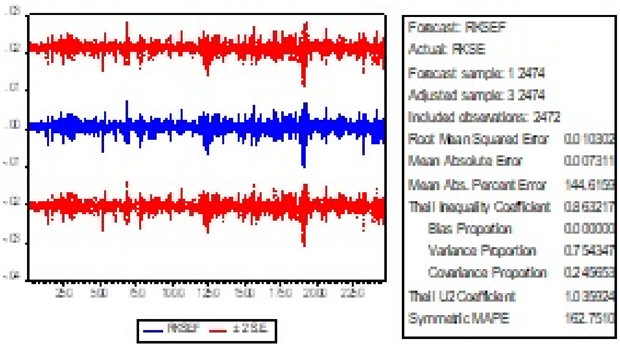

FIGURE 4.6: Static Model (KSE Return)

4.2.9.1 Selection of Best Model

TABLE 4.3: Selection of Model (KSE)

Measure	Static Model	Dynamic Model	Decision Rule
Root Mean Squared Error	0.0103	0.0104	Lower
Mean Absolute Error	0.0073	0.0073	Lower
Theil Inequality Coefficient	0.0004	0.9589	Lower

Table 4.3. The value of measuring parameters lowest values are shows the best model. So the Static Model is lower than the Dynamic Model.

4.2.10 Seasonal ARIMA Model (p, d, q) sar, sma

As per the correlogram findings, using the best fitted Seasonal ARIMA model (p, d, q) as (1, 1, 1) sar(1) sma(1) for the KSE returns. In the table 4.4 below, the equation is run and the results are presented in table 4.4.

Table 4.4: SARIMA Model (KSE)

Possible Model	**Coefficient**	**AR(1)**	**MA(1)**	**SAR(1)**	**SMA(1)**
ARIMA (1 ,1, 1)	10.18806	-0.909684	0.133338	0.999715	0.918414
Measure	SARIMA(1,1,1)		Decision Rule		
Significant	0		Number of Variables		
SIGMASQ	0.0001		Lowest		
Adj R Square	0.9988		Highest		
AIC	-6.3043		Minimum		
SBC	-6.2902		Minimum		

According to the above result, the values of all parameters are used to determine the seasonality in this model. This model shows that the seasonality is in return and shocks at 1 lag. When period is long, there is more uncertainty, whereas when period is short, there is less uncertainty.

4.2.11 SARIMA Through Dynamic and Static Model

Figure 4.7 and 4.8 show the SARIMA Model through two models. This can be accomplished by utilizing dynamic and static forecasting methods.

4.2.12 Selection of Model

TABLE 4.5: Selection of SARIMA Model (KSE)

Measure	**Static Model**	**Dynamic Model**	**Decision Rule**
Root Mean Squared Error	0.01029	0.01040	Lower
Mean Absolute Error	0.00733	0.00735	Lower
Theil Inequality Coefficient	0.85988	0.95895	Lower

Table: 4.5. The value of measuring parameters lowest values is showing the best model. So, the Static Model is lower than the Dynamic Model. This model shows that the seasonality is in return and shocks at 1 lag. When period is long, there is more uncertainty, whereas when period is short, there is less uncertainty.

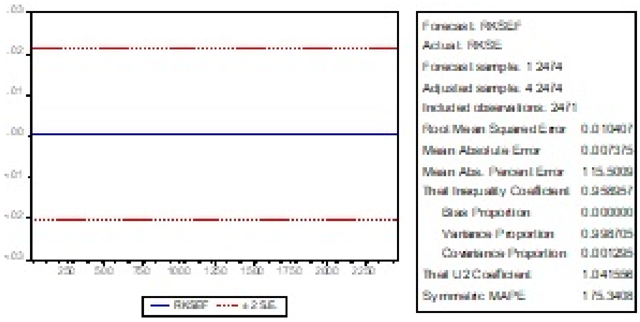

FIGURE 4.7: SARIMA Dynamic Model (KSE Return)

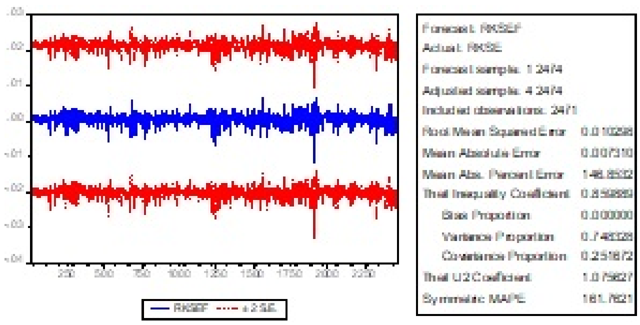

FIGURE 4.8: SARIMA Static Model (KSE Return)

4.3 Bombay Stock Exchange (India)

4.3.1 Graphical Representations

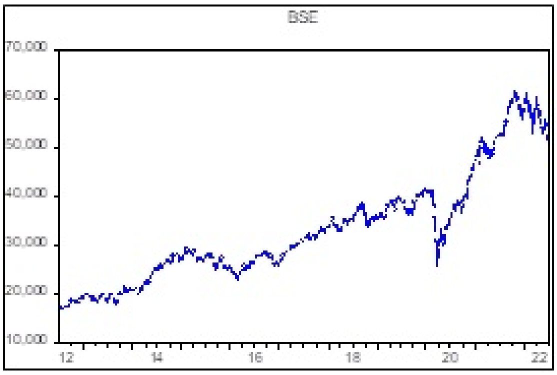

FIGURE 4.9: BSE Index

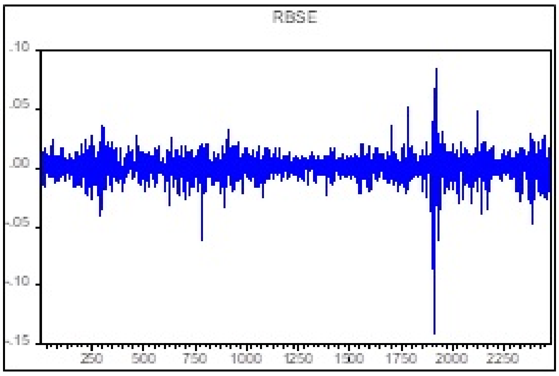

FIGURE 4.10: BSE Return

Figure 4.9 and 4.10 shows the trend of the BSE index and return respectively. Index has growing trend in 2012 to 2014, and then downfall started in 2015 to 2016, then again rising period started from 2017 to 2020. In 2020 stock market is downfall. But mid of 2020 the growing trend was again started. First graph of BSE index shows that the data of the time series is not stationary. While the returns of BSE Index are replaced in the second graph as stationarized.

4.3.2 Descriptive Statistics of BSE

The figure 4.11 covers the descriptive statistics for the BSE index the 2474 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022. The mean value of the BSE Index is 33187.75. So, the mean value is positive. It also shows the mean average returns of the index in this time period are positive, which indicates a long-term regressive trend. The median value of BSE Index is 30889.57. The maximum value of BSE Index is 61765.59. The minimum value of BSE Index is 16639.82. The standard deviation value of BSE Index is 11262.07. The skewness value of BSE Index is 0.0805548. The kurtosis value of BSE Index is 2.893456. The value of Jarque-bera BSE Index is 268.7366.

