AN INVESTIGATION OF TESTING ADAPTIVE MARKET HYPOTHESIS USING ARTIFICIAL NEURAL NETWORKS

By

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Abstract

The purpose of the study is to investigate the consistency of a newly introduced framework of adaptive market hypothesis. This study examines the two implications of adaptive market hypothesis Pakistan stock market. The first implication is that the stock market efficiency is not a static nature but it follows a cyclical fashion. And second one is that these shifts of efficiency to inefficiency and vice-versa are driven by changing market conditions. On the basis of these implications this study investigates the shifts of efficiency to inefficiency and inefficiency to efficiency. And it also investigates whether the changing market conditions can explain these shifts of efficiency and inefficiency.

KSE-100 index is used as a proxy for the Pakistan stock exchange. A nonlinear autoregressive artificial neural network model under a rolling window is employed to investigate the nonlinear dependency of returns. The changing market dynamics are investigated by examining the response of PSX on political and economic events occurs during the time frame of this research study.

This study reports strong evidence that under a rolling window framework the repeated patterns of efficiencies and inefficiencies are observed. These cyclical patterns confirm the idea of AMH which claims that markets follow evolutionary process, switching from efficiency to inefficiency and vice-versa as new information is received. It also confirms that the return predictability is driven by changing market conditions.

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List of Abbreviations

ADF	Augmented Dickey-Fuller
AMH	Adaptive Market Hypothesis
ANN	Artificial Neural Network
CTS	Computerized trading system
EMH	Efficient Market Hypothesis
MAE	Mean Absolute Error
MSE	Mean Square Error
NAR	Nonlinear Auto-Regressive
NARNN	Nonlinear autoregressive neural network
PSM	Pakistan steel mills
PSO	Pakistan State oil
PSX	Pakistan stock exchange
RMSE	Root Mean Square Error
SECP	Securities and Exchange Commission of Pakistan.
USA	United States of America
PIDE	Pakistan Institute of Development Economics

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DEDICATION

To my beloved parents

to whom I owe my whole life.

Without their prayers this work was not possible.

To my lifeline my husband and my daughters,

Abeeha and Aleeha.

To my sisters, brothers who are the guiding star to my sky.

With millions of thanks and gratitude.

1 INTRODUCTION

1.1 INTRODUCTION

"An economy without a capital market just cannot grow since the market is responsible for long term growth, capital formation and allocation to development uses efficiently" Osaze (2000). The role of the financial markets is to allocate productive resources for effective investment decisions. The financial markets are the connection point through which people's money can be mobilized and participate in the economy's growth[1]. The importance of financial markets can be observed by looking at its essential functions that are performed. First of all, it allows the movement of funds from persons who possess them and have no investment opportunities for those who have new investment opportunities. It enables them to increase production and achieve economic efficiency and improve society's level of prosperity.

Financial markets are independent entities with their influence on growth, interest rates, inflation, and foreign exchange rates having a significant impact on economic growth[2]. So the development of financial markets is considered a provider of smooth processes of growth in the real sector and economic development. Some factors are key role players in the development of the stock market, such as the size, liquidity, and efficiency of the market and the quality of the environment. In cases where there are inefficiencies in the financial sector, productive projects are often unexploited for developmental purposes. The quality of the environment is regarded as the social and economic conditions of the countries involved. In countries with high political instability and perceived risks, stock markets would be constrained (Agbetsiafa, 2003).

[1] Henry, 1997
[2] Kunt & Maksimovic, 1996; Singh, 1997; Levine & Zervos, 1998

Al-Awad and Nasri Harb (2005) further state that capital markets also attract foreign portfolio investors to supplement domestic savings levels.

Since capital accumulation is a fundamental determinant for any firm's long-term growth and an efficient financial system is essential for developing an economy. Only through a specialized network of financial institutions can it be possible to accumulate the necessary funds to achieve the firms' long-term goals. Alfaki (2006) defined capital market 'as a network of specialized financial institutions, series of mechanisms, processes, and infrastructure that, in various ways, facilitate the bringing together of suppliers and users of medium to long–term capital for investment in socio-economic development long term.' A large part of an economy's savings is intermediated with productive investments through financial markets and intermediaries [3]. Financial markets constitute the stock market, the bond market, commodities markets, derivatives market, and forex market (Mishkin and Eakins, 2006). Financial intermediaries are determined as being: commercial banks, savings banks, investment banks, and specialized lending institutions, insurance companies, pension funds. These institutions play the crucial role of mediator to transfer funds from lenders to borrowers. The improvement in the size, activity, efficiency, and stability of the financial system is regarded as the development in the financial market (Demirguc-Kunt et al., 2009).

1.2 EFFICIENCY AND CAPITAL MARKETS

The capital markets play a central role in the relevant economy that mobilizes and allocates financial recourses and plays a crucial role in the pricing and allocation of capital. For the best allocation of these financial resources and giving fair returns on the

[3] Levine, 1997

investor's income while keeping it safe, a capital market needs to be efficient. The financial markets' efficiency is considered in three different, but interconnected viewpoints: allocative efficiency, operational efficiency, and informational efficiency[4]. The market's allocative efficiency describes how good the markets are in allocating scarce capital resources to the firms that can achieve the best marginal returns. Operational efficiency is also known as transactional efficiency, which measures the cost of raising capital and the investors' cost for transferring funds. The informational efficiency relates to the extent to which asset prices incorporate all the available information about the assets' fundamental value.

Moreover, in an informationally efficient market, this information is widely available to all investors at a low cost. The amount of informational and operational efficiency determines the degree to which markets are allocationally efficient. So, misleading information or transaction costs that are too high can impede allocational efficiency and economic growth.

The markets' informational efficiency provides the bases for the theory of efficient market hypothesis (EMH), which states that asset prices should reflect all available information[5]. A direct implication of EMH states that it is impossible to consistently make above-average returns because the market prices are randomly distributed and react only to new information. EMH further refined market efficiency levels, depending on the extent to which the information is available to market participants. A market is "weak form" efficient if only the past prices are contained in the current price. All the historical information is incorporated in current prices. Future stock prices cannot be predicted based on the analysis of past stock prices. In a "semi-

[4] To see more on market efficiency Buckle, M., & Thompson, J. L. (1992) and Bauer, G. (2004).
[5] Theory of EMH by Eugene Fama (1965,1970)

strong form" of market efficiency, the stock prices incorporate all publicly available information, historical and current, and no delay in response to information disclosure. A "strong form" efficient market is where stock prices reflect all information, public and private.

The theory of EMH is one of the theories that can help the participants analyze the investing opportunities. As for gaining returns from their investments and safe those from losses, entrepreneurs want to know whether the market share price fully reflects the company's value. The literature on EMH remains contradictory throughout the period from its inception[6]. Literature suggests that the research during 1960-1970 mainly supports the market efficiency; during 1970-1980, it reported mixed outcomes while challenging outcomes were reported in the 1990's and the recent studies 1988-2004 report unsupportive evidence of the EMH. After the 1980's the immense literature is available, which tries to answer the question of market efficiency has contradictory outcomes. The emerging field of behavioral finance, which brings the most contradictory research findings, makes the validity of EMH uncertain[7].

1.3 SHORTCOMINGS OF EFFICIENT MARKET HYPOTHESIS

The EMH is broadly criticized on its two perspectives, one of its failure to explain some predictability patterns and secondly its ignorance to slot in psychological parameters in an investor's decision process. Kahneman and Tversky (1979) criticize the expected utility and provide a new model of prospect theory. Grossman and Stiglitz (1980) criticize that a perfectly efficient market is impossible, as assumed in the theory of EMH. Banz (1981) found that the relationship between firm size and stock return is highly correlated. Other behavioral researchers as DeBondt and Thaler (1985)

[6] Park &Irwin (2007) and Yen &Lee (2008) and Martin Sewell (2011)
[7] Kahneman & Tversky (1979), Grossman & Stiglitz (1980), DeBondt & Thaler (1985)

documented that Investors are not always entirely rational, and the number of behavioral biases is involved in investor decisions such as overreaction and overconfidence. Another criticism by Tversky and Kahneman (1986) comes on traditional finance's decision-making theory, which only considers the normative decision-making process. The concepts of framing and prospect theory involved judgment based decisions under an uncertain situation.

Jegadeesh and Titman (1993) presented devastating evidence against EMH. They show that buying past winners and selling past losers can be used to gain high returns. One can be rewarded with high returns without additional risk, which is inconsistent with the efficient market. These patterns of returns, named as momentum and reversal, can yield abnormal returns. Fama and French (1993) also documented the possibility of average returns while investing in firms with low market capitalization. Such returns are explained as the risk premium for investing in firms with higher risk factors. Fama and French (2000) further shows that such anomalies do not persist long and vanish over time.

The anomalies appearing in financial literature confirms that many anomalies get weaker after manipulation by sharp investors (Schwert's, 2003). Financial market anomalies can be categorized into three subparts[8]. Seasonal anomalies or calendar anomalies the anomalies relate to the fundamental analysis techniques and technical anomalies. From seasonal anomalies, the "January effect," "January barometer," and "Turn-of-the-Month Effect" gain significant attention from researchers3. However, these anomalies are difficult to manipulate in real life because of high transaction cost

[8] Latif et al (2011)

(Malkiel's, 2003). The stock market seasonal anomalies show diverse patterns due to change in data frequency and on the bases of firm size (Schwert, 2003).

There are possible predictability patterns on the bases of valuation parameters, but these patterns persist for a short period. The small-cap effect, Low Price to Book, high dividend yield, Low Price to Sales, Low Price to Earnings is the anomalies based on valuation parameters[9]. Predictability parameters based on examining the past prices for forecasting purposes called "technical analysis." Researchers argue that technical anomalies' validity does not persist so long, as the prices are adjusted very quickly in response to new information. However, the financial analyst uses these anomalies efficiently to forecasting future profit opportunities.

Malkiel (2003) critically review the areas where the behavioral school of thoughts can better explain the deviation from EMH. He summarises irrational investors' behavioral biases as significant contributors to errors and mistakes while reasoning and processing information collectively. The challenges belong to irrational behavior raises contradictions to market efficiency as it doubted the investor's judgment on securities. The behaviorists pointed out the number of investors' cognitive and emotional biases and heuristics in making financial decisions. As loss aversion, Anchoring, herd behavior, overconfidence, and confirmation biases are different irrational behavior documented by researchers.

[9] Degutis & Novickytė (2014)

1.4 THE NEW WORLD: ADAPTIVE MARKET HYPOTHESIS

In financial literature, the concept of behavioral finance takes importance after the seminal work of Amos Tversky and Daniel Kahneman [10], when they provide the behavioral explanation on the critique of the expected utility theory of traditional finance. Prospect theory claims that investors follow the heuristics to choose from the alternatives in a real-world situation. The psychological principle derives the judgment and decision-making process. It demonstrates that investors' irrational behavior through cognitive psychology and decisions are based on the preferences given by individual investors. It also assumes that individuals are more risk-averse than risk-taker (Riccardi and Simon, 2000). Investors will go for a sure gain option if investors are given two investing options like with sure gain and unsure gain; this is a risk aversive behavior.

These researchers introduce the three terms of heuristics, which are "representativeness," "availability," and "anchoring and adjustment," on which individual investors rely to make decisions under uncertain situations. There are several financial anomalies that traditional finance fails to explain and are being explained by behavioral finance such as short term momentum, long term reversal, and weekend effect and value premium anomaly.

The introduction of behavioral finance also helps find solutions for financial problems, just like the theory of EMH or old finance concepts does. Behavioral finance theories suggest that ignoring the importance of psychological factors leads to decision errors and causes financial crises. Without considering these two models, it would e challenging to answer the primary reasons for financial and economic crises.

[10] Kahneman &Tversky (1979)

The bounded rationality assumptions of the efficient market hypothesis and the behavioral finance approach in finance contradict the debate on truly efficient markets. These contradictory concepts need to be reconciled through a new perspective. The adaptive market hypothesis is that concept, based on the principles of evolution, and traditional finance concepts are also considered. This new framework suggests that the content of information reflected in shares' prices depends on the market environmental circumstances and market participants (Lo, 2005). According to this new approach at any stage, the market efficiency can be determined based on prevailing competition and the development stage of the market.

The changing market environment is considered as a significant explanation for the irrational behavior of the investors. The irrationality of the investors is considered as a rational behavior over the changing market conditions. Investors are characterized by changing psychological patterns, so each individual will show different decisions pattern over changing the market environment. These decisions work as a learning experience for investors; they make rules of thumb through their feedback. In changing market conditions, investors tend to formulate new heuristics instead of the old ones. People's emotional-based judgment plays a significant role in the decision-making process. The new investment strategies are modified based on previous successes or mistakes which are away from the rational approach of EMH. Changing market conditions bring and take away profit opportunities, and the investors set their strategies accordingly.

Lo (2005) relates the investor's adaptation to new environmental factors with the Darwinian evolution as the one who wants to survive in the market must have to learn how to adapt. AMH's concept is based on the idea of individual self-interest, learning from mistakes, and adaptability through competition and evolution (Lo, 2008). Lim and brooks (2011) conclude that AMH's implications as market efficiency are not an all or nothing concept, but it has a changing nature over time. Moreover, the level of changing efficiency is dependent on the prevailing market conditions over that time (Kim et al., 2011 and Lim et al., 2013).

The concept of the evolving nature of market efficiency by Campbell et al. (1997) and Lo and MacKinlay (1999) provides the grounds for dynamic natures of market efficiency, as explained by Lo (2005). As compared to the conventional static nature of market efficiency over some predetermined time frame, the AMH proposed a cyclical nature of efficiency, which changes relative to time. When efficiency is measured over different time intervals, it can be efficient in some periods and can be inefficient in other periods (Lo, 2008). Some research work employed on the deviation of return series under the rolling window framework identify the periods of non-random movement (Alvarez-Ramires et al., 2008 and Cajueiro et al., 2009).

1.5 TESTING ADAPTIVE MARKET HYPOTHESIS

As the AMH is in its infancy stage, no formal methodology is developed to capture AMH's dynamic view. The time-varying and evolving nature of market efficiency is the most common implication of AMH, widely investigated. To examine the evolving efficiency of different developed and underdeveloped countries, Lim and Brooks (2006), Todea et al. (2009), Ito and Sugiyama (2009), Kim et al. (2011), Smith (2011), Lim, et al., (2013) and Urquhart and Hudson (2013) used the number of traditional and non-traditional statistical techniques. The dependability of stock returns investigated through non-linear statistical techniques provides substantial shreds of evidence for periods of predictability and periods of no predictability. Findings from these studies support the oscillating movement of returns as described by AMH.

The Sub-period investigation approach to investigate the stock market efficiency and rolling window approach has been widely used by researchers to inspect the degree of market efficiency over time. Hiremath and Kumari (2014) investigate the market efficiency of the Indian stock market using sub-period analysis. Furthermore, a rolling window analysis approach is employed by Urquhart and McGroarty (2014). Sub-period analysis divides the whole data set into different subgroups. Each subgroup is investigated separately by implementing the same set of statistical techniques. These subgroups are fixed and provide the return predictability over that specific period. In rolling window analysis, the group's fixed time rolls forward to include the next time interval only by skipping some data from that sample. The periods of dependency and independence can be better captured using the rolling window framework (Urquhart and McGroarty, 2016).

The traditional and non-traditional time series forecasting models remain essential and helpful for institutional investors, academicians, and financial analysts. These models can further be categorized into two broad categories linear and non-linear. The linear models are the traditional models. These are linear in the parameters that have to be estimated and describe a statistical situation explained by one observed variable by several other quantities. The non-linear models are based on the fact that an analysis based on linear models assumes linear independence; however, there is a possibility of non-linear dependence[11].

[11] Guo and tseng (1997)

Non-linear models are also known as non-traditional as they move from the linear assumption of the series. After introducing machine learning methods, recent research focuses on overcoming the limitation of traditional statistical tools and investment analysis tools by taking advantage of technological advancements[12]. One of these is the use of Artificial Neural Networks (ANN) in finance. Due to its data-driven approach, ANN can forecast financial time series by detecting patterns in it, even without the assistance of experts (Zhong and Enke, 2017). They provide a proven methodology to forecast the data even when the data set is having non-linear properties without any restrictions to it (Bao et al., (2017).

1.6 IMPLICATION FOR PAKISTAN STOCK MARKET

Pakistan's economy is the most important emerging economy of central Asia regarding its socio-cultural, political, and economic environment. It is a center of trade between Asian countries. Pakistan's importance cannot be ignored internationally due to its position in significant organizations like a member of the Organization of Islamic Cooperation (OIC), Commonwealth, United Nations, and G20.

At the economic front, the GDP is growing by 3 percent with the .85 percent growth of agriculture, 1.4 percent industry, and 4.7 percent by the services sector[13]. The slow growth rate is due to the political instability in the economy, and the devaluation of money also has a significant impact on economic growth. Still, with having uncertain economic conditions, the region is rich in the workforce. Its youngest population makes 64 percent of the nation, making Pakistan the second largest country with a younger population in south Asia[14]. The economy of Pakistan is considered an economy with

[12] Hussain et al. (2008)
[13] Economic Survey of Pakistan 20018-19
[14] United Nation Human Development Report 2018

high potentials for development. O'neill (2011) identified Pakistan as one of the next eleven countries that can become the world's largest economies in the 21 century and the BRICS economies.

Pakistan stock market is one of the most influential organizations that take part in economic growth like other capital markets of the world, which play a pivotal role in developing an economy (Boubaker and Raza, 2016). The stock market of Pakistan is characterized by high turnover and high price volatility. In 2016, it was ranked as the fifth best-performing stock market in the world and the best market in Asia[15]. Previously Pakistan had three stock exchanges, one international stock exchange that is Karachi stock exchange, and two regional stock exchanges: the Lahore stock exchange and Islamabad stock exchange. These stock exchanges were merged into a unified Pakistan stock exchange (PSX). This emerging stock exchange was done to attract a more effective partnership and strategic expertise and reduce market fragmentation[16]. The PSX comprises six different indices for the convenience of the investors. The KSE-100 index is considered the benchmark of the Pakistan capital market and used by many researchers to investigate (Asif and Aziz, 2015).

The Pakistan stock market was established in 1947, but it was initially working on the out-cry system. The computerized trading system was introduced in 2002. The performance of the Pakistan stock market was not that stable in the initial years. However, after 2002 its performance becomes a little stable. The Pakistan stock market remains highly volatile, and the reason behind this volatility is documented as political instability and investor's discriminatory behavior while making decisions (Ghufran et al., 2016). The literature on the efficiency of the Pakistan stock market does exist.

[15] Bloomberg.com
[16] "Pakistan Stock Exchange formally launched Index". *DAWN News*. 11 January 2016

However, these are limited in number, and it concludes that the random walk behavior of stock return is not supported as the stock returns are strongly correlated.

The previous studies and the importance of the stock market in economic growth propose a need to understand the behavior of the Pakistan stock market in more depth. Some studies try to evaluate the level of stock market efficiency in Pakistan as Chishti et al., (2018), Asif et al., (2015), Amna (2011), Abdul Rashid and Fazal Husain (2010), Chakraborty (2006), characterized the Pakistan capital market as week form inefficient. Such findings of the Pakistan stock market invalidate the efficiency theories about the Pakistan capital market. Moreover, allow the new areas of finance to answer the behavior of the Pakistan stock market. As a strong emerging economy, it is vital to investigate the Pakistan capital market's pricing behavior under a new perspective.

A study to understand the Pakistan stock market level of efficiency and its change in efficiency due to the market environment is needed to guide the investors about its true nature. It will help investors and policymakers to formed strategies according to the prevailing market scenarios. A better and proven methodology is required to examine market behavior according to the newly proposed hypothesis.

1.7 OBJECTIVE OF THE STUDY

The Objectives of the research study are as follows:

1. This thesis aims to test the cyclical efficiency hypothesis proposed through AMH. The movement of return predictability on the KSE-100 Index from January 2000 to December 2018 is checked against AMH's concept. Ether, the patterns are according to the proposed hypothesis, or the behavior of its return movement does not support the AMH implications.

2. The level of market predictability is highly context-dependent or not is investigated by comparing the return predictability measures with the changing market conditions. The evolving nature of market efficiency demonstrates that the environmental factors and competition among investors impact the market movement. This phenomenon is investigated by looking into the political and economic conditions of the market.

3. The emerging markets are more relevant to test when we talk about market inefficiencies, and the status of Pakistan's secondary market is not exact. This study will investigate the patterns of efficiency and inefficiency in an emerging market that is Pakistan's stock market.

4. This thesis aims to provide a practical means of testing the AMH as there is no proposed or tested framework to investigate efficiency's cyclical nature. The behavior of the Pakistan equities market is analyzed under this research work. Monthly frequency data from January 2000 to December 2018 is used to try to explain past price behavior; either it shows signs of cyclicality or not. The methodology of the study is divided into three stages. At the first stage, the optimal neural network parameters are selected through a trial and error process. The second stage is followed by implementing the selected parameters to the optima neural network model. This optimal neural network model is then used to model the return predictability pattern. The relevant market conditions are correlated with predictability patterns to provide insights on market behavior on changing market conditions. In the end, wavelet analysis is conducted as a robust technique to investigate these cyclical movements' significance.

1.8 THEORETICAL SCOPE OF THE STUDY

From a theoretical perspective, this study will participate in the existing literature on AMH relevant to an emerging economy. The adaptive market hypothesis is under consideration, which postulates that markets have cyclical efficiency and this efficiency is dynamic. This study is concerned with the issue of market behavior under two significant considerations. The movement of the stock market level of predictability either cyclical or not over the changing time frames. And the dependability of this variable prediction level on the changing market conditions. This study will examine the dynamic of market conditions that participate in the cyclical movement of the market.

1.9 EMPIRICAL SCOPE

The study's empirical analysis focuses on developing an appropriate methodology to investigate the fluctuations in return predictability. For empirical testing, the methodology is divided into four stages. A new model of ANN is developed. The model development requires selecting parameters—the selected parameters than used to run an optimal model of ANN. The generated results from the designed model are analyzed for pattern recognition compared with the existing market dynamics. Rolling window analysis is incorporated to overcome the barriers of missing values from data. It enables us to look at the fluctuations in stock market returns without any delay in time.

1.10 DATA SCOPE

KSE-100 index is used as a proxy for the PSX. The data used for the estimation purpose of the study consist of historical data of the KSE-100 index. From the year 2000 to the year 2018 is included in the estimation window. The data set going to be used in this research study comprises a longer time frame relevant to the Pakistan stock market. The frequency of data persists on the monthly observations to detect the fluctuations in predictability patterns and validate the results with the previous studies (Urquhart and McGroarty, 2016). The daily observations and weekly observations are positively correlated in their price fluctuations and away from normality assumptions (Joseph et al., 2017).

To check the results' robustness and validate them, we took the important news related to the stock market. The criterion specified is that the news of the stock market is reported on the front page. The events determine the changes in the index at that time. The changes are assessed in terms of validating the results as well as for robustness.

1.11 SIGNIFICANCE OF THE STUDY

This study will provide a new approach to understanding the characteristics of the Pakistan secondary market in light of proposed concept by Lo (2004). Investors will be able to look at the behavior of stock market efficiency as an ever-changing phenomenon that depends on the market conditions. It will answer the state of market efficiency in the Pakistan secondary market that efficiency is not a guaranteed outcome, and that profit opportunity is available from time to time.

This study will offer productive imminent to investors to recognize stock price predictability and the market conditions while driving stock return predictability. It will provide information about the market condition so that appropriate policy measures should be taken. It is important for investors and policy makers to thoroughly investigate the market conditions while making any investment decisions. Furthermore, the assumptions of AMH consider that the trends, panics, bubbles, and crashes exist in the market, arbitrage opportunities arise from time to time, and market timing is critical to catch the profit opportunities.

As the AMH is trying to settle the debate between the two schools of thought, the proponents of behavioral finance and the traditional finance will further support the literature. The findings from this research work will fulfil the gap between literatures about AMH globally by providing insights into how the Pakistan stock market has perform previously. To our knowledge, this is the first study evaluating the PSX from beginning to end from the viewpoint of the AMH.

1.12 CONTRIBUTION OF THE STUDY

The contribution of the study can be justified in two significant areas. One is its contribution to augment the existing literature in the field of finance. It explains the intensity to which the new hypothesis of AMH proposed in recent years[17] applies to the Pakistan stock market. The proposition of cyclical efficiency under the AMH hypothesis is monitored in the Pakistan stock market. This proposition is also tested with shifting market conditions. The testing of this proposition will document the behavior of the stock market based on its recurring movement. Such an examination of stock market behavior will contribute to the investor's understanding of establishing strategies by looking at the economy's political and economic situation.

The other contribution is developing a new framework that will help in the representation of the degree of return predictability in the Pakistan stock market. This new framework is designed using the latest technique of financial time series forecasting that is ANN. The ANN is gaining importance in financial time series forecasting. For an emerging market like Pakistan with more nonlinearity in data, an

17 Lo(2004,2005)

effective method was much needed. The documented method to analyze the behavior of the time series will be a significant contribution.

1.13 STRUCTURE OF THE STUDY

The research study is organized in the following structure. The nest chapter is based on a review of the relevant literature. Starting with the literature on the traditional approach towards market efficiency and shortcomings provided by these theories are examined in behavioral finance theories. The statistical developments in analyzing the behavior of time series are reviewed in detail. Need for a new methodology to examine the stock market behavior under the AMH perspective is discussed. The third chapter documented the detailed methodology of the thesis. The data set's construction, the process followed to detect optimal parameters, and the optimal ANN model is presented. Obtained results and discussion is presented in chapter four. Five chapters are comprised of concluding remarks on the thesis.

2 Review of Literature

2.1 INTRODUCTION

The relevant literature of the subject area is documented in this chapter. Starting with the historical background of the market efficiency theories and their allegation in real life is discussed. The topic of market efficiency discussed a great deal among scholastics, and specialists since Eugene Fama (1970) thought of the notable structure of the Efficient Market Hypothesis (EMH). This theory was widely accepted in the years just after its inception, but many other studies come after it, which shows that prices are predictable. Their stock prices do not exhibit randomness (Fama and French, 1988). Jegdeesh and Titman (1993) explore that it is easy to predict future returns of stocks by using some trading strategies.

The legitimacy of EMH in the developing and developed economies was broadly analyzed by various measurable tests in an absolute condition. The idea of relative efficiency and speculations of the behavioral school of thought moved past research towards new transformative methodology. The AMH rose out of standards in transformative science, brain research, and humanism and depicted proficiency as market members' cooperation. The literature on this new approach to market effectiveness is talked about in detail. Given the AMH advancement, no conventional methods for testing repetitive levels of forecast ability have been set up in the literature. Instead of using traditional methodologies, the new approach is put into practice to overcome traditional techniques' limitations.

2.2 EVOLUTION OF MARKET EFFICIENCY

2.2.1 Market efficiency roots in Economics

The Father of economics, Adam Smith, has quality work about economic and financial markets' efficiency, which can be linked to current market efficiency. Adam Smith's book Wealth of Nations 1766 helps economists when they overlook economy and market theory. He clarified in his book about balancing out the nature of economic markets through a hypothesis. Further, numerous specialists announced that Smith believed financial and economic related markets to be competent and any form of market interference to be supplanted. However, what these researchers neglect to perceive is that Adam Smith delivered something beyond his book on nations' wealth. In 1759 Smith, composed this in his book about the theory of moral sentiments; the reason for this theory is human basic leadership biasness in their Behavioral primary leadership control.

These perceptions are engaging with the contention that he accepted financial markets to be impeccably productive. To forestall further savvy maltreatment of Adam Smith's work, Smith (1998) composed a paper on the apparent inconsistencies between the two works, presuming that the convictions held by Adam Smith were undeniably more nuanced than one would accept when just reading, and the Wealth of Nations book by Adam smith. All in all, it would be reasonably unfair to contend that even Adam Smith accepted that monetary and budgetary markets were capable.

2.2.2 Foundations for testing market efficiency

The origins of the present day efficiency theory can be traced back to the theory of probability which provides important building block for the development of efficiency theory. The basis of probability theory leads to the world of gambling. The principal scientific work on the probability hypothesis was given by the Italian mathematician, who is additionally a manual for gambling (Hald, 1990). Cardano characterized the terms probability and chances just because and even introduced what he accepted to be the basic rule of betting: identical conditions. Alongside crafted by Cardano, most early research that was fundamental in the latest advancement of a hypothesis on proficient markets was directed in the nineteenth century. Dark-colored (1828) saw what we currently call a Brownian movement just because when he was glancing through the magnifying lens and saw the clear arbitrary development of particles suspended in water. Regnault (1863) proposed a hypothesis on stock costs when he found that the deviation of a stock's cost is legitimately corresponding with the square base of time: a connection that is as yet substantial in the realm of money today. The primary proclamation about the productivity of budgetary markets originated from Gibson (1889) in his book about the financial exchanges of London, Paris, and New York: "When offers become freely known in an open market, the worth which they secure there might be viewed as the judgment of the best insight concerning them." Marshall (1890) changed financial matters into an increasingly accurate science, drawing from arithmetic, measurements, and material science. He promoted interest and supply bends and minor utility and united various components from welfare financial aspects into a more extensive setting.

The impact of Marshall on economic matters was huge because his book on the standards of financial aspects turned into a fundamental work in the field. At the end of the 19thcentury, (Bachelier, 1900), in a hypothetical report, foresees the productive markets' hypothesis, expressing that securities exchange theory is a good game. Neither the vendors nor the purchasers, no one, increase a net benefit in general. Thus, we would be able to state that the possibility of a significant market, as it is comprehended in the present writing, has its foundations with the work of (Bachelier, 1900).

2.2.3 The theoretical foundation of the Efficient Market hypothesis 1900 to 1965

Bachelier's stochastic procedure got one of the focal points of money, which was presented by Pearson (1905). An exceptionally unmistakable specialist around then was Fisher, who made different commitments to the field of finance. He gained extraordinary ground on the quest for a general equilibrium hypothesis and gave significant knowledge to the utility hypothesis. Fisher turned out to be significantly progressively celebrated because of his available articulations before the Great Depression that began in 1929.

Fisher was upholding the accumulation of information to move toward the monetary market significantly more logically than previously. Through his progressive factual investigation of financial exchange costs, he had the option to make expectations about future value levels, which drove him to openly declare that the blast in stock costs before the 1929 accident was the prelude of a "for all-time high level." At the point when just a couple of days after the fact, stock costs dove more than ever, Fisher was freely embarrassed. Fisher's resulting work was gotten with extraordinary doubt, even though it later seemed, by all accounts, to be as splendid as the majority of his pre-1929 work.

Fisher's work was later demonstrated valuable for von Neumann and Morgenstern (1944) in their complete book on the general utility hypothesis. Despite a portion of his splendid commitments, Marshall, Fisher and Cowles (1933, 1944) attempted to transform financial aspects into an increasingly accurate science and found that speculators cannot beat the market through price forecasting methods. Working (1934) came up with similar ideas stating that stock returns exhibit behavior is comparable to lottery numbers. Together, crafted by Cowles and Working point towards what was later called an enlightening productive stock market.

In 1936, Keynes published his original book General Theory of employment, interest, and money. In his work, which generally affected and molded macroeconomics, Keynes presented the idea of animal spirits. As per him, financial specialists base their choices on a "spontaneous urge to activity, as opposed to inaction, and not on the result of a weighted average of quantitative advantages increased by quantitative probabilities." After one year, Cowles and Jones (1937) published a paper that gave early verification of serial correlation in time arrangement of stock costs. With Keynes's more theoretical work, this experimental proof framed an early challenge to the presence of proficient markets.

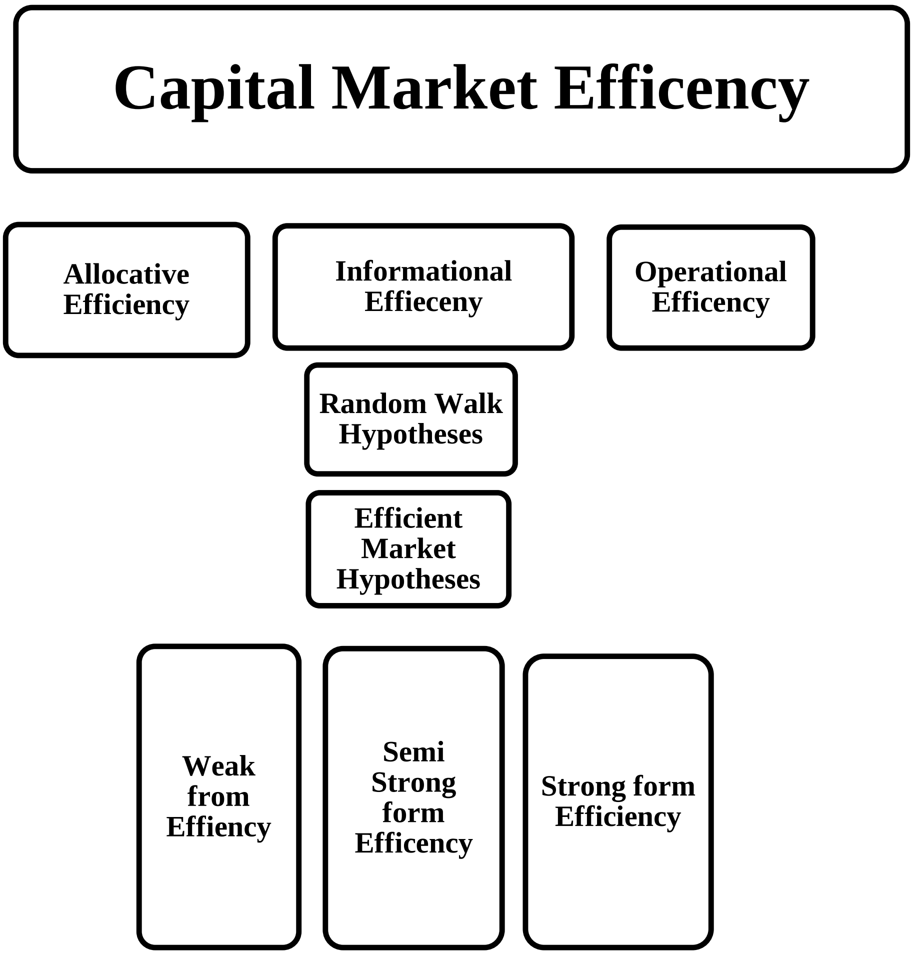
A genuine exchange on budgetary showcases' productivity just rose after the foundation of the EMH by Fama in 1970. Because of their coordinated effort during the war, Neumann and Morgenstern (1944) distributed their book on games and financial conduct theory. Not exclusively was the book the beginning stage of game theory, it additionally demonstrated to be fundamental in the advancement of a theory on proficient markets. The most significant bit of theory in their book was about maximizing what was called anticipated utility: another idea for managing vulnerability by multiple probabilities with utilities of possible results. After the Second World War, Markowitz (1952) published his paper on portfolio determination. Working inside the mean-fluctuation system, he introduced a model in which it was conceivable to decide the ideal arrangement of protections, giving a most extreme degree of return given a specific level of hazard. Key to his theory was the idea of diversification as a method for disposing of all orderly or associated hazards, leaving just the supposed danger of individual protections. Markowitz's methodology in exchanging off risks and return was fundamentally the same as what different financial analysts had been busy with during the war: considering the exchange off among power and exactness of bombs.