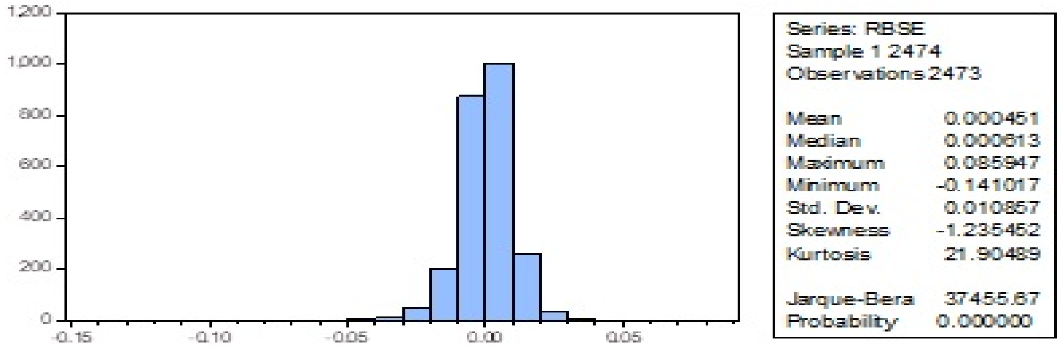

FIGURE 4.12: Descriptive Statistics of BSE Return

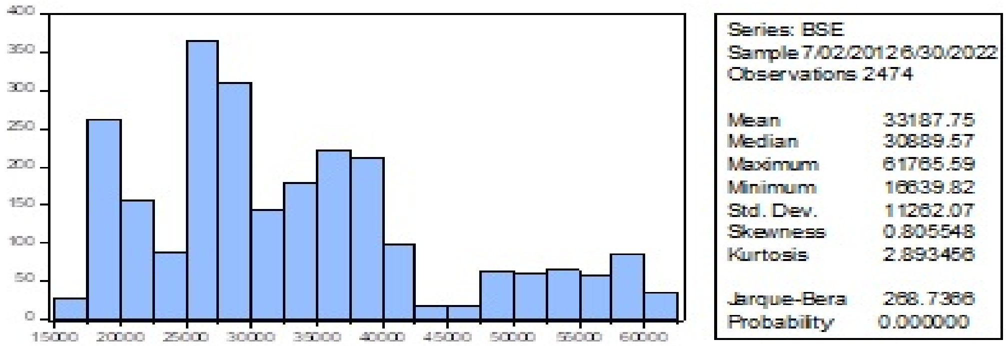

FIGURE 4.11: Descriptive Statistics of BSE

4.3.3 Descriptive Statistics of BSE Return

Figure 4.12 covers the descriptive statistics for the BSE Return with 2473 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022. The mean value of the BSE Return is 0.0004. So, the mean value is positive. It also shows the mean average returns of the index in this time period are positive, which indicates a long-term regressive trend. The median value of BSE Return is 0.0006. The maximum value of BSE Return is 0.0859. The minimum value of BSE Return is -0.1410. The standard deviation value of BSE Return is 0.0.0108. The skewness value of BSE Return is -1.2354. The kurtosis value of BSE Return is 21.9048. The value of Jarque-bera BSE Return is 37455.65.

4.3.4 Unit Root Test (BSE)

ADF test use to test the stationarity of data. It assumed that data is i. i. d. However, there may be week dependence in data so PP, and KPSS are also used the Unite root test. The Unite Root analysis is done with the assumption of no intercept and no trend, intercept and trend and intercept only.

The results show that the data is nonstationary at the level and stationary at the first difference which is shown in the table 4.6.

TABLE 4.6: Unit Root Test (BSE)

Unit Root Test of BSE				
Test Type			T-stats	Prob.
ADF	Level	None	2.0298	0.9903
		Intercept	-0.4946	0.8898
		T&I	-2.2706	0.4494
	1st diff	None	-49.0213	0.0001
		Intercept	-49.0816	0.0001
		T&I	-49.0744	0.0000
PP	Level	None	1.572947	0.9721
		Intercept	-0.529574	0.883
		T&I	-2.35661	0.4025
	1st diff	None	-49.0478	0.0001
		Intercept	-49.0965	0.0001

		T&I	-49.0892	0.0000
KPSS	Level	Intercept	5.2259	0
		T&I	0.6294	0
	1st diff	Intercept	0.0575	0
		T&I	0.0374	0

4.3.5 ACF and PACF Through Correlogram

The correlogram in this study is an image that describes the correlation statistics of the data set at the level and first-differencing with 36 lags. But only 10 lags are selected.

This method is used to calculate the proper p, d, q parameters for the ARIMA model.

The tables of correlogram of the BSE index is as under Table 4.7.

Table 4.7: ACF and PACF (BSE)

ACF and PACF at Level						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—******	—******	1	0.998	0.998	2468.5	0
—******	— —	2	0.997	0	4929.5	0
—******	— —	3	0.995	0.003	7383	0

—******	— —	4	0.993	0	9829.1	0
—******	— —	5	0.991	0.003	12268	0
—******	— —	6	0.99	-0.029	14699	0
—******	— —	7	0.988	0.038	17123	0
—******	— —	8	0.986	-0.034	19539	0
—******	— —	9	0.984	0.005	21947	0
—******	— —	10	0.983	0.004	24349	0

ACF and PACF at 1st Difference

Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
— —	— —	1	0	0	0.0002	0.99
— —	— —	2	-0.013	-0.013	0.4292	0.807
— —	— —	3	0.006	0.006	0.5244	0.914
— —	— —	4	-0.003	-0.003	0.5403	0.969
—* —	—* —	5	0.087	0.087	19.344	0.002
*— —	*— —	6	-0.081	-0.082	35.666	0.001
— —	— —	7	0.063	0.067	45.6	0

— —	— —	8	-0.017	-0.023	46.349	0
— —	— —	9	-0.012	-0.007	46.688	0
— —	— —	10	0.03	0.021	48.983	0

4.3.6 ARMA Model Estimation

The results of the correlograms for identifying the model using ACF and PACF for the BSE show that 2 lags are sufficient for running the ARMA model. So the possible ARMA models may be.

- ARMA (5,5)
- ARMA (5,6)
- ARMA (6,5)
- ARMA (6,6)

Parsimonious Models are always preferred on over identified Models. Higher lags can be examined at diagnostic phase. After deciding on a model, the parameters must be calculated. These models are built using the least squares approach. After run the different equations in eviews software. The following result are shown.

Table 4.8: ARMA Model BSE

Possible Model	**Coefficient**	**AR(5)**	**MA(5)**	**AR(6)**	**MA(6)**
ARMA (5,5)	10.3324	0.9985	0.05770	-	-
ARMA (5,6)	10.3321	0.9985	-	-	0.0407

ARMA (6,5)	10.3354	-	0.2303	0.9974	
ARMA (6,6)	10.3309	-		0.9982	0.03288

4.3.7 Selection of Model through ARMA (BSE)

After run the equations of ARMA (p, q) the below table 4.9 shows the result.

Table 4.9: Selection of ARMA Model (BSE)

Measure	**(5,5)**	**(5,6)**	**(6,5)**	**(6,6)**	**Decision Rule**
Significant	**2**	2	2	2	Variable
SIGMASQ	**0.0005**	0.0005	0.0006	0.0007	low
Adj R Sq	**0.9945**	0.9945	0.9935	0.9932	High
AIC	**-4.5894**	-4.5878	-4.4253	-4.3736	Min
SBC	**-4.5800**	-4.5784	-4.4159	-4.3642	Min

According to the above result, the values of all parameters are used for making of the model. The significance value is based on the number of variables with less than 5% confidence. The result shows that the significant number of variables are two. The Sigma Q value for the index is the lowest. According to the rules, the adjusted R-squared value must be higher. AIC and SBC, both values must be minimized to fit in the model for forecasting. As per the correlogram finding, using the best-fitted ARMA model (p, q) as (5, 5) for the BSE Index.

4.3.8 Forecasting the Return by using ARIMA Model

Once ARMA model is fitted, it could be used to forecast future returns. This is possible with two forecasting methods: dynamic and static. The previously forecasted values are used in dynamic forecasting. The actual present and lagged values were used in static forecasting. So the possible ARIMA models may be.

- ARIMA (5,1,5)
- ARIMA (5,1,6)
- ARIMA (6,1,5)
- ARIMA (6,1,6)

4.3.8.1 Selection of Model through ARIMA (BSE)

After run the equations of ARIMA (p, d, q), the below table 4.8 shows the result. Parsimonious Models are always preferred on over identified Models. Higher lags can be examined at diagnostic phase. After deciding on a model, the parameters must be calculated. These models are built using the least squares approach. After run the different equations in eviews software. The following result are shown.

Table 4.10: Selection of ARIMA Model (BSE)

Possible Model	**Coefficient**	**AR(5)**	**MA(5)**	**AR(6)**	**MA(6)**
ARIMA (5 ,1, 5)	0.000448	0.699229	-0.631104	-	-
ARIMA (5 ,1, 6)	0.00045	0.083403	-	-	-0.070895
ARIMA (6 ,1, 5)	0.00045	-	0.079468	-0.076887	
ARIMA (6 ,1, 6)	0.00045	-		-0.451358	0.368764

Measure	**5,1,5**	**5,1,6**	**6,1,5**	**6,1,6**	**Decision Rule**
Significant	2	2	**2**	2	Number of Variable
SIGMASQ	0.000117	0.000116	**0.000116**	0.000117	lowest
Adj R Square	0.007844	0.011748	**0.011904**	0.007317	Highest
AIC	-6.214269	-6.218215	**-6.218372**	-6.213744	Minimum
SBC	-6.204866	-6.208813	**-6.208969**	-6.20E+00	Minimum

Table 4.10 show the result, the values of all parameters are used for making of the model.