2.3 FORMS OF CAPITAL MARKET EFFICIENCY

There are three kinds of productivity in the capital market in the financial related world, which incorporate instructive, allocative, and operational/practical efficiencies. EMH manages the data handling proficiency of related financial markets, not with the standard economic ideas of designation and operational effectiveness. Bauer (2004) portrays the three principal meanings of market efficiency: educational, operational, and allocative. These ideas are portrayed as they are utilized in finance theory.

Market efficiency is less prohibitive than the idea of flawless capital markets: in a proficient market, costs completely and immediately mirror all accessible, pertinent data. Furthermore, in educationally significant market value, changes must be unforecastable on the off chance that they are appropriately envisioned, for example, if they ultimately consolidate all market members' desires and data. A financial market can be instructively proficient without being operationally allocational productive. For example, there can be a flawed challenge in item advertises (allocational wastefulness) with a monopolist ruling the market and still have efficient capital markets, with the monopolist's value being judiciously estimated.

Figure 1. Forms of Capital Market Efficiency



2.3.1 Informational Efficiency

In an instructively significant market, there is a direct relationship between accessible information in the market and stock prices. In such markets, the prices of stock are nearer to the intrinsic values (Padalko, 2004). A significant market must be delicate to the new information. On any occasion, the new information is accessible, and the prices are adjusted. The informational proficiency is divided into a weak-form, a semi-strong structure, and a strong form of efficiency, each of which has different implications on how markets work. In the weak form efficiency, the market prices pursue an arbitrary walk design, and the historical information cannot give the future pattern of the costs. In semi-solid structure efficiency, it is suggested that offer prices can change following openly accessible new information quickly and in a fair design, to such an extent that no abundance returns can be earned by exchanging on that information. Finally, in strong form efficiency, share prices mirror all information, openly and private and nobody can earn enough returns.

2.3.2 Allocative Efficiency

An immediate result of an efficient market is that the assets are utilized in an ideal way. A market is allocatively efficient when the minimal pace of return is equivalent to all borrowers and savers. In this manner, the makers produce just those sorts of merchandise and enterprises that are progressively favorable in society and high demand. One of the binding obligations of the capital market is that it should financially support the organizations. A characteristic of an allocative efficiency financial related market is that it gives assets from a definitive loan specialist to a definitive borrower. The assets are utilized in the most productive manner (Zorn, 2004). The most productive utilization of assets happens when a more significant part of the capital is designated to the most profitable activity. Allocative efficiency infers investors to give funds to projects with the highest net present worth and that "nothing more than trouble" speculation ventures go unfunded. The central portion of the literature on investment choices debated on allocative efficiency. It is likewise identified with the consumption and saving choices of buyers.

The finance literature is, all in all, worried about an alternate arrangement of inquiries. However, a significant and too late strand in the literature demonstrated how allocative efficiency is affected by fake information and operational efficiency. For instance, Easley et al. (2002) demonstrated the influence of measuring private information and its impact on market equilibrium. Pástor and Stambaugh (2003) documented the role of liquidity in equilibrium rates of return. It is protected to state that the literature has not dealt with the different jobs played by informational and liquidity in asset prices. It is clear, however, that these microstructure wonders affect balance rates of return. Consequently, it is safe to state that the microstructure account never again gives just "little responses to little questions," which was a typical impression of early writing.

2.3.3 Operational Efficiency

Operational efficiency alludes to the effortlessness and speed of exchanges in the market to deliver products or services to the clients in high-quality and cost-effective ways. This efficiency prompts increment the benefit liquidity (McPhail, 2003).

Work on operational efficiency is regularly concerned about the "liquidity" of a specific market: would investors be able to exchange "sensible" size without paying huge transaction costs? (D'Souza, 2002). Finance theory shows that advanced speculators, those with private data, trade markets where there are numerous liquidity-based, i.e., non-educated, financial specialists so they can conceal their trade. Accordingly, the level of informational efficiency, the more significant measure of data in costs, is connected to operational efficiency, the more prominent liquidity measure in the market.

2.4 RANDOM WALK HYPOTHESIS

The primary theory, "Random walk," is the uneven development of financial assets' prices. Expounded during the sixth decade of the twentieth century, it supports the possibility that the future movement of an asset is free from past movements of assets on a market., which proposed the model of irregular advances: "Random Walks" or "Fair Game," reproduced in English article (Cootner, 1964): "The Random Character of Stock Market Prices." The inceptions of the EMH are likewise found with (Samuelson, 1965), whose commitment is summarized by the title of its article "evidence that appropriately foreseen costs fluctuate randomly." As indicated by his hypothesis, in an informationally efficient market, value changes must be unforecastable on the off chance that they mirror the desires and data of all market members entirely.

Thus, it expresses that it is preposterous to expect to misuse any data set to foresee future value changes. Around the same time, Fama (1965a) likewise characterized an efficient market for the first time. Fama characterized a productive market as a market: with an enormous quantity of rational profit boosts effectively going up against one another to anticipate future market estimations of individual protections. Crucial current data is openly accessible to all members. "In an efficient market, on the normal, rivalry will cause the full impacts of new information on intrinsic qualities to be reflected quickly in actual prices" (Fama, 1965).

In light of the empirical examination of stock market prices, he perceives that financial markets pursue a random walk. "If the flow of information is unimpeded and immediately reflected in stock prices, at that point, tomorrow's value change will reflect just tomorrow's news and will be free of the value changes today. Since news is, by definition, unusual, the subsequent value changes additionally must be unpredictable. Another paper by Fama (1965b) elaborated on the random walk design in stock market prices to show that specialized and major investigation could not in any way, shape, or form yield chance balanced overabundance returns. Fama and Blume (1966) considered the productivity of specialized exchanging rules as the mainstream channel decides that was portrayed by Alexander (1961 and 1964). They presumed that no financial benefits could be made utilizing these channel rules since trading expenses would be too high in any event, while receiving the most productive little width filters. This additionally affirmed their convictions in finance-related markets being informational efficient.

The second hypothesis, which alludes to the theory of efficient markets, was built up in the mid-60s and accepted that advantage markets process with extraordinary affectability the monetary insight they get and respond rapidly to change financial resources. The hypothesis of efficient markets legitimizes the need for adjusted markets. Roberts (1967) and Fama (1970) have operationalized this hypothesis. In his renowned study, which will conclusively highlight the hypothesis of efficient markets, Efficient Capital Markets: A Review of Theory and Empirical Work, composed by Fama (1970), he gives the accompanying definition: "A market where costs consistently mirror the accessible information is called a proficient market." In this paper, he understands a blend of past research concerning the consistency of capital markets, fair game thoughts, and random walk getting very much figured.

The first thought of making an obvious distinction between various market efficiency types originates from Roberts (1967). However, Fama (1970) was best acquainting the idea with the general public. The complete paper on the EMH was distributed by Fama (1970) as his first of three surveys of the hypothetical and experimental work on efficient markets. He characterized an efficient market that ultimately considers all accessible information and presented three unique kinds of informational efficiency.

Outlining results from weak form, semi-strong form, and strong form efficiency tests, Fama (1991) summarized that practically the entirety of the initial proof pointed towards a financial market that was effective in at any w sense. Fama concluded that almost all of the early evidence pointed towards an efficient financial market in at least the weak sense. Although he discovered some value conditions, they never did the trick to be utilized in beneficial exchanging instruments, making markets weak-form efficient.

Fama likewise thought about the joint-hypothesis issue. He contended that it is difficult to effectively test the EMH because no scholarly accord was found on the genuine asset-pricing model. At whatever point a trial of market efficiency would dismiss the hypothesis's effectiveness, there was consistently the likelihood that it was essentially because of the fundamental asset pricing model estimating an incorrect theoretical asset. The main finding produced using efficiency tests is that a market is efficient or not regarding a specific basic asset pricing model. A similar conclusion would never be made independently of the basic model.

2.4.1 Assumptions of Market Efficiency

Fama (1970) proposes that if there are no transaction costs in trading protections in a market, all accessible information is costless available to all market members, and all concede to the implications of current data at the current cost and dispersions of future costs of each security. In such a market, the current cost of security clearly "completely reflects" all accessible information. These conditions will lead a market towards effectiveness. Fama (1970), while clarifying the adequate states of capital market efficiency, proposes that a frictionless market wherein all information is entirely accessible and investors concede to its implications is not engaging in business sectors met practically. Luckily, these conditions are adequate for market effectiveness; however, a bit much. These conditions guarantee that investors that approach available data can't acquire above-competitive returns. In any case, an infringement of any of the conditions doesn't quickly suggest inefficiency since abnormal returns may, in any case, be missing.

Fama (1991) further characterizes the efficient market theory expresses that "I take the market proficiency hypothesis to be the straightforward statement that security prices reflect all available data entirely. A precondition for this stable variant of the theory is that the information and trading costs, the expenses of getting prices to reflect the information, are constantly zero (Grossman and Stiglitz, 1980). A flimsier and financially increasingly sound form of the productivity theory says that costs reflect data to the point where the minor advantages of following up on data, the benefits to be made, don't surpass (Jensen's, 1978) marginal costs. The hypothetical establishments for the EMH lay on the accompanying presumptions (Shleifer, 2000).

Investor's rationality explains that Investors are thought to be rationally objective, which implies that they appreciate securities consistently and correctly update their beliefs when new data is available. Arbitrage is associated with the degree that a few financial specialists are not rational. Rational investors use an exchange to remove these trades without influencing prices. Collective rationality is regarded as the irregular blunders of investors that are counteracted in the market. A few investors may not be rational; however, they counteract each other without influencing the prices since they exchange randomly. Costless data and transactions refer to the availability of free data and promptly available to each investor in the market, and there are no transaction costs.

Haugen (2001) likewise composed an efficient market's characteristics as an efficient market that ought to be competitive. The conditions for a competitive market incorporate yet not restricted to great demand and supply, accessibility for the public, and many members for trades. On the off chance that a market has a predetermined number of trades and has limited members, it can't be named an efficient market. The information must be available to all participants in minimal effort and high speed. The members should be guaranteed that the prices they are paying or getting for the offers are near the characteristic qualities. The members are guaranteed that they are exchanging on the intrinsic values for the merchandise and ventures. The trade expenses ought to below, and the participants must have the option to acquire and loan with current financing costs in the market. In a productive market, the stock merchants don't have an extreme capacity to control and also rule the market prices.

The irony of efficient markets is that on the off chance that each investor undertakes that markets were productive and efficient; at that point, the market would be inefficient as nobody would investigate stocks or trade because no profits could be made (Grossman and Stiglitz, 1980). Subsequently, the effectiveness of a market relies upon market participants who accept that the market is inefficient, and it is advantageous trading stocks request to increase considerable profits (Shleifer, 2000).

If the EMH is legitimate in a stock market, it will, at that point, mirror that the market prices of stocks are sensible evaluations of the hidden worth of the stocks. This doesn't imply that the mistake in prices does not occur or incorrect, yet it implies that the errors in prices are randomly divided about the real values. Prices might be high on specific occasions and low in others, yet it is unimaginable to expect to recognize a pattern. Along these lines, we have a well-working stock market. If the EMH doesn't hold, at that point, gainful investment rules might be conceived to win better than expected average risk-adjusted returns. Such a condition might be adverse to the future advancement of the market while it will likewise impact moving the market towards efficiency.

In this way, market 'inefficiencies' propose an exchange of wealth from naive investors to refined and well-specialized investors. Fama (1970), different analysts have endeavored to figure the exact meaning of what is implied by an efficient market. Jensen (1978) expressed "a market is efficient as for the information set θt if it is difficult to make monetary benefits by exchanging based on data set θt." Malkiel (1992) expressed that a stock market is efficient when the prices of stocks stay unaltered, despite data being uncovered to every single market participant.

2.4.2 Theory of Efficient Market Hypothesis

We can define efficiency dependent on the work by Fama (1970). When he composed a survey of before looking into the efficiency of financial markets, he chose to bundle the proof in another idea called the efficient market hypothesis (EMH). The essential job of the capital market is allotment of ownership for the economy's capital stock. As a rule term, the perfect is a market where prices give precise signals to resource allocation: that is, a market wherein firms can make production, and financial investors can pick among the protections that speak to ownership of firms' activities under the assumption that security costs whenever "completely reflects" all available data. As Fama (1970) indicated, a market where costs, in every case, reflect entirely available data is called efficient. The meaning of available information is further explained by elaborating on the three types of efficient markets based on data's information set. The random walk model, according to Fama (1970), can be stated as the price of a share at the current time is equal to the price of a share at a previous time and the additional value that depends on the new information (unpredictable) arriving between the current time and last time.

Other researchers also try to define the term of market efficiency. Jensen (1978) defines market efficiency as if no irregular or high profits can be achieved by manipulating information contained in the old prices. Malkiel (1992) states that in an efficient market, the flow of information should be like that until the whole information is disseminated to all investors, the share price does not change.

After the proposed hypothesis of an efficient market number of researchers tries to explain its applicability. Jones (1993) and Shleifer (2000) describes that an efficient market can exist if a large number of rational investors actively participate in the securities' valuation process to earn maximum profit. Shleifer (2002) concludes that due to the costless and quickly available information, irrational investors' actions are cancelled out by rational investors. If some irrational investors in the market, Investors react quickly and thoroughly to the new information, causing stock prices to adjust accordingly.

2.4.3 The levels of market informational efficiency

Three different forms of market efficiency are provided by Fama (1970), weak-form market efficiency, semi-strong form market efficiency, and strong form market efficiency. In its weak form efficiency, the market regards that the current securities prices mirror all the past information regarding price fluctuations. By analyzing past prices, it is not possible to predict future prices. Brown and Easton (1989) describes the sufficient condition for a market to be sufficient to hold the random walk model. Moreover, weak-form efficiency is when a sequence of future returns could not be formulated by looking at past prices.

Clarke et al. (2001), while explaining the weak-form market efficiency, comments that the reason behind giving a market named weak-form efficient is that a thing that is known to everyone so quickly should not contain any predicting ability. Weak form efficiency also implies that it is impossible to generate excess returns based on past price information. It implies that stocks' so-called technical analysis is obsolete and does not generate any risk-adjusted excess returns over the general market's return.

The second form of market efficiency is semi-strong form efficient market described by Fama (1970). This form of market efficiency holds that the information relevant to the past movement of prices, along with all the publically available information, must be reflected in securities prices. Public information stands for the firm's information regarding its financial and managerial matters, the reports by securities exchange commission's (SEC).

Reilly and Brown (2003) elaborating the definition of semi-strong form efficiency claims that if at any time stock prices reflect all public information, it is being referred to as the semi-strong form efficient market. It suggests that if the semi-strong form of efficiency holds, investors cannot earn abnormal returns after publicly available information. Suppose that a particular company announces the news that affects its stock market price in today's newspaper. The arrival of this new information would not allow investors to make high returns because this publically available information is already reflected in stock prices. It can also be included as when market fulfils the semi strong market efficiency assumptions the fundamental analysis would not work.

Strong form efficient market demands that an information set must contain all relevant information, either public or private. This form of efficiency refers to insider information, which is not readily available to individual investors. The directors and other managerial authorities may be able to use this information to gain higher returns from securities trading. Schwert (2003) describes that if insider trading is not legal, then a strong form of efficiency could have prevailed.

Palan (2004) assumes a market to be a strong form of market efficiency for evaluating stocks and options. The market is acknowledged to be inefficient at this level of definition. Malkiel (2011) states that it is impossible to earn an excess profit while trading on insider information, which seems unlikely. The strong form efficient market theory has never been believed to be accurate. The results of the semi-strong market efficiency studies vary considerably. In contrast, the strong form of market efficiency has not been broadly investigated, and the obtained results indicate market inefficiencies (Mishkin and Eakins, 2012).

2.5 EVIDENCE ON EFFICIENT MARKET HYPOTHESIS

Just after the inception of EMH, quite favorable pieces of evidence were recorded during the 70's research studies. However, the more in-depth analysis and introduction of new methodologies documented that this hypothesis may not be entirely accurate. The detail on the evidence in its favor, and it is against is documented in the following section.

2.5.1 Empirical findings on the EMH in the '60s and '70s

The documented studies on the theory of EMH can be found even just after World War-II. Kandall (1953) and Friedman (1953) were the two surprising the other when discussing the random behavior of the stock return and the arbitrage opportunities. After these studies, some other scholars demonstrate that a random walk will look very much like an actual stock series, and it confirms the existence of EMH. Granger and Morgenstern (1963) performed a spectral analysis to the conclusion that a simple random walk can be observed in the short-run momentum stock series. Simultaneously, the researchers working on the randomness of the stock market also documented the opposite results. Alexander (1964) documented that the SandP does not follow a random walk.

Meanwhile, the martingale model presented by Samuelson (1965) hypothesizes that there is no way of making an expected profit by extrapolating past changes in the future price, by a chart or any other esoteric devices of magic or mathematics. Eugene Fama is considering as the father of the efficient market hypothesis, documented the comprehensive literature on this topic in his different papers. In his first paper, he reassesses the challenges provided by the random walk theory to the use of charts and other information for making higher profits (Fama, 1965). In his review paper, he concludes that the previous studies focus on the independence of the successive price changes by using two approaches: using simple statistical tools and then assessing different trading strategies to test them empirically. The second article by Fama (1965) documented the empirical shreds of evidence for the random walk movement of the stock prices and introduces the term efficient market in finance literature.

The impression of an efficient market hypothesis and the two stages of market efficiency strong form market efficiency and weak form market efficiency were developed by Roberts (1967). The description regarding an efficient market and one more division of market efficiency, semi-strong form market efficiency, was set up by (Fama, 1970). An efficient market is described as a market in which securities prices fully reflect Fama's available information (Fama, 1970). Fama (1970) sums up the literature by telling that most of the documented research on EMH is in favor of its applicability, and the limited studies which documented against it could be reconsidered under the problem of joint hypothesis (Fama, 1970).

2.5.2 Mixed Empirical Evidence on EMH in the Late 1970s to 1980s

The research on the topic of market efficiency during the time of the late 70s up to 80s was gaining importance among educationalists. However, it is still not very known to the professionals. The popularity of market efficiency was suddenly increased among the practitioner by the publication of a book named "A Random Walk down Wall Street" by Malkiel (1973). In his book, he assesses the different techniques used to gain high abnormal returns and reported noteworthy flaws in technical and fundamental statistical techniques. He further suggests that these means of predicting above-average returns will not provide supportive results to investors.

The fluctuations in the stock prices were regarded as an essential tool for information seeking. However, in their number of papers, Grossman and Stiglitz (1976) try to switch the discussion towards the aggregation of information by securities prices and the dissemination of information to different investors. Grossman (1976) suggests that only looking at the stocks' prices is not enough for traders and a perfectly competitive market, a market must be noisier. Grossmanand Stiglitz (1976), while trying to assess the validity of EMH, suggests that in a market where prices are accumulated through competition, the costly arbitrage makes it difficult. In a centralized system of price accumulation, the monitoring cost creates a hurdle.

The theory of EMH was one of the most documented research areas in economics (Jensen, 1978), but not all the studies support the validity of this hypothesis. After the studies, details by Grossman and Stiglitz mixed outcomes are reported by different other researchers. In the year 1978, eight papers were published on the theory of EMH.

These papers were providing anomalous findings on this topic. Four of them were against the proposed hypothesis, one is going in favor of EMH, and the three are considered with no definite conclusion (Jensen, 1978).

2.5.3 Challenging Empirical Evidence on EMH in the 1990s and onwards

End of the 20th century, several studies were conducted on EMH. Grossman and Stiglitz (1980) explore that the market is inefficient since information costs exist. Information costs must be lower than ROI. Later on, Shiller found the difference between EMH and excess volatility. He studied that the stock prices actual volatility must be higher after calculated based on necessary information. Grossman and Stiglitz (1980) present, division on the topic of efficient markets became apparent. Many researchers focused on pricing anomalies.

Bondt and Thaler (1985) again confirmed Shiller's hypothesis of excess volatility. According to them, people are disposed to overlay company statements, resulting in stock prices. These results showed inefficiencies. Shleifer and Vishny (1994) studied the same research, using alternatives for value in its place of historical price information. Their findings also exposed market inefficiencies. Moreover, BondtandThaler (1985) first observed that in stock returns (January) were generally higher than in other months, which might not be clarified by essential information only.

Black (1986) was the first author who defines "noise traders" who trade on anything other than information and explore that noise trading is vital to liquid markets. However, Black (1975) stated that noise traders might have a substantial influence on market prices. Bondt and Thaler (1985) studied the research of (Kahneman and Tversky, 1979), which is seen as the start in behavioral finance. The traditional theory of finance is merged in it with the idea of other social sciences, for example, sociology and psychology. Behavioral finance tries to frame a substitute for the EMH by supposing that investors are not entirely rational, indicating anomalies in-stock pricing. On 19 October 1987, world stock markets around crashed.

The crash started in Hong Kong, fetch west to Europe, then reaching the United States affecting the most significant daily % loss in the Jones Industrial Average history, -22.61%. Fama and French (1988) explored big adverse auto-correlations horizons of stock portfolio return outside a year. Lo and MacKinlay (1988), using the variance-ratio test, strongly forbidden the random hypothesis for weekly stock market returns. Poterba and Summers (1988) explore the stock returns, which show positive auto-correlation for a short period and negative auto-correlation for longer horizons. Conrad and Kaul (1988) considered the expected returns of stochastic behavior on common stock. Fama (1991) searched the 2nd of his three review papers. Instead of weak tests, the first-class now shields the more general area of tests for return probability. Chan (1997) stated that the global stock markets were weak to form efficient. Fama (1998) said that an over-reaction in the stock market was as typical as underestimation, which, therefore, did not lead to inefficiency.

2.5.4 Evidence on EMH in emerging economies

Some studies conducted to explore emerging markets' efficiency likened to the volume of research published in the developed market. It is usually assuming, and the emerging stock markets are low-efficient than developed markets. The efficient market hypothesis has been tested with different statistical techniques. There is much evidence on market efficiency in developed markets. However, it is not valid for emerging markets.

Empirical research on market efficiency is divided into two parts. First is technical analysis, which is mostly concerned with testing for the obtainability of consumable information in past security prices, which is broadly used in testing the weak-form efficient market hypothesis. The other is a critical analysis, assuming that factors about past security prices are applicable for future prices. The first part of the week form of efficient market hypothesis testing is further divided into two sub-methods. One is to determine predictability using past price information or return series. The second is to use practical trading rules if they can misuse it as a profit-making strategy. The detail regarding empirical shreds of evidence of EMH in emerging markets can be seen in (Appendix A).

2.6 CRITICISM ON THE THEORY OF EFFICIENT MARKET HYPOTHESIS

2.6.1 The bounded rationality

Shiller (2000) explained the irrational behavior of market players in his book, published just after the technology collapse in the nineties. He listed twelve significant factors, such as the arrival of the Internet, triumphalism and the decline of foreign economic rivals, cultural changes favoring business successes, capital gain tax cuts, the baby boom and its perceived effects on the market, increasing business news reporting, analysts' optimistic forecasts, increasing pension contribution, the fast-growing mutual funds, disinflation, more discount brokers and day traders, and increasing gambling opportunities all contributing to the irrational attitude of the market from 1982 to early 2000.

Gabaix and Laibson (2000) have developed an algorithm to test bounded rationality and rejected the rational model. When feelings and emotions are considered, human behavior may change significantly from rationality to irrationally. Tseng (2006) applied the concept of bounded rationality to the stock exchange and proposed a more realistic and practical, efficient market hypothesis. However, he did not term bounded rationality as irrationality by stating that market participants are bounded rational but not irrational.

Trammel (2006) reported that theories related to rational behavior are targets for both practitioners and finance academia. Although defenders of rationality declare that no wall has been breached, assailants do not consider themselves defeated. If anything, they are sharpening their swords, and their numbers are multiplying. From analyst conferences to academic papers, neoclassical finance is under siege.

2.6.2 The limited arbitrage

The efficient Market Hypothesis was challenged by various researchers based on the argument that arbitrage failed to wipe out mispricing caused by irrational investors. Shleifer and Vishny (1997) mentioned that arbitrage might be limited owing to the high cost. Arbitrageurs may require a higher amount of capital because of marking-to-market, as prices depart more and more from their efficient values. Besides, Daniel et al. (2001) stated that due to risk aversion, arbitrageurs might not correct mispricing. Hirshleifer et al. (2006) reported that when stock prices influence fundamentals by affecting corporate investment, irrational players can earn greater expected profits than rational ones. Abnormal returns happen because irrational investors act on emotions. Investors who act on emotions benefit earlier than an irrational one. Irrational investors may outperform the market as a group if private information is available.

The research has discovered that in an economy where rational and irrational traders interact, it will have a long-term effect on prices (HojeJo and Kim, 2008). According to limited arbitrage theory, irrational traders became more potent by deviation from fundamental values. Behavioral finance considers that deviations from fundamental values are triggered by irrationality. In the event of investors' irrationality, there is mispricing, which may trigger limited arbitrage, which is a reason for changes in stock price even though without changes in fundamental values.

2.6.3 The foundation of the prospect theory

Utility theory put forward the truly rational behavior of investors under certain conditions. The utility theory seems attractive to represent the rational behavior but it is still failed to systematically predict the human behavior under its assumptions.

Theories which are based on the assumptions of non-expected utility provide more appropriate solutions to predict human behavior. Weighted-utility theory (Chew and Crimmon, 1979), Implicit expected utility (Chew, 1989), Disappointment Aversion (Gul, 1991), Regret Theory (Bell, 1982) and Rank-Dependent Utility Theories (Quiggin, 1982, Segal, 1987, and Yaari, 1987) are the best-known models based on the assumptions of non expected theories. Among all the non-expected utility theories, prospect theory is a mathematically formulated alternative to the theory of expected utility maximization and maybe the most promising for financial applications.

2.6.4 The prospect theory

Kahneman and Tversky (1979) have developed the prospect theory. The theory is considered as the most significant attempt to question the applicability of utility theory. The loss aversion, representativeness, mental accounting, herding behavior, affect heuristics are some of the concepts developed later to support behavioral finance. The prospect theory suggests that individuals have different frames of mind and preferences for outcomes.

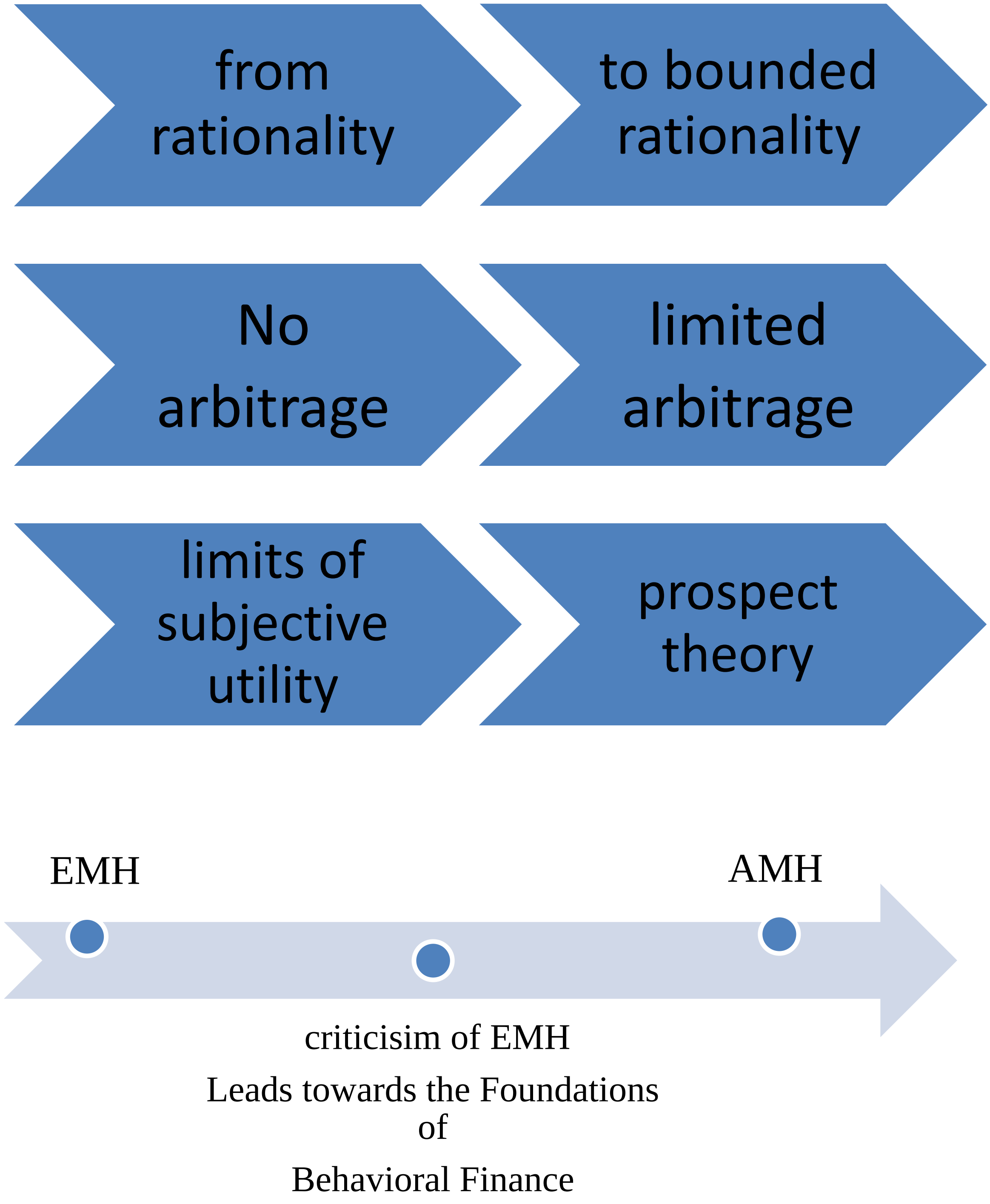
Another foundation of the prospect theory is the value function. According to Kahneman and Tversky (1979), the value functions differ from the utility function due to a reference point in utility theory, which is determined by the individuals' subjective thinking. In expected utility curve is concave. On the other hand, according to value theory, the utility function is upward sloping under the reference point and downward for the level of wealth. Investors are risk seekers under the reference point. For the level of wealth above the reference point, the value function is downward sloping and depicting investors' risk-averse.

2.6.5 The limits of the subjective utility function

The investment decision process is very technical and complicated for people investing; it is because so many internal and external factors affect asset prices across the globe. The markets are sensitive; some of these factors are dynamic, given limited time to adjust accordingly. Assumption of best alternatives and choice of best alternatives under utility maximization theory is under criticism. Lack of knowledge and the prediction of the future accurately make it challenging to find the best alternatives due to uncertainty surrounding.

It is always tricky for investors to evaluate the alternatives accurately, not knowing the probability distributions of all future events. Due to a high degree of uncertainty, it becomes difficult to estimate utility functions. The limits of human cognitive ability to discover alternatives, calculate their outcomes and make comparisons may lead the decision-maker to settle for some satisfying strategy (Simon, 1982).

Figure 2. EMH VS AMH



2.7 BEHAVIORAL FINANCE

While a large portion of the empirical research of the 1970s upheld advertise productivity, various apparent irregularities emerged by the late 1970s and mid-1980s. Since its rise, the EMH has been the most significant hypothesis that clarifies the conduct of the different financial markets' conduct disregards practically any potential effect of human conduct in the investment procedure. However, from the end of the 1970s and the start of the 1980s, emerging researchers presented the differences in this philosophy.

The differences among the new portfolio models have encouraged the progress, which is now recognized as Behavioural finance. Behavioral finance integrates psychology and financial aspects into account hypothesis and has its foundations in the leading work of psychologists (Kahneman and Tversky, 1979). Psychology plays a significant part in describing the financial behavior of investors and making a financial decision. When investors face doubtful conditions, they settle on various choices (Kahneman and Tversky, 1979).

To settle on benefit from the ideal investment decisions, they may pursue the professional investor's proposal or gather the related data from different sources. The literature on Behavioural finance falls into two essential sections: the distinguishing proof of anomalies in the productive market theory that Behavioural models may clarify (Bondt and Thaler, 1985) and the identification of individual investor behaviors or biases inconsistent with classical economic theories of rational behavior. In this manner, behavioral finance challenges the viewpoint of the capacity market and focuses on how investors interpret and follow up on freely accessible data. It aids us in better understand the investors' behavior and genuine market practices, which help investors make better investment decisions in challenging and complicated financial marketplaces.

Progressively genuine difficulties in the EMH rose out of research on long-term returns. In his work, Shiller (1981) claimed that stock record returns are excessively irregular comparative with total profits, and many accept this as help for Keynes' view that stock costs are driven more by examiners than by basics. According to Bondt and Thaler (1985), he documented proof of evident eruption in singular stocks over long distances of three to five years. In particular, the costs of stocks that had performed generally well more than three-to-five-years would, in general, return to their methods over the ensuing three to five years, bringing about negative overabundance restores; the costs of stocks that had performed moderately inadequately would in general return to their methods, bringing about positive abundance returns, termed as "mean reversion" or "reversion to the mean." Summers (1986) revealed the erotically that costs could take long, slow swings from basics that would be imperceptible with short-horizon returns.

These alleged irregularities incorporate, among others, the "small firm impact" and the "January impact," which together archives the propensity of low capitalization stocks to procure over the top returns, particularly in January. However, today's financial analysts attribute a majority of the inconsistencies to either misspecification of the quality pricing model or market frictions. For instance, the small firm and January impacts are currently ordinarily seen as premiums substantial to repay speculators in little stocks, which will, in general, be illiquid, particularly at the turn of the year. Extra experimental funding for mispricing comes from Jegadeesh and Titman (1993), who revealed that earning in stocks comparatively great or little yields an interval of approx.3 to 12 months sustained the pattern over the successive 3 to 12 months. Fama (1998) reported that the anomalies at times required under response and once in a while overcompensation and, therefore, could be seen as rare events that frequently left when specific timeframes or methods were applied.

These clearing-competences added to the development of another way of thinking called Behavioural finance, which countered the suspicion of discerning desires with proof from the field of psychology that individuals will, in general, make organized intellectual mistakes when forming expectations. Behavioral finance researchers have experimentally demonstrated that financial specialists don't generally act reasonably or consider the accessible data's entirety in their necessary decision-making procedures. They have Behavioural inclinations that lead to deliberate errors in the manner they process data for an investment verdict. These errors, in light of their distinct character, are regularly unsurprising and avoidable. However, they keep on happening as often as possible and are made by amateur and expert financial specialists alike. Behavioral finance is developing science that reviews the irrational attitude of the investors. It mainly focuses on the applications of economic and psychological philosophies for financial decision-makers (Olsen, 1998).

Weber (1999) explains in their study, Behavioural Finance intently joins singular conduct and market wonders and uses the information taken from both the financial theory and the psychological field. Behavioral finance attempts to detect the Behavioural biases commonly presented by investors and gives procedures to defeat them. As per the studies done from the mid-1980s to 2002, psychology might be exceptionally compelling to money-related financial specialists since it's the premise of madness, which prompts the center of

Behavioural account. Behavioral finance is a portion of finance, which tries to comprehend and anticipate systematic financial market allegations of psychological decision methods. As indicated by Fromlet (2001), Behavioural finance intently consolidates singular conduct and market phenomena and uses information taken from both the financial theory and psychological field. The discussion in theoretical finance among efficient market speculation and the field of Behavioural finance is of great concern. Sewell (2001) characterized Behavioural finance as the investigation of the impact of psychology on financial practitioners' conduct and the subsequent impact on business sectors. Behavioral finance is of interest since it clarifies why and how markets may be inefficient. Behavioral finance is a new example of finance, which pursues to supplement modern finance theories by introducing Behavioural aspects to the decision-making process.

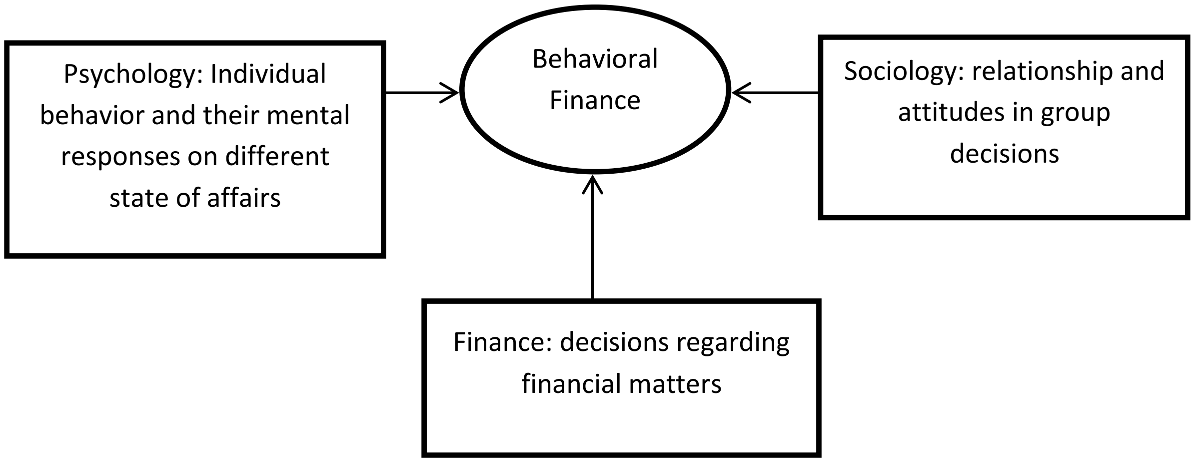
2.7.1 Foundations of Behavioural Finance

Numerous researchers and creators have given their very own understanding and meaning of the field. The discussion on the definition of Behavior Finance could be impressive and genuine as the field is still at the refinement stage. In the search for causes, practitioners and academics equally turning towards Behavioural finance for signs. It is an investigation of us. We are human, and we are not frequently in the way equilibrium models might want us to be. Alternatively, maybe we mess around that entertain personal responsibility. Financial markets are a real game. They are the field of greed and fear. Our fears and goals are showcased consistently in commercial centres. Thus, maybe costs are not frequently rational, and proficiency might be a textbook hoax (Wood, 1995). Wood (1995) of Martingale Asset Management defined Behavioural finance along these lines: Evidence is abundant that money managers infrequently satisfy hopes. Fuller (1998) depicts his perspective of Behavioural finance, noticing his conviction that individuals deliberately make mental blunders and misconceptions when they invest their cash.

Behavioral finance can be defined in terms of sociological and psychological factors that affect the financial choices making procedure of groups, entities, and individuals Olsen (1998). Another definition provided by Linter (1998) expresses the BF in terms of investor's interpretation and decision making against some new information provided. This developmental procedure keeps on happening because some researchers have such a varied and wide variety of professional and academic expertise. The selection method for deliberating the particular perspectives and definitions of BF depends upon the professional experience of the researcher. Two leading teachers from Santa Clara University, (Statman and Shefrin, 1999), work in behavioral finance. Statman (1999) describes that while making investment decisions, the decision-makers have to face two significant risk assessment issues and frame the presented information. He reviews these issues in terms of psychological barriers, as (Kahneman and Tversky, 1979). Shefrin (1999) defines BF as "Behavioural finance is a rapidly growing area that deals with the influence of psychology on the behavior of financial practitioners."

Ricciardi and Simon (2000) characterize behavioral finance (BF) in addition to finance the concepts of sociology and psychology. He expresses that when examining BF's ideas, one should consider the behavioral aspects of psychology and sociology along with the vehicle of traditional finance. In this way, the individual considering BF must have a fundamental comprehension of sociology, finance, and psychology to get familiar with BF's general ideas

Figure 3. Relationships of behavioral finance



Source: Ricciardi and Simon (2000)

The study of Individual behavior and their mental responses towards outside situations is referred to as human beings' psychology. When this psychology is interconnected with the behavior of human beings in the group, their relationship and attitudes reflect humans' social norms. Finance is the study of managing and investing and acquiring financial resources (Ricciardi and Simon, 2000). Fromlet (2001) defines behavioral finance as the combination of financial theory and knowledge from the individuals' psychological behavior and applies them to the market facts. The influence of psychology on investor behavior and its other effect on the market is the considerations of BF (Sewell, 2007).

The psychological barriers such as heuristics and behavioral biases create a problem for individual investors to make a profound investment decision, so the need for financial specialists arises who can perform better-investing decisions (Barberis, 2007). Alexakis and Xanthaki (2008) also pointed out that psychological processes formulate bad decisions by individual investors.

2.7.2 Building blocks of Behavioural finance

Thaler and Barberies (2003) studied the developments of behavioral finance. They found that few operators are not entirely up to date, but the rational agents avoid them influencing security prices, which are known as arbitrage. According to Barberis and Thaler theory of behavioral finance is conceptualized on two pillars: limits to arbitrage and prospect theory. Due to irrational traders, from market dislocation, the arbitrageurs may be able to make a profit. This behavior is mostly found in financial markets.

2.7.2.1 Limits to Arbitrage

Arbitrage is an essential concept in finance; Sharpe and Alexander (1990) characterized it as "the simultaneous purchase and sale of the same, or essentially similar, security in two different markets for advantageously different prices." Hypothetically such trading does not require any capital, and it is considered as having no capital hazard. When an arbitrager sells expensive security and buys a cheaper one, the future cash flow is zero. In the study of securities, market arbitrage has significant value; its result is to take the securities prices to its essential worth besides retaining market competence. Conventional finance assumes that there must not exist any arbitrage opportunities in an efficient market, and if it exists, it should be risk-free. Conversely, many analysts found the opposite and provide reliable verification for a risky and limited arbitrage (Shleifer andVishny, 1997).

In reality, the situations at hand are having chances of arbitrage that stay for long. According to literature, such situations are characterized as limits to arbitrage. In some conditions, social and behavioral psychology explain limit to arbitrage fail better than classical finance theory. The question is that why the prospect of arbitrage stays so long is still to be answered.

2.7.2.2 Fundamental Risk

It means terrible information came after new security was purchased. It resists buying an interrelated product. Absolute risk is removed by substitute securities, which are rarely perfect. Suppose investors buy two shares from different brokers from the same industry. Moreover, both are closely related. Investors retain one and another sold. So this buying and selling process removes absolute risk.

2.7.2.3 Noise Trader Risk

Noise trader risk indicates the risk of mispricing during the short run. Long et al., (1990) and Shleifer and Vishny (1997) suggest that when the formulation of prices deteriorates during the short run due to the suspicious behavior of traders, which becomes even more pessimistic about the future. Commotion broker risk is significant on account of its connection to other organization issues. It can compel individuals, for example, institutional financial specialists and fence investment chiefs, to sell their positions early, bringing them undesirable and superfluous soak misfortunes. Henceforth if financial specialists come up short on the information to assess the director's system, they may essentially assess him dependent on his profits. On the off chance, the intensive mispricing in the short run and generation of negative returns, speculators made choose to pull back their assets and power him to exchange his business.

Educators Thaler and Barberis contend that dread of such untimely liquidation causes proficient chiefs to be less forceful in fighting the mispricing in any case. Even though commotion chance most normally happens while shorting resources, it might likewise be available in the guarantee of a repurchase understanding (repo) or if the first proprietor of the stock requests his stock before our procedure remedied the mispricing. Besides, Educators Shleifferand Summers (1990) call this wellspring of risk: "resale chance" since it originates from the capriciousness of future resale costs. This risk will significantly influence speculators and expert supervisor's time skyline. Specifically, if the resale risk is high, financial specialists will have a relatively shorter time skyline since speculators dread exchanging due to external judgments.

2.7.2.4 Implementation Costs

Implementation costs are outstanding to any financial specialist. They refer to exchange costs, such as commissions, offer to ask spread, premium expenses for hot insurance in repurchase understandings, and expanded commissions for shorting protection. Other than money related costs, there can likewise be lawful requirements and bookkeeping issues. This classification additionally incorporates the expense of finding and finding out about mispricing, just as the expense of the assets expected to misuse it (Shleifer and Vishny, 1997). Specifically, discovering mispricing can be costly and tedious. Finding out about them will require painstaking work. Last misusing mispricing requires cutting-edge innovation and costly IT frameworks that can exchange at the high-recurrence speed.

2.7.2.5 Psychological beliefs and Overconfidence

Different psychological beliefs lead investors towards the overoptimistic arrogance is the inclination that individuals overestimate their capacity. Shefrin (2007) refers to carelessness "relates to how well individuals comprehend their very own capacities and breaking points of their insight." As a rule, individuals consistently place excessive weight on their endeavors, information, and aptitudes, mainly when the certainty level is very high.

There are a few different ways for carelessness to show itself. One model referenced in the Shefrin (2001)work is that there are over 65 and 80 percent individuals rate themselves better than expected (characterizes as the middle) when they have posed the inquiry "comparative with every one of the individuals you work with, how you would rate yourself as a driver?" This infers "with regards to troublesome and testing undertakings; the vast majority are arrogance about their very own capacity and their insight."

The vast majority show ridiculously blushing perspectives on their capacities and possibilities (Weinstein, 1980). Regularly, over 90% of those reviewed think they are better than expected in such areas as driving aptitude, coexisting with individuals, and comical inclination. They additionally show a precise arranging deception: they foresee that undertakings (for example, composing review papers) will be finished a lot sooner than they are (Buehler, Griffin, and Ross, 1994).

2.7.2.6 Heuristics

Heuristics are the shortcut decision-making approach based on self cognitive power, which does not guarantee optimal output. The two main heuristics on which investors make biased decisions in unsure situations were introduced by the two splendid analysts Kahneman and Tversky (1974). These heuristics are named as the availability heuristic, representativeness heuristic, and anchoring and adjustment heuristic. In later years one more name of heuristic came in the literature that is named as affect heuristic. Affect heuristic was introduced by Damasio (1994) and Slovic at al. (2002), who selects its name based on the essential contribution of affective judgment in decision-making.

Representativeness considers the decision making based on looking into how much it belongs to specific groups. Representative heuristics do have some features like conjunction fallacy and data sample insensitivity (Fisk, 1996), (Hertwig and Chase, 1998). The second heuristic is the availability heuristic; under this heuristic, the decision is made based on some events in mind. It assesses the importance of some outcomes based on probabilities given to them under some retrievable memory. For such decisions, one must have muscular memory strength. If the memory strength is not healthy, it can lead to biased judgment, resulting in misleading results.

The availability heuristic can be explained by overestimating some unfavorable outcomes if the same is available in retrievable memory (Marsh, 2002). Anchoring and Adjustment is the third most common heuristic presented by (Kahneman and Tversky, 1974). This heuristic suggests that while making a judgment regarding quantitative analysis relying on one dimension will leads towards biased judgments. The stay might be recommended by the definition of the issue or the consequence of fractional calculation. In either case, changes are ordinarily deficient.

While representativeness prompts an underweighting of base rates, there are circumstances where base rates are over-accentuated comparative with test proof. In a test run by Edwards (1968), two runs contain three blue balls and seven red ones, and the other containing seven blue balls and three red ones. An irregular draw of 12 balls, with substitution, from one of the urns, yields eight reds and four blues. What is the likelihood the draw was produced using the primary urn? While the right answer is 0.97, a great many people gauge a number around 0.7, obviously overweighting the base pace of 0.5. From the start locate, the proof of conservatism shows up inconsistent with representativeness.

Nonetheless, there might be a characteristic manner by which they fit together if an information test illustrates a basic model. At that point, individuals overweight the information. In any case, if the information is not illustrative of any striking model, individuals respond excessively little to the information and depend a lot on their priors. In Edwards' investigation, the draw of 8 red and four blue balls is not especially illustrative of either urn, perhaps prompting earlier data overreliance.

A fundamental element of any model attempting to comprehend resource costs or exchanging conduct is a supposition about financial specialist inclinations or how speculators assess hazardous bets. Most by far of models accept that financial specialists assess bets as per the standard utility structure. The hypothetical inspiration for this returns to (Von Neumann and Morgenstern, 1947). They show that if inclinations fulfill various conceivable maxims, at that point, they can be spoken to by the desire for a utility capacity. Shockingly, exponential work in the decades after this has demonstrated that individuals methodically abuse expected utility hypothesis while picking among dangerous bets. In light of this, there has been a blast of work on purported non-expected utility speculations—every one of them attempting to make a superior showing of coordinating the trial proof.

Many other models try to realize the ambiguity in expected utility, among which the better-realized models incorporate prospect hypothesis (Kahneman and Tversky, 1979) and (Tversky and Kahneman, 1992). Of all the speculations, the prospect hypothesis is getting more critical in developing behavioral finance theory.

2.7.2.7 Prospect theory

The most referred to paper ever to show up in Econometrics, the famous scholastic diary of financial matters, was composed by Kahneman and Tversky (1979). These investigators conferred an evaluation of the anticipated utility hypothesis as an enlightening system essential leadership underneath hazard. They built up an elective model that is represented as a prospect hypothesis. Kahneman and Tversky (1979) found that people underweight results, which merely likely correlates the results that are acquired with assurance; likewise, that individuals, for the most part, dispose of components that are shared by all possibilities viable.

The concept of prospect theory utilizes the decision weights to choose incentives according to the possibility of appointed value to the gains and losses rather than outcomes. Deviations from a reference point characterize the worth capacity. It is typically sunken for gains suggesting hazard avoidance, usually curved for misfortunes chance to chase, and is commonly more extreme for misfortunes than for gains misfortune abhorrence. For the most part, choice loads are lower than the comparing probabilities, except for in the scope of low probabilities. This proposed hypothesis concluded through the experiments suggests distinguishing features of risk attitudes. Individuals show risk aversive behavior for benefits with sensible to high probability and low probability losses and show risk-seeking behavior for benefits with minimum to high probability.

Thaler (1980) contends that there are conditions when shoppers act in conflict with a financial hypothesis. He recommends that prospect hypothesis by Kanneman and Tversky's (1979) be utilized as the reason for an expressive option hypothesis. The Prospect hypothesis is marked to clarify a typical example of a decision. It is graphic and observational. The Prospect hypothesis sees two essential leadership pieces: the altering, or surrounding stage, and the assessment stage. The altering stage incorporates what is broadly known as encircling impacts.

The assessment stage includes picking among choices; this choice is affected by two procedures, one identified with abstract worth, the other to perceptual probability. Surrounding impacts allude to how a decision, or an alternative, can be influenced by the requestor way where it is exhibited to a leader. This is a critical idea for various reasons. Much of the time, a leader does not have the foggiest idea about the critical accessible choices. She should develop and make sense of the alternatives or have accomplished for her before a decision. Behavioral finance theorists explain some psychological factors behind the explanation of prospect theory. The psychology of investors and beliefs regarding choices is considered a central aspect of the expansion and working of the Arbitrage theory and prospect theory (Tversky and Kahneman, 1981).

The concept of limited arbitrage indicates that when some irrational investors do not give importance to the original value, rational investors cannot correct the mispricing. The structure of deviations is better explained by the behavioral models which are based on the appropriate form of irrationality. The experimental research from cognitive psychologist contributes towards the explanation of behavioral economic theories. The beliefs and the preferences associated with the decisions studies under cognitive psychology give rise to the new field of behavioral biases. And provide a new direction to investigate the behavioral biases under experimental models. A critical section of any model of financial markets is an arrangement of how agents form prospects. Based on the investor's psychology and beliefs, different investor's behaviors are documented in behavioral finance.

2.8 ADAPTIVE MARKET HYPOTHESIS (AMH)

The conventional financial prototype seeks to recognize financial markets using models in which agents are "rational." To explain rational behavior, researchers reported two perspectives: the agents update their viewpoints on the new information and select the best alternative following the alternative's normative value, which fulfills the subjective utility function. As this rational framework is simple to understand, and as data or information shows, it satisfies predictions. However, after years of research, it becomes clear that it is not easy to understand individual trading behavior in this framework. How individuals aggregating average returns to make the investment decision is not clear under this framework.

From the past few decades, standard finance is falling to answer the behavioral aspect of decision making. To overcome these difficulties, the field of behavioral finance has emerged. The behavioral school of thought argues that if some irrational behavior of agents is incorporated in the financial models, they can better explain the financial issues (Shefrin, 2000). Many past investigations find out that market efficiency and rationality cannot be handled with human decision making power, but reveals definite Behavioural bias that is not giving fruitful results from the financial viewpoint. The famous biases documented in the behavioral finance literature are over-confidence, Overreaction, loss aversion, psychological accounting, and miss calibration of probabilities, hyperbolic discounting, and regret. For the mentioned rationale, Behavioural economists concluded that investors are frequently, if not constantly illogical, exhibiting conventional and economically disastrous behavior that is not likely to permit efficient markets.

The Behavioural school of thought considers that investors are not always entirely rational and, consequently, it is not possible for a market to be efficient at all time (Shefrin, 2000). Along with the documented proof of behavioral biases and the presence of anomalies considering this behavior of market efficiency and average construct of time-varying degree following theories presented to deal with Behavioural finance and EMH theories, the new settlement in light of adaptive markets hypothesis (AMH) proposed by Lo (2004, 2005, 2012). These theories aimed to adopt new market conditions, including biological evolution, concepts of bounded rationality, and satisfying behavior towards adoptive market theories. For new market ecology, specific new techniques have been adopted for competition in the market, and the natural structure helps to adopt this theory.

The evolutionary dynamics that occur in the market are natural selection and competition among investors by entering new investors to the market and moving out of old investors from the market, which shows the level of efficiency in the market (Lo, 2012). Formerly an actual occurrence generates contest and natural selection; markets befall provisionally with a reduction of competent traders. Stock markets remain somewhat efficient if no longer market shock causes market ecology to change the market. The efficiency of financial markets returns to the pre-shock level when new market ecology is formed. During the development of the 2008-2010 financial crises, Lo's theory elements can also be recognized.

2.8.1 Adaptive Market Hypothesis (AMH) Lo's Theory

In his article "The Adaptive Markets Hypothesis: Market efficiency from an evolutionary perspective," Lo (2004) reviews the current condition of the controversy surroundings the EMH and recommends a new perception that reconciles the two opposite schools of thought. The projected settlement, which He called the Adaptive Markets Hypothesis (AMH), is based on an evolutionary approach to economic connections and some recent research in the cognitive neurosciences that have been transforming and invigorating the junction of psychology and economics. Before amplification, the theory of adaptive market hypothesis Lo reviews behaviorist behavior on the Efficient Market Hypothesis.

Opposing to the neo-classical hypothesize that individuals exploit estimated effectiveness and have coherent potential, an evolutionary perception makes significantly more reserved claims, performance individuals as organisms that have been sharpening through generations of natural selection to exploit the endurance of their inherited substance (Dawkins, 1976). This perception involved that behavior is not essentially inherent and exogenous, but developed by natural selection and depend on the challenging situation through which assortment occurs.

The AMH's primary mechanism includes the subsequent ideas: Individuals make mistakes, Individuals discover and settle in, Individuals work in their self-interest, and usual selection shape market environmentalism, antagonism drive alteration, and modernism, and Evolution determine market dynamics. Both EMH and AMH are two different paradigms from each other and have a common starting point as individuals act in self-interest. In a competitive market where the market is always in equilibrium, and the environment is stationary, an investor does not take the risk or made any mistakes.

AMH additionally states that adjustment does not happen autonomously of market forces, but is determined by struggle, i.e., the push for survival (Lo, 2004). The connections between varieties of market contributors are managed by natural assortment. In our circumstance and AMH, the endurance of the richest implies that the current market environment is a creation of this collection process. It additionally affirmed that the total of these workings selfish individuals, competition, adaptation, natural selection, and environmental conditions are what we examine as market dynamics.

2.8.2 Allegations of AMH

Lo (2012) recommends the following allegation of AMH. The first allegation is that, to the degree that there is a link among possibility and incentive, it is not likely to be constant over time. Such a relation is indomitable by the relative size and preference of various populations in the market ecology and institutional characteristics such as the authoritarian environment and tax laws. As these aspects change over time, any risk/reward relation is expected to be exaggerated. A consequence of this suggestion is that the equity risk premium is also time-varying and path-dependent. The idea of time-varying efficiency is not so innovative an idea as it might first appear even in the framework of a rational opportunity symmetry model. If risk preference change over time, then the impartiality risk premium must diverge.

A second suggestion is that opposing the classical EMH; arbitrage opportunities arise from time to time in the AMH arbitrage opportunities. As Grossman and Stiglitz (1980) find out, there will be no incentives to gather information without such opportunities, and the financial market will collapse due to the price discovery aspect. From an evolutionary perspective, the very continuation of dynamic liquid financial markets implies that revenue opportunities must be there. As they are subjugated, they withdraw. However, new opportunities are also continuously being formed as definite variety die out, as others are born, and as institution and business circumstances vary.

Comparatively, then the inescapable propensity toward complex efficiency expected by the EMH, the AMH involved significantly more multifaceted market dynamics, with the cycle and trends, and panic, manias, bubbles, crashes, and other phenomena that are regularly observed in everyday market ecologies. These dynamic give the inspiration for dynamic management, as Bernstein (1998) suggests, and give to Niederhoffer's (1997) "decomposers" and "carnivores."

A third allegation is that speculation strategies also wax and wane, performing well uncertain environments and performing poorly in other environments. Opposing to the classical EMH in which arbitrage prospect has contended away, ultimately eradicate the profitability of the strategy intended to develop the arbitrage. When environmental conditions become more favorable to trade, profitability strategy may decline for a time and then return to profitability.

A fourth suggestion is that novelty is the key to continued existence. According to classical theory, bearing a sufficient level of risk, a certain level of expected reruns can be achieved. The AMH involved that because the risk/reward relation differs during the time, to adapt changing market conditions, a certain level of expected returns can be achieved. By developing a diversity of competency that is suitable to a multiplicity of ecological conditions, speculation managers are less expected to develop into extinct as an effect of quick alteration in business conditions. Considering the contemporary theory of the dinosaur's failure, ask where the next financial killer asteroid might come from (Alvarez, 1997). The only objective in this is survival in the market. Other relevant aspects of market ecology include utility maximization, profit maximization, and general equilibrium. The evolution of market and financial technology merely is surviving as the organizing principle in determining.

2.8.3 Adaptive Market Hypothesis in Evidence

AMH theory was first empirically investigated by the Lo (2004, 2005). The degree of market efficiency idea was confirmed underlying dynamics; many factors like calculating rolling first-order autocorrelations of monthly returns as a measure of market efficiency find a cyclical pattern through time.

However, Lo's anticipated rolling autocorrelation procedures are not in line with the suggestion of markets individual comparatively competent for an extended period, until a market crash causes a short period of relatively lower efficiency. In afterward years, the researcher observed the AMH by way of trading approach. A study finds out that AMH cyclical efficiency patterns are confirmed in investigating the profitability of moving average strategies on the Asia-Pacific financial markets, (Todea, Ulici and Silaghi, 2009).

Another study reveals that trading rules on the foreign exchange market cause excess return (Neely et al., 2009). This study shows that due to behavioral and institutional factors, a slower pace than expected, one results in a decline of returns over time. These results are constant, with the AMH view of markets being dynamic systems focused on the underlying evolutionary procedures.

Kim et al. (2011) confirm Lo's idea of time-varying market efficiency being driven by changing market conditions, results in a higher degree of stock market predictability in times of economic and political crises. No return predictability is found during market crashes and market bubbles. This result contradicts a theory of Lo's Adaptive Market Hypothesis, which shows that lower degrees of efficiency must have been found in market-mania and higher predictability degrees.

In his study, Kim et al. (2013) also examined that important factors influencing stock return predictability over time while implementing an ordinary least square regression are stock market volatility, inflation, and risk-free rates. Verheyden (2013) empirically test the ideas underlying the AMH using a rolling variance ratio test. Time variant efficiency and dynamic ought to be valid during the test. Though, the theoretical prototype of efficiency forecasted the AMH is redundant from the consequences, which is somewhat due to the incapability of the certainty proxy to detain the conventional perception on market efficiency.

Ghazani and Araghi (2014), in his study about Tehran's stock market, finds out that the existence of the adaptive market hypothesis (AMH) as an evolutionary substitute to the efficient market hypothesis (EMH) by applying daily returns on the TEPIX index in the Tehran stock exchange (TSE). The consequences from linear (automatic variance ratio and automatic portmanteau) and nonlinear (generalized spectral and McLeod–Li) tests represent the oscillatory manner of returns about dependency and independence, which correspond with the adaptive market hypothesis.

A previous study regarding the adaptive market hypothesis finds out that AMH initiates a better explanation of India's new stock market, (Hiremath and Kumari, 2013). To evaluate the empirical hypothesis, linear and nonlinear approaches were used. The study shows that the Indian stock market switched between efficiency and inefficiency because of the linear dependence of linear tests cyclical patterns. Besides, the results from nonlinear tests reveal strong evidence of nonlinearity in returns throughout the sample period with a sign of tapering magnitude of nonlinear dependence in the recent period. The findings suggest that the Indian stock market is moving towards efficiency.

Popovic et al., (2013) examined three factors that affect market efficiency in the adaptive markets hypothesis (AMH). These three factors time horizon represented by a rolling window, observation period, and data aggregation level. Rolling window analysis is a factor where a particular parameter fixed in each window is employed to measure the consistency of deviations from a random walk hypothesis (RWH) over the period. In fact, by adopting the rolling sample method, they find out whether short linear dependence is changing over some time or not. Previous studies find out that all of the above factors affect the weak form money equity market, which leaves serious cost on profit opportunity or rate overtime on this market. The detail of evidence regarding research studies on AMH can be seen in (appendix B).

2.9 MAJOR EVENTS AND STOCK MARKET MOVEMENT IN PAKISTAN

Economic, non-economic, and political events impact the performance of the stock market. Interest rate, inflation, monetary and fiscal policy are the macroeconomic variables that impact the stock market as a whole, whereas microeconomic variables influence individual firms. In recent years, these macroeconomic variables and political news are under great attention in Pakistan's case.

2.9.1 Economic variables affect on stock market

Macroeconomic variables such as interest rate, inflation, and exchange rate are considered significant variables that affect the stock market return (Khan et al., 2018). Khan et al. (2018) investigated the impact of the exchange rate, inflation rate, and interest rate on monthly stock price data of 15 firms listed on PSX for five years from January 2008 to December 2012. They observed a positive impact of the exchange rate on the stock return, whereas the inflation rate and interest rate showed a significant negative impact on the stock return. The results of variance decompositions discovered that the inflation rate among the three macroeconomic variables showed a more significant forecast error for the KSE 100 Index.

In another recent study, (Pervaiz et al., 2018) empirically investigated the influence of macroeconomic variables: inflation, exchange rate, the interest rate on Karachi stock market returns. Pervaiz et al., (2018) observed the monthly data KSE-100 index from January 2007 to May 2017. From the three macroeconomic variables, inflation showed a negative impact on the stock market performance. The result revealed that it takes time for the market to react to changes in the inflation rate. Pervaiz et al., (2018) concluded that the KSE market investors prefer to invest in the market instead of foreign currency, and they do not care about the exchange rate variation.

2.9.2 Global Financial Crisis

Sohail et al., (2017) empirically examine the investor's reaction to the 2008 Global Financial Crisis. Employing trading volume for investor's reaction and relating it with events study, this research study provides evidence of significant overreaction in the first two weeks and significant under- reaction in the 12th and 24th week following precisely in the financial sector. It suggests that the arrival of good or bad news can bring about a rise or decline in the stock price even if the news does not directly impact its performance.

Ali and Afzal (2012) investigate the distressing global financial crisis which initiated from United States and extend all over the world and harmfully affected real and financial sectors of developed as well as developing countries. They particularly study the consequence of these biggest crises on Pakistan and Indian economy. The findings from Ali and Afzal (2012) disclose that the bad waves from developed markets impact with intensity to the developing markets s compare to the good news from developed markets. While comparing the fluctuations in volatility between India and Pakistan they advocate that the Indian economy is highly volatile to this crisis.

Sohail and Javid (2014) inspect the investor behavior during the financial crash of 2008. They consider 2 years for investigating the over and under reaction of investors in PSX during and after the financial crisis of 2008. The findings from Sohail and Javid (2014) indicates that in PSX the short term under and over reaction could not be seen, but in long run PSX behaves differently.

2.9.3 Non-economic variables affect on stock market

Non-economic variables as catastrophic events like earthquakes, floods, plane crashes, and natural catastrophes can also lead to consequent significant influence on the stock market performance. The PSX shows reactive behavior on unanticipated shocks (Javid, 2009). Javid (2009) and Nazir and Anwar (2014) investigated the Pakistani stock market's reaction to the earthquake of October 8, 2005, and its impact on the price, volume, and volatility behavior of sixty firms listed on PSX. She concluded that PSX seems flexible and recovers soon from these catastrophic events. The results depict a rise in returns of cement, steel, food, and banking as expected. However, no significant volatility has been observed. The economic consequences of these natural disasters impact the country's economy and the global economy altogether. The destruction of the 2004 Indian Ocean tsunami spread over to almost 11 economies of the world.

Hanan et al. (2012) examined the impact of natural disasters, terrorism, and political news on the KSE-100 index. The study considered 21 news events: 2 natural disasters, nine terrorism, and ten political events. According to their findings, natural disasters, terrorism, and political news infer a substantial impact on the KSE-100 index. The impact of terrorism-related news is more profound than those of natural disasters or political news. The study also validated the view that good news impact positively, and lousy news impacts negatively on the KSE-100 index. Finally, it is revealed that more important news in terms of its consequence has a substantial impact on KSE-100 Index.

2.9.4 Political events affect on stock market

Political events are not directly related to stock markets but are among the potential factors affecting the stock markets. Jorion and Geotzmann (1999) concluded that political events lead to an interruption in the market transactions whereas, Chiu et al. (2005) confirmed that South Korean political elections altered the pattern of foreign investment in financial markets. Frey and Waldenstrom (2004), (2005), Aktas and Oncu (2006), Bailey et al., and Beaulieu et al. (2006) contended that political events strongly impact the trading volume and returns of the financial markets. According to Bechtel (2009), in a stable political situation, systematic investment risk is low that boosts growth, capital investment, and develops the overall economy's performance.

Suleman (2012) investigated political headlines 'headlines' outcomes to check their impact on the Karachi Stock Exchange market return and how much market volatility results from this gossip. News is categorized into two classes as Good news and Bad news; variation in returns due to other political news is evaluated utilizing the GARCH model. The findings confirm that low volatility of the market and high returns prevail with various optimistic news. In contrast to that, political affairs and shocking news induce higher volatility and lower returns of KSE.

Nazir et al. (2014) examined the political events and their consequent repercussions on the PSX returns. Their results confirm that political events impact on market returns of PSX. Moreover, analysis shows that the PSX remains inefficient for a short duration of time; after a lag of 15 days, PSX adjusts to perturbing information.

Mahmood et al., (2014) analyzed fifty significant events from 1998-2013 since the nuclear test of Pakistan to study the impact of these events on returns volatility. The designated events are selected to analyze how these events cause much volatility in returns. One month before the event day and two months past event day, KSE-100 Index returns are also recorded to substantiate the null hypothesis. The findings conclude that mostly events accompany negative abnormal returns and instability of the government.

To study the impact of political events on the Karachi stock exchange, Murtaza et al., (2015) segregated nine major political events into two categories; one of those events that caused a change in government policy and those that did not cause a change in government policy. Major political events from 2007 to 2012 were selected which included the Emergency rule of Musharaf, the Assassination of Benazir Bhutto Assassination, 2008

General Elections of Pakistan, the Resignation of Musharaf, the Restoration of the Chief Justice of Pakistan, Abbottabad Operation, the Salala Attack, De-seating Prime Minister of Pakistan and 2012 Elections of USA. Results demonstrated that the events that caused a change in government policy affected the Karachi Stock Exchange's returns, and the event that did not cause a change in government policy did not affect returns. Besides, it was also observed that KSE readjust itself very quickly, i.e., the effect of such news did not last for more than two days.

After Benazir's assassination on 27th December 2007, KSE started its operations after a gap of 3 days. The market showed a high degree of response to this event, and the market moved downward in response to this event. The market took three days to revive from this event (Abrar ul Haq, 2015). Javid and Ahmad (2019) investigated the impact of terrorist attacks and political events on returns and volatility of the Karachi Stock Exchange's oil and gas sector from the period of 2004 to 2014. By employing an event study methodology, they conclude that the oil and gas sector reacts to terrorism and political events.

2.10 CONCLUSION

This chapter outlined the literature on market efficiency, beginning with the evolution of market efficiency and how it emerged in finance academia. The roots of market efficiency can be found in the economics theories. The concept of the EMH asserts that asset returns are unforecastable, and can be traced back to the pioneering theoretical contribution of (Bachelier, 1900) and the empirical work of (Cowles, 1933). Operational, allocative, and informational efficiencies of the financial market were under consideration. Market efficiency is not a new concept in the literature as the term has been used since the late 19th century.

However, the concept became popularized by Fama (1970) in defining the theory of the Efficient Market Hypothesis (EMH), which laid the foundations for the capital markets' informational efficiency. It became a dominant paradigm in financial economics during the mid-1960s since Fama's seminal work (1965; 1970). The idea of EMH suggests that in an efficient market, the arrival of new information is reflected in the price fluctuations. Moreover, the level of market efficiency is described through the pace with which prices reflect new information. Three levels of market efficiency, weak, semi-strong, and strong form of efficiency have been documented in the literature. According to EMH, as the information is fully reflected in stock prices and price fluctuations are random, so one trader can't earn abnormal returns from investments. Weak-form efficiency implies that stock market returns must be independent and unpredictable. It also assumes that in an efficient market, many rational investors rationally value investment opportunities. Due to the timely actions of rational investors, prices of stocks quickly adjust to the new information.