The significance value is based on the number of variables with less than 5% confidence. The result shows that the significant number of variables are two.

The Sigma Q value for the return is the lowest. According to the rules, the adjusted R-squared value must be higher. AIC and SBC, both values must be minimized to fit in the model for forecasting. As per the correlogram finding, using the best-fitted ARIMA model (p, d, q) as (6, 1, 5) for the BSE Return.

ARIMA technique is used to forecast the future stock returns. This can be accomplished by utilizing dynamic and static forecasting methods, which employ dynamic and static forecasting methods.

4.3.9 ARIMA Model Through Dynamic and Static Models.

Figure 4.13 and 4.14 shows the ARIMA Model through the dynamic and Static models.

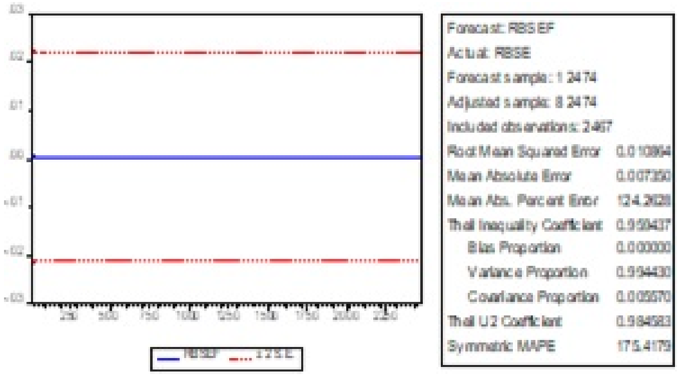

FIGURE 4.13: Dynamic Model (BSE Return)

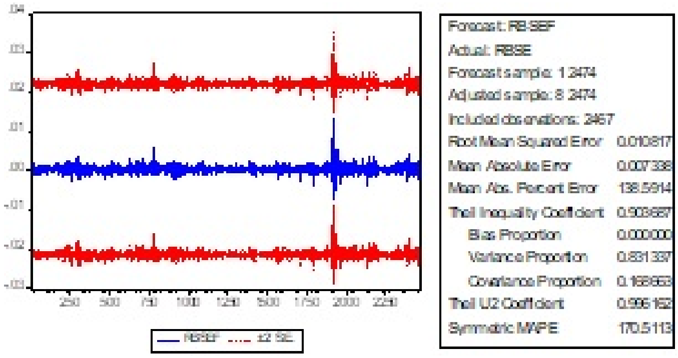

FIGURE 4.14: Static Model (BSE Return)

4.3.9.1 Selection of Best Model

TABLE 4.11: Selection of Model (BSE)

Measure	**Static Model**	**Dynamic Model**	**- Rule**
Root Mean Squared Error	**0.01081**	0.01086	**Lower**
Mean Absolute Error	**0.00733**	0.00735	**Lower**
Theil Inequality Coefficient	**0.9036**	0.95943	**Lower**

Table 4.11 show the best model according to the lowest Decision rule. The Static model values are lowest. So the best model is Static model.

4.3.10 Seasonal ARIMA Model (p, d, q) sar, sma

As per the correlogram findings, using the best fitted Seasonal ARIMA model (p, d, q) as (6, 1, 5) sar(1) sma(1) for the BSE Index. In the table below, the equation is run and the results are presented.

Table 4.12: SARIMA Model (BSE)

Possible Model	Coefficient	AR(6)	MA(5)	SAR(1)	SMA(1)
ARIMA (6 ,1, 5)	0.00045	-0.070105	0.071488	-0.910989	0.923857
Measure	**SARIMA(6,1,5)**		**Decision Rule**		
Significant	4		Number of Variables		
SIGMASQ	0.000116		Lowest		
Adj R Square	0.011948		Highest		
AIC	-6.217607		Minimum		
SBC	-6.203503		Minimum		

According to the Table 4.12, the values of all parameters are used to determine the seasonality in this model. This model shows that the seasonality is in return and shocks at 1 lag. When period is long, there is more uncertainty, whereas when period is short, there is less uncertainty.

4.3.11 SARIMA Through Dynamic and Static Model

Figure 4.15 and 4.16 show the SARIMA Model through two models. This can be accomplished by utilizing dynamic and static forecasting methods.

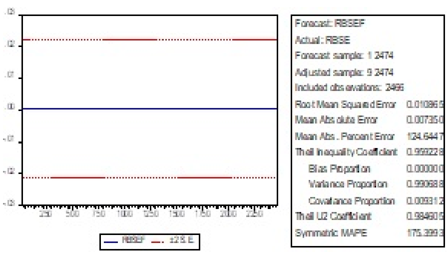

Figure 4.15: SARIMA Dynamic Model (BSE Return)

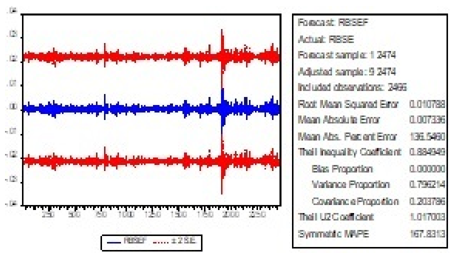

Figure 4.16: SARIMA Static Model (BSE Return)

4.3.11.1 Selection of Model

Table 4.13 show the result for the selection of best SARIMA Model. The value of measuring parameters lowest values is showing the best model. So, the Static Model is lower than the Dynamic Model.

TABLE 4.13: Selection of SARIMA Model (BSE)

Measure	Static Model	Dynamic Model	Decision Rule
Root Mean Squared Error	**0.01078**	0.01086	**Lower**
Mean Absolute Error	**0.00733**	0.00735	**Lower**
Theil Inequality Coefficient	**0.88494**	0.95922	**Lower**

4.4 Dhaka Stock Exchange (Bangladesh)

4.4.1 Graphical Representations

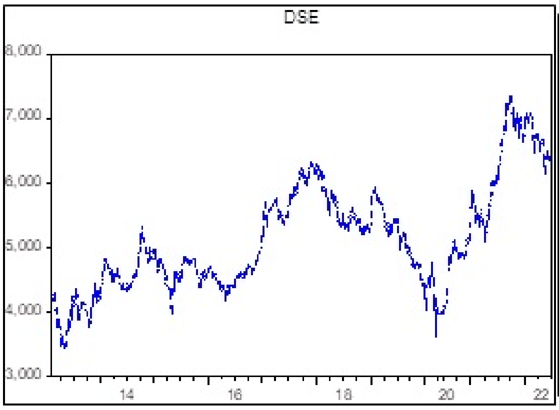

FIGURE 4.17: DSE Index

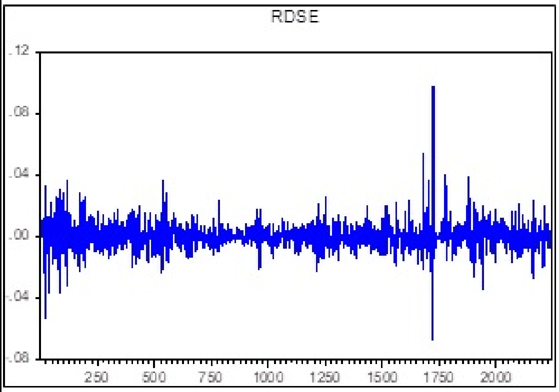

FIGURE 4.18: DSE Return

Figure 4.17 and 4.18 shows the trend of the DSE index and return respectively. Mix trends shown in the first graph during 2012 to 2015. In 2017 and 2018 the market trend is high. But in 2019 downward spike is shown due to COVID-19 pandemic. After 2020 the spick trend was rising. But overall graph shows the mix trend. While the returns of DSE Index are rationalized in the second graph. First graph of DSE index shown that the data of time series is not stationery.