The empirical examination of the EMH is vast, and not surprisingly, there is no agreed consensus on its validity. Early research supported the EMH, although recently, several necessary studies have found predictability in stock returns. Numerous stock market anomalies have been found in the data, not discussed in this thesis. The emerging field of behavioral finance, which brings the most contradictory research findings, makes the validity of EMH uncertain. Behavioral finance integrates psychological factors while describing the behavior of investors in making financial decisions. Behavioral finance attempts to detect the behavioral biases commonly presented in investors' interpretation and decisions against new information's arrival. It focuses on the fact that investors are not always rational, have limits to their self-control, and are influenced by their own biases. It claims that irrational investment activities and arbitrage opportunities are limited in markets because some market anomalies are inconsistent with the efficient market hypothesis.

Over 40 years of research studies have examined the EMH in great detail through various testing procedures. To forecast future trends in the stock prices, different technical and fundamental analysis approaches have been introduced. The statistical procedures which try to verify the implications of EMH are generally based on the test for independence. The traditional test mainly examines the linear independencies within the stock prices. More recently, the new statistical procedures have been developed, which focuses on the nonlinear independencies. However, the tests for independence may fail to pick up some predictability in the market. Predictability refers to anomalies or trading rules that produce abnormal returns. Another problem that is noted in testing procedures of EMH is the selection of time frame. The majority of the studies check the market efficiency for a specified period, while the efficiency of a market may change over time.

The growing strength of anomalies that counter the classic EMH has asked the question, 'is there a more appropriate model to describe stock prices' behavior?' The adaptive market hypothesis (AMH) that initially appears to unify the EMH and stock market anomalies tries to overcome this problem. Although the AMH is in its infancy, it has been supported by some strong evidence in the literature. A further examination of it will deem whether it is an appropriate model in describing stock market return behavior.

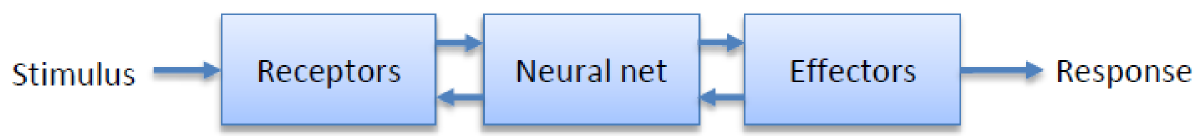
Thus, this thesis aims to investigate the Pakistan stock market efficiency as proposed by AMH. Linked to AMH market efficiency is explained through the cyclical evolution of return predictability. It argues that continually changing market conditions govern key market features such as return predictability. From the literature of different market conditions in the Pakistan stock market, it is concluded that the Pakistan stock market is highly volatile and responds to the news very quickly. This news can have a positive or negative effect on the Pakistan stock market movement. Events that have affected the movement of KSE-100 over different periods are different, like political, economic, non-economic, natural calamities, terrorism, and Pakistan-US relationship.

3 Artificial Neural Network

3.1 ARTIFICIAL NEURAL NETWORK

The possibility of ANNs had been stirred from the organic systems. Organic cerebrums contain immense amounts of cells called neurons, and they fill in as gatherings of thousands, which are known as systems. The accompanying figure shows a common place structure of an organic neuron (Fraser, 1998). People's sensory system can be exemplified as a three-stage model, as showed up in (Haykin, 1999). The central unit of the sensory system is the cerebrum, which is appeared by the neural net. The psyche reliably gets input information from receptors, shapes the information, and afterward chooses. The receptors' receptors adjust the boost into the main electrical thrusts that give the cerebrum information. When the cerebrum has dealt with this improvement, it conveys the effectors that convert these main electrical thrusts made by the brain into structure responses—the bolts showing from left to right exhibit a feed-forward system.

Figure 4. Block diagram representation of the human nervous system

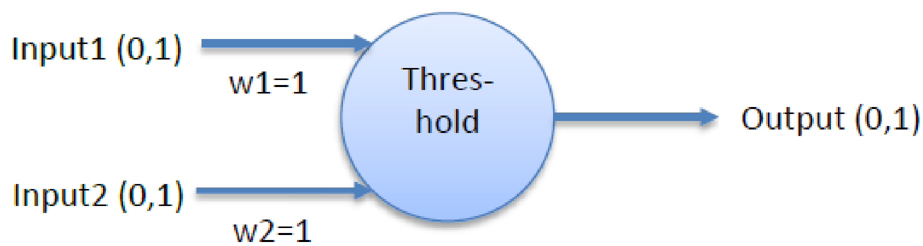


In the organic mind, learning occurs through the changing of the neurotransmitters' reasonability with the objective that the effect that one neuron has on its interconnected neurons changes (Stergiou and Siganos, 2010).

3.1.1 The history of artificial neuron

The historical backdrop of neural systems can be followed back to (McCulloch and Pitts, 1943). They proposed the first ANN and recommended that neurons with binary inputs and binary threshold activation functions were the same as first-order logic sentences.

Figure 5. First artificial neural network Model

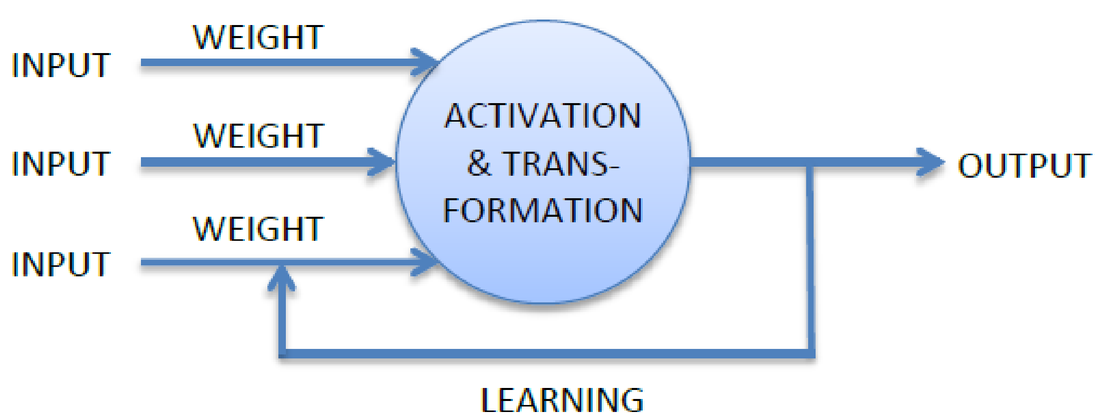


McCulloch and Pitts (1943) noticed that a neuron would not enact if just one of the information sources were dynamic; their neuron has become referred to as a logic circuit. Equivalent weight was given to each input, and the output was binary. As far as the inputs are summarized to a specific threshold level, the output would stay zero. Hebb (1949) proposed the following meaningful step forward in the artificial neuron. Hebb's hypothesis endeavored to clarify the wonder of cooperative learning whereby the terminating of one neuron, for the most part, prompts the terminating of another neuron. Not at all, like the McCulloch-Pitts framework where weights of inputs are generally indistinguishable, has Hebb's rule given a hypothetical premise to modifying weights between neurons. The weight factor can be expanded where two neurons by and large enact at the same time and decrease in different circumstances.

Hebbian theory gave some part of the accompanying genuine advance forward, which was the perceptron model recommended by Rosenblatt (1958). The perceptron proposed by Rosenblatt had a couple of key differences from the McCulloch-Pitts model (1943). For one thing, loads of info was not all fixed at one since they could be unique and reach out between different qualities, and could be damaging. In the subsequent spot, inhibitory data sources never again flat out the intensity of veto over excitatory information sources. Thirdly, the perceptron contains a learning limit reliant on Hebb's Standard.

Since these first models of the counterfeit preparing part were theorized, upgrades in science, details, and PC dealing with control empowered this model to be changed and, for the most part, applied in the resulting work (Mehrotra, Mohan and Ranka, 1997). Figure 6 shows the ANN handling unit's typical structure, as found in most neural frameworks today.

Figure 6. The typical neural processing element



As can be seen, the present neuron model is the same in structure as the early models. The present model of the typical neuron has a few vital distinctive highlights: Some input signals often including a bias input signal; a weight factor that is applied to each input signal; an activation and transformation function; an output signal; and, a learning algorithm.

3.1.2 Types of ANNs and its architecture

The existing literature on the artificial neural network generalized its types based on its approximation and classification ability. Few Classification has been provided in terms of the general characteristics of the artificial neural networks. Feed-forward Networks (FNs), like a multilayer perceptron, can be found in the first group. Its primary component is that their association is forward, so they do not set up any associations between the hubs on a similar layer or past hubs[18].

In the second group, we can find the Recurrent Networks described by their availability dynamism, so these systems store data that will be utilized later[19].

In the third group, we can see Polynomial Networks, which ordinarily offer efficient polynomial input factors. We would apply the sigmoid or Gaussian capacities in the preparation, although it would be thorough[20].

The fourth bunch is the Modular Networks that comprise different modules that permit tackling independently and afterward, consolidating the appropriate responses consistently.

18 The systems that offer this component are:the Radial Basic Function (RBF) (Bildirici*et al*. 2010; Dhamija & Bhalla, 2011; Cheng, 1996); the Cerebellar Model ArticulationController (CMAC)(Chen, 1996); the Group Method of Data Handling Network (GMDHN) (Pham and Lui, 1995); the Probabilistic Neural Network (PNN) (Enke & Thawornwong 2005; Thawornwong & Enke, 2004); the Dynamic Neural Network (DNN) (Guresen, Kayakutlu&Daim, 2010) and the Generalized Regression Neural Network (GRNN) (Enke& Thawornwong,2005;Mostafa,2010).

19 Partially Recurrent Networks (PRN) (Kodogiannis and Lolis, 2002; Rodriguez et al. 2005) and Autoregressive Networks (ARN) (Kodogiannis and Lolis, 2002) Elman Network (Kuanand Liu 1995; Selvaratnam and Kirley 2006; Sitte, 2002; Yumluet al. 2005); the modifications to Elman organize (Kodogiannis and Lolis, 2002; Rodriguez et al. 2005).

20 Pi-sigma networks such as Ridge Polynomial Networks and its dynamic rendition (Ghazali *et al*. 2007, 2009 and 2011), just as the Function Link Network (FLN) (Hussain et al. 2008).

One plausibility is to utilize diverse arrange models (Zhang and Berardi, 2001), and another option is to apply distinctive initialization weights leaving similar system designs (Zhang and Berardi, 2001) and (Adeodatoet al., 2011).

In the fifth group, we can find the Support Vector Machine. This system has a place with the kernel base model, so the nucleus. The thought is to develop a hyperplane as a choice surface which amplifies the edge of detachment (Carpinteiro et al., 2011), (Kara et al., 2011), (Shen et al., 2011). Gómez and Venegas (2013) completed a thorough survey of the particular writing on artificial neural networks and made a comparative investigation of various types of ANNs, as indicated by their performances in anticipating stocks and trade rates. They distinguish that the MLP is one of the most utilized systems in financial time series analysis since it is a feed-forward multilayer model with non-linear hub capacities (Cao and Tayn, 2001), (Kodogiannis and Lolis, 2002) and (Ghazali et al., 2006).

3.1.3 Architecture of ANN

Whatever the researchers follow the type of ANN, it must constitute the essential components of its architecture. The architecture of ANN is based on its number of perceptron and numbers of its layers. Two types of network architecture are available in literature (Russrll and Norving, 2009), Feed-forward (acyclic), and recurrent neural network (cyclic). A feed-forward network works with the input and the weights within an internal state while a recurrent network feeds its outputs back into its inputs (Svozil et al., 1997). The feed-forward neural network was the first and most straightforward type of artificial neural network devised. A feed-forward neural network can be a single-layer perceptron and multilayer perceptron. The single-layer perceptron is the most straightforward feed-forward neural network and does not contain any hidden layer. The inputs are fed directly to the outputs via a series of weights. Due to their simplicity, they cannot solve non-linearly separable problems (Minsky and Papert, 1959). To overcome this problem, multilayer feed-forward neural networks were developed in 1986.

Multilayer perceptron (also called multilayer feed-forward neural networks) is an extension of the perceptron model with the addition of hidden layer(s) that have nonlinear transfer functions in the hidden neurons (Clarence, 1997). A multilayer perceptron has one or more hidden layers, with one input and one output layers. Input layers present input variables, sometimes called the visible layer. It can have different nodes depending on the input data set (Taskaya-Temizel and Casey, 2005). No computation is performed in the Input layer. The data from the input layer is fed into the hidden layer. The Input nodes provide information from the outside world to the network and are referred to as the "Input Layer."

The Output nodes are collectively referred to as the "Output Layer" and are responsible for computations and transferring information from the network to the outside world (Maciel and Ballini, 2008). The Output layer has nodes that take inputs from the Hidden layer and perform similar computations as in the hidden layer node. The values commutated act as outputs of the Multilayer perceptron.

Layers of nodes between the input and output layers are hidden layers. There may be one or more of these layers. The data in hidden layers nodes depend on the outputs from the input layer, and the weights associated with the connections come from the input layers nodes. These outputs are then fed to the nodes in the Output layer. The Hidden nodes have no direct connection with the outside world (hence the name "hidden") Clarence (1997). They perform computations and transfer information from the input nodes to the output nodes. A collection of hidden nodes forms a “Hidden Layer.” While a feed-forward network will only have a single input layer and a single output layer, it can have zero or multiple

The selection of input nodes, hidden layers, and output nodes is essential in selecting the network parameters. Lippmann (1987) and Tang and Fishwick (1993) suggest that there are some guidelines for defining the number of hidden nodes as it can be as ‘2n+1’ (Lippmann, 1987), ‘n’ (Tang and Fishwick, 1993), but the most common way for the number of hidden nodes and (c) number of hidden layers is through the experiment or trial and error (Zhang, 1998).

Some suggested that a single hidden layer is sufficient for an MLP to uniformly approximate any continuous function with support in a unit hypercube (Cybenko, 1988) and (Cybenko, 1989); based on this fact, we use in this study only one hidden layer will be used. The best-hidden node will be selected for hidden nodes through trial and error, with minimum error performance.

The nature of the problem usually determines the size of the output layer. For example, in most forecasting problems, one output node is naturally used for one-step-ahead forecasting. However, one output node can also be employed for multi-step-ahead forecasting, in which case iterative forecasting mode must be used. Forecasts for more than two steps ahead in the time horizon must be based on earlier forecasts. This may not be effective for multi-step forecasting, as pointed out by (Zhang et al., 1998), which is in line with (Chatfield, 2001), who discusses the potential benefits of using different forecasting models for different lead times. Therefore, for multi-step forecasting, one may use multiple output nodes or develop multiple neural networks, each for one particular step forecasting.

3.1.4 Learning algorithms and Activation Function

A significant trait of neural networks is their capacity to learn and simplify. The training procedure of a neural network is accomplished by regulating the weights associated with the neurons' connections. Approximately there are three types of learning used in neural networks: supervised, unsupervised, and reinforcement learning. Reinforcement Learning can be considered an intermediate form of the above two kinds of teaching (Williams, 1992). (Donalek, 2011) and (Sathya and Abraham, 2013) explained the supervised and unsupervised neural networks learning. They suggested that when a neural network is provided with both inputs and the corresponding desired outputs, it is supervised learning. This method allows the network to learn and to infer the relationship between provided input and output.

When a neural network is provided by inputs and the system train itself by looking at the patterns in the provided input is called an unsupervised learning. The parameters are adjusted in response of environmental factors. The adjustment of parameters continued to the point when it reaches to the equilibrium state. For multilayer feed-forward networks most of the time researchers used the Back-propagation learning algorithm (Rumelhart and Williams, 1986).

The Back-propagation learning algorithm works by calculating the error terms. It uses a predefined error function to calculate the difference between the actual and desired outputs. These errors are used to modify the weights of inputs by back propagating the errors through the hidden nodes. To minimize the error and get the maximum accuracy this process of back propagating is repeated. The repeated iteration converge the differences and stops when minimum error solution reaches. However having an appropriate method for neural network training the backpropagation algorithm has its some shortcomings. The slow convergence and easy trapping in local minima make it less important. The shortcomings associated with back=propagation algorithm fetch the new improved learning algorithms including Scaled Conjugate Gradient (Moller, 1993), Levenberg-Marquardt (Hagan and Menhaj, 1994) and Resilient Propagation (Martin and Heinrich, 1993).

The activation functions used in ANNs have been said to play an essential role in the convergence of the learning algorithms. In a network with limited layers, the activation function's choice affects the representation learning and the network performance (Agostinelli et al., 2014). They decide which nodes to fire in a particular layer. The activation function is applied to the sum of the product of weights and inputs in the hidden layer, and then the result is transferred to the output layer. These functions are applied to hidden as well as to the output layers of a neural network.The outcomes for an output layer are obtained by employing linear functions. The non linear activation function at the output layer may cause distortion to the predicted outcomes. The activation function controls the amplitude of the output of the neuron.

There are few activation functions which are used by neural networks. The identity function also named as linear activation function. In this activation function the returns are produces as the input was feeded. The identity function is equivalent to having no activation function.

Neural Networks supports some activation functions: a linear activation function (i.e., Identity function) returns the same number as was fed to it. The identity function is equivalent to having no activation function. A log-sigmoid activation function (sometimes called unipolar sigmoid function) squashes the output to the range between 0 and 1. This function is the most widely used sigmoid function. A hyperbolic tangent activation function (also called bipolar sigmoid function) is similar to a log-sigmoid function, but it generates outputs between -1 and 1.

The asymmetric saturating linear function is a piecewise linear version of the sigmoid function, which provides output between -1 and 1. Moreover, a hard Limit function converts the inputs into a value of 0 if the summed input is less than 0, and converts the inputs into one of the summed input is more significant than or equal to 0. In artificial neural networks (ANNs), the most commonly used activation function is the logistic sigmoid function and the hyperbolic tangent function (Khashei, 2010) and (Gomes et al., 2011). The type of activation function depends on the situation of the neuron (Khashei, 2010).

Some types of activation functions have been proposed. Pao (1989) used various functions, such as polynomial, periodic, sigmoidal, and Gaussian functions. Gomes et al. (2011), while comparing the performance of activation function in forecasting time series, conclude that logistics sigmoid activation showed good performance while using with Levenberg-Marquardt algorithm. Logistic sigmoid activation function reached better results due to the use of this particular algorithm.

3.2 TRADITIONAL TEST VS ARTIFICIAL NEURAL NETWORKS

Estimating the securities exchange is one of the most testing and fascinating jobs for academicians, individual and institutional speculators, and financial experts. In any case, EMH states that ideal capital markets are productive, and stock costs mirror all freely accessible data just as private data, in this way, making consistency of costs unimaginable, if not, tough (Fama, 1970). Despite this ubiquity of EMH, the previous decades are loaded up with rich writing on endeavors to anticipate and beat the market. From the random walk hypothesis and Efficient Market Hypothesis, two unmistakable exchanging theories to deal with forecasting financial markets technical analysis and fundamental analysis have emerged (Falinouss, 2007).

3.2.1 Technical trading rule:

Technical analysis is a crucial way to deal with stock investment where the past prices are contemplated, utilizing diagrams as an essential tool. It depends on mining rules and examples from the past stock prices, called mining of time series. The fundamental standards incorporate ideas, for example, the trending idea of costs, affirmation and disparity, and the impact of exchanged volume. A vast number of stock price prediction strategies have been established but still being developed on the ground of these fundamental standards. The technical analysis depends on numeric time-series information and attempts to predict securities exchange utilizing technical analysis variables. It depends on the broadly acknowledged theory, which says that all market responses to all news are contained in current stock prices. Along these lines, this analysis overlooks news. Its principal concern is to distinguish the current patterns and foresee the future financial stock exchanges from charts. In any case, numeric data or charts data contain just the event and not why it occurred. It is accepted that market timing is necessary, and opportunity can be found through the cautious averaging of historical volume and price fluctuations and looking at them against the current price.

Experts use diagrams and demonstrating strategies to recognize patterns in volume and price. They depend on historical information to anticipate future results. There are many promising forecasting techniques established to anticipate fluctuations in stock markets from numeric time series. AR and MA are the stock patterns forecasting methods that have ruled the time series forecast for various decades. These models can additionally be ordered in two general classifications non-linear and linear. The linear models are straight in the parameters that must be evaluated and depict a factual circumstance clarified by one observed variable by a few different amounts. Furthermore, the dependent indicator can be communicated as the linear function of a particular arrangement of independent factors in addition to an error term.

Linear models depend on how an examination dependent on linear models accepts linear independence, but non-linear models accept non-linear dependency plausibility. The limitation with these linear models, such as the ARIMA, GARCH, and other random walk models, is that it does not capture the prices' non-linear patterns. They only assume that the time series values have a linear correlation structure (Wangand Zhang, 2012). While different econometric techniques are accessible in money-related time series forecasting, investment analysis tools are increasingly utilized by industry specialists, exceptionally fundamental and technical analyses.

3.2.2 Fundamental trading rule

The fundamental analysis explores the variables that influence demand and supply in the market. The objective is to assemble and interpret this data and act before the data is fused in a stock price. The lag time between an occasion and its subsequent market reaction displays an exchanging opportunity. Fundamental investigation depends on the financial information of organizations. It attempts to predict markets utilizing financial information that organizations need to publish consistently, for instance, yearly and quarterly reports, examiner's reports, accounting report, statement of income (Falinouss, 2007).

When applying data mining and machine learning to data, we are progressively keen on doing a technical investigation to check whether our calculation can precisely become familiar with the actual examples in the stock time series. This machine learning can likewise assume a vital role in assessing and forecasting an organization's performance and other similar parameters helpful in fundamental analysis. Indeed, the best-automated stock forecast and suggestion frameworks utilize a type of hybrid examination model, including both fundamental and technical analysis (Falinouss, 2007).

3.2.3 Artificial Neural Network

Fundamental analysis spins around studying a company's value dependent on published bookkeeping data (Bauman, 1996). Technical investigation utilizes historical price fluctuations and scientific formulae to foresee future returns (Cohen et al., 2011). These two analyses experience weak hypothetical structure, absence of experimental investigations, and dependability on expert assessments and information in understanding trends. Current studies centre on conquering the constraint of conventional measurable devices and speculation analysis devices by exploiting the progressions in technology. One of these is the application of ANN in finance.

Moreover, it depends on the human cerebrum's neural structure that re-enacts the fundamental elements of a natural neuron in trend acknowledgment. The merit of Artificial Neural Network is that it has a nonlinear modelling capacity (Kumar and Thenmozhi, 2012). It is also ready to forecast by distinguishing trends in financial time series, even without specialists' help.

Thus, the meaning of a neural system has differed as to the field wherein they are utilized. Because of this reality, we will consider the depiction given by Haykin (1998) that a neural system is an enormously parallel distributed processor that has a characteristic affinity for sorting experiential information and making it accessible to apply, looking like the human mind in two primary regards: A system obtains the information during a learning process. During this process the synaptic weights are used to store the knowledge. To separate a neural system from conventional statistical models utilizing this definition, we may imagine that the classical linear regression model can gain information through the OLS technique and store that information in the regression coefficients. one can contend that classical linear regression is an extraordinary instance of individual neural systems. Nonetheless, linear regression has a rigid model structure and set of forced presumptions before learning from the information. On the other hand, the definition above makes insignificant requests on model structure and presumptions.

However, a neural system can rough a broad scope of measurable methods without requiring that one speculate individual connections between the independent and dependent factors. Instead, the type of connections is resolved during the learning procedure. If a linear relationship between the independent and dependent factors is fit, the neural system's consequences ought to firmly rough those of the linear regression method. If a nonlinear relationship is progressively proper, the neural system will estimate the "right" model structure. As Enke (2005) says, neural systems offer the adaptability of various design types, learning calculations, and approval methods.

There are numerous potential preferences offered by the ANNs, for example, non-linearity, that is, the neural processor is fundamentally nonlinear, ii) input and output mapping, through administered learning, the system learns as indicated by the models, iii) versatility, in other words, the system can adjust their synaptic weights even progressively, iv) reaction capability, with regards to trend characterization the system gives an example choice as well as the unwavering quality of essential leadership, v) adaptation to internal failure because of the vast interconnection, vi) incorporated colossal scale, that is, its parallelism makes it conceivably quicker for specific tasks and accordingly catching problematic practices, vii) consistency in the investigation and patterns, in other words, similar documentation is utilized in all fields drew in with systems, and viii) neurobiology relationship (Haykin, 1994). All in all, the ANNs are information drive, self-versatile, and nonlinear techniques that don't require explicit presumptions about the underlying technique.

3.2.4 ANN and Finance in Pakistan

Financial utilization of artificial neural network models in Pakistan was mostly cantered around time series and bankruptcy forecasting. Zia and Zia (2005) apply NN Models in KSE to anticipate stock prices. They have chosen the Backpropagation Technique and infer that the positive outcomes can be accomplished by modifying weights. Haider and Hanif (2009) estimate inflation in Pakistan by utilizing ANN strategy based on free month to month information and compare forecast execution of the ANN model with that of univariate AR(1) and ARIMA based models. They noticed that results dependent on ANN are more exact than those dependent on AR (1) and ARIMA techniques. Hanif.et al. (2018) found that inflation forecasts from the thick Artificial Neural Network model beat those from Pakistan's various inflation forecasting techniques.

(Inam.et al., 2018) shows that the NN model performs better in the forecast of insolvency while contrasting and investigating the techniques for expectations.

3.3 APPLICATION OF ANN IN EMH AND AMH

From a comprehensive standpoint, there are three distinctive ways in which the new method of artificial neural networks could be employed. The artificial neural network can be used to predict future rules through learning from the current state. The inputs from the current data work as learning data for the network. The current data set works as input which is used to predict future values from it. The recurrent connections are used to learn the relationship between the input and the future prediction values (Soni, 2011).

As the AMH is in its infancy stage, no formal methodology is developed to capture AMH's dynamic view. The time-varying and evolving nature of market efficiency is the most common implication of AMH, widely investigated. To examine the evolving efficiency of different developed and underdeveloped countries, (Lim and Brooks, 2006), (Todea et al., 2009), (Ito and Sugiyama, 2009), (Kim et al., 2011), (Smith, 2011), (Lim et al., 2013) and (Urquhart and Hudson, 2013) used the number of traditional and non-traditional statistical techniques. The dependability of stock returns investigated through non-linear statistical techniques provides firm shreds of evidence for predictability periods and periods of no predictability. Findings from these studies support the oscillating movement of returns as described by AMH.

Sub-period investigation (Hiremath and Kumari, 2014) and rolling window analysis (Urquhart and McGroarty, 2014) are the two approaches that have been widely used by researchers to inspect the degree of market efficiency over time. Sub-period analysis divides the whole data set into different subgroups. Each subgroup is investigated separately by implementing the same set of statistical techniques. These subgroups are fixed and provide the return predictability over that specific time. In rolling window analysis, the groups fixed time rolls forward to include the next time interval only by skipping some data from that sample. The periods of dependency and independence can be better captured using the rolling window framework (Urquhart and McGroarty, 2016).

The traditional and modern time series forecasting models remain essential and helpful for institutional investors, academicians, and financial analysts. These models can further be categorized into two broad categories linear and non-linear. The linear models are the traditional models. These are linear in the parameters that have to be estimated and describe a statistical situation explained by one observed variable by several other quantities. The non-linear models are based on the fact that an analysis based on linear models assumes linear independence; however, there is a possibility of non-linear dependence.

Non-linear models are also known as non-traditional as they move from the linear assumption of the series. After introducing machine learning methods, recent research shifted towards the use of new machine learning technology. By implementing the advance machine learning techniques researchers could overcome the limitations of traditional statistical tools. The Artificial neural network is the one of the machine learning techniques. Due to its data-driven approach, ANN can forecast financial time series by detecting patterns in it, even without having any professional support (Zhong and Enke, 2017). They provide a proven methodology to forecast the data even when the data set is having non-linear properties without any restrictions to it (Bao et al., 2017).

4 Methodology

4.1 INTRODUCTION:

The capital market in Pakistan is dynamic. By looking at the specific features of the market, the stock market's performance could be evaluated. Before going into the detail of the process followed by this research first, some relevant comparison is documented. Working on time series analysis always requires following specific data collection steps, its transformation, and data secreting. After comparing the Pakistan stock market with other markets, this section follows the detail regarding the procedure undertaken to conduct this research work. First, it describes the procedure to collect data, its transformation, and deciding about data frequency to be used in the study. Statistical measures that can provide insight into the data characteristics are mentioned.

To achieve the research study's objective, that is to check the implications of AMH in the Pakistan stock market. The research design is divided into three stages: Designing Optimal ANN model, rolling window analysis, and analysis of return predictability patterns in response to market conditions.

This study uses a new approach of ANN under rolling window analysis to model the nonlinear properties of stock returns and overcome traditional techniques' shortcomings. The designing of ANN architecture or the selection process of parameters for an ANN's optimal model is reported at the first stage. Generally, designing optimal artificial neural network architecture follows five necessary steps: Firstly, data collection occurs. We gather data from secondary sources and transform it into a condition in which it can be used for statistical inferences. The second step is to select the optimal number of hidden layers. The third step is to select the optimal number of hidden nodes. The fourth step is to select the best input variable, and the last is to select the best data split ratio for rolling window analysis. The return generating process is modeled by the optimal architecture of the ANN model under rolling window analysis. The Rolling window analysis approach enables us to investigate the changing market predictability level over an evolving period.

The optimal model generates the error terms, which are correlated with the market fluctuations. Market fluctuations are determined through the news regarding the stock market on the front page of the newspaper. At this stage, data relevant to market dynamics is collected and documented. Through event analysis, the Behavioural of stock market return movement is correlated will the prevailing market conditions. Market response to political, economic, and non-economic factors and its effect on evolving efficiency elaborates the implications of the Adaptive market hypothesis.

4.2 PAKISTAN STOCK EXCHANGE: BACKDROPS

Pakistan stock exchange (PSX), named Karachi stock exchange, was the first security exchange in Pakistan, incorporated on 10 March 1949 in Karachi. After a few decades, three stock exchanges were functional in Pakistan by 1992. Although, initially, in all stock exchanges, old trading methods were used until 2000, when the CTS (Computerized Trading System) was introduced, replacing the "Out Cry Method." The stock exchanges were gradually modernized through computerized trading, and the current instant trading facility through the internet is increasing the stock exchanges' efficiency and effectiveness. Furthermore, on 11 January 2016, the Government of Pakistan had issued an award, ordering the merging of the three stock exchanges into a single security exchange market, recognized as PSX.

The KSE-100 index is the primary index of the PSX. It constituted based on the market capitalization of the 100 significant stocks listed with Pakistan's stock exchange. This value-weighted index first takes the major companies from each sector of the economy, and the remaining companies are taken into consideration with high market capitalization. Different types of securities are traded on the PSX. From the ordinary shares, preferred shares, term certificates, and redeemable securities, most of the trading takes place in common shares.

Basically, through an index, one can capture a group of companies' overall performance movement over a while. Among the Pakistani financial markets, KSE-100 is the best indicator to uncover this central economic zone's market adaptiveness. It represented more than ninety percent business of overall stock markets trading previously. PSX was also listed amongst the ten best stock markets in the whole world in the year 2015. The following graph shows the historical development of KSE-100 from 2000 to 2019-03-05.

Figure 7. Pakistan Stock Market (PSX-100) 18 Years Performance

Source: Trading Economics, 2019

The 20th April 2008 was the best date in the Pakistan stock exchange history when the PSX-100 index peaked up to 15,737.32 points, which was the highest position at which the PSX-100 index reaches for the first time. Pakistan stock exchange was considered one of the best performing stock markets among the other emerging stock markets21. Moreover, the increase of seven percent in 2008 made it the best performer among major emerging markets. The end of this year was not favored able for the Pakistan stock market. A sharp decline was recorded by the PSX-100 index, which was considered as the effect of an unforeseen increased interest rate.

The decline of the KSE-100 index during the last five months of 2008 was the worst ever period. Due to the prevailing crises in the global market the PSX declined by fifty-seven percent. The sharp decline can be seen in 2008, due to the worst-ever crisis during the year

[21]www.gulfnews.com

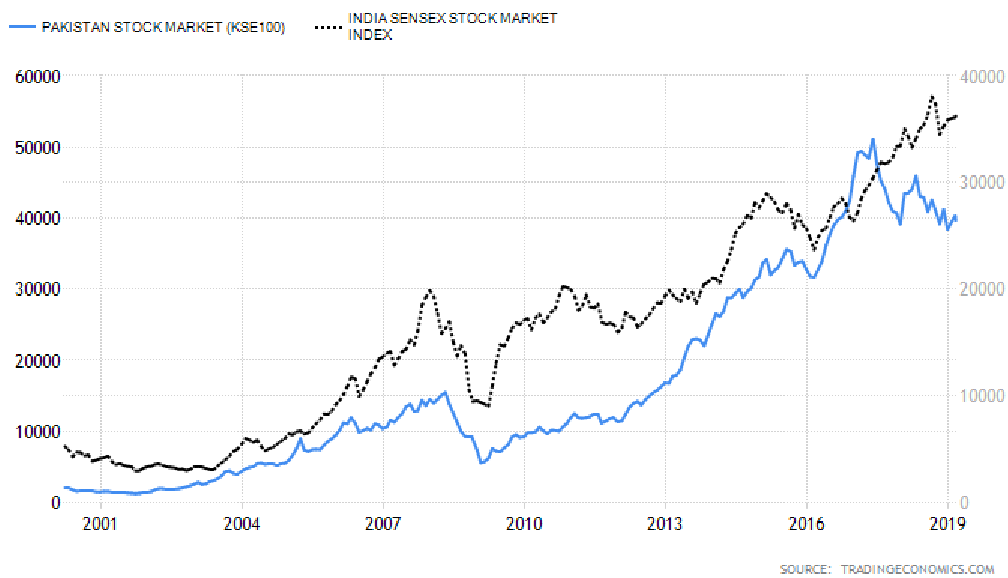
2008 when the benchmark KSE-100 index declined by fifty-seven percent to close at 6,037.38 points on 30 December 2008. As of 07 November 2012, the KSE-100 index reaches to its highest level of 16,218 points. The PSX was considered as the best-emerging market in Asia after recording highest returns up to 40%-50% during year 2011-2012. Pakistan's stock market positioned another highest point in history on 07 November 2012 and again pointed out as the best market in Asia's emerging markets. It produced the 40 to 50 percent higher returns to investors.

The amalgamation of stock markets has positively impacted the market competency, and market proficiency is continuously growing. This continuous development leads towards another milestone by positioning at another highest end in June 2017. However, the end of 2017 was the worst ever since after 2008. Again the political instability caused the stock market crash, and this crash worsens the return posted by PSX, and returns go down by fifteen percent.

The equity market of any nation plays an integral part in any nation's advancement and economic progress. The performance of equity market returns manipulates the decision of investors. The equity market helps in mobilizing and saving the people. It channelizes these saving into industrial fertile and productive perseverance. The equity market is also supportive in inviting and dragging the foreign capital in different shares of well-established companies (Sohail and Hussain, 2009). As compared to the other Asian economies the PSX was showing good performance in year 2016 and considered as the top performing index during that time. It provides a good source of channelling financial resources to investors by integrating higher returns on their investments.

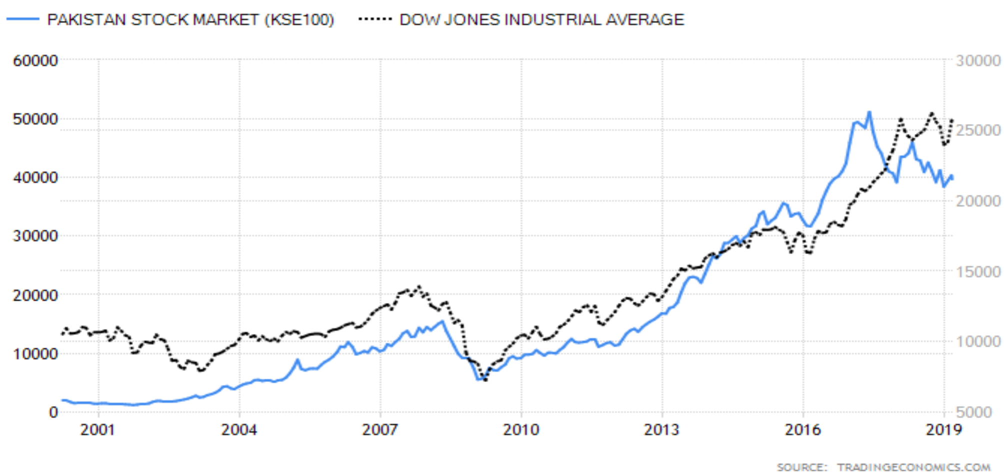
Pakistan stock exchange and Indian stock exchanges are considered as the hottest stock exchanges of Asia. The size of the Pakistan market is indeed very small. The volumes and turnover, too, is no match with Indian stock exchanges. But the performance comparison of Bombay stock exchange (SENSEX) and Pakistan stock exchange (KSE-100) reviles that both the stock exchanges showing similar movements and struggling towards the higher achievements.

Figure 8. Comparison of KSE-100 and SENSEX Performance



Source: Trading Economics, 2019

Figure 9. Comparison of KSE-100 and DJIAV Performance



Source: Trading Economics, 2019

The U.S stock market's overall health can be analyzed by looking at The Dow Jones Industrial Average (DJIA). DJIA is considering as one of the accurate representation of the broader market. It comprises the 30 top leading corporations. Any financial inaccuracies in the financial world the stocks of these companies affected.

In this analysis of the worldwide index, we analyze that during the year 2016, the figure 9 shows that Pakistan Stock Exchange shows a higher index than the U.S stock exchange; PSX shows fluctuations in index rate more than the Dow Jones Industrial average. Pakistan stock exchange shows a more stable position than the U.S index rate.

4.3 DEVISING METHODOLOGY FOR AMH

Before going to the detail of AMH's methodology, we need to understand EMH and behavioral finance methodology. EMH says the markets quickly adjust the new information by incorporating it to the stock prices and not allowing for abnormal profits. Investors and financial analysts cannot earn abnormal returns by looking at historical prices. It indicates that the lag prices are not correlated. If the lag values of the prices are correlated, it suggests that the market is not efficient. IF a market qualifies this implication, then it is suggested that the market weak-form efficient. The three forms of EMH states that initially, a market can be weak-form efficient. When it qualifies the implication of week form efficiency, it can move towards the other forms of market efficiency as semi-strong and strong form efficiency. In the weak-form market efficiency, the stock prices and its lags are not correlated.

In contrast, behavioral finance assumes that, in some circumstances, financial markets are informationally inefficient. Markets that are less than fully efficient open an opportunity for making profits because the inefficiency causes mispricing in stocks. The behavioral finance school suggests that the investors show irrational behavior, and cognitive and psychological variables influence stock investment decision-making. The irrational decision-making patterns caused the stock market not to remain fully efficient and have no specific efficiency pattern.

While the adaptive market hypothesis attempts to reconcile economic theories based on the efficient market hypothesis with behavioral alternatives by applying the principles of evolution to financial interactions, the adaptive market hypothesis explains the efficiency as an evolutionary process which suggests that the arrival of new information, participants brings competition in the market it will lead to inefficiency. However, after adjusting and adapting to the new environment, the market moves towards efficiency. This evolutionary model of individuals adapting to a changing environment caused the market to show cyclical patterns of efficiency and inefficiency.

Cycles of efficiency and inefficiency show that the lag series are sometimes correlated with historical prices. There are some periods in which the lag series does not correlate with historical prices. Periods in which lag prices are not correlated with historical prices will lead to a higher mean square forecasting error and represents market efficiency during that period. Moreover, periods in which lag prices correlate with historical prices will lead to the lower mean square forecasting error and represent market inefficiency during those periods.

When a stock market exhibits some specific inefficiency patterns to efficiency and then efficiency to inefficiency, it can be concluded that the market is behaving according to the adaptive market hypothesis. If a stock market shows an efficient trend throughout time, it behaves according to the efficient market hypothesis. Furthermore, if a market shows a weak trend over the full sample time frame, it can be concluded as market behavior can be better understood under the behavioral finance approach.

The methodology for investigating the adaptive market hypothesis is devised based on patterns of efficiency and inefficiency in the market. The level of efficiency is checked by investigating the forecasting error within the original prices and lag values. For this purpose, this study uses a new ANN technique, which is considered a more appropriate model for forecasting.

4.4 METHODOLOGY

The methodology followed by the research study can be divided into two parts. The first one is the methodology of overall research work, and the second is the methodology for selecting the optimal model of ANN. The overall research methodology constitutes on four stages. First of all, these stages are the data collection and transformation stage. The second stage comprises the steps followed to achieve all the parameters for an optimal ANN model and Identify performance measure error to be used in further analysis. The third stage pursues to uses the selected parameters in a rolling window analysis to run a non-linear autoregressive NN model. In the fourth stage, the generated results from a non-linear autoregressive NN model are used to analyze the prevailing movements in these results according to the market ups and downs. The fifth and last stage is comprised of the robustness analysis.

4.4.1 First stage: collection of Data its transformation and characteristics

4.4.1.1 Collection of Data

The data set comprises the PSX-100 index values from the period of January 2000 - December 2018. There are several important factors behind the selection of this data sample. First of all, this time frame is included in the study to ensure that all the latest information can be incorporated in the study to make it up to date. The data period, i.e., from January 2000 to December 2018, forms the most significant, most reliable, and up-to-date data set of PSX.

The inclusion of data set from January 2000 to December 2018 can help us understand the proposed relationship between the market fluctuations and return predictability patterns. In this time frame number of significant events is considered most important in developing the Pakistan stock market. The reforms of 2002, the stock market crash in the year 2005, the stock market going down, and even out for four months in the year 2008, the policy to emerge the three stock exchanges into one as Pakistan stock exchange are many other political events occurred in this period.

The monthly data of the KSE-100 index is taken to investigate the hypothesis. This study uses monthly data on the KSE-100 index. The data comprises the historical monthly index point of KSE-100. The latest data of the KSE-100 index is in the form of daily observations. From these daily observations, the monthly data values are extracted to make the monthly index values. The data given on the website of PSX is in the form of open price, low price, high price, close price, and volume traded. The opening prices show the price of a stock at the time when trading starts on that day. The minimum price level of the stock on that day is quoted as the stock's minimum price. The closing price denotes the price of the stock at the end of that trading day.

4.4.1.2 Transformations of Data

The second step is the data transformation. For the ANN to be efficient, the collected data must be normalized before using the ANN. That is because mixing data variables of overall values and small values will confuse the network's learning process, resulting in omitting some variables of smaller magnitude, which will affect the training process (Tymvios, 2008). The closing price of the monthly index is transformed into returns to model and prediction purposes. The computation of return for the specific period is based on the continuously compounded annual rate of return (Nissar and Hanif, 2012).

Simply, the value of Index at the current time ‘t’ is divided the value of Index at previous time ‘t-1’ and then log of this value represents the return. It can be written in equation form as follows:

$R_t = \ln(I_t / I_{t-1})$ ……………….. (1)

Where, R_t is used to indicate the return for any time'‘t’, I_t is used to represent Index value at current time‘t’, I_{t-1} is showing the value of the index at the previous time‘t-1’ and the Ln represents the natural log of the values.

Forecasting financial time series is based on univariate and multivariate analyses. This study is based on univariate time series analysis, where forecasting features are limited to one variable. In univariate analysis, the successive return values will be used as output variable or we can say it as the dependent variable. Artificial neural network (ANN) can model both univariate and multivariate financial time series (Cao and Tay, 2001).

The non-linear relationship will be used to forecast the desired future output. The values are being normalized by taking the natural log of the series. A normalization technique scaled the series to fall within a specified range (e.g., between 0 and 1 or -1 and 1) is particularly useful for modelling the ANNs. It minimizes the effect of magnitude among the variables and thus facilitates the ANNs in learning the relevant relationships.

Now for input variables of the ANN model, we create time lags of the series. Lags are very useful in time series analysis because of a phenomenon called autocorrelation, which is a tendency for the values within a time series to be correlated with previous copies of it.

4.4.1.3 Describing Data characteristics

The fundamental descriptive analysis is conducted along with the two nonparametric and two parametric tests to observe the characteristics of data. The descriptive analysis will explain mean, median, skewness, kurtosis, and variances of return, and a histogram of return is constructed. The parametric and nonparametric test is conducted to capture more insights regarding the data set.

4.4.1.3.1 Unit Root (Augmented Dicky Fuller Test)

A unit root is conducted to detect the stationarily in the data. The stationary and nonstationarity of time series can be accomplished through a unit root. For a time series to be non-stationary, it must have unit root in the series. If there is no unit root in the series, the data must be stationary. A stationary series is not behaving a random process.

4.4.1.3.2 Kolmogorov Smirnov goodness of fit test (k-s Test)

A nonparametric test that is Kolmogorov Smirnov goodness of fit test (k-s Test) is performed to identify whether the series is having a normal distribution or not. To check the distribution for being a uniform or normal distribution, the K-S test compares the cumulative distribution of data with normal or uniform distribution. If the z score value is having the probability of .000 it means that distribution is not fitted with any of the distribution.

4.4.1.3.3 Run Test

Another nonparametric test called run test is performed to check the data sequence. It counts the occurrence of the + values and – values. The run test is also called as Geary test is a nonparametric statistical test that checks the randomness hypothesis for a two-valued data sequence, more precisely it can be used to test that elements of the sequence are mutually independent. The run test counts the number of runs of values greater than the median and the values less than median and omits the values equal to the median. Through this process, it calculates the number of runs in the data set. It also gives the z statistics against the probabilities to which extent the runs are lying within the range of acceptance region. If z value falls within the $\pm$ 1.96than we will accept the null hypothesis.

4.4.1.3.4 Parametric test- Serial correlation: Auto Correlation test

A parametric test named as autocorrelation is reported to verify the correlation within the return values. It suggests that the return on stock at present is correlated with the returns of a previous time. Most of the technical analysts use autocorrelation techniques to predict future stock prices through past prices. If the correlation is positive it indicates a positive relationship between two variables. If the correlation is negative it indicates the negative relation between the prices. The value of correlation with zero indicates no relationship.

4.4.2 Second stage: Identifying Optimal Artificial Neural network Architecture

Artificial Neural Networks (ANNs) construct an expert system with a strong ability to model and solve real-time issues through pattern recognition. IN the financial time series, these new techniques are taking importance. These models can forecast the linear and nonlinear characteristics of any time series better to understand the outcomes of (Yegnanarayana, 2005).

However, these methods required little work while creating an optimal model. Boyd (1996) elaborated on the optimal neural network model process as first selecting neural network paradigms as some hidden layers, number of hidden neurons, number of output neurons, and selection of transfer functions. An important decision is taken for the split data ratio for training, testing, and validation sets. In the end, performance measures are selected for measuring accuracy.

This stage identifies the optimal ANN model's best parameters; the number of steps is involved. The Neural network paradigm is determined; the number of hidden nodes and layers is selected; the data split ratio for training, testing, and validation purposes are selected. The number of lag values is also determined at this stage, as this study follows a univariate time series analysis, so the selection of the best lag is essential. The lag series will be used as an independent variable, so its importance could not be ignored. The parameter selection is based on performance measure errors. All the parameters which help minimize the error term are considered for the optimal model.

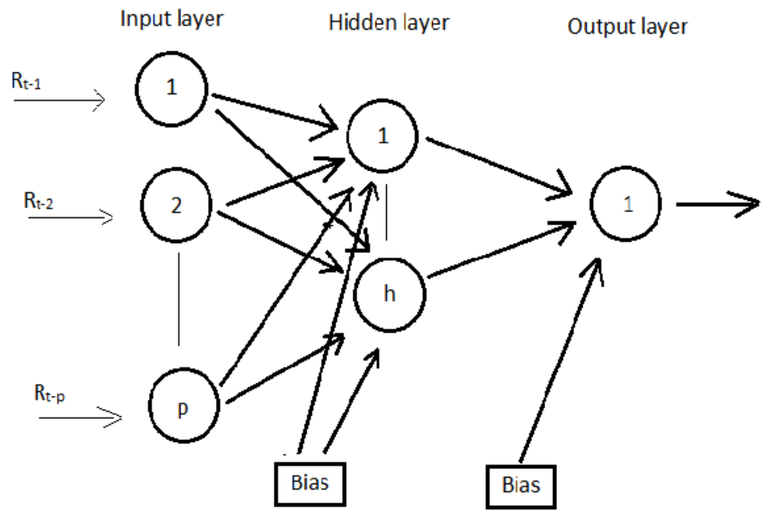
4.4.2.1 Neural network paradigms

This step involves the selection of parameters involved in making multi-layer artificial neural network architecture. A multi-layer perception is a feed-forward artificial neural network with one or more layers of nodes between the input and output nodes (Khotanzad and Lu, 1990), (Zhang, 2003) and (Adebiyi et al., 2014).

Ramos and Martínez (2015) have reviewed thirty applications in the literature and found that more than 40% of the analyzed researches support the idea that the multilayer perceptron is the best network, or at least it has the same performance as the proposal networks. The output nodes produce the forecast value while the input nodes receive the incoming signal from the out world. The network must have one or more hidden layers, with appropriate nonlinear activation functions that help to increase the ability to learn (Oztemel, 2006).

Figure 10 depicts a typical MLP with p input, h hidden, and one output node. The feed-forward FANN model has the excellent capability of approximating any nonlinear function to any desired degree of accuracy, provided no restriction is put on the network structure (Zhang, 2003) and (Kriese, 2005) summarize the types of layers in an MLP as the input layer, hidden layers, and output layer.

Figure 10. Structure of a p × h × 1 MLP network



Source: Adhikari and Agrawal (2014)

The Feed-forward artificial neural network for time series forecasting is a nonlinear autoregressive (AR) model. In the FANN formulation, the input nodes are the successive observations of the time series, return at time t is explained by the return on the previous day. Equation 2 explains the relationship among the output and the inputs using linear and nonlinear activation functions, of a multilayer feed-forward neural network.

$$R_t = G\left(\alpha_0 + \sum_{j=1}^{h}(\alpha_j)\ F\left(\beta_{0j} + \sum_{i=1}^{p}\beta_{ij}\, R_{t-i}\right)\right) + \varepsilon_t \text{ .... (2)}$$

where j (j = 0; 1; 2;:::;h) and ij (i = 0; 1; 2;:::;p; j = 1; 2;:::;h) are the model parameters often called the connection weights; p is the number of input nodes and h is the number of hidden nodes' F and G are hidden and output layer activation functions, respectively. For hidden and out-put layers the sigmoid and linear functions are given in Eqs. 3 and 4, respectively (Zhang, 2003) and (Khashei and Bijari, 2011).

$$F(x) = \frac{1}{1+e^{-x}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(3)}$$

$$G(x) = x \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(4)}$$

Through activation functions, ANN can learn, train, and transfer data. Adebiyi et al. (2014) use a feed-forward back propagation algorithm for inputting the training and target data. They use different activation functions as for Training the network; the training function Gradient descent with momentum back propagation was used for selecting the adaptation learning function, Gradient descent with momentum weight and bias learning function, selecting the performance function (MSE), and selecting the transfer function Hyperbolic tangent sigmoid transfer function. The logistic function and hyperbolic functions have been widely used in the literature. The Khashei (2010) suggested widely used logistic and hyperbolic activation functions for the input layer as the ANN is the nonlinear mapping for the future values based on past observations. The type of activation function depends on the situation of the neuron (Khashei, 2010).

This study employed a nonlinear autoregressive feed-forward artificial neural network having multi-layer perception as (Zhang, 2003) and (Adebiyi et al., 2014) with little modifications. This study will apply the nonlinear autoregressive neural networks model or Multilayer perceptron model to predict a time series from past values. Using the Matlab software, Matlab R2018a, model Levenberg-Marquardt algorithm is used for training the network. The output is determined through a nonlinear activation function. The activation function is usually a logistic function that transforms the output to a number between 0 and1.

4.4.2.2 Selection of hidden nodes and Layers

In financial time series forecasting the minimum number of the hidden layers is recommended for optimal working, because by increasing the hidden layers it increases its complexity. To model the time series forecasting the most of the researchers employed only a single hidden layer neural network (Zangh, 2003). By following the research design of (Zhang, 2003) this research study limited the hidden layer to one, to minimize the complexities in the model.

The decision regarding to the neural network architecture and its hidden layer in it is an important task. Although the hidden layers do not directly influence the given data set but the resulted outcome are highly dependent on the correct incorporation of hidden layers. There are different methodologies which have been used by researchers to decide about the size of hidden layer. Not anyone of these methods considers valid all the time to determine the optimal number of hidden neurons (Karsoliya, 2012). These methods can be classified as follows.

4.4.2.2.1 Try and Error Method Sheela and Deepa (2013)

Try and error method characterized by repeated varied attempts which are continued until reaches to optimal point success or until the agent stops trying. The maximum developer uses a "structured trial and error" method for creating a neural network's layer approximation (Zhang, 2003) and (Karsoliya, 2012). This method divides into two approaches.

Forward Approach: This approach begins by selecting a small number of hidden neurons. We usually begin with two hidden neurons. After that, train and test the neural network. Then they increased the number of hidden neurons. Repeat the above procedure until training and testing improved.

Backward Approach: This approach is the opposite of the Forward approach. In this approach, we start with a large number of hidden neurons. Then train and test the NN. After that, gradually decrease the number of hidden neurons and again train and test the NN. Repeat the above process until training and testing improved.

4.4.2.2.2 Rule of thumb method Karsoliya (2012)

The rule of thumb method is for determining the number of neurons to use in the hidden layers, as follows: The number of hidden neurons should be in the range between the size of the input layer and the size of the output layer. The number of hidden neurons should be 2/3 of the input layer size plus the output layer's size. The number of hidden neurons should be less than twice the input layer size.

4.4.2.2.3 Simple Method Karsoliya (2012)

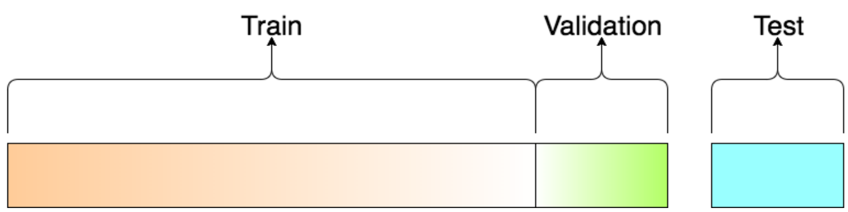
It is a simple method to find out neural network hidden nodes. Assume a backpropagation NN configuration is l-m-n. Here l is input nodes, m is hidden nodes, and n is output nodes. If we have two inputs and two outputs in our problem, we can take the same number of hidden nodes (Karsoliya, 2012). So our configuration becomes 2-2-2 where 2 is input nodes, 2 is hidden nodes, 2 is output nodes.

In this research study the one hidden layers is used (Zhang, 2003). The number of hidden nodes is selected through trial and error step by running nonlinear autoregressive NN on the data set (Karsoliya, 2012). The nodes at which the model will show the best-fitted performance will be selected as the best nodes. Under the trial and error from 50 nodes the best performing node is selected for optimal ANN model (Panchal and Panchal, 2014). The *nodes at which performance measure error is minimum is selected as the best optimal nodes (Paola and Schowengerdt, 1997), (Zhang, 2003) and (Bandyopadhyay and Chattopadhyay, 2007).*

4.4.2.3 Selection of best combination of data split ratio

For an optimal ANN model, one has to decide the best combination of the data split ratio. The ANN divides the data into three distinctive sets. Training, testing, and validation sets are the three sets used by ANN to process the data. Training sets use the same percentage of data for training purposes; the testing data set uses the data for testing purposes based on the previous data set training. This training and testing were then validated by using the validation set of data.

Figure 11. Data set Division



Source: Shah, T. (2017)

These data sets are used in different ratios. For dividing the data into its training testing and validation subset there is no specific rule. Palit and Popovic (2006) provide different options for data split ratios. He suggests the choice from ninety percent to ten percent ratio, fifty percent to fifty percent ratio. The training data set is used to give higher percent of data set and the testing data set is allotted with lower data set ratio (Tsai, 2008). In a number of research studies while using artificial neural network different combinations have been incorporated for testing data set for example ten percent, fifteen percent , twenty percent and thirty percent (Alpaslan et al., 2012) and (Kitapcı et al., 2014)

The Literature support that the use of minor ratio of data set for testing will provide (Alpaslan, 2012). On the basis of literature review the strategy for the selection of data split ratio can be drawn as whatsoever ratio is selected the training set should be large which envelop all the central features of the data. For a better forecast the training data set should be able to explain all the relevant features of the dat. The data set which is left will be used for testing and validation purposes. The data set should be divided in such a way that every subset could have enough data for testing and validation purposes.

Just like other machine learning techniques in ANN the learning of neural network model is very important. The learning will be done through training data set. The remaining data set should have sufficient data which could be further divided into testing and validation purposes. It the training of the data get appropriate the model will learn more abot the data se, having an appropriate learning will leads to accurate forecasting. The data split ratio followed under this work is presented in Table 1.

Table 1. ***Data split ratio***

Comb	Layers	Nodes	Training set	Testing set	Validation set
1	1	1, 2, 3,4,…., 50	60%	20%	20%
2	1	1, 2, 3,4,…., 50	65%	15%	20%
3	1	1, 2, 3,4,…., 50	65%	20%	15%
4	1	1, 2, 3,4,…., 50	70%	15%	15%

5	1	1, 2, 3,4,…., 50	70%	20%	10%
6	1	1, 2, 3,4,…., 50	70%	10%	20%
7	1	1, 2,3,4,…., 50	75%	10%	15%
8	1	1, 2,3,4,…., 50	75%	15%	10%
9	1	1, 2,3,4,…., 50	75%	20%	05%
10	1	1, 2,3,4,…., 50	75%	05%	20%
11	1	1, 2, 3,4,…., 50	80%	10%	10%
12	1	1, 2, 3,4,…., 50	80%	05%	15%
13	1	1, 2, 3,4,…., 50	80%	15%	05%
14	1	1, 2, 3,4,…., 50	85%	05%	10%
15	1	1, 2, 3,4,…., 50	85%	10%	05%
16	1	1, 2, 3,4,…., 50	90%	05%	05%

From the above possible combination of data split ratio, the best combination of data split ratio is selected after trial. The best combination is selected based on the minimum performance measure reported by the generated results.

4.4.2.4 Evaluation criteria

The prediction performance accuracy of the neural network model is evaluated by introducing different statistical performance evaluation measures. These statistics measure how much error there is between two data sets. In other words, it compares a predicted value and an observed or known value. The simplest and most commonly used error function in neural networks used for regression is the mean square error (MSE) Niels (2014). The MSE criterion measures the average of the squared error terms. Typically, the better regression is that which has a lower MSE. The square root of the MSE criterion gives rise to the Root MSE (RMSE) criterion.

As forecasting accuracy evaluation criteria, the mean square error (MSE), mean absolute error (MAE), and root means square error (RMSE) have been used. The optimal ANN should have the highest correlation coefficient (R) and the lowest root means square error (RMSE) for every combination of input variables Shamisi, et al., (2013). RMSE is a measure of the variation of predicted values around the measured data. The lower the RMSE, the more accurate is the prediction. RMSE is calculated using equation (7). The R-value provides information about the relationship between the predicted output and target data. If R = 1, this shows that there is an exact linear relationship between outputs and targets. If R is close to zero, then this means that there is no linear relationship between outputs and targets.

Three statistical performance evaluation measures mean absolute error (MAE), mean squared error (MSE) and root mean square error (RMSE) is being used by this study Shamisi, *et al.*, (2013). These performance error statistics can be defined as follows:

$$MAE = \frac{1}{\mathrm{N}}\sum_{\mathrm{t}=1}^{\mathrm{N}} |\mathrm{R_t} - \hat{R}_{\mathrm{t}}| \text{ .... } (5)$$

$$MSE = \frac{1}{N}\sum_{\mathrm{t}=1}^{\mathrm{N}} \left(\mathrm{R_t} - \hat{R}_{\mathrm{t}}\right)^2 \text{ .... } (6)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{\mathrm{t}=1}^{\mathrm{N}} \left(\mathrm{R_t} - \hat{R}_{\mathrm{t}}\right)^2} \text{ .... } (7)$$

Where $\mathrm{R_t}$ and $\widehat{\mathrm{R}}_{\mathrm{t}}$are, respectively, the actual returns and forecasted returns, and N is the size of the testing dataset. Forecasting errors need to be less for forecasting accuracies for financial time series. The point at which the minimum MSE, RMSE or MAE is reported will be selected as the best lag point.

4.4.2.5 Neural network training

In this study feed-forward, neural networks are trained using the Levenberg-Marquardt learning algorithm as used by Shayea (2017). Matlab software is used for training the network. Matlab uses trails function to updates weight and bias values according to Levenberg-Marquardt optimization. This function uses 100 maximum numbers of epochs to train the network. The output is determined through a non-linear activation function. The activation function is usually a logistic function that transforms the output to a number that is between 0 and1.

4.4.2.6 Implementation

A nonlinear autoregressive neural network is implemented under the above-selected parameters. This experiment helps us to select an optimal model for further analyses.

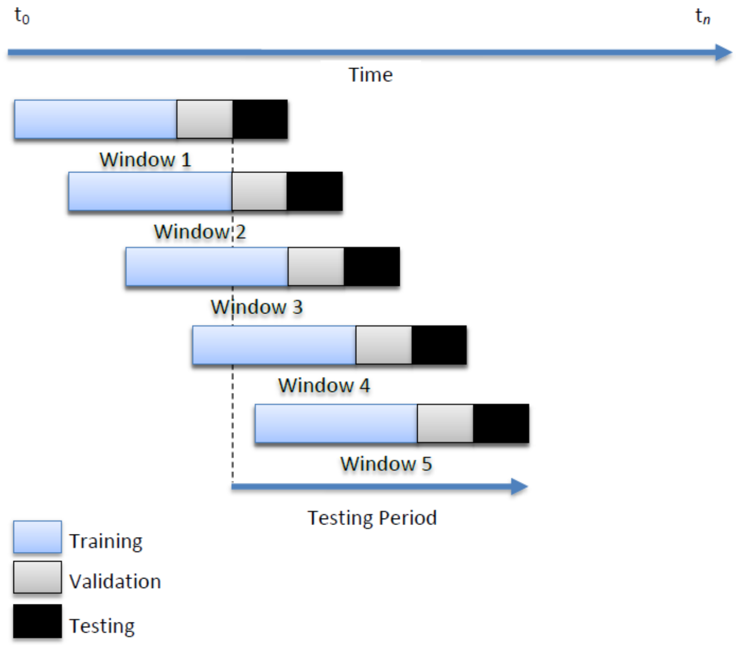
4.4.3 Third stage: Using Optimal Architecture under rolling window analysis

After construction of the best combination of hidden layers (x), nodes (y) and lags (z) the point which reports minimum errors the next step is to constitute a rolling window. Rolling window will be using the estimation window of 36 months with one-month rolling. The equation for feed-forward artificial neural network for a rolling window is:

$$R_t = G\left(\alpha_0 + (\alpha_{j(m)})\ \mathrm{F}\left(\beta_{0j(m)} + \beta_{1j(m)}\mathrm{R}_{t-N}\right)\right) \ldots\ldots\ldots\ldots\ldots\ldots \text{(8)}$$

Proper selection of the optimal training data window is important because, “If the minimum training window is too long the model will be slow to respond to state changes., If the training window is too short, the model may overreact to noise” (Arlot and Celisse, 2010).

Figure 12. Schematic diagram of rolling window analysis



To determine the optimal length of the training window, training periods of 36 months will be created and tested. The use of the moving window analysis is based on the fact that financial time series are volatile and contain certain trends. The use of the moving window approach will enable us to capture certain trends over moving periods.

The movement of the error term in response to market conditions is analyzed according to the following rule. If the error term is high in some market the prediction level is low and the market is little efficient in that position as compare to the points where the error term is low. These levels of predictability are due to the prevailing market condition. So different scenarios are given in the table which will help to explain the KSE-100 movement towards efficiency or inefficiency or it is providing a better explanation of the adaptive market hypothesis by showing cyclical efficiency.

4.4.4 Fourth stage: Incorporating news where major fluctuations of MSE are reported

After detecting the specific movement of the market return over the moving period the next step is to analyze these movements in light of major events. The evaluation of the specific historical events, such as different financial and political crises, having an impact on stock return will increase the understanding of the underlying principles of the AMH. The defined patterns of the stock market when correlates to the major events will explain the underlying market condition. And the market conditions which are governed by the period of predictability and no predictability could be analyzed.

4.4.4.1 News selection criteria

Major events which this study is going to incorporate to relate with the movement of stock returns are based on the facts of reported news on the front page of the newspapers. The newspaper DAWN is selected for scrutinizing news relevant to stock market of Pakistan. The DAW newspaper is selected because the back dated newspapers source of DAWN are available in national library. The old news papers from 2003 to 2018 are inspected to dig out the relevant news. The news appears on the front pages of the newspaper are market as relevant. The total 83 news were turn out as to show major events regarding Pakistan stock market. The list of news is reported in table.

Table 2. ***List of news incorporated in this study***

S.No.	Major news about stock market	News Date
1	2002 ends with all-time high index, volume	06-Jan-03
2	Index moves further higher across a broad front	03-Jul-03
3	KSE 100-share index crashes by 95.77 points	29-Oct-03

4	Stocks gain 195 points	02-Dec-03
5	Index recomposition to be reviewed next month: Stock market	25-Feb-04
6	KSE 100-share index recovers 30.26 points	25-Feb-04
7	KSE 100-share index posts fresh rise of 30.85 points	28-Feb-04
8	Contain the bears in the stock market	08-Mar-04
9	Quetta incident makes no ripples in KSE	08-Mar-04
10	KSE 100-share index recovers 14.23 points	01-Jul-04
11	KSE 100-share index recovers another 18.67 points	08-Jul-04
13	KSE index loses 83 points	03-Aug-04
14	KSE 100 index reshaped	15-Sep-04
15	KSE-100 index rose by 55pc in 2003-04	28-Oct-04
16	OGDC determines KSE index rise or fall	13-Mar-05
17	SECP amends Companies Ordinance	16-Mar-05
18	Re-composition of KSE 100 index	16-Mar-05
19	Stocks cross 10,000 barrier	16-Mar-05
20	Stock market faces double trouble: PTCL, CVT issues	05-Jun-05
21	KSE 100-share index up by 47.2pc in nine months	05-Jun-05
22	KSE ended 2005 with 54pc rise in index	01-Jan-06
23	KSE reforms to benefit stakeholders	01-Jan-06
24	KSE crosses 10,000 mark	17-Jan-06
25	Stocks add 18 points as default fears allayed	02-Mar-06
26	KSE acts to stem market decline, biggest single day fall	15-Jun-06
27	KSE Index gets masive battering	27-Jun-06
28	SECP defers in house bada ban	21-Sep-06

29	US experts clear KSE brokers	22-Nov-06
30	KSE crash: follow up investigation	27-Nov-06
31	KSE index all time high	25-May-07
32	steel mil sale, stock market crash, reference filed against shaukat aziz	22-Jun-07
33	Bull run takes KSE to new high	25-Dec-07
34	KSE index keeps surging in post-election euphoria	22-Feb-08
35	KSE stays above 15,000	27-Feb-08
36	stocks on a high after new rule drowns small fry	25-Jun-08
37	Putting floor under the fall	28-Aug-08
38	global shares dive as fear grips investors	17-Sep-08
39	trading halted as global markets nosedive	07-Oct-08
40	SECP, KSE keep market open	13-Oct-08
41	Rs50 billion lifeline for stock market	23-Oct-08
42	stocks short selling against islam: FSC	25-Oct-08
43	stock market in state of chaos	26-Oct-08
44	Stock exchanges to remove floor on 15th	12-Dec-08
45	Investors buoyed by stocks rebound	03-Jan-09
46	KSE under pressure as foreigners dash for the door	24-Jan-09
47	SECP rule relaxation likely to boost stocks	14-Feb-09
48	Bull run at KSE amid agitation on streets	12-Mar-09
49	Bull-run at KSE despite agitation on streets	13-Mar-09
50	Buoyant KSE absorbs record foreign selling	17-Mar-09
51	KSE shrugs off lahore attack, goes up by 3pc	31-Mar-09
52	Stockout churn on;Us order probe	08-May-10

53	KSE 100-index settles above 10,000-level	15-Sep-10
54	2.5 trn wiped off global stocks in a week	06-Aug-11
55	KSE joins world turmoil	10-Aug-11
56	KSE 100-share index loses 133 points	23-Nov-11
57	Stocks record modest gains	17-Jun-12
58	KSE to introduce free-float based 100-index	17-Jun-12
59	Stocks shed 20 points on economic uncertainty	11-Dec-12
60	Three companies listed on KSE in 2012	11-Dec-12
61	KSE welcomes 2013 with new peak	01-Jan-13
62	KSE-100 all time high	11-May-13
63	Stocks hit all-time high	18-Jul-14
64	KSE index worst ever one day fal	12-Aug-14
65	KSE blood bath after global wquity meltdown	25-Aug-15
66	Stocks close at record high	11-May-16
67	Stocks soar after bourse upgraded	16-Jun-16
68	Shrugging off war clouds, stocks soar to 41,000 points	04-Oct-16
69	PSX to sell 40pc stake next week	10-Dec-16
70	PSX sells 40pc stake to Chinese consortium	23-Dec-16
71	stock hit record high	25-Jan-17
72	PSX rewrites history	27-Jan-17
73	PSX hits record high of 50,936 points	09-May-17
74	stocks see steepest ever tumble	02-Jun-17
75	stocks see biggest one day fall	13-Jun-17
76	KSE 100-Share Index Fluctuations	18-Sep-17

77	Pakistan Stock Exchange down but not out	18-Sep-17
78	PSX opens 2018 higher as KSE-100 Index gains 240 points	01-Jan-18
79	Global markets take heart as wall street bounces back	07-Feb-18
80	Stocks close weekend session with minor gains	07-Jul-18
81	Stock tumble 880 points	13-Oct-18
82	Financial markets buoyed by Riyadh's rescue deal	25-Oct-18
83	Stocks tumble over chiness response	6-Nov-18
84	Rupee sees plunge as volality sweeps financial markets	01-Dec-18
85	Stocks tumble on policy rate hike	4-Dec-18

By critically analyzing the major events in the Pakistan political, economic and non economic sector we can conclude that the periods in which there is any type of uncertainty the market working drops down. From the graph showing in figure and the event occurring in different time elaborate that uncertainty leads towards the possibility of gaining abnormal returns.