4.4.2 Descriptive Statistics of DSE

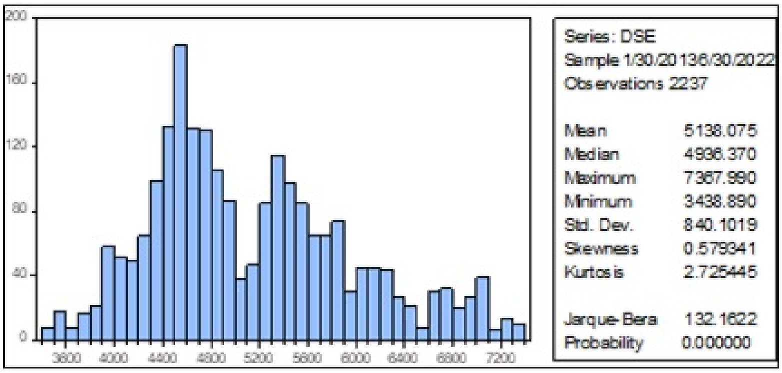

FIGURE 4.19: Descriptive Statistics of DSE

Figure 4.19 the descriptive statistics for the DSE index the 2237 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

The mean value of the DSE Index is 5138.75 So, the mean value is positive. It also shows the mean average returns of the index in this time period are positive, which indicates a long-term regressive trend. The median value of DSE Index is 4936.370. The maximum value of DSE Index is 7376.990. The minimum value of DSE Index is 3438.890. The standard deviation value of DSE Index is 840.1019. The skewness value of DSE Index is 0.579341. The kurtosis value of DSE Index is 2.725445. The value of Jarque-bera DSE Index is 132.1622.

4.4.3 Descriptive Statistics of DSE Return

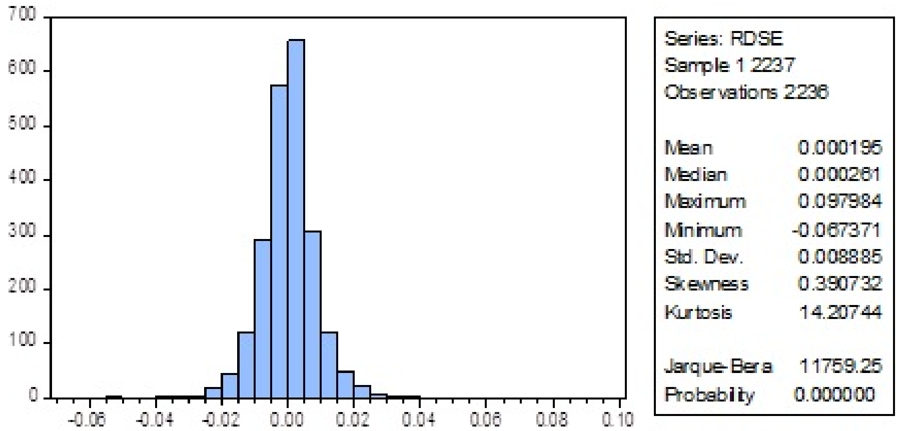

FIGURE 4.20: Descriptive Statistics of DSE Return

The figure 4.21 covers the descriptive statistics for the DSE Return with 2236 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

The mean value of the DSE Return is 0.000195 So, the mean value is positive. It also shows the mean average returns of the index in this time period are positive, which indicates a long-term regressive trend. The median value is 0.000261. The maximum value is 0.097984. The minimum value is -0.67371. The standard deviation value is 0.008885. The skewness value is 0.390732. The kurtosis value is 14.20744. The value of Jarque-bera is 11759.25.

4.4.4 Unit Root Test (DSE)

TABLE 4.14: Unit Root Test (DSE)

Unit Root Test of DSE				
Test Type			**T-stats**	**Prob**
ADF	Level	None	0.5818	0.8420
		Intercept	-1.4264	0.5707
		T&I	-2.1590	0.5118
	1st diff	None	-20.1682	0.0000
		Intercept	-20.1835	0.0000
		T&I	-20.1800	0.0000
PP	Level	None	0.626805	0.8516
		Intercept	-1.429877	0.569
		T&I	-2.124891	0.531
	1st diff	None	-41.3678	0.0000
		Intercept	-41.3623	0.0000
		T&I	-41.3538	0.0000
KPSS	Level	Intercept	2.9221	0
		T&I	0.3240	0

1st diff	Intercept	0.0582	0
	T&I	0.0565	0

ADF test use to test the stationarity of data. It assumed that data is i. i. d. However, there may be week dependence in data so PP, and KPSS are also used the Unite root test. The Unite Root analysis is done with the assumption of no intercept and no trend, intercept and trend and intercept only. The results show that the data is nonstationary at the level and stationary at the first difference which is shown in the table 4.14.

4.4.5 ACF and PACF Through Correlogram

The correlogram in this study is an image that describes the correlation statistics of the data set at the level and first-differencing with 36 lags. But only 10 lags are selected. This method is used to calculate the proper p, d, q parameters for the ARIMA model. The tables of correlogram of the DSE index is as under Table 4.15. The below table shows that the data is not stationary. So the next step is Correlegram test at 1st difference level.

Table 4.15: ACF and PACF (DSE)

ACF and PACF at Level						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—******	—******	1	0.998	0.998	2230.5	0
—******	— —	2	0.995	-0.087	4450.8	0
—******	— —	3	0.993	0.015	6661.2	0
—******	— —	4	0.99	-0.032	8861.1	0
—******	— —	5	0.988	-0.051	11050	0
—******	— —	6	0.985	-0.037	13226	0
—******	— —	7	0.981	-0.02	15389	0
—******	— —	8	0.979	0.041	17541	0

—******	— —	9	0.976	0.018	19681	0
—******	— —	10	0.973	-0.028	21809	0
ACF and PACF at 1st Difference						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—* —	**—* —**	**1**	**0.132**	**0.132**	**39.216**	**0**
— —	— —	2	-0.01	-0.028	39.427	0
— —	— —	3	0.038	0.044	42.749	0
—* —	**—* —**	**4**	**0.087**	**0.077**	**59.738**	**0**
— —	— —	5	0.075	0.056	72.474	0
— —	— —	6	0.055	0.041	79.276	0
— —	— —	7	-0.058	-0.075	86.711	0
— —	— —	8	-0.043	-0.036	90.955	0
— —	— —	9	0.017	0.011	91.604	0
— —	— —	10	0.031	0.019	93.772	0

4.4.6 ARMA Model Estimation

The results of the correlograms for identifying the model using ACF and PACF for the DSE index show that 2 lags are sufficient for running the ARMA model. So the possible ARMA models may be.

- ARMA (1,1)
- ARMA (1,4)
- ARMA (4,1)
- ARMA (4,4)

Parsimonious Models are always preferred on over identified Models. Higher lags can be examined at diagnostic phase. After deciding on a model, the parameters must be calculated. These models are built using the least squares approach.

4.4.7 Selection of Model through ARMA (DSE)

TABLE 4.16: Selection of ARMA Model (DSE)

Possible Model	**Coefficient**		**AR(1)**	**MA(1)**	**AR(4)**	**MA(4)**
ARMA (1,1)	8.5355		0.9983	0.1401	-	-
ARMA (1,4)	8.5356		0.9984	-	-	0.0981
ARMA (4,1)	8.5347		-	0.9854	0.9908	
ARMA (4,4)	8.5346		-		0.9908	0.1963
Measure	**(1,1)**	**(1,4)**	**(4,1)**		**(4,4)**	**Decision Rule**
Significant	**2**	2	2		2	Variable
SIGMASQ	**0.0077**	0.0078	0.0001		0.0003	lowest
Adj R Sq	**0.9969**	0.99694	0.9939		0.9856	Highest
AIC	**-6.6218**	-6.6117	-5.9219		-5.0583	Minimum
SBC	**-6.6116**	-6.6014	-5.911		-5.0481	Minimum

Table 4.16 shows result, the values of all parameters are used for making of the model. The significance value is based on the number of variables with less than 5% confidence. The result shows that the significant number of variables are two. The Sigma Q value for the index is the lowest. According to the rules, the adjusted R-squared value must be higher. AIC and SBC, both values must be minimized to fit in the model for forecasting. As per the correlogram finding, using the best-fitted ARMA model (p, q) as (1 , 1) for the DSE Index.

4.4.8 Forecasting the Return by using ARIMA Model

Once ARMA model is fitted, it could be used to forecast future returns. This is possible with two forecasting methods: dynamic and static. The previously forecasted values are used in dynamic forecasting. The actual present and lagged values were used in static forecasting. So the possible ARIMA models may be.

- ARIMA (1,1,1)
- ARIMA (1,1,4)
- AIRMA (4,1,1)
- ARIMA (4,1,4)

Table 4.17 show the selection of best ARIMA model.

TABLE 4.17: Selection of ARIMA Model (DSE)

Possible Model	**Coefficient**	**AR(1)**	**MA(1)**	**AR(4)**	**MA(4)**
ARIMA(1,1,1)	0.000195	-0.114191	0.250981	-	-
ARIMA(1,1,4)	0.000196	0.124436	-	-	0.0831
ARIMA(4,1,1)	0.000196	-	0.132841	0.075466	
ARIMA(4,1,4)	0.000196	-		-0.508404	0.60329
Measure	**(1,1,1)**	**(1,1,4)**	**(4,1,1)**	**(4,1,4)**	**Decision Rule**
Siginicant	1	2	2	**2**	Variable
SIGMASQ	7.74E-05	7.71E-05	7.70E-05	**7.80E-05**	lowest
Adj R Square	0.017302	0.02231	0.022609	**0.010704**	Highest
AIC	-6.624474	-6.629573	-6.629881	**-6.617759**	Minimum
SBC	-6.614255	-6.619354	-6.619662	**-6.607539**	Minimum

4.4.8.1 Selection of Model through ARIMA (DSE)

According to the above result, the values of all parameters are used for making of the model. The significance value is based on the number of variables with less than 5% confidence. The result shows that the significant number of variables are two. The Sigma Q value for the return is the lowest. According to the rules, the adjusted R-squared value must be higher. AIC and SBC, both values must be minimized to fit in the model for forecasting. As per the correlogram finding, using the best-fitted ARIMA model (p, d, q) as (4, 1, 1) for the DSE Return.

ARIMA technique is used to forecast the future stock returns. This can be accomplished by utilizing dynamic and static forecasting methods, which employ dynamic and static forecasting methods.

4.4.9 ARIMA Model Through Dynamic and Static Models

Figure 4.22 and 4.23 shows the ARIMA Model through the dynamic and Static models.

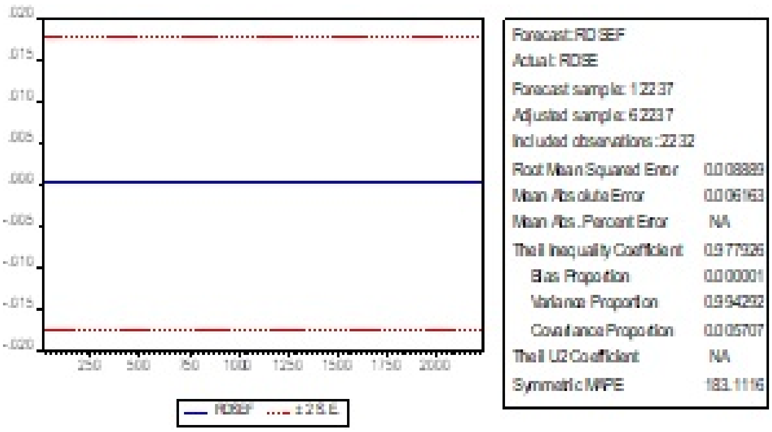

FIGURE 4.21: Dynamic Model (DSE Return)

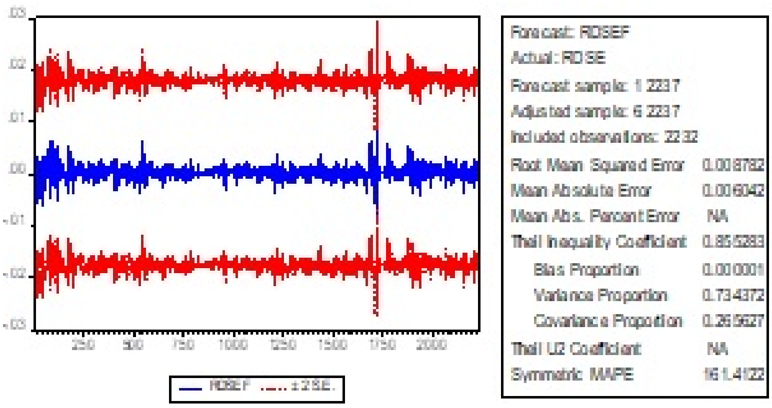

FIGURE 4.22: Static Model (DSE Return)

4.4.9.1 Selection of Best Model

Table 4.18 show the result. According to the lowest Decision rule for the selection of best model. The Static model values are lowest. So the best model is Static model.

Table 4.18: Selection of Model (DSE)

Measure	**Static Model**	**Dynamic Model**	**Decision Rule**
Root Mean Squared Error	**0.00878**	0.00888	Lower
Mean Absolute Error	**0.00604**	0.00616	Lower
Theil Inequality Coefficient	**0.85528**	0.97792	Lower

4.4.10 Seasonal ARIMA Model (p, d, q) sar sma

Table 4.19 show the SARIMA Model. As per the correlogram findings, using the best fitted Seasonal ARIMA model (p, d, q) as (4, 1, 1) sar(2) sma(1) for the DSE Return. In the table 4.11 below, the equation is run and the results are presented.

Table 4.19: SARIMA Model (DSE)

Possible Model	Coefficient	**AR(4)**	**MA(1)**	**SAR(2)**	**SMA(1)**
ARIMA (4 ,1, 1)	0.000196	0.087311	-0.48097	0.278815	0.610674
Measure	**SARIMA(4,1,1)**		**Decision Rule**		
Significant	4		Number of Variables		
SIGMASQ	7.69E-05		Lowest		
Adj R Square	0.023661		Highest		
AIC	-6.630062		Minimum		
SBC	-6.614733		Minimum		

According to the above result, the values of all parameters are used to determine the seasonality in this model. This model shows that the seasonality is in return at lag 2 and shocks is random, there is no seasonality. When period is long, there is more uncertainty, whereas when period is short, there is less uncertainty.

4.4.11 SARIMA Through Dynamic and Static Model

Figure 4.24 and 4.25 shows the SARIMA Model through two models. This can be accomplished by utilizing dynamic and static forecasting methods.

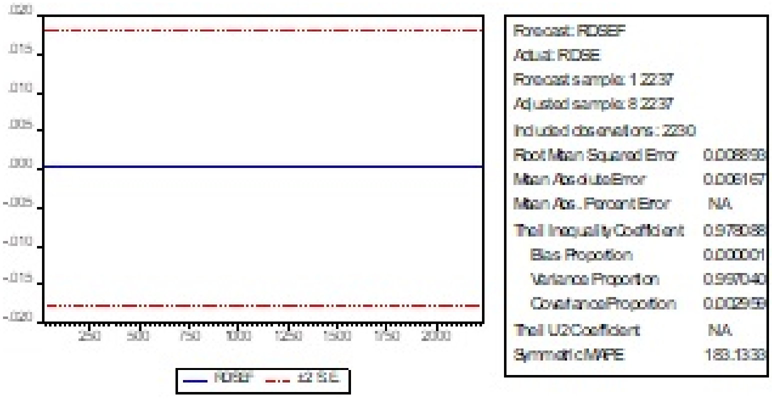

FIGURE 4.23: SARIMA Dynamic Model (DSE Return)

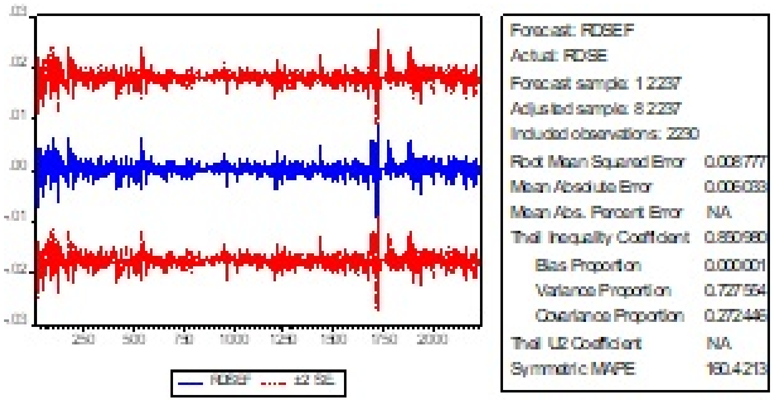

FIGURE 4.24: SARIMA Static Model (DSE Return)

4.4.11.1 Selection of Model

TABLE 4.20: Selection of SARIMA Model (DSE)

Measure	Static Model	Dynamic Model	Decisioin Rule
Root Mean Squared Error	**0.00877**	0.00889	**Lower**
Mean Absolute Error	**0.00603**	0.00616	**Lower**
Theil Inequality Coefficient	**0.85098**	0.97808	**Lower**

Table 4.20 show the the value of measuring parameters lowest values is showing the best model. So, the Static Model is lower than the Dynamic Model.