4.4.5 Fifth stage: Analysis of performance measure error movement with response to market predictability

The movement of performance measure error in response to market conditions also giving an idea of stock return predictability in some cases and vice versa. If the mean square error are high in some market the prediction level is low and market is little efficient in that position as compare to the points where the mean square errors are low. These levels of predictability are due to the prevailing market condition. So different scenarios are given in the table which will help to explain the PSX-100 movement towards efficiency or inefficiency or it is providing a better explanation of adaptive market hypothesis by showing cyclical efficiency.

Table 3. ***Movement of Mean square error and levels of predictability***

Measuring error fluctuation	State of market performance
Large Measuring Error represents	Low predictability --- efficiency
Small Measuring error	High predictability--- inefficiency
Moving from Large measuring error to small measuring error	Low predictability to high predictability---- inefficiency
Moving from small measuring error to large measuring error	High predictability to low predictability--- adaptiveness
Moving from large measuring errors to small measuring error and then to large measuring errors	Cyclical pattern showing adaptiveness
Moving from small measuring error to large measuring error and then again to small measuring errors	Cyclical pattern but inefficiency

Figure 13. Movement of error term and levels of predictability

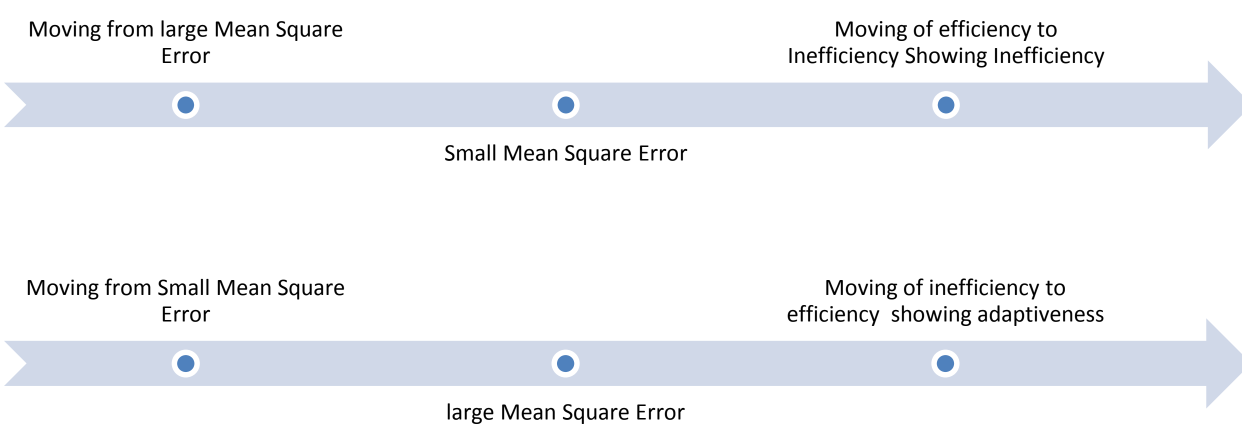


Table 3 explains the designed rule for deciding the market behavior using the ANN model's forecasting error results. When forecasting measuring error showing large measuring fluctuations, the decision would be that the market has low predictability, and the market is in showing a state of efficiency. According to the designed decision rule, the small forecasting measuring error states high predictability in the market, and the market is passing through an inefficient state. The movement of forecasting error from a large measuring error to a small measuring error will state that market is shifting from low levels of predictability to high predictability level, which can be concluded as an inefficient state of the market.

The movement of market prices from small forecasting error to large forecasting error will show the market's movement from high predictability to low predictability. Such movement of the market from inefficiency to efficiency can be concluded as the market shows adaptive behavior. If the forecasting error movement is tracked as it moves from large measuring errors to small measuring errors and then again to large measuring errors, such tracking will show cyclical patterns of efficiency and inefficiency. Tracking such patterns of inefficiency and efficiency in a market will firmly accept the adaptive market hypothesis proposition.

The last possible pattern of forecasting measuring error, which could be reported by the forecasting model, is that if the forecasting errors are moving from small measuring error to large measuring error and then again to small measuring errors, it will conclude that market is behaving inefficiently.

5 Results and Discussion

5.1 INTRODUCTION

This chapter contributes towards the documentation of results from empirical testing and detailed discussion on the documented results. The detailed view of all the resulted outcomes is discussed following the study's aim in light of literature support.

In a time series analysis, the allocation of data plays an important role. A time series may portray different characteristics over time that could be helpful in forecasting and measuring volatility. The descriptive statistics are conducted to look at the characteristics of the data. All the results given in tables and figures are explained through their relevant interpretation. To check the serial correlation and stationarily of the data unit root test is conducted. The normality of distribution or the goodness of fit is determined by implementing Kolmogrove Smirnov a non-parametric test. A discussion on the data series's characterization, which comprises the monthly data of KSE-100, follows the data transformation process.

After looking at the data set, the next portion of the chapter presents the detail working on the parameter selection results and their relevance to ANN's new application. The undefined neural network model is moving towards defined and optimal neural network to generate error terms. The results for determining the best ANN model to test if the return generation's movement is cyclical or not are presented. The optimal ANN model, which is a nonlinear autoregressive neural network, presents the values of error preferences. The optimal model performance is evaluated based on three performance measure error conferred in the methodology. The lower value of these errors is considered best. These values of error preferences show the predictability level of the ANN model. The periods at which these error preference measures are low, the model is the best predictable model. Moreover, the data points at which these error preference measures are high, the model does not show the best predictability.

Further, the Rolling window analysis gives a detailed insight to interpret index movement hence the market level of predictability or unpredictability. A rolling window analysis must distribute the data set in an appropriate data split ratio. Training data must be of suitable size so that it can deal with noise and non-stationarity in data. In the case of smaller training data, the ANN estimation is not of fair value. Results from rolling window analysis are documented to detect that if there any possible seasonal patterns or not. The detection of error terms movement upward or downwards suggests a low level of predictability or high predictability, respectively.

The neural network model is used to detect the predictability movement. These movements are then compared with the changing environment in the stock market and political and economic situation. By digging out the historical newspapers, the total number of news is eighty-three selected. When correlated with the order of performance measure error, this selected news handover the remarkable interpretation. The data points showing low error terms responding to the good times, and most of the good news is surrounding the market. Whenever there is positive news regarding stock market reforms or policies, the error term reports a downward movement.

5.2 FIRST STAGE: COLLECTION OF DATA ITS TRANSFORMATION AND CHARACTERISTICS)

The pattern of return on the KSE-100 can be seen in figure 14. By plotting the KSE-100 return series, it can be visualized that in the year 2000 to 2009, the Pakistan stock exchange was more volatile than post-2009 time in both daily returns and at monthly return series. Ahmed and Farooq (2008) ascertain the 9/11 terrorist attacks' significant reaction to the Karachi Stock Exchange's volatility. After 2009 onward till 2018, the daily return series of KSE-100 shows smaller deviations, signifying more market stability. The figure also shows that in the year 2009, the market records the lowest return. There are different reasons behind the improved volatility in PSX after 2009 Ghufran et al., (2016). This study shows that investors consider the political situation the most critical factor causing turbulence in the stock market. During 2009 the political situation was not stable, and it was just a time that the stock market comes out from a massive financial crisis of 2008. At that time, the government has taken various initiatives to minimize the riskiness of stocks.

State Bank of Pakistan (SBP) announced a reduction in the discount rate by 100 bps on April 20, 2009, bringing it down to 14 percent[22].

Declining interest rates provided the significant boost to Pakistani equities, resolution of capital gains tax-related issues, improved foreign portfolio inflows, rising consumerism, and healthy corporate earnings[23].

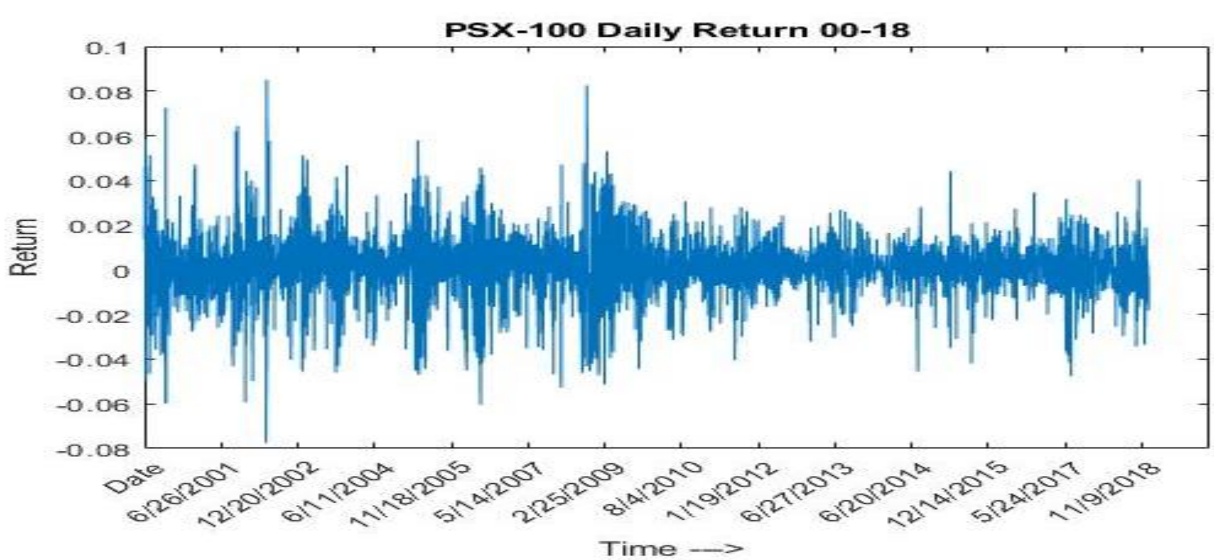
The advent of China Pakistan Economic Corridor (CPEC) is an ambitious project that focuses on improving connectivity and cooperation among both the neighboring giants.

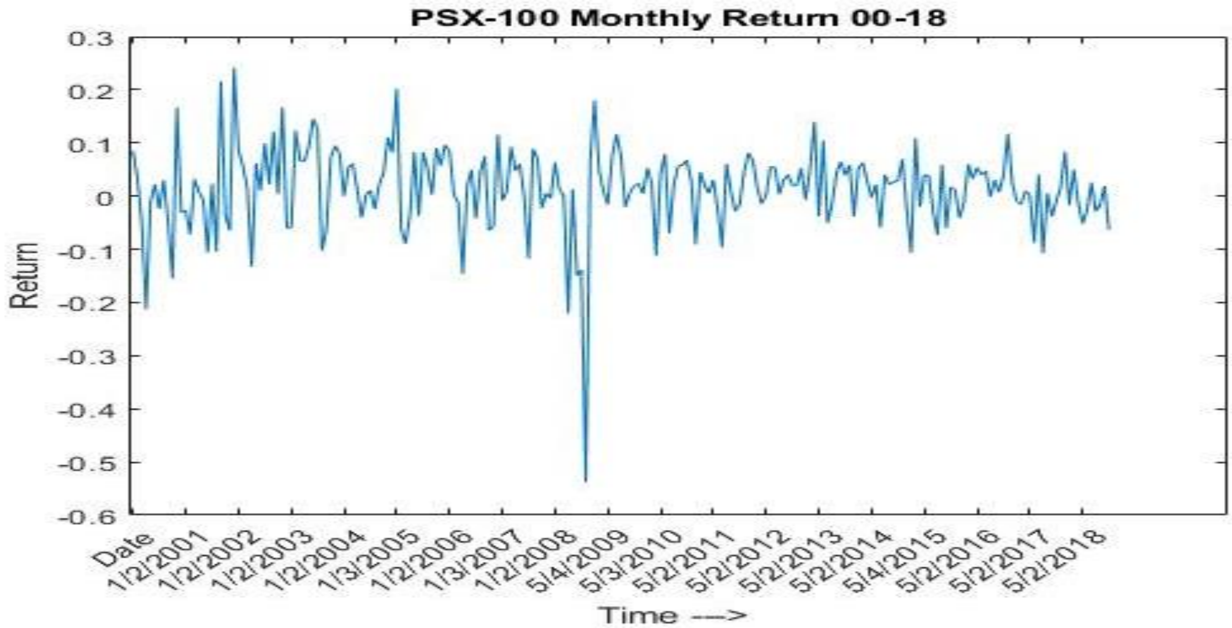
[22] http://www.sbp.org.pk/publications/q_reviews/q_review_march_09.pdf

[23] Mohammad Sohail, CEO of Topline Securities Dawn news January 1-2013

Different research studies reveal that pre and post-CPEC, the PSX shows low volatility and market stability, which is a sign of encouragement for business people, traders, and investors to invest Wahid (2018), and Ahsanuddin et al., (2019). It offers better opportunities for traders and investors. CPEC is a game-changer, and it brings boom for Pakistan's economy and adjoining economies Ahsanuddin et al., (2019). PSX merger is a good move for the Pakistani market. It has promised significant investments essential to upgrade and mobilize the market while keeping exchanges' activities under direct surveillance Masood (2017). Since PSX emergence, the market stability has increased manifold, and the findings are supported by Morgan Stanley Capital International (MSCI) Khalid and Khan (2017). Recently Bloomberg has ranked Pakistan amongst the first five best-performing stocks around the world. The up-gradation of Pakistan's economic position in Moody's global rating agency from 'negative' to 'stable ' and an increase in Pakistan's weight in the MSCI Frontier index further improves the volatility of the PSX.

Figure 14. KSE-100 index returns from 2000-2018



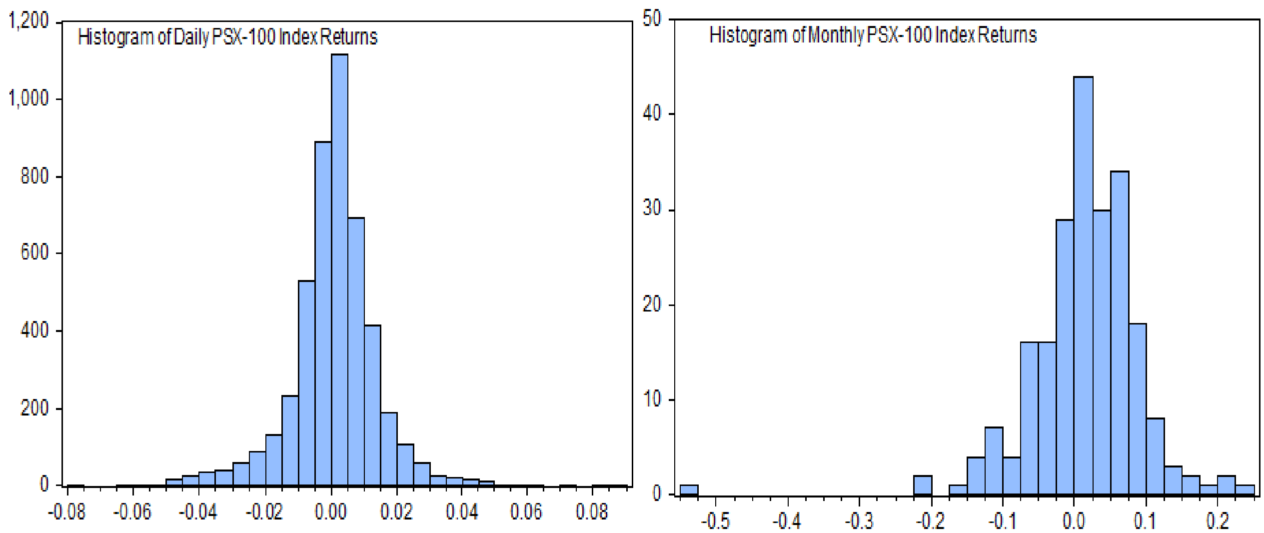


5.2.1 Characteristics of KSE-100 Return series

For a detailed glance at the return series' characteristics, the descriptive statistics are conducted on the KSE-100 index daily and monthly return series. Figure 15 displays the histogram of the daily and monthly return series of the KSE-100 index. Histogram depicts how much percent of data falls in each class. The monthly returns of the KSE-100 index are positively skewed. A positively skewed histogram indicates the more positive returns at monthly frequency. By only looking at such distribution, investors can interpret positive future returns. In comparison, the histogram of daily return series is cantered to its mean value. Throw which it is interpreted that the daily return series is showing the symmetric return distribution.

The detailed statistical values for describing the data characteristics of the KSE-100 index return series are documented in table 4. KSE-100 index is showing the .013879 average turn out on its monthly data. The average turnout on the daily return of the KSE-100 index is .000782, with having .013115 of standard deviation. Statistics of the higher moment like skewness and kurtosis are 1.656239 and 13.74757 for monthly return series, respectively. The skewness and kurtosis for daily return series are reported as .223907 and 6.766270, respectively. The Jarque-Bera statistics for monthly and daily return series are 1175.235 and 2825.517, highly significant with a p-value of .0000.

Figure 15. Histograms of PSX-100 index returns from 2000-2018



The data sample under inspection is comprised of monthly frequency. The descriptive statistical analysis explains the temperament of the monthly KSE-100 index. The average return on the KSE-100 Index is 1.3 percent, with the maximum limit of return reaching to 2.4 percent, and the average return drops down to the minimum level of minus 5.3 percent. The highly significant Jarque-Bera statistics of the monthly return of the KSE-100 index confirms that the return series does not follow the regular distribution pattern. With skewness and kurtosis measures equal to 1.656239 and 13.74757, respectively.

The significant jarque-Bera test compares the values of skewness and kurtosis. For distribution to best fit along with a normal distribution, its skewness should approach zero, and the value of kurtosis should be equal to 3. In this case, the values of skewness and kurtosis are different from the accepted range. So the null hypothesis is firmly rejected as the distribution is not following a normal distribution. The histogram of monthly return also rejects the null hypothesis as it is positively skewed.

Table 4. ***Statistical Characteristics of KSE-100 returns from 2000-2018***

Statistics	**Daily Return**	**Monthly Return**
Mean	0.000782	0.013879
Median	0.000844	0.019762
Maximum	0.085071	0.241114
Minimum	-0.077414	-0.537892
Standard deviation	0.013115	0.078258
Skewness	-0.223907	-1.656239
Kurtosis	6.766270	13.74757
Jarque-Bera	2825.517	1175.235
Probability	0.000000	0.000000
Sum	3.687387	3.095088
Sum Sq. Dev	0.810626	1.359601
Observations	4714	223

The comparison of monthly and daily return frequencies indicates that the PSX is showing high volatility at its daily alterations. In both frequencies, the deviation on Pakistan stock exchange is high during the periods before 2009. There is a bid drop in the distribution against the year 2008, which indicates the crash of 2008. In the last four months, the stock market put the floor seeling, so there was no trading in that period. After 2009 the volatility on the stock market is little decreased.

Literature indicates different factors which contribute towards the market volatility. Ghufran et al., (2016) show that, according to investors and brokers, the political situation is the most important in causing turbulences in the stock market. The research findings suggest some other factors: the most important factors are the herd behavior, manipulations by the big investors, government policies, and change in the earnings of listed companies and media stories to contribute to market volatility.

5.2.2 Stationarily and Normality check

Some parametric and non-parametric treatments are applied on the monthly return series to unfold its irregular temperament. Unit root, run test, autocorrelation test, and KS test are narrated in this regard.

5.2.2.1 Non-parametric test

The financial time series are usually characterized by stationarily and behaving like a non-regular pattern of distribution. In the case of monthly returns of the KSE-100 index, the run test statistics lies in the critical region.

Table 5. ***Run Test for PSX-100 Monthly Returns (2000-2018)***

Test Value$^{(median)}$	.02
Cases < Test Value	112
Cases >= Test Value	113
Total Cases	225

Number of Runs	104
Z statistics	-1.269
Asymp. Sig. (2-tailed)	.204

The value of the run test reported in table 5 is -1.269. This value accepts the null hypothesis of randomness and concludes that the monthly returns are not acted like a normal distribution. It also validates the findings of the histogram presented in figure 15.

Table 6. ***Kolmogrov Smirnovfor PSX-100 Monthly Return (2000-2018)***

Number of Observations		225
Normal Parameters[a]	Mean	.0140
	Std. Deviation	.07542
Most Extreme Differences	Absolute	.083
	Positive	.063
	Negative	-.083
Kolmogorov-Smirnov Z		1.246
Asymp. Sig. (2-tailed)		.090

The Kolmogorov Smirnov (KS) test is conducted to check the goodness of fit at the monthly return series. The KS test value is 1.246, and its corresponding P-value is .09. This statistics measure does not reject the null hypothesis of randomness for PSX-100 Monthly Return. It put forward that the monthly series is random and follows a random walk.

5.2.2.2 Parametric Test for PSX-100 Monthly Return

As a parametric measurement tool, the unit root test and autocorrelation are carrying out. The unit root test for monthly PSX-100 returns indicates that the series does not contain unit root and depicts that series is stationary. The test statistics from the unit root test are -14.02041 is less than the critical value at a 1 % level with a P-value .000. Based on the unit root test, it is concluded that the monthly return at KSE-100 does not follow a random walk.

Table 7. ***Unit Root RSX-100 Monthly Return(2000-2018)***

Exogenous: Constant	**t-Statistic**	**Prob***
Lag Length: 0 (Automatic - based on SIC, maxlag=31)	-14.02041	0.0000
Test critical values:	1% level	-3.459494
	5% level	-2.874258
	10% level	-2.573625

*MacKinnon (1996) one-sided p-values

Autocorrelation test results of PSX-100 monthly returns are shown in table 8.

Table 8. ***Autocorrelation Test PSX-100 Monthly Return (2000-2018)***

			Box-Ljung Statistic		
Lag	**Autocorrelation**	**Std. Error[a]**	**Value**	**Df**	**Sig.[b]**
1	.062	.066	.887	1	.346
2	-.041	.066	1.273	2	.529
3	-.014	.066	1.315	3	.725
4	.036	.066	1.619	4	.805

5	.098	.066	3.865	5	.569
6	.108	.065	6.580	6	.361
7	-.069	.065	7.681	7	.362
8	.016	.065	7.740	8	.459
9	.058	.065	8.544	9	.480
10	.020	.065	8.640	10	.567
11	-.039	.065	8.996	11	.622
12	.013	.065	9.034	12	.700
13	.008	.064	9.048	13	.769
14	.005	.064	9.055	14	.828
15	-.107	.064	11.832	15	.692
16	.029	.064	12.037	16	.741

a. The underlying process assumed is independence (white noise).

b. Based on the asymptotic chi-square approximation.

The monthly return series do not illustrate any autocorrelation up to sixteenth lag. The value of the autocorrelation coefficient is not significantly different from zero, which gives an idea about independence in series; hence we can say that there is no autocorrelation between current and previous months' return in the KSE-100 monthly return series. From these autocorrelation results, it can be pointed out that the past prices at KSE-100 do not influence future prices.

Figure 16. Autocorrelation Co efficient of KSE-100

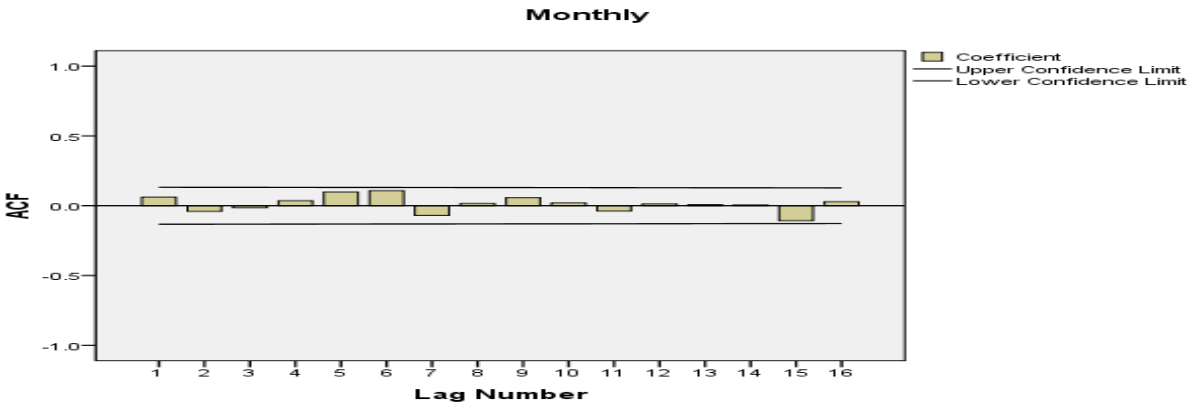


Figure 16 displays the autocorrelation results for the KSE-100 monthly return series. It confirms the results from Box-Ljung statistics and illustrates that up to lag 17, the autocorrelation coefficient exceeds the critical value at 95% confidence interval.

Parametric and non-parametric approaches in their capacity answer the irregular disposition of return series as non-random. The value of the run test as -1.269 describes the non-normal distribution of return series. The KS test value is 1.246, and its corresponding P-value is .09. This statistics measure does not reject the null hypothesis of randomness for KSE-100. The test statistics from the unit root test are -14.02041 is less than the critical value at a 1 % level with a P-value .000.

Based on the unit root test, it is concluded that the monthly return at KSE-100 does not follow a random walk. The monthly return series do not illustrate any autocorrelation up to sixteenth lag. The autocorrelation coefficient value is not significantly different from zero, which gives an idea about independence in series; hence, we can say that there is no autocorrelation between current and previous months' return in KSE-100 monthly return series. From these autocorrelation results, it can be pointed out that the past prices at KSE-100 do not influence future prices.

5.3 SECOND STAGE: OPTIMAL SELECTION OF PARAMETERS FOR ARTIFICIAL NEURAL NETWORK

The best model structural design selection requires much work before it. For an optimal ANN structure, the process of parameter selection is followed by some steps. The steps performed for the selection of the optimal parameters are presented in this section. Moreover, a debate on the selection of parameters for ANN is expressed. The architecture of ANN is based on a multilayer perceptron. The multilayer model consists of an input layer, hidden layers, and an output layer. The input and output layer's decision is based on the dependent and independent variables of the study. This study uses a nonlinear autoregressive neural network model in which the dependent variable is regressed against its lag variable. The decision for the best lag value is also part of this process. The return data series is monitored through trial and error up to four lags to select the best lag for them as an independent variable. One independent variable that is the best lag selected the ANN architecture will have one input layer. Furthermore, the original return series will be the output layer of the ANN model. So the optimal ANN model constitutes one input layer and one output layer.

The decision regarding the hidden layer is followed by the evidence reported in the literature. The number of layers in this study will remain only one as literature support that in financial time series analysis, the more hidden layers make the problem more complex Maciel and Ballini (2010), so the minimum number of layers is recommended. Literature supports the presence of minimum hidden layers in modeling problems related to financial time series. So the number of the hidden layer is keeping only one in this research work. The nodes on the hidden layer are selected through trial and error processes.

The ANN works on learning and training through data. For its working, it needs to divide the data into training, testing, and validation sets. The best combination of data split ratio for training, testing, and validation is also selected through the trial and error process. The performance of ANN is interpreted through the three performance measure error. The MAE, MSE, and RMSE are used to assess the performance of the ANN model. The model which reports minimum measuring error is considered the best performing model. The steps followed to select the parameters are interrelated.

5.3.1 First step: selection of Optimal Parameters

Three significant parameters are going to be decided through this selection process. The best lag, how many hidden neurons, and the best combination of data split ratio is done by following this exercise. The results are as follows.

5.3.1.1 Selection of best hidden nodes for each lag

In the trial and error process for selecting hidden nodes, an ANN up to 50 nodes is run on four different lags. The trial and error process results for the selection of hidden nodes suggest that as long as we move from the minimum number of nodes towards the maximum number of nodes, the performance measure error of any ANN model increases. The ANN model gives low error terms on the nodes from 1 to 10 in most cases. If we look at the individual values of MAE, RMSE, and MSE for each lag in appendices C, D, E, and F, the MSE and MAE reports more than one node, which has low error terms. While the RMSE reports only one node as the optimal node. So the best node at which the lowest RMSE is reported is believed as the optimal node for the optimal model. RMSE considers the best evaluation criterion when the data distribution is not normal Chai and Draxler (2014). Table 9 reports the trial and error process's preliminary results for selecting optimal hidden nodes for all four lags.

Table 9. ***Optimal Hidden nodes for all four lags***

Lags	1st lag		2nd lag		3rd lag		4th lag	
ME / HN	No. of nodes	ME Value	No. of nodes	ME Value	No. of nodes	ME Value	No. of nodes	ME Value
MSE	2	0.005994	3	0.005915	1	0.005828	3	0.0057389
MAE	14	0.036839	8	0.053798	2	0.054306	2	0.0542126
RMSE	3	0.062266	1	0.076459	2	0.077547	4	0.077593

When every combination of training, testing, and validation employing fifty nodes were used for first lag, the generated outcomes for MAE, MSE, and RMSE respectively are reported in Table 13, 14, and 15 in (appendix C). Table 13 in appendix C reports that MSE values for the first lag. When an ANN model is run for first lag incorporating fifty hidden nodes and sixteen different combinations, it generates 800 MSE values. From these 800 values, we have to choose the lowest value of MSE. Table 13 (appendix C) shows that node two is giving the lowest MSE value that is 0.005994. It also shows that the values of errors are increasing as the numbers of hidden nodes are increasing. Results clearly depict that the increasing number of hidden nodes decreases the predictive power of the ANN model. As the number of hidden nodes increases, the generated error terms from using the different training combinations, testing, and validation ratios do not make any difference.

Table 14 (appendix C) reports the MAE values generated through the trial and error process of ANN for the first lag. With fifty hidden nodes and sixteen data split ratio combinations, 800 error terms have been recorded. The hidden node at which the minimum MAE is recorded is 14. The value of MAE is 0.036839 at 14 nodes.

Table 15 (appendix C) reports the RMSE values generated through ANN's trial and error process for the first lag. With fifty hidden nodes and sixteen data split ratio combinations, 800 error terms have been recorded. The hidden node at which the minimum RMSE is recorded is node 3. The value of RMSE is 0.062266 at the third node. Table 15 (appendix C) also reports that after node 20, the values of RMSE are not changing even when the split data ratio is being changed. From the documented results of ANN, run for first lag to choose the best node using 50 different nodes; in tables 13, 14, and 15 in (appendix C), we come across with following results. The lowest value of MSE is reported at node 2, the lowest performance measure error for MAE has resulted in node 14 and for RMSE, and the lowest error term is noted at node 3. So node three is confirmed as the optimal node for the first lag.

When every combination of training testing and validation employing fifty nodes was used for a second lag, the first node is reported with the lowest root to mean square error. Tables 16, 17, and 18 in (appendix D) report the generated outcomes for MAE, MSE, and RMSE respectively for second lag using 50 nodes. From the table 16 (appendix D), we can see that node 08 is giving the lowest MAE for second lag. The lowest mean absolute error value is 0.053798, recorded at the eighth node. Table 16 also reports that after node 30, MAE values are not changing even when the split data ratio is being changed.

Table 17 (appendix D) reports the ANN model's MSE values using the second lag as an independent variable. In table 17 (appendix D), the lowest value of MSE is recorded by 0.005915. This value of low MSE suggests that if researchers want to choose the best node for an optimal model based on MSE value, then that node could be node 03. Table 17 (appendix D) also reports that the hidden nodes up to 20 can generate different training sets outcomes. However, increasing the number of hidden nodes of more than 20 makes no difference in resulted outcomes.

Table 18 (appendix D) reports the RMSE values for ANN employing second lag as an input variable. Sixteen combinations of data split ratio and fifty nodes as parameters for the model resulted in 800 outcomes. Table 14 recommend that node 01 is giving the lowest RMSE for the second lag. The RMSE recorded at node one is 0.076459, showing the lowest RMSE from the 800 outcomes. Table 16, 17 and 18 (appendix D) reports the best node's selection process for second lag through trial and error. The second lag's resulting outcome could be summarized as the lowest value of MSE for the second lag is documented at node 3. The lowest value of MAE is illustrated at node 8. Moreover, for RMSE, the performance measure error is minimum at node one as we are choosing the best node using RMSE, so the best node for the second lag is node 1.

The best node selection for the third lag is made through the reported results in table 19, 20, and 21 in appendix E. For the third lag, when performing a nonlinear autoregressive neural network with sixteen combinations and fifty hidden nodes, the performance measuring errors are reported in the following tables. Table 19 (appendix E) recorded the MAE resulted from ANN while using the third lag as an input variable. The trial and error process outcomes for the third lag documented in table 19 (appendix E) shows that the node which can bring the optimal results is node 2. The lowest value of MAE is recorded 0.054306. Table 19 (appendix E) depicts that MAE's value gradually increases with the number of hidden neurons.

Table 20 (appendix E) reports the ANN model's MSE values using the third lag as an independent variable. In table 20 (appendix E), the lowest value of MSE is recorded 0.0058286. This value of low MSE suggests that if we want to choose the best node for the optimal model based on MSE value, then that node could be node 01. Table 20 (appendix E) also reports that the hidden nodes up to 25 can generate different training sets outcomes. However, increasing the number of hidden nodes of more than 25 makes no difference in resulted outcomes.

Table 21(appendix E) reports the RMSE values generated through ANN's trial and error process for the third lag. With fifty hidden nodes and sixteen data split ratio combinations, 800 error terms have been recorded. The hidden node at which the minimum RMSE is recorded is node 2. The value of RMSE is 0.077547 at the second node. The outcomes of the trial and error process for third lag documented in tables 19, 20, and 21 in appendix E, bring us to the conclusion that the node which can be used for the optimal model is node two as the response of performance error at third lag remains low at the minimum number of nodes. All three performance measuring errors used in the study illustrates that an optimal reaction can be achieved by keeping fewer hidden nodes. The response of MSE at node 1 is lowest. The values of RMSE and MAE are noted low at node 2.

For the fourth lag, when performing a nonlinear autoregressive neural network with sixteen combinations and fifty hidden nodes, the lowest performance measuring errors are reported in tables 22, 23, and 24 in Appendix F. Table 22 (appendix F) shows that node 02 is giving the lowest MAE for the fourth lag. The lowest mean absolute error value is 0.0542126 recorded at the second node. Table 22 (appendix F) also reports that after node 20, MAE values are not changing even when the split data ratio is being changed.

Table 23 (appendix F) reports the ANN model's MSE values using the fourth lag as an independent variable. In table 23 (appendix F), the lowest value of MSE is recorded by 0.0057389. This value of low MSE suggests that if we want to choose the best node for the optimal model based on MSE value, then that node could be node 03. Table 23 (appendix F) also reports that the hidden nodes up to 20 can generate different training sets outcomes. However, increasing the number of hidden nodes of more than 20 makes no difference in resulted outcomes.

Table 24 (appendix F) reports the ANN model's RMSE values using the fourth lag as an independent variable. The lowest value of RMSE recorded in table 24 (appendix F) is 0.077593. This value of low RMSE suggests that the best node for the optimal model based on RMSE value could be node 04. Table 24 (appendix F) also reports that using less than 15 hidden nodes can increase ANN's performance. The increasing number of hidden nodes will not contribute towards the optimal working of ANN. By administrating the lag four for providing optimal node, the conclusion is drawn to choose node four based on the lowest

RMSE at that node. The other two performance measure errors reported the lowest node three and node 2 for MSE and MAE.

5.3.1.2 Selection of best data split ratio combination for each lag

This stage the optimal combination of data split ratio is selected through trial and error process for all four lags. The optimal combination of data split ratio is selected from the minimum performance measuring error. The data split combination resulted with minimum values of MSE, MAE and RMSE is consider as the optimal combination of training, testing and validation.

The performance measure results from the processing of first lag at different combinations of data split ratios of training; testing and validation are reported in figure 17. Figure 17 shows the three graphs for the three performance measuring errors selected for decision criteria. The horizontal axes of the graph show the number of neurons. The vertical axes report the value of the error term. Using the first lag as input data, multiple neural networks are processed on sixteen combinations of data split ratio. These all combinations are run at fifty different neurons to select the best optimal combination.

From the trial and error process of ANN for the selection of the best combination of data, split ratio discloses some interesting facts. The measuring error of MSE is recorded lowest error term of .005994 at eight different data split ratios. These combinations are 80:15:05, 75:15:10, 70:15:15, 65:15:20, 75:20:05, 70:20:10, 65:20:15 and 60:20:20 for training, validation and testing respectively. It shows that if we choose the optimal combination of data split ratio for the ANN model based on MSE, we have eight different options to choose from them. While the other combinations of data split ratios report relatively high error term for MSE. The best data split ratio for MAE on the first lag is 85:10:05 training, validation, and testing, respectively. Findings explain that if we are making our choice of best combination based on MAE, we have to locate eighty-five percent of the data set for training purposes, ten percent for validation, and five percent for testing.

The lowest value of RMSE is noted in one combination that is 80:05:15. Lowest RMSE means that if we are making our choice of best combination based on RMSE, then we have to locate eighty percent of the data set for training purposes, five percent for validation. Fifteen percent will go for testing of data set. In all combinations, up to twenty neurons, we have low performance measuring error, and after that error becomes higher, this is verified by the graph.

The performance measure results from the processing of second lag at different combinations of data split ratio for training, testing, and validation are reported in figure 18. All the three performance measure errors that are MSE, MAE and RMSE for lag two are reported in figure 18.

Figure 18 explains that if we look at the MSE graph for second lag, all the combinations represent very low performing errors up to eight neurons. Division of data set for training, testing, and validation for second lag using MSE illustrates three different combinations as having the lowest MSE value. These combinations, one is 70, 20, and 10, the second is 65, 20, and 15, and the third combination is 60, 20, and 20 for training, validation, and testing, respectively.

Errors are getting higher when we move towards other combinations. Using MAE for choosing the best combination of data split ratio illustrates two combinations that can be used for the best-fitted model. One combination is 70, 20, and 10, and the second is 65, 20, and 15 for training validation and testing, respectively. The lowest error term of RMSE leading towards the selection of data split ratio with 70 percent training, fifteen percent validation, and fifteen percent for testing. So if we chose the best data split ratio using RMSE, then for the best-fitted model using a second lag, the data split ratio should be 70:15:15.

The performance measure results from the third lag processing, along with different combinations of training, testing, and validation, are reported in figure 19. It shows the graphs of MAE, MSE, and RMSE for the third lag. All the sixteen combinations are used to run a neural network using fifty neurons for the third lag.

The best data split ratio for the third lag is undertaken by looking at three performance measure errors. Again MSE brings out two data split ratio to choose from them. One combination is 65, 20, and 15, and the other one is 60, 20, and 20 for training, validation, and testing, respectively. While the MAE suggests that the data split ratio should be like 75 percent for training, five percent for validation, and twenty percent for testing. Moreover, the best combination through RMSE is 90 percent for testing and five percent for each validation and testing.

Figure 17. Performance measure at first lag at 7 nodes

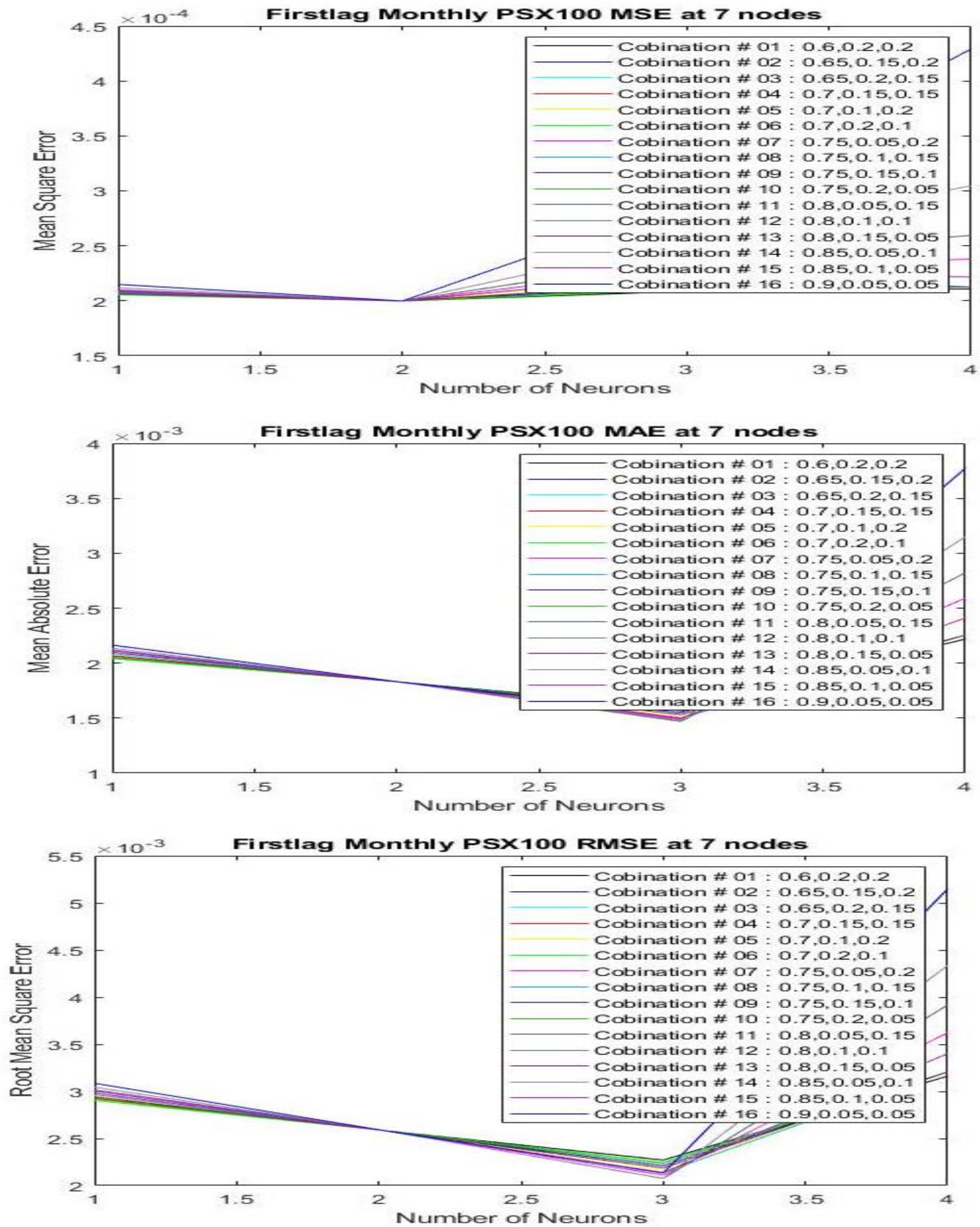


Figure 18. Second lag monthly data MSE, MAE, RMSE

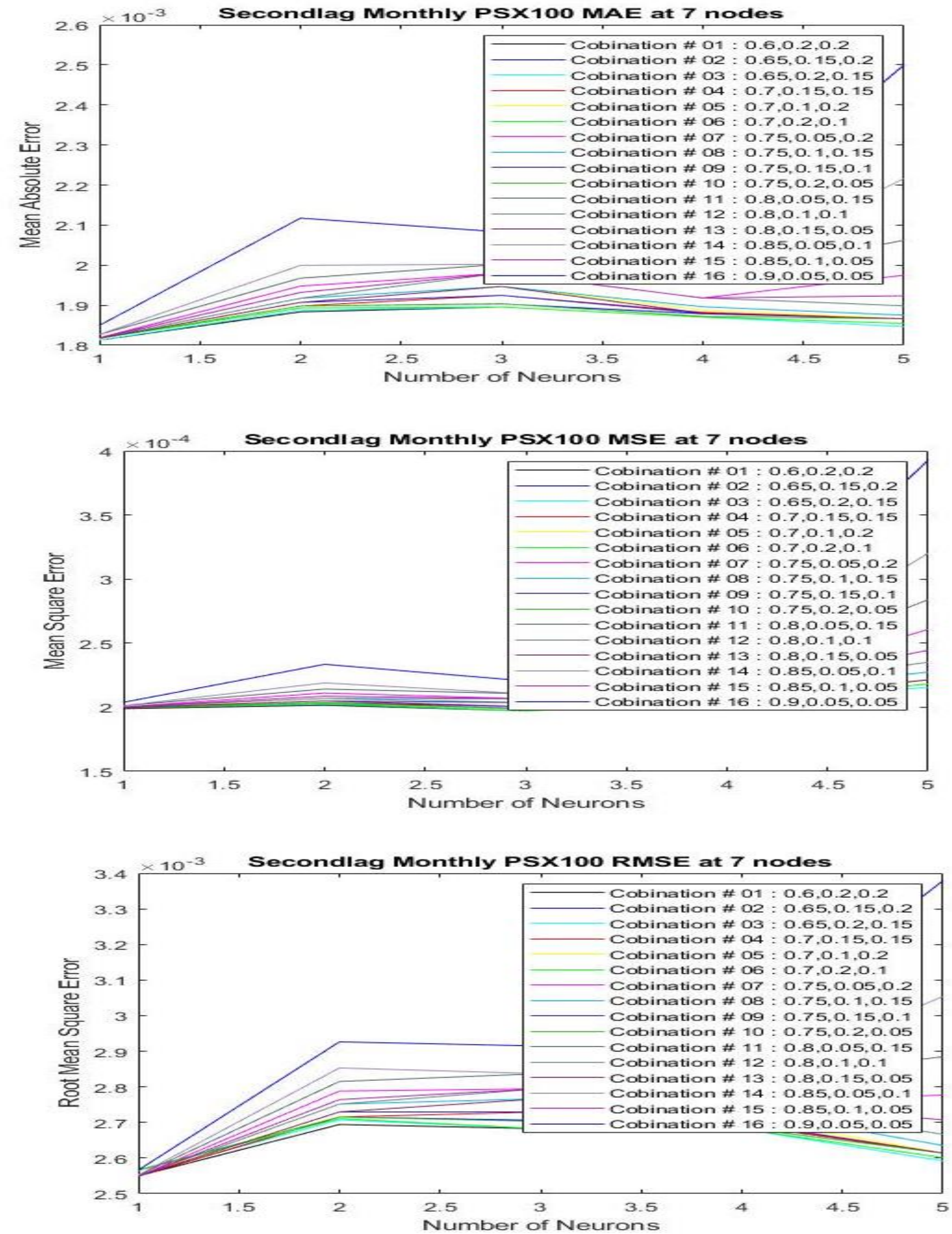
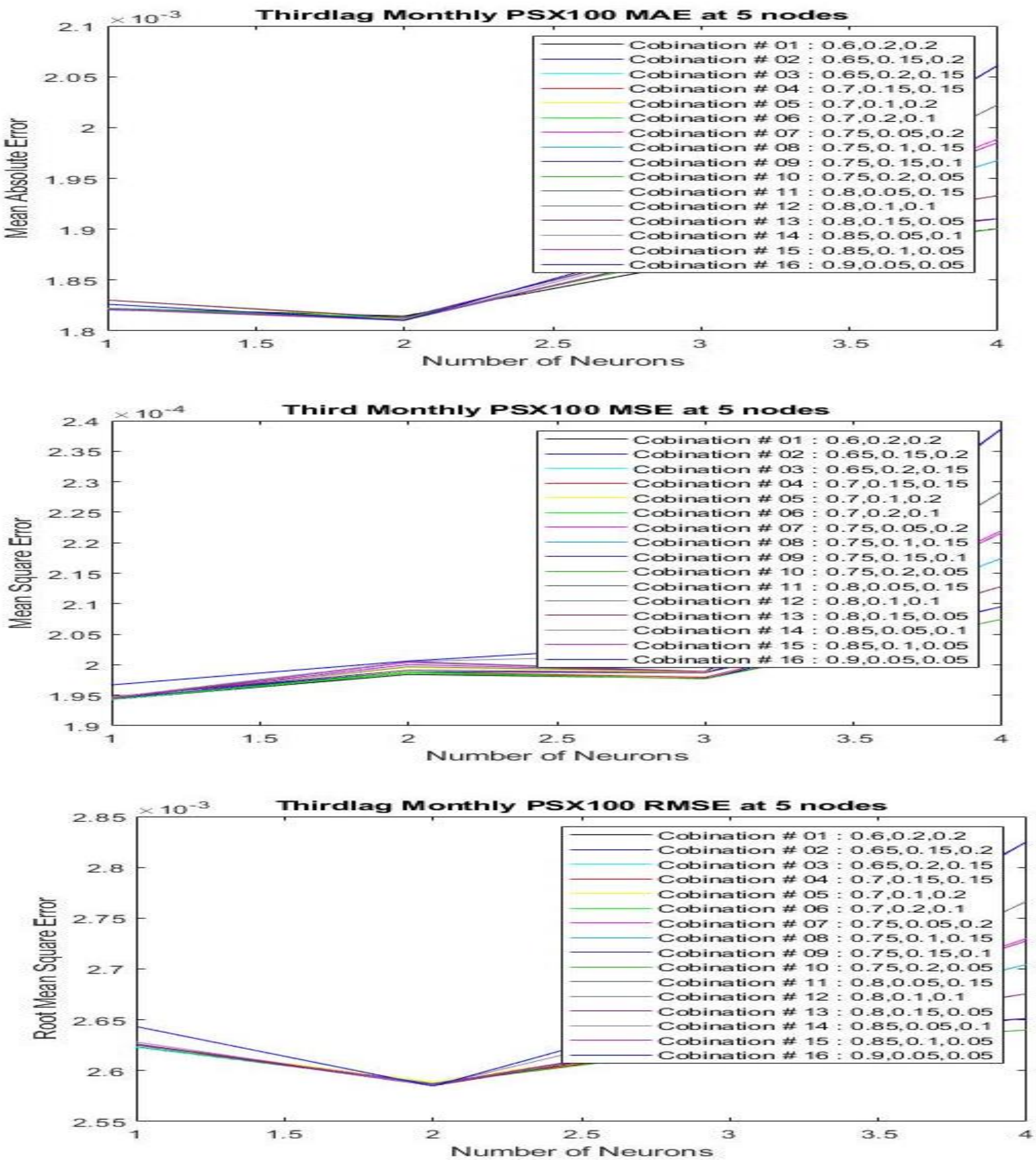


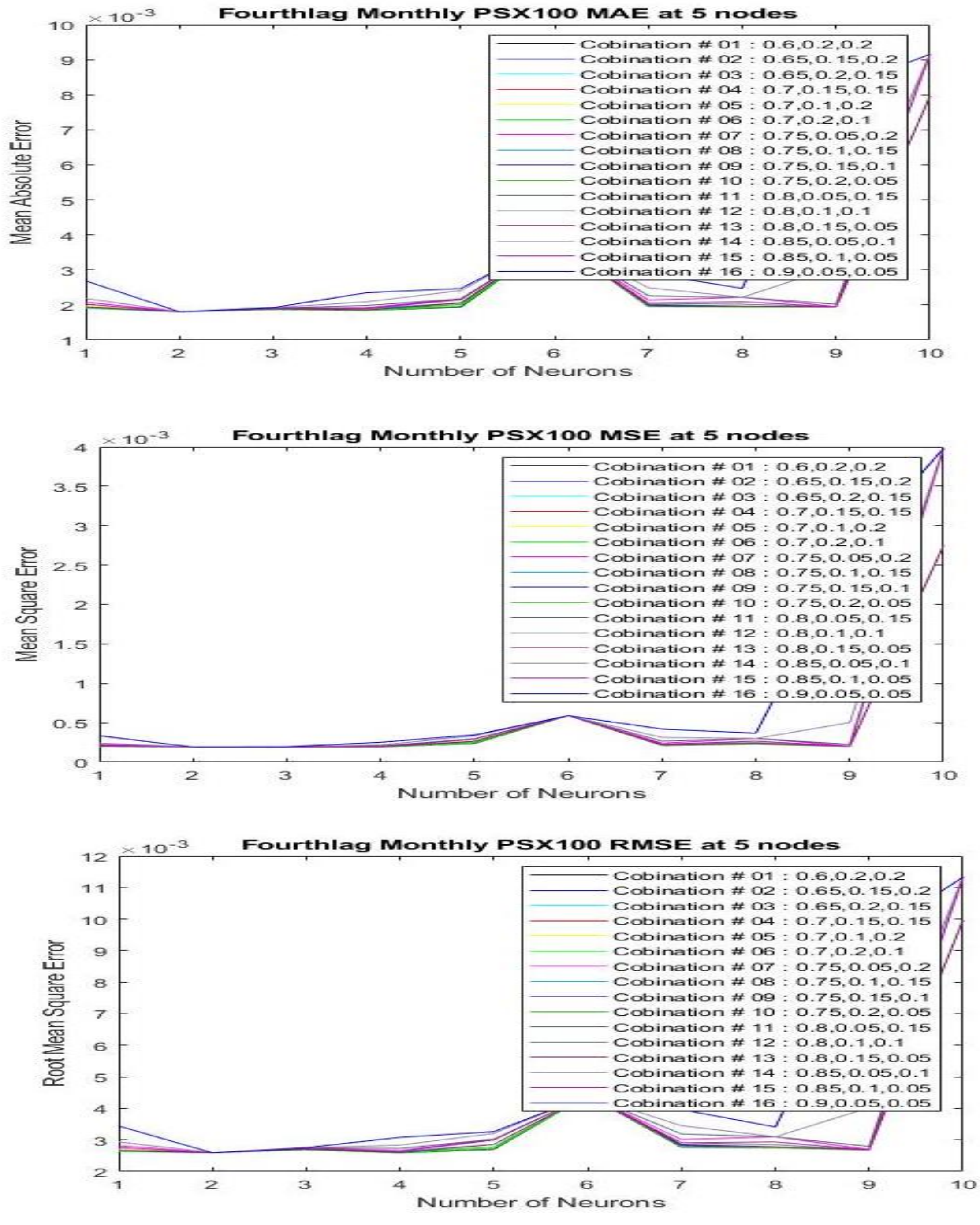
Figure 19. Third lag monthly data MAE,MSE,RMSE



The combination with seventy percent training, twenty percent testing, and ten percent validation shows the lowest mean absolute error, mean square error, and mean square error from the processing of fourth lag along with different combinations. Simultaneously, the other combinations of training, testing, and validation have relatively higher mean square errors. These combinations show that the mean square error is low up to ten neurons error, and after that, results become worst; the graph verifies this. The performance measure results from the processing of the fourth lag at different combinations of training, testing, and validation are reported in figure 20.

The decision regarding the fourth lag's best data split ratio is also undertaken by looking at three performance measure errors. MSE brings out one split data ratio to choose from them: sixty, twenty, and twenty for training, validation, and testing. At the same time, the MAE suggests that the data split ratio should be like eighty-five percent for training, five percent for validation, and ten percent for testing. The resulting outcome on the fourth lag processing reported three different combinations of data split ratios as having the lowest RMSE value. These three combinations are 70:20:10, 65:20:15 and 60:20:20.

Figure 20. Fourth lag monthly data MAE,MSE,RMSE



The above experiment brings us to the point at which we can document the two parameters of the architecture of the optimal model. The two parameters which we could select from the previous experiment are the hidden nodes for each lag and the best combination of data split ratio. The optimal-hidden nodes and the optimal combination for each lag are documented in table 10.

Table 10. ***Best hidden nodes and Best data split ratio for all four lags***

Parameters	**Lag one**	**Lag second**	**Lag third**	**Lag fourth**
Training set	80	70	90	70
Testing set	15	15	05	20
Validation set	05	15	05	10
Nodes	03	1	2	4
Layers	1	1	1	1
Window size	36 months	36 months	36 months	36 months
Architecture	(1-03-01)	(1-01-01)	(1-04-01)	(1-04-01)

We come to know about the optimal combination for training validation and testing sets from the above experiment. The optimal combination of data split ratio for the first lag is eighty percent for training, fifteen percent for testing, and five percent for validation. Moreover, the optimal node for the first lag is three, at which the root mean square error term is lowest. The optimal combination for training validation and testing set is seventy percent for training, fifteen percent for testing, and fifteen percent for validation for the second lag. Furthermore, the optimal node is one at which the mean square error term is lowest.

The above experiment on third lag reports the optimal combination for training validation and testing set is ninety percent for training, five percent for testing, and five percent for validation. Moreover, the optimal node is two, at which the mean square error term is lowest. The optimal combination for training validation and testing set is seventy percent for training, ten percent for testing, and 20 percent for validation for the fourth lag. Moreover, the optimal node is four, at which the root mean square error term is lowest.

5.3.1.3 Selection of lag variable

For the selection procedure of lag for deciding as an input variable, we need to run a non-linear autoregressive neural network for different lag values. The lag series will report the lowest mean square error, mean absolute error, and root means square error will be selected as the best lag for further analysis. At this step, to select the best lag as an input variable, a non-linear autoregressive rolling window analysis is conducted for each lag, by taking all the selected optimal parameters.

The graph in figure 21 represents the root mean square error, mean square error, and means absolute error from performing of thirty-six month non-linear autoregressive neural network rolling window analysis on all four lag's. The purpose of this analysis is to look at the return behavior at all four lags. This analysis explains that at all four lags, stick returns' movement is showing the same pattern. The movement of returns is recurring in all four lags. The low level of performance measuring errors shows that the forecasting error is least, and it is relatively easy to forecast the return opportunities in these periods. Model giving the minimum forecasting error is the best model because these models give the best fit to the target market.

Furthermore, the periods in which performance measuring errors are higher than it is challenging to forecast the market. Figure 21 depicts that the predictability level is changing over time, and this change can be attributed to seasonal change.

Figure 21. Performance measure error at all lags

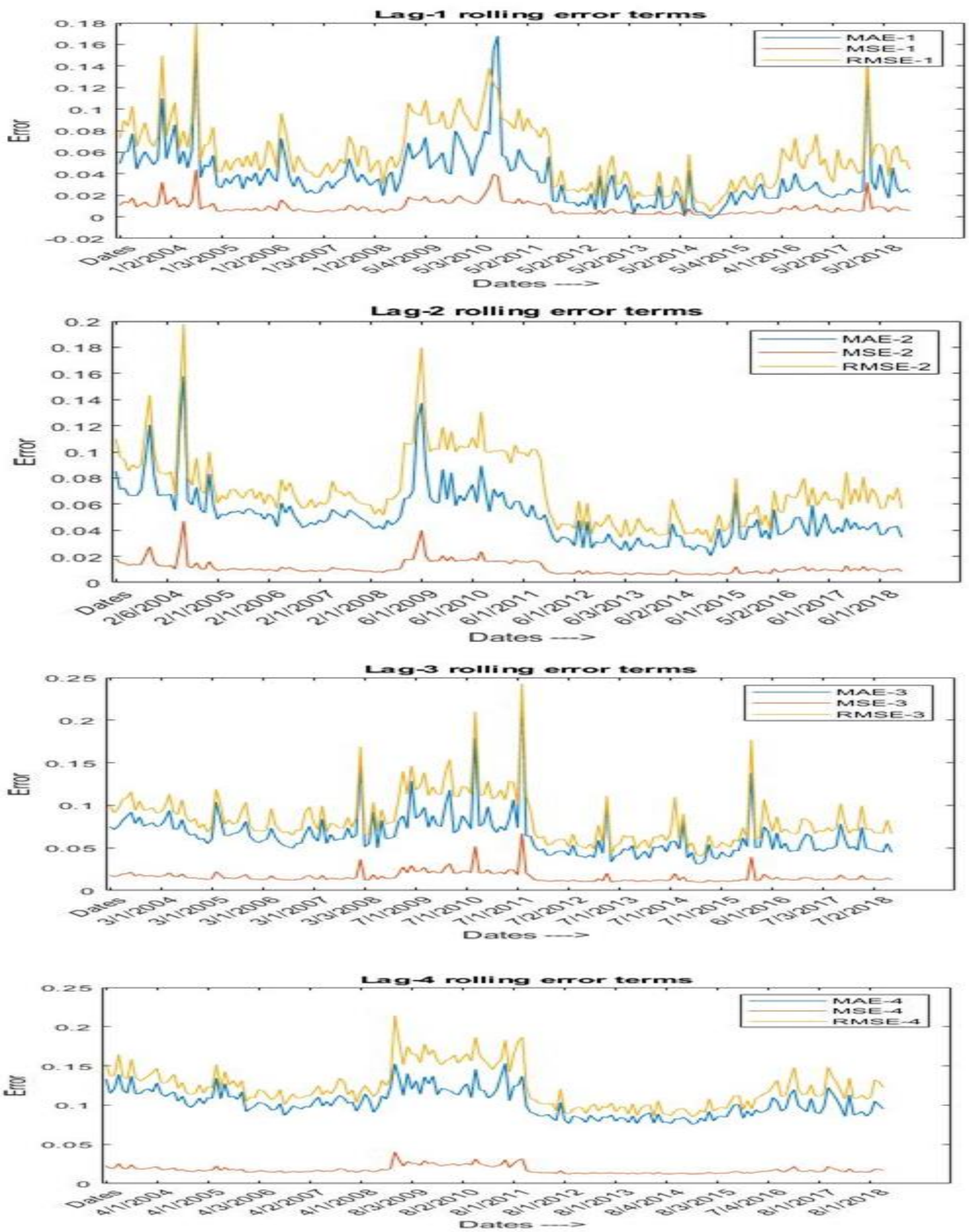
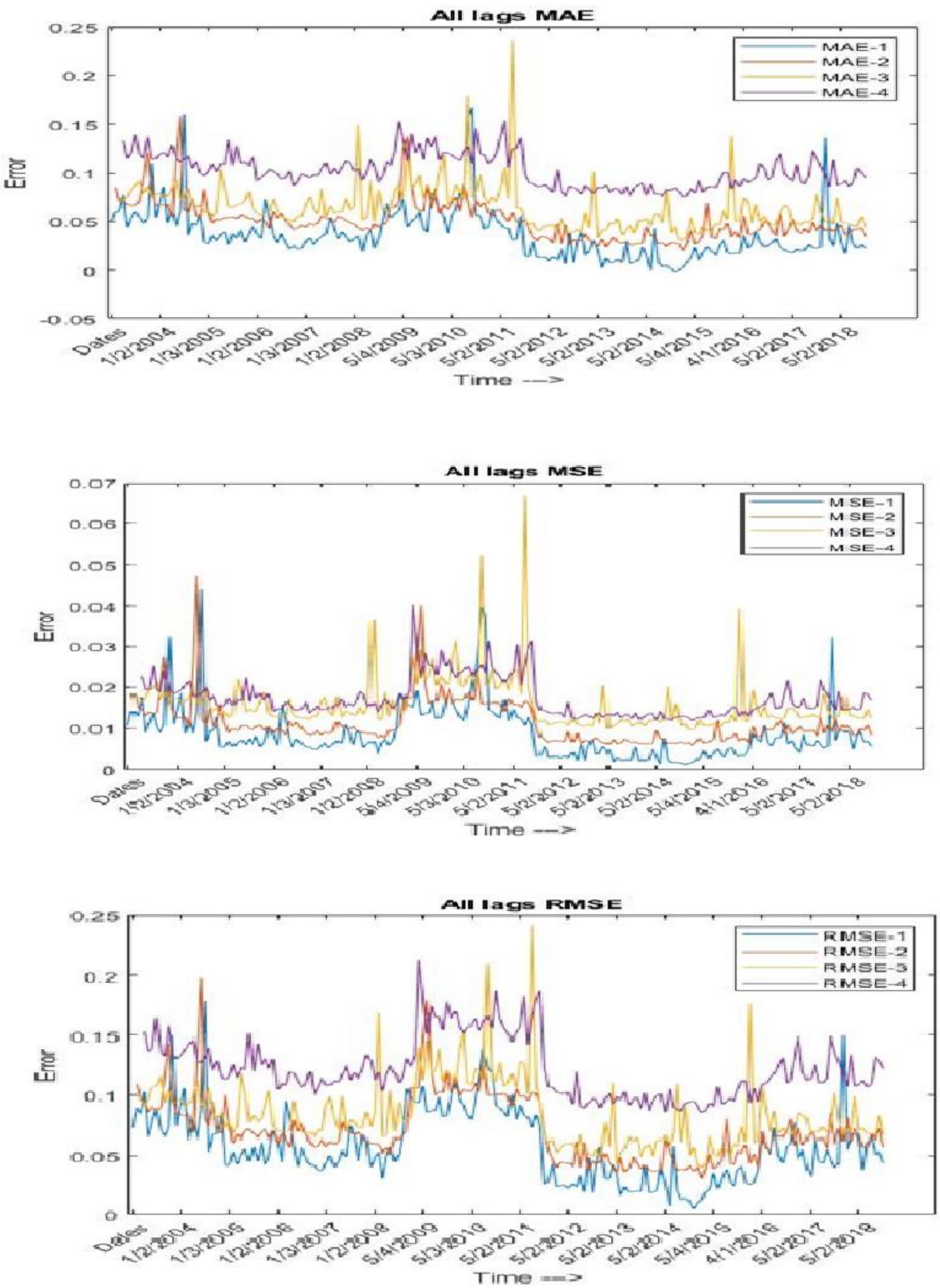


Figure 22. Comparison of lags at performance measure



The movement of the level of predictability upward and some periods is downward, which can be attributed as the movement of efficiency upward and downward.

The above figure 21 provides the performance error terms of all four lags individually. It tells the overall movement about the returns at different lags. However, to compare the model's performance at different lags and select the best lag at which the performance measure error is lowest, we have to combine them. Figure 22 shows the four lags with the three performance measure error terms reported in the combined graph. From this figure, we can conclude that the lag one is showing the lowest error performance measure. Here we select the best lag for our optimal neural network model. The best lag is lag one, working as an independent variable for the non-linear autoregressive neural network.

The best lag selection is undertaken by performing a non-linear autoregressive neural network on all four lags using the above-selected parameters. In previous steps, the node and data split ratio for each lag is decided. The best lag is selected by modeling and comparing the outcomes from a non-linear autoregressive neural network for each lag. Again performance measure errors are the helping agents for making the decision. The lag at which the performance measure error reports the narrow values is the best lag. When plotted against four lags, each model's outcomes resolve the problem for the selection of the best lag. Inspecting such a plot can figure out that the lag which provides the best-fitted values is lag one. In each different lag, one can figure out that lag one is plotted against the minimum values of RMSE, MAE, and MSE.

The above-discussed exercise makes the development of an optimal neural network model possible. The architecture, followed by the optimal model, is as follows. The optimal *model has one input, one output layer, and one hidden layer. The input layer responds to the lag one. The hidden layer contains three nodes. The optimal model follows an 80%, 15%, and 5% data split ratio for training, validation, and testing, respectively.*

5.4 THIRD STAGE: ROLLING WINDOW ANALYSIS

After selecting all the parameters, we are now able to run a non-linear autoregressive neural network. The parameters for the optimal model are reported in table 11.

Table 11. ***Parameters for Optimal model***

Parameters	Training %	Testing %	Validation%	Nodes	Layers	Lag	Window size
Model	80	15	05	03	1	1	36 months

The non-linear autoregressive neural network sheltered by the optimal parameters under rolling window estimation offered valuable results. The outcomes from this model are in the form of performance measure estimations. The evaluation criterion for the best-fitted model is based on RMSE. The rolling window approach contributes towards the understanding of response over the full data sample. 36-month rolling window estimation on 224 months data, it brings out with 187 outcomes of error terms. These outcomes from the optimal non-linear autoregressive neural network are reported in table 12 and also inspected by plotting against the time frame of the study in figure 23.