4.5 Colombo Stock Exchange (Sri Lanka)

4.5.1 Graphical Representations

The figure 4.25 and 4.26 shows the trend of the CSE index. First graph shows the Mix trends during 2012 to 2018. The downward spike is shown the COVID 19 pandemic period in 2019. After 2020 the market starts the rising trend. But in 2021 the market is down due the political instability. While the returns of CSE Index are rationalized in the second graph. First graph of CSE index shown that the data of time series is not stationery.

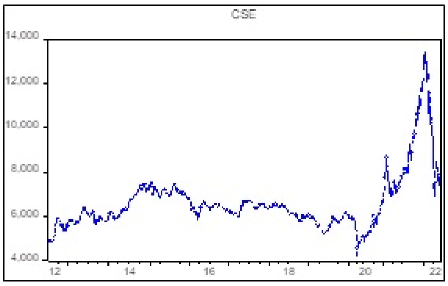

FIGURE 4.25: CSE Index

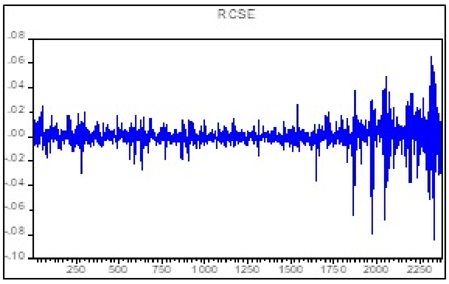

FIGURE 4.26: CSE Return

4.5.2 Descriptive Statistics of CSE

Figure 4.27 covers the descriptive statistics for the CSE index the 2376 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

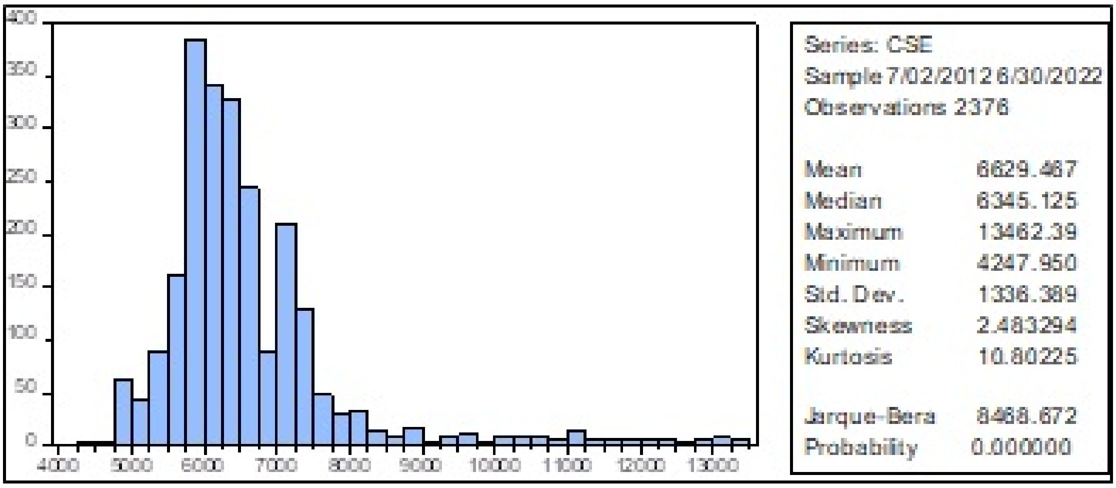

FIGURE 4.27: Descriptive Statistics of CSE

The mean value of the CSE Index is 6629.467. So, the mean value is positive. It also shows the mean average returns of the index in this time period are positive, which indicates a long-term regressive trend. The median value of CSE Index is 6345.125. The maximum value of CSE Index is 13462.39. The minimum value of CSE Index is 4247.950. The standard deviation value of CSE Index is 1336.389. The skewness value of CSE Index is 2.483294. The kurtosis value of CSE Index is 10.80225. The value of Jarque-bera CSE Index is 8468.672.

4.5.3 Descriptive Statistics of CSE Return

Figure 4.28 covers the descriptive statistics for the CSE Return with 2475 observations for this research. The sample period is taken of 10 years daily data starting from 1/7/2012 to 30/6/2022.

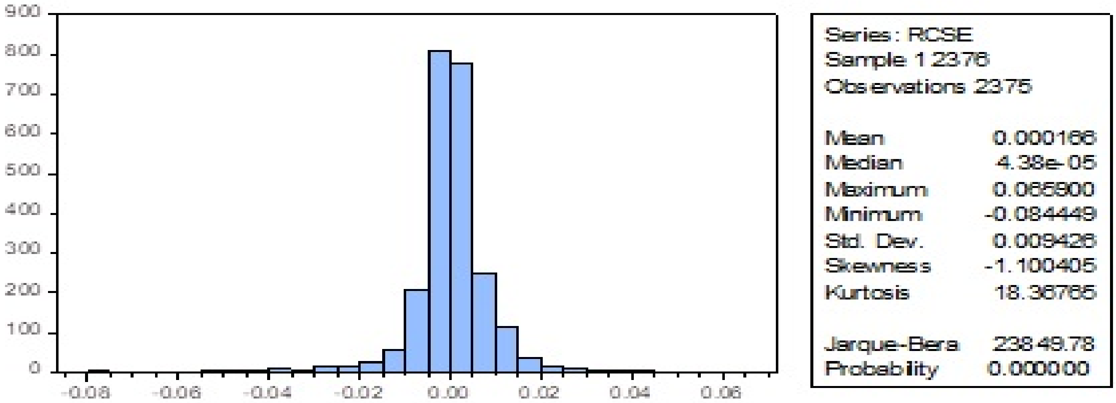

FIGURE 4.28: Descriptive Statistics of CSE Return

The mean value of the CSE Return is 0.000166. So, the mean value is positive. It also shows the mean average returns of the return in this time period are positive, which indicates a long-term regressive trend. The median value is 4.38. The maximum value is 0.065900. The minimum value is -0.084449. The standard deviation value is 0.009426. The skewness value is -1.100405. The kurtosis value is 18.36765. The value of Jarque-bera is 18.36765.

4.5.4 Unit Root Test (CSE)

ADF test use to test the stationarity of data. It assumed that data is i. i. d. However, there may be week dependence in data so PP, and KPSS are also used the Unite root test. The Unite Root analysis is done with the assumption of no intercept and no trend, intercept and trend and intercept only. The results show that the data is nonstationary at the level and stationary at the first difference which is shown in the table 4.21.

TABLE 4.21: Unit Root Test (CSE)

Unit Root Test of CSE				
Test Type			**T-stats**	**Prob**
ADF	**Level**	None	-0.1058	0.6472
		Intercept	-2.4937	0.1171
		T&I	-2.5828	0.2883
	1st diff	None	-9.7143	0.0000
		Intercept	-9.7200	0.0000
		T&I	-9.7229	0.0000
PP	**Level**	None	-0.0209	0.6757
		Intercept	-2.2430	0.1912
		T&I	-2.3217	0.4214
	1st diff	None	-40.2106	0.0000
		Intercept	-40.1923	0.0000
		T&I	-40.1832	0.0000
KPSS	**Level**	Intercept	1.1052	0
		T&I	0.5041	0
	1st diff	Intercept	0.0565	0
		T&I	0.0562	0

4.5.5 ACF and PACF Through Correlogram

The correlogram in this study is an image that describes the correlation statistics of the data set at the level and first-differencing with 36 lags. But only 10 lags are selected. This method is used to calculate the proper p, d, q parameters for the ARIMA model. The tables of correlogram of the CSE index is as under Table 4.22.

Table 4.22: ACF and PACF (CSE)

ACF and PACF at Level						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—******	—******	1	**0.998**	**0.998**	**2368.8**	**0**
—******	— —	2	0.995	-0.173	4725	0
—******	— —	3	0.992	0.031	7068.6	0
—******	— —	4	0.989	-0.056	9398.7	0
—******	— —	5	0.986	-0.033	11714	0
—******	— —	6	0.982	0.008	14016	0
—******	— —	7	0.979	-0.085	16301	0
—******	— —	8	0.975	-0.043	18569	0
—******	— —	9	0.971	-0.044	20818	0
—******	— —	10	0.966	-0.022	23048	0
ACF and PACF at 1st Difference						
Auto Correlation	Partial Correlation		A C	P A C	Q-Stat	Prob
—** —	—** —	1	**0.242**	**0.242**	**139.01**	**0**
— —	— —	2	-0.005	-0.068	139.08	0
— —	— —	3	0.057	0.08	146.75	0
— —	— —	4	0.053	0.019	153.32	0
— —	— —	5	0.005	-0.008	153.39	0
—* —	—* —	6	**0.107**	**0.116**	**180.42**	**0**
— —	— —	7	0.109	0.053	208.93	0
— —	— —	8	0.08	0.053	224.09	0
— —	— —	9	0.054	0.022	231.06	0
— —	— —	10	-0.005	-0.037	231.12	0

4.5.6 ARMA Model Estimation

The results of the correlograms for identifying the model using ACF and PACF for the CSE index show that 2 lags are sufficient for running the ARMA model. So the possible ARMA models may be.

- ARMA (1,1)
- ARMA (1,6)
- ARMA (6,1)
- ARMA (6,6)

Table 4.23 parsimonious Models are always preferred on over identified Models. Higher lags can be examined at diagnostic phase. After deciding on a model, the parameters must be calculated. These models are built using the least squares approach.

Table 4.23: ARMA Model (CSE)

Possible Model	**Coefficient**	**AR(1)**	**MA(1)**	**AR(6)**	**MA(6)**
ARMA (1,1)	8.7603	0.9979	0.2708	-	-
ARMA (1,6)	8.7569	0.9983	-	-	0.1183
ARMA (6,1)	8.7637	-	0.9979	0.9858	-
ARMA (6,6)	8.7676	-		0.9813	0.2621

4.5.7 Selection of Model through ARMA (CSE)

Table 4.24 show the result of ARMA (p, q)

Table 4.24: Selection of ARMA Model (CSE)

Measure	**(1,1)**	**(1,6)**	**(6,1)**	**(6,6)**	**Decision Rule**
Significant	**2**	2	2	2	Variables
SIGMASQ	**0.0001**	0.0001	0.0003	0.0007	lowest
Adj R Sq	**0.9972**	0.9970	0.9908	0.9750	Highest
AIC	**-6.5530**	-6.4984	-5.3578	-4.3620	Minimum
SBC	**-6.5433**	-6.4887	-5.3481	-4.3523	Minimum

As per the correlogram finding, using the best-fitted ARMA model (p, q) as (1, 1) for the CSE index.

4.5.8 Forecasting the Return by using ARIMA Model

Once ARMA model is fitted, it could be used to forecast future returns. This is possible with two forecasting methods: dynamic and static. The previously forecasted values are used in dynamic forecasting. The actual present and lagged values were used in static forecasting. So the possible ARIMA models may be.

- ARIMA (1,1,1)
- ARIMA (1,1,6)
- ARIMA (6,1,1)
- ARIMA (6,1,6)

TABLE 4.25: Selection of ARIMA Model (CSE)

Possible Model	**Coefficient**	**AR(1)**	**MA(1)**	**AR(6)**	**MA(6)**
ARIMA (1 ,1, 1)	0.000165	-0.084393	0.347783	-	-
ARIMA (1 ,1, 6)	0.000163	0.235198	-	-	0.098748
ARIMA (6 ,1, 1)	0.000163	-	0.267955	0.096253	
ARIMA (6 ,1, 6)	0.000165	-		-0.205122	0.319849

Measure	**1,1,1**	**1,1,6**	**6,1,1**	**6,1,6**	**Decision Rule**
Significant	2	2	**2**	2	Number of Variable
SIGMASQ	8.30E-05	8.29E-05	**8.23E-05**	8.76E-05	lowest
Adj R Square	0.064163	0.065686	**0.072277**	0.012318	Highest
AIC	-6.55534	-6.556952	**-6.564026**	-6.501414	Minimum
SBC	-6.545618	-6.54723	**-6.554303**	-6.49E+00	Minimum

4.5.8.1 Selection of Model through ARIMA (CSE)

Table 4.25 show the result, the values of all parameters are used for making of the model. The significance value is based on the number of variables with less than 5% confidence. The result shows that the significant number of variables are two. The Sigma Q value for the return is the lowest. According to the rules, the adjusted R-squared value must be higher. AIC and SBC, both values must be minimized to fit in the model for forecasting. As per the correlogram finding, using the best-fitted ARIMA model (p, d, q) as (6, 1, 1) for the CSE Return. ARIMA technique is used to forecast the future stock returns. This can be accomplished by utilizing dynamic and static forecasting methods, which employ dynamic and static forecasting methods.

4.5.9 ARIMA Model Through Dynamic and Static Models

Figure 4.29 and 4.30 show the ARIMA Model through the dynamic and Static models.

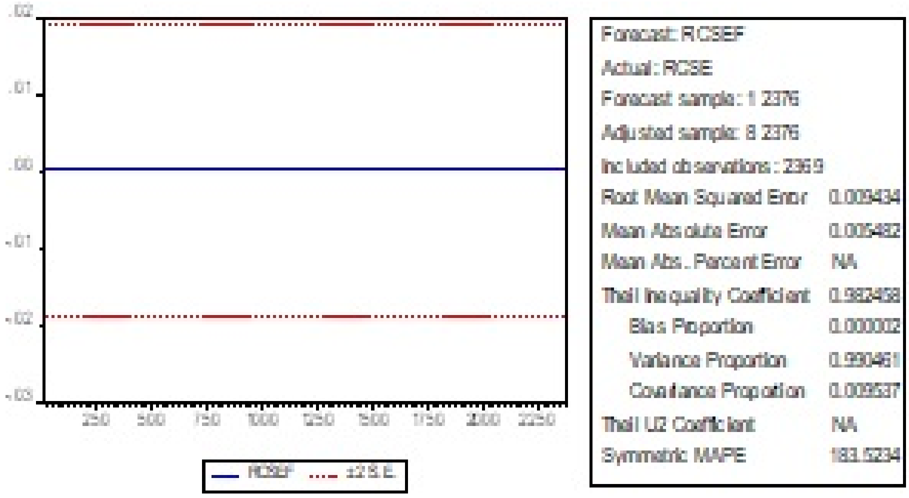

Figure 4.29: Dynamic Model (CSE Return)

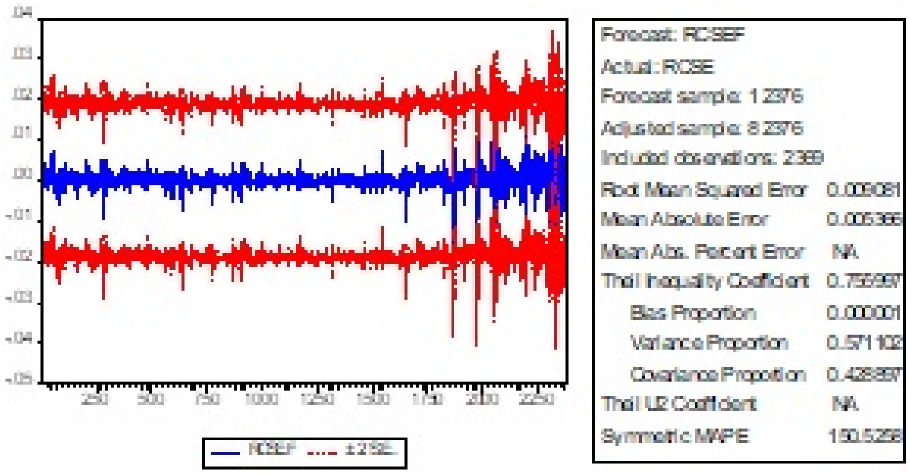

Figure 4.30: Static Model (CSE Return)

4.5.9.1 Selection of Best Model

TABLE 4.26: Selection of Model (CSE)

Measure	**Static Model**	**Dynamic Model**	**Decision Rule**
Root Mean Squared Error	**0.009081**	0.009434	**Lower**
Mean Absolute Error	**0.005366**	0.005482	**Lower**
Theil Inequality Coefficient	**0.755997**	0.982454	**Lower**

Table 4.26 show the lowest Decision rule for the selection of best model. The Static model values are lowest. So the best model is Static model.

4.5.10 Seasonal ARIMA Model (p, d, q) sar sma

As per the correlogram findings, using the best fitted Seasonal ARIMA model (p, d, q) as (6, 1, 1) sar(1) sma(2) for the CSE Return. In the table 4.27 below, the equation is run and the results are presented.

TABLE 4.27: SARIMA Model (CSE)

Possible Model	**Coefficient**	**AR(6)**	**MA(1)**	**SAR(1)**	**SMA(2)**
ARIMA (6 ,1, 1)	0.000162	0.089735	-0.363067	0.616467	-0.179098
Measure	**SARIMA(6, 1, 1)**		**Decision Rule**		
Significant	4		Number of Variables		
SIGMASQ	0.000082		Lowest		
Adj R Square	0.074506		Highest		
AIC	-6.565586		Minimum		
SBC	-6.551003		Minimum		

According to the above result, the values of all parameters are used to determine the seasonality in this model.

This model shows that the seasonality is in return at lag 2 and shocks is random, there is no seasonality. When the period is long, there is more uncertainty, whereas when the period is short, there is less uncertainty.

4.5.11 SARIMA Through Dynamic and Static Model

Figure 4.31 and 4.32 shows the SARIMA Model through two models. This can be accomplished by utilizing dynamic and static forecasting methods.

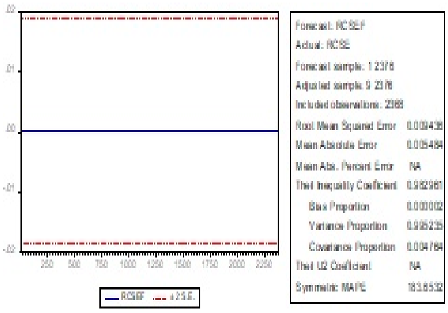

FIGURE 4.31: SARIMA Dynamic Model (CSE Return)

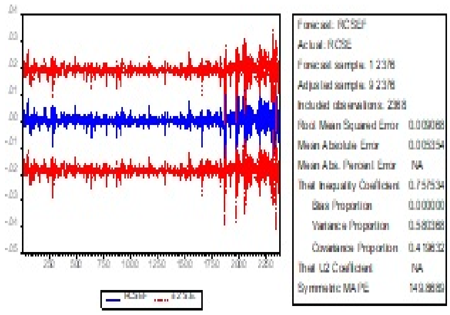

FIGURE 4.32: SARIMA Static Model (CSE Return)

4.5.11.1 Selection of Model

Table 4.28 show the the value of measuring parameters lowest values is showing the best model. So, the Static Model is lower than the Dynamic Model.

TABLE 4.28: Selection of SARIMA Model (CSE)

Measure	**Static Model**	**Dynamic Model**	**Decision Rule**
Root Mean Squared Error	**0.009068**	0.009436	**Lower**
Mean Absolute Error	**0.005354**	0.005484	**Lower**
Theil Inequality Coefficient	**0.757534**	0.982961	**Lower**

Chapter 5

Conclusion and Recommendations

5.1 Conclusion

The present research is cover to see the forecasting ability of ARMA and ARIMA model in stock markets. The countries included Pakistan, India, Bangladesh, and Sri Lanka. The analysis is conducted for the time period of 10 years starting from July 2012 to June 2022. This study used Box-Jenkins methodology (ARIMA) to forecast the stock market returns of the selected indices of South Asian Countries. One of the most widely used stock market forecasting techniques is the ARIMA technique. This model will help investors and policymakers in forecasting overall stock market behavior and developing effective strategies. Each markets have different parameter for ARIMA model. The historical data of all indices are discovered to be non-stationary in the mechanism of model development, but the first order difference of all indices data is converted as stationarity. SARIMA is an ARIMA modification that enables direct seasonal component modelling of series.

5.1.1 Karachi Stock Exchange (Pakistan)

Pakistan is an emerging market with a rapidly growing economy. It has faced massive problems, and instability, in recent years. There is a significant amount of volatility and rate of interest in Pakistan. It is to examine the efficiency of the Pakistani stock market in order to develop a useful technique for forecasting of stock prices and making investment strategies. The appropriate model of KSE-100 ARIMA (1,1,1), which is best model for the forecasting of stock returns. The ARIMA model is evaluated using both dynamic and static models. The static model is better than the dynamic model. Therefore, the ARIMA (1,1,1) is appropriate for the forecasting of stock returns in Pakistan. Seasonal effect also exists and Seasonal shock is significant at sma (1).

5.1.2 Bombay Stock Exchange (India)

Among the seven largest developing and emerging markets, India is expected to have the fastest-growing economy. India has emerged as the world's fastest-growing major economy, because its strong democracy and strong partnerships among the institutions. It is to examine the efficiency of the Indian stock market (BSE) in order to develop a useful technique for forecasting of stock prices and making investment strategies. The appropriate model of BSE-30 ARIMA (6,1,5), which is best model for the forecasting of stock returns. The ARIMA model is evaluated using both dynamic and static models. The static model is better than the dynamic model. Therefore, the ARIMA (6,1,5) is appropriate for the forecasting of stock returns in India. Seasonal effect also exists in India. Seasonal shock is significant at sma (1).

5.1.3 Dhaka Stock Exchange (Bangladesh)

Bangladesh's economy is mixed. It emphasizes a significant market economy, with private businesses controlling the majority of sectors of production and distribution of goods and resources. It has struggled with vast issues such as low urbanization, bad governance, splotchy and insufficient physical infrastructure, and a lack of entrepreneurship. It is to examine the efficiency of the Bangladesh stock market (DSE) in order to develop a useful technique for forecasting of stock prices and making investment strategies.

In DSE the appropriate model of ARIMA is (4,1,1), which is best model for the forecasting of stock returns. The ARIMA model is evaluated using both dynamic and static models. The static model is better than the dynamic model. Therefore, the ARIMA (4,1,1) is appropriate for the forecasting of stock returns in Bangladesh. Seasonal effect also exists, and Seasonal shock is significant at sma (1).

5.1.4 Colombo Stock Exchange (Sri Lanka)

Sri Lanka is an emerging market. Political instability in Sri Lanka will remain due to high inflation and deficiencies of important goods such as food, fuel, and medicine. Sri Lanka is experiencing its worst economic crisis since independence It is to examine the efficiency of the Sri Lanka stock market (CSE) in order to develop a useful technique for forecasting of stock prices and making investment strategies.

In CSE the appropriate model of ARIMA is (6,1,1), which is best model for the forecasting of stock returns. The ARIMA model is evaluated using both dynamic and static models. The static model is better than the dynamic model. Therefore, the ARIMA (6,1,1) is appropriate for the forecasting of stock returns in Sri Lanka. Seasonal effect also exists, and Seasonal shock is significant at sma (2).

5.2 Recommendations

The findings showed that the mean returns for all indices are positive but near to zero. This indicates a long-term regressive trend. These findings are significant. Investors can make investment decisions based on the predicted returns examined in this research. The investor should consider following while making decision.

1. ARIMA model can be used for forecasting.
2. Static models are better than dynamic models.
3. Seasonality be considering by the investor.

This study helps to investors, portfolio managers, companies, and policy makers in making sound stock market decisions. Companies can develop appropriate techniques to generate profitable returns on their investments. Individual investors can construct optimal portfolios, and policymakers can make relevant and important decisions to ensure the smooth operation of the stock market.

5.3 Direction for Future Research

Future research could look into stock price prediction and comparison in developed and emerging stock markets. The focus will be on comparing various sectorial indices between developed and emerging economies to gain a better understanding of their portfolio management, risk and return, achievement, and trading performance.

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