Table 12. ***Rejection and Acceptance of efficiency in response to RMSE***

Dates	RMSE-1	EFF/INEFF	Dates	RMSE-1	EFF/INEFF	Dates	RMSE-1	EFF/INEFF
Jan-03	0.072906	Efficiency	Mar-08	0.030467	Inefficiency	Sep-13	0.019264	Inefficiency
Feb-03	0.089396	Efficiency	Apr-08	0.05015	Inefficiency	Oct-13	0.020086	Inefficiency

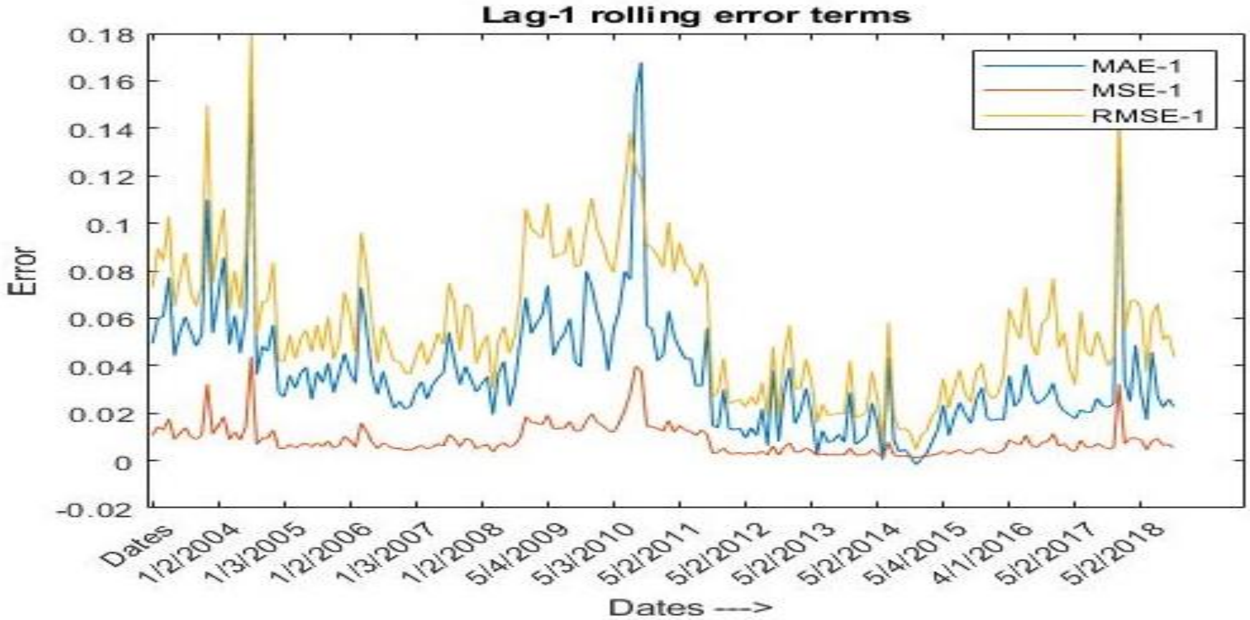
Mar-03	0.084233	Efficiency	May-08	0.056613	Inefficiency	Nov-13	0.019667	Inefficiency
Apr-03	0.102687	Efficiency	Jun-08	0.04516	Inefficiency	Dec-13	0.04213	Inefficiency
May-03	0.06478	Efficiency	Jul-08	0.052501	Inefficiency	Jan-14	0.018192	Inefficiency
Jun-03	0.077071	Efficiency	Aug-08	0.069147	Efficiency	Feb-14	0.01882	Inefficiency
Jul-03	0.087644	Efficiency	Jan-09	0.106097	Efficiency	Mar-14	0.020597	Inefficiency
Aug-03	0.071017	Efficiency	Feb-09	0.097836	Efficiency	Apr-14	0.037633	Inefficiency
Sep-03	0.065049	Efficiency	Mar-09	0.095497	Efficiency	May-14	0.026309	Inefficiency
Oct-03	0.074105	Efficiency	Apr-09	0.093692	Efficiency	Jun-14	0.007686	Inefficiency
Nov-03	0.149662	Efficiency	May-09	0.108361	Efficiency	Jul-14	0.05815	Efficiency
Dec-03	0.074806	Efficiency	Jun-09	0.085383	Efficiency	Aug-14	0.01915	Inefficiency
Jan-04	0.091676	Efficiency	Jul-09	0.087047	Efficiency	Sep-14	0.012877	Inefficiency
Feb-04	0.106149	Efficiency	Aug-09	0.087092	Efficiency	Oct-14	0.013766	Inefficiency
Mar-04	0.063556	Efficiency	Sep-09	0.098374	Efficiency	Nov-14	0.011341	Inefficiency
Apr-04	0.079878	Efficiency	Oct-09	0.081421	Efficiency	Dec-14	0.00481	Inefficiency
May-04	0.064012	Efficiency	Nov-09	0.082459	Efficiency	Jan-15	0.010683	Inefficiency
Jun-04	0.08788	Efficiency	Dec-09	0.098601	Efficiency	Feb-15	0.012565	Inefficiency
Jul-04	0.179279	Efficiency	Jan-10	0.110497	Efficiency	Mar-15	0.01923	Inefficiency
Aug-04	0.052891	Inefficiency	Feb-10	0.097107	Efficiency	Apr-15	0.021875	Inefficiency
Sep-04	0.066754	Efficiency	Mar-10	0.091444	Efficiency	May-15	0.034621	Inefficiency
Oct-04	0.067387	Efficiency	Apr-10	0.083329	Efficiency	Jun-15	0.021943	Inefficiency
Nov-04	0.083474	Efficiency	May-10	0.079205	Efficiency	Jul-15	0.030996	Inefficiency
Dec-04	0.041947	Inefficiency	Jun-10	0.096995	Efficiency	Aug-15	0.038264	Inefficiency
Jan-05	0.041803	Inefficiency	Jul-10	0.115673	Efficiency	Sep-15	0.028126	Inefficiency
Feb-05	0.052885	Inefficiency	Aug-10	0.138189	Efficiency	Oct-15	0.024488	Inefficiency
Mar-05	0.04282	Inefficiency	Sep-10	0.12297	Efficiency	Nov-15	0.03755	Inefficiency

Apr-05	0.051494	Inefficiency	Oct-10	0.118428	Efficiency	Dec-15	0.041113	Inefficiency
May-05	0.055016	Inefficiency	Nov-10	0.091181	Efficiency	Jan-16	0.028182	Inefficiency
Jun-05	0.045731	Inefficiency	Dec-10	0.089258	Efficiency	Feb-16	0.026009	Inefficiency
Jul-05	0.057088	Inefficiency	Jan-11	0.086088	Efficiency	Mar-16	0.028511	Inefficiency
Aug-05	0.046209	Inefficiency	Feb-11	0.081435	Efficiency	Apr-16	0.036229	Inefficiency
Sep-05	0.060576	Efficiency	Mar-11	0.10057	Efficiency	May-16	0.063872	Efficiency
Oct-05	0.042555	Inefficiency	Apr-11	0.079315	Efficiency	Jun-16	0.056606	Inefficiency
Nov-05	0.049792	Inefficiency	May-11	0.091765	Efficiency	Jul-16	0.051222	Inefficiency
Dec-05	0.070982	Efficiency	Jun-11	0.082931	Efficiency	Aug-16	0.073133	Efficiency
Jan-06	0.061298	Efficiency	Jul-11	0.080776	Efficiency	Sep-16	0.050186	Inefficiency
Feb-06	0.045132	Inefficiency	Aug-11	0.073056	Efficiency	Oct-16	0.044237	Inefficiency
Mar-06	0.096149	Efficiency	Sep-11	0.083429	Efficiency	Nov-16	0.058028	Efficiency
Apr-06	0.080886	Efficiency	Oct-11	0.074495	Efficiency	Dec-16	0.059691	Efficiency
May-06	0.058263	Efficiency	Nov-11	0.0266	Inefficiency	Jan-17	0.076859	Efficiency
Jun-06	0.040967	Inefficiency	Dec-11	0.02874	Inefficiency	Feb-17	0.047542	Inefficiency
Jul-06	0.056611	Inefficiency	Jan-12	0.043056	Inefficiency	Mar-17	0.054041	Inefficiency
Aug-06	0.048372	Inefficiency	Feb-12	0.024003	Inefficiency	Apr-17	0.038494	Inefficiency
Sep-06	0.041997	Inefficiency	Mar-12	0.024772	Inefficiency	May-17	0.031892	Inefficiency
Oct-06	0.041794	Inefficiency	Apr-12	0.025869	Inefficiency	Jun-17	0.062815	Efficiency
Nov-06	0.037047	Inefficiency	May-12	0.022562	Inefficiency	Jul-17	0.046095	Inefficiency
Dec-06	0.036647	Inefficiency	Jun-12	0.026932	Inefficiency	Aug-17	0.043926	Inefficiency
Jan-07	0.044123	Inefficiency	Jul-12	0.023421	Inefficiency	Sep-17	0.054444	Inefficiency
Feb-07	0.050044	Inefficiency	Aug-12	0.032824	Inefficiency	Oct-17	0.047334	Inefficiency

Mar-07	0.040388	Inefficiency	Sep-12	0.018725	Inefficiency	Nov-17	0.039685	Inefficiency
Apr-07	0.045912	Inefficiency	Oct-12	0.048061	Inefficiency	Dec-17	0.043693	Inefficiency
May-07	0.053802	Inefficiency	Nov-12	0.018243	Inefficiency	Jan-18	0.149396	Efficiency
Jun-07	0.048797	Inefficiency	Dec-12	0.044069	Inefficiency	Feb-18	0.054219	Inefficiency
Jul-07	0.074806	Efficiency	Jan-13	0.057028	Inefficiency	Mar-18	0.066919	Efficiency
Aug-07	0.066118	Efficiency	Feb-13	0.030191	Inefficiency	Apr-18	0.067723	Efficiency
Sep-07	0.046278	Inefficiency	Mar-13	0.030489	Inefficiency	May-18	0.063984	Efficiency
Oct-07	0.066040	Efficiency	Apr-13	0.042662	Inefficiency	Jun-18	0.037210	Inefficiency
Nov-07	0.063728	Efficiency	May-13	0.033872	Inefficiency	Jul-18	0.060897	Efficiency
Dec-07	0.040696	Inefficiency	Jun-13	0.015852	Inefficiency	Aug-18	0.066008	Efficiency
Jan-08	0.04848	Inefficiency	Jul-13	0.023768	Inefficiency	Sep-18	0.050925	Inefficiency
Feb-08	0.052822	Inefficiency	Aug-13	0.019228	Inefficiency	Oct-18	0.052935	Inefficiency

Table 12 illustrates the level of predictability at a different point in time. Results are showing a clear identification of cyclical behavior of stock returns on the Pakistan capital market. It explains the resulted outcomes from employing the non-linear autoregressive neural network using a rolling window approach from January 2003 to December 2018. It suggests that some periods in which the possibility to predict the market can be accepted through this optimal model of ANN. These periods of possible predictability shows the level of inefficiencies in the market. Moreover, there are specific periods in which this optimal model cannot predict the market accurately. The periods where the possibility to predict the market is relatively easy are considered as inefficient in structure. Moreover, the periods in which predicting the market is not accessible are considered efficient market structures.

Figure 23. Optimal model of Nonlinear Autoregressive NN



The graph in figure 23 explains the resulted outcomes of forecasting errors MSE, MAE and RMSE from employing the non-linear autoregressive neural network using a rolling window approach from January 2003 to December 2018. Figure 23 depicts the cyclical pattern of all the forecasting errors used in the study. The cyclical movement of MSE, MAE and RMSE in response to market conditions is analyzed according to the following rule. If the error performance term is broad, the prediction level is low. The market is considered efficient compared to the points where the error performance term is small, and prediction is accessible, reflecting inefficiency. This rule can be elaborated on in two different notions. The first one is that if the small error terms move towards the broad error terms, it will represent the movement of inefficiency to efficiency, which shows the market's adaptiveness. The second notion is that moving from broad error terms to small error terms will represent efficiency to inefficiency, showing the market's inefficiency.

However all the performance measuring errors are showing cyclical movement of market behavior but the values of RMSE is giving clearer picture of the movement. Based on root mean square error periods of predictability and non-predictability, can be divided into three cycles. This finding validates AMH's implications as proposed by Lo (2012) that market efficiency is not an all-or-nothing condition but a continuum. These cycles are the first cycle from January 2003 to July 2008, the second cycle from August 2009 to March 2016, the third cycle from April 2016 to November 2018. The decision regarding efficiency and inefficiency is set in table 4.

The first phase of the first cycle from Jan 2003 to November 2004, shows the low level of predictability due to the high RMSE, and in the second phase of the first cycle from December 2004 to July 2008 shows low RMSE, which reflects the high level of predictability which is an indication of inefficiency in the market. The movement of RMSE in this cycle explains that the market is moving from efficiency to inefficiency.

The first phase of the second cycle started in January 2009 and ended in September 2011; it was low predictability as the RMSE was high. The market is considered efficient during this period. Moreover, in the second phase of the second cycle from October 2011 to March 2016, the market is behaving like an inefficient market as the values of RMSE are low, and the market is highly predictable. The movement of RMSE in the second cycle explains that the market is moving from efficiency to inefficiency. In the third cycle from April 2016 to November 2018, the market's response is the mix.

From the AMH point of view, the investigation of the full sample for efficiency or inefficiency might negate the sample dynamics through time. This analysis is based on the rolling window framework, which allows us to investigate PSX dynamics through varying time, which is also consistent with the AMH view of time-varying varying efficiency (Urquhart et al., 2015). These cyclical movements of return predictability indicate that there are some periods when PSX is predictable, and at some periods PSX is not predictable are consistent with the AMH (Gourishankar, 2014), (Urquhart and McGroarty, 2016).

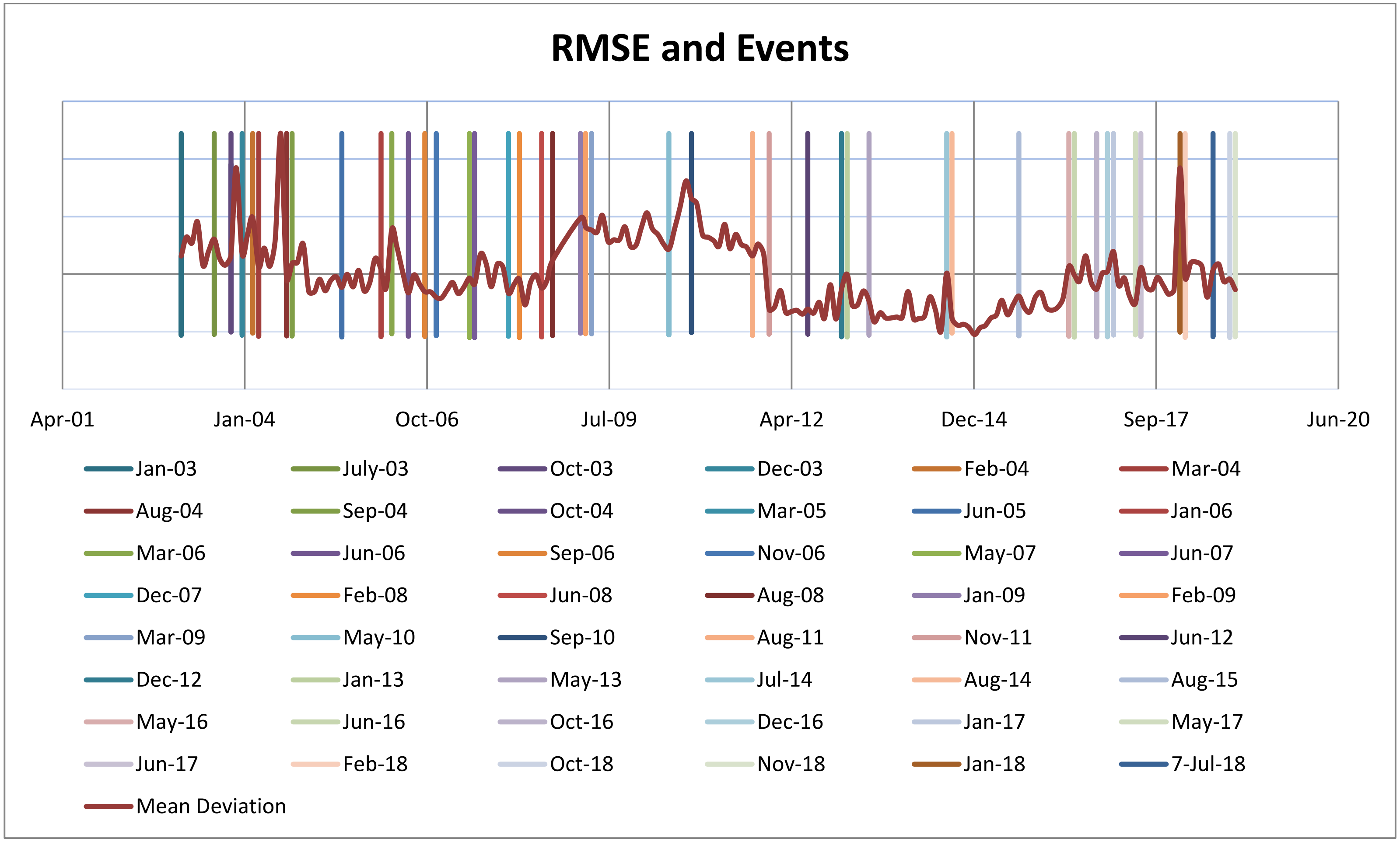
5.5 FOURTH STAGE: MARKET DYNAMIC ANALYSIS

By correlating the historical events with the cyclical movement of predictability would further increase the AMH's understanding. The evaluation of specific historical events can explain what sort of necessary market conditions govern periods of predictability and periods of non-predictability. Figure 24 shows the high and low movement level of performance measuring errors. The point at which RMSE is high, showing the low level of predictability and low level of the RMSE, presenting high volatility in the market, leading to higher predictability. High economic uncertainty makes the market more volatile. In situations where the economic environment is more uncertain, the Pakistan stock market behaves abnormally.

At this fourth stage, we are now able to analyze the response of the PSX at different events. For critically analyzing the Pakistan equity market's market dynamics, these periods of predictability and periods of non-predictability are evaluated in the context of changing market conditions. This analysis supports the proposition of AMH of (Lo, 2004) that claims that return predictability and market efficiency depend on each other.

Identification of the changing stock market conditions is made by publishing news relevant to the Pakistan stock market. News that shows the stock market fluctuations and describes the relevant cause of that fluctuation is selected for analysis. News published on the front page of Dawn newspaper from January 2003 to December 2018 is selected to consider the events that have a significant impact on the fluctuations of the KSE-100 Index. The total number of news selected from the newspaper is eighty-three. Not all of the news shows the reflections of fluctuation in the KSE-100 index. News plotted against the response of the KSE-100 index can be seen in figure 24.

Figure 24. Root mean square error and events

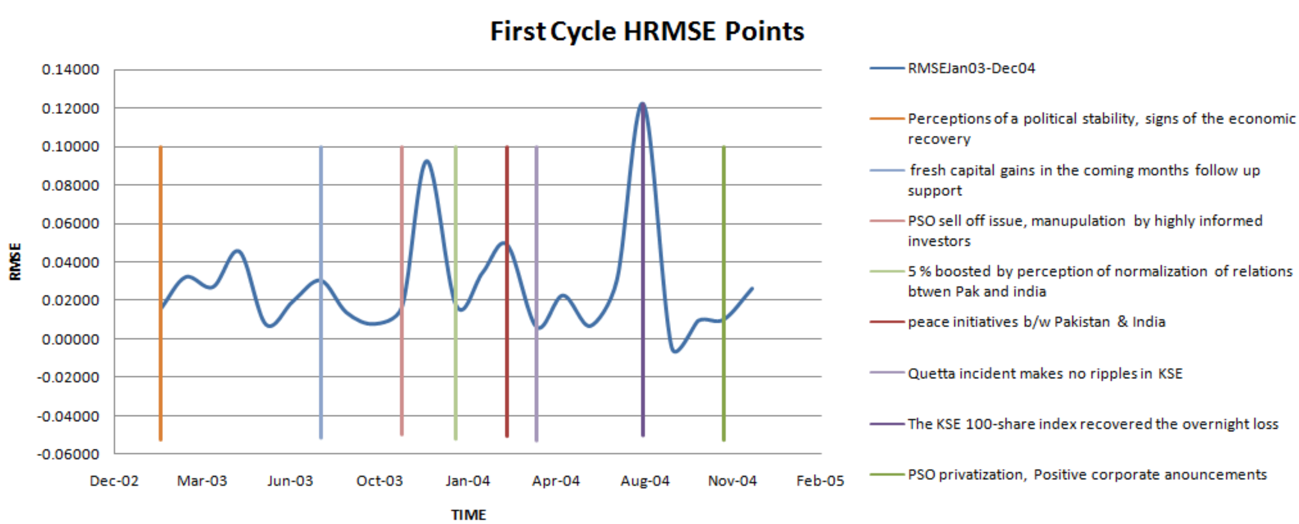


To further evaluate the occurrence of events and their impact on the PSX, only some significant events will be selected. The point at which the RMSE is showing higher fluctuations is being used to select the date of stock market response. A detailed analysis of the index's time fluctuations and the economic situation enabled us to relate the market dynamics and market adaptability.

5.5.1 The first cycle of High root mean square error and Low root mean square error

Figure 25 shows the eight data points from the high RMSE observations. These data points' responses indicate eight news published during this period. During November 2003, several peace initiatives had been taken by the government of Pakistan, which contributes towards the normalization of relations between India and Pakistan. India's positive response boosted the investor's confidence, and in the first week of December, the KSE-100 reported a five percent increase in its index point. With the boost in the market and a more favorable environment for investment, it reduces uncertainty in the market. The improved level of certainty moves the market toward efficiency.

Figure 25. High root mean square data points



The second data point with high RMSE in this cycle is March 2004. During February 2004, the news regarding the privatization of Pakistan state oil (PSO) and India's investment in the petrochemical industry, and upbeat corporate announcements gives constructive signals to the PSX. These positive signals remain strong even during March 2004 when a terrorist attack on an Ashura. Quetta Ashura massacre on 2nd March 2004, 42 persons killed and more than 100 persons are wounded the procession did not make any ripples in the KSE-100, and investors resumed regular trading activity with grief the deaths.

The positive and successful economic and privatization policies of the government resulted in restoration of investors' confidence in Pakistan's economy. The monetary and exchange policies of the SBP also contribute towards the increase of KSE-100 index by 55 percent in 2003-04.

After January 2005, the trend in this first cycle is moving towards lower RMSE. Data points from January 2005 to February 2009 are showing low root mean square error. However, not very low peaks are visible from the plotting of root mean square values during this period.

Figure 26. Low root mean square data points

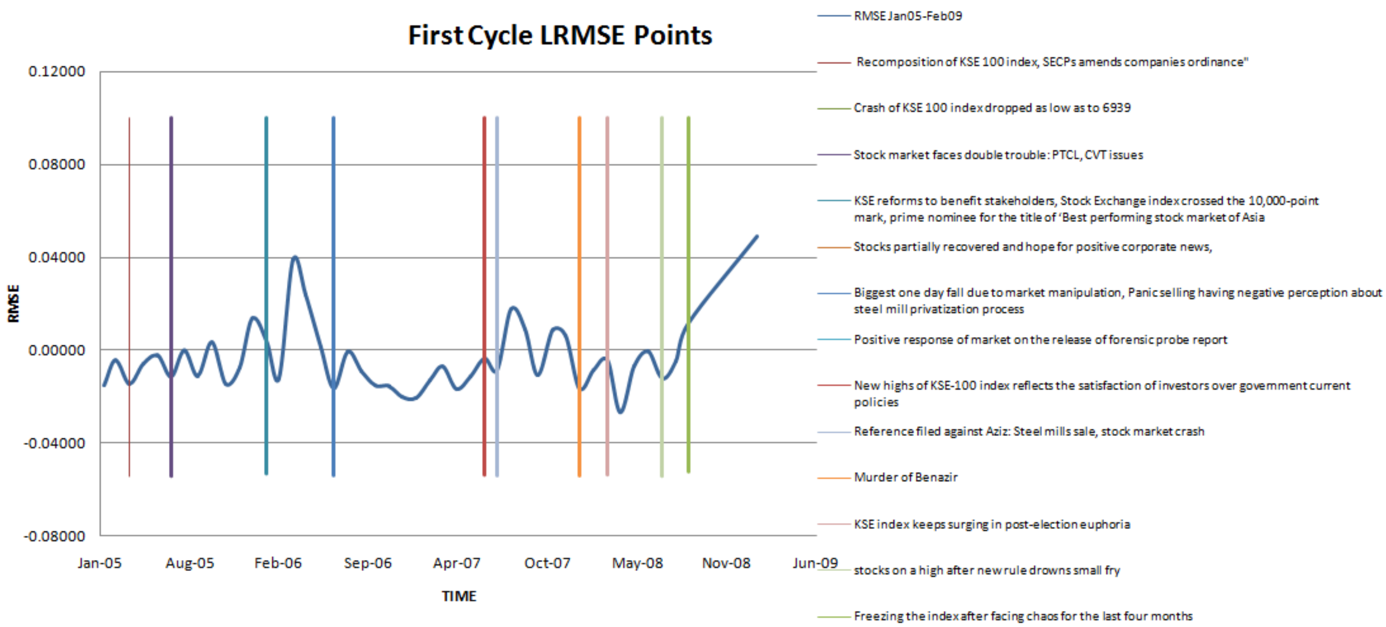


Figure 26 shows the movement of stock returns predictability from February 2005 to December 2008. Overall, this period shows the low root mean square values, which conclude that prediction ability is high during this period, and the market is behaving inefficiently. Moreover, when these data points are contrasted with the prevailing market, economic and political conditions, it explains the reason behind these low levels of RMSE values. Significant events that make the cause of market inefficiency are the crash of the stock market in 2005, the assassination of the former two times PM of Pakistan, the slower process of Pakistan steel mill (PSM) privatization, Pakistan's president Musharaf Former army chief of Pakistan resignation, 2008 elections and crash of 2008.

Although from January 2005, the market is already showing a rising trend. The strategic measures taken by the Securities and Exchange Commission of Pakistan (SECP) for an amendment in the Companies Ordinance and an announcement regarding the recomposition of the index have sent positive signals among the local brokers; it lifted the market to a new high. However, this situation does not sustain for a long time, and the KSE-100 index dropped by 32 percent in one month only on 12 April 2005. After the crash of 2005, different reforms have been taken by the government to compensate for the losses of stakeholders, and the year 2005 was the 4th consecutive year in which Pakistan stocks posted above-average returns. The above-average returns make it one of Asia's best markets for the title of 'Best performing stock market of Asia.'

The year 2006 comes with some positive signals of the market achieving new highs like the nomination of the Pakistan stock market as the best performing market of Asia and US President Bush's visit to Pakistan. In June 2006 again, the Pakistan stock market faced the most significant one-day fall due to market manipulation. Negative perception about the slowdown process of Pakistan steel mill privatization brings panic selling, which causes massive damage to the KSE-100 index. The release of the investigation report by USA experts in November on the crash of 2005, which gives a clean sheet to brokers, fetches positive responses.

The stock market movement is a little smooth in the year 2007 as compared to other years in this cycle of low root mean square errors (RMSE). The reason behind it was the satisfied foreign and local Investors with the policies of that time government. They were happy over the possibility of forming a pro-Musharaf government and continuing the current policies. However, the former Prime Minister of Pakistan Benazir Bhutto's assassination and political instability disturbs the PSX. Increased uncertainty increases the possibility of predictability. Figure 26 shows a low level of root mean square error on first January 2008, when the market reopens after the three-day holiday because of Benazir's assassination. RMSE is moving up after the election 2008.

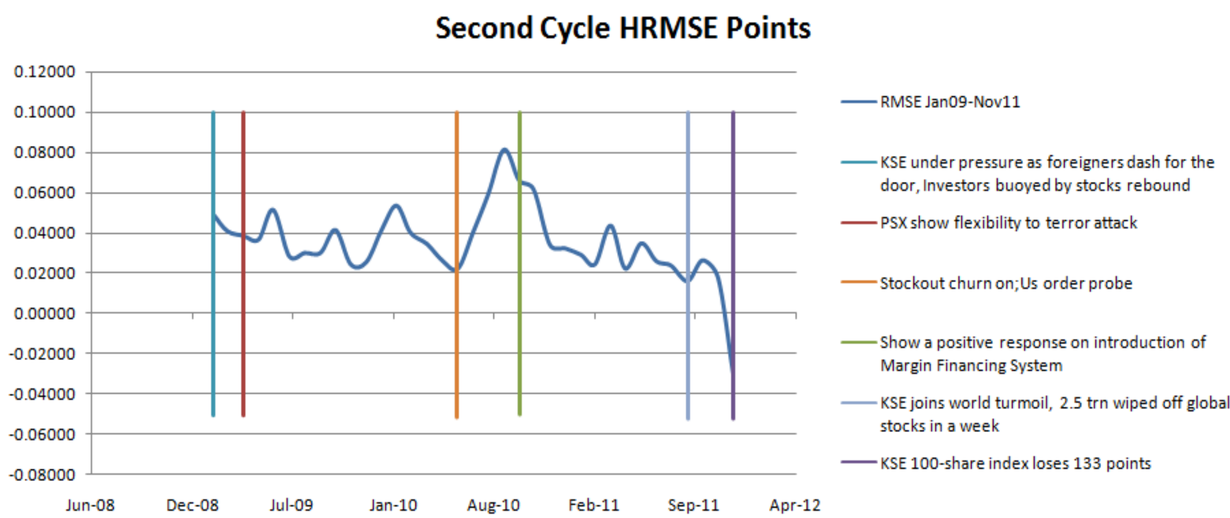
News shows that the stock market rises within a week after the election. The rise of KSE-100 is a clear indication from elections that political stability is a significant cause for the smooth movement of the market. Confidence in the economic policies of the government takes the index to high value. These springing surprises did not remain pleasant for long. In April 2008, the index started facing troubles. In four months, the market faces a scary sinking of 42 percent. To give a short breathing space to the market, regulators have decided to put the floor under the index at level 9,144 on August 28. It was a big crash of the Pakistan stock market and a prolonged closure of the world's stock market. The floor was removed after four months on December 15, 2008.

5.5.2 Second cycle of high root mean square error and low root mean square error

The second cycle of high and low RMSE starts from January 2009 to April 2016. In the first two years, from January 2009 to November 2011, high RMSE is reported. High root means square error explains the low level of predictability in the stock market, which indicates efficiency in the market during these two years. Moreover, from December 2011 to May 2016, the RMSE is showing low values. Due to the lower values of RMSE, the level of predictability increased. When it became easy to predict a market's future movement, it is considered an inefficient market, so these remaining years show the market's inefficiency during this period.

From January 2009 to November 2011, the period with higher root means the square error is plotted in figure 18. New Year brings a stable political situation, which causes new hope of development for the Pakistan stock exchange (PSX). After the crash of 2008 now this is the time of market revival. The reinstatement of judges of the Supreme Court of Pakistan on 31 March 2009 brings a positive impact on the stock market.

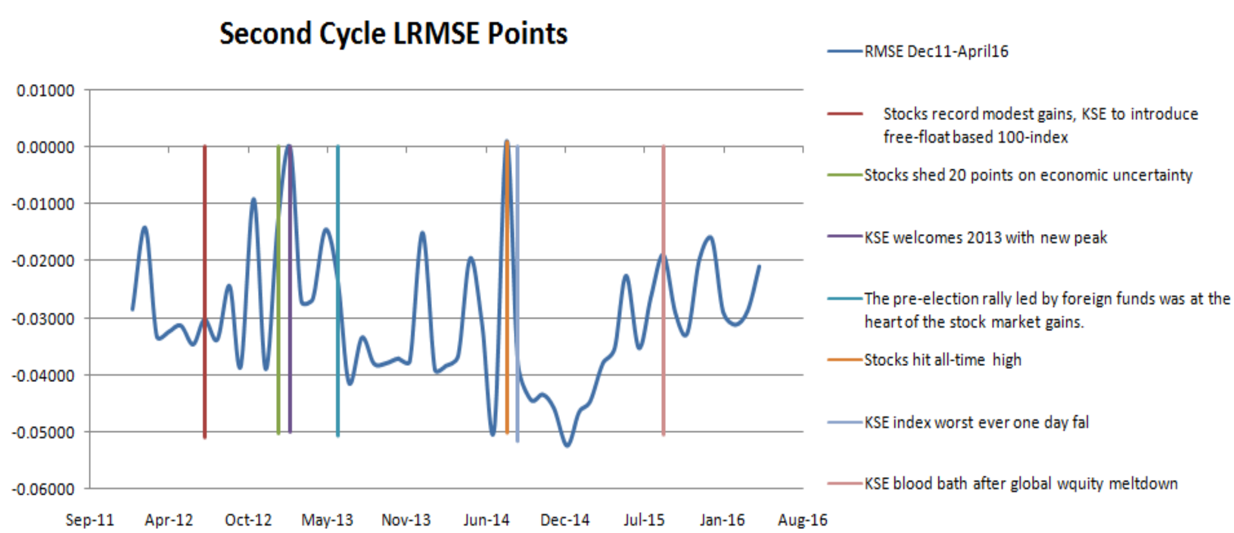
Figure 27. High root mean square data points Feb09-Nov11



THE lower RMSE plotted from December 2011 to April 2016 shows the second cycle's lower movement. When we relate these data points to the news published in Dawn newspaper, we know that 2012 was good. PSX show modest gain in June. This year, PSX was the best performing stock market in the region. However, during December 2012, the economy's prevailing uncertainties due to terrorism lowers the market's performance. These periods of economic turbulence impact return predictability in a negative way. Moreover, it leads the market to inefficiency.

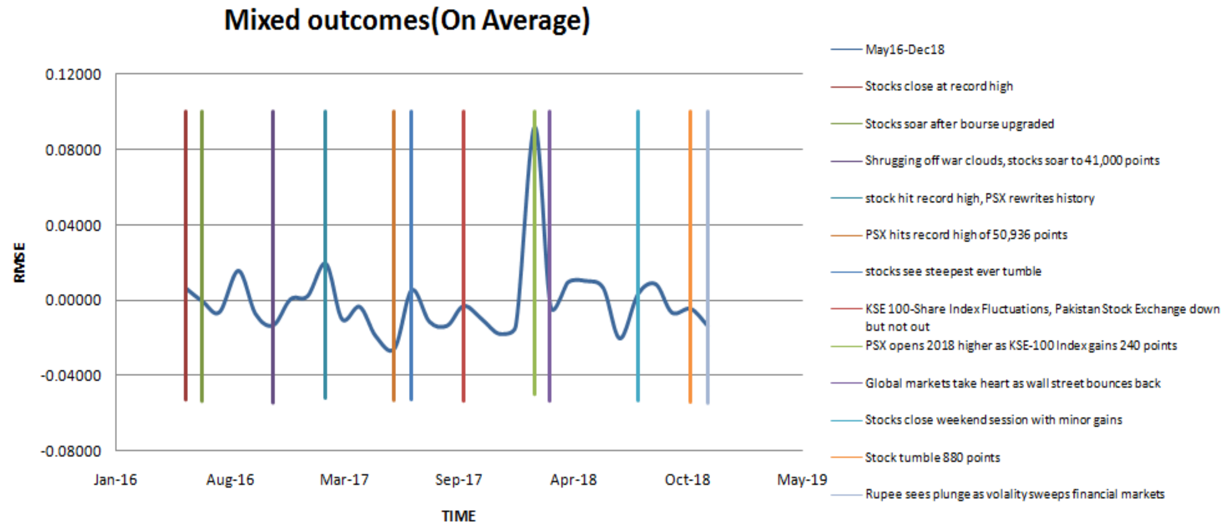
The year 2013 begins with some good news. The major boost to Pakistani equities was provided by declining interest rates, resolution of capital gains tax related issues, improved foreign portfolio inflows. Inflow of foreign investment to Pakistani stocks from January 2013 to onward makes the major cause for this all time high KSE-100 Index. However the foreign funds for the pre-election rally were also at the heart of the stock market gains. Although there were good news in year 201, if we look at the graph and but the impact was not very strong.

Figure 28. Low root mean square data points Dec11-April16



An up gradation of Pakistan economic position in Moody's global rating agency from 'negative' to 'stable ' and an increase in Pakistan weight in MSCI Frontier index causes that all time high index. Uncertain political situation during August 2014 when threats were coming to step down the government and planning to march on Islamabad, KSE-100 index crash down by 4% due to global equity meltdown.

Figure 29. Root mean square values on average threshold point



After April 2016, the KSE-100 errors of predictability are showing mixed outcomes. The values of root mean square error plotted from April 2016 to December 2018 are moving around the average value of root mean square error in figure 28. If we compare this period with Pakistan's economic and political situation at that time, it explains the mixed outcome.

By critically analyzing the significant events in the Pakistan political, economic, and non-economic sectors, we can conclude that the periods in which there is any type of uncertainty, the market goes down. The graph showed in figure and the event occurring at different times elaborate that the market fluctuations are related to the degree of return predictability.

5.6 FIFTH STAGE: CHANGING MARKET CONDITIONS AND PREDICTABILITY

The nature of varying predictability over time is dependent on the market situation. Kim et al., (2011) explained AMH's implication through market fluctuation and suggested that each market is unique and should be monitored individually to check AMH's implications. This section discusses the comparison of return predictability with the changing market conditions. To identify the market condition at any specific time, the study gathers the information from newspapers. Significant events that show a substantial impact on the stock market fluctuations are sorted out by digging out the old newspapers. The news relevant to the stock market and published on the DAWN newspaper's front pages is selected as important news. The total number of news selected is eighty-three to compare the degree of predictability and market condition.

Out of eighty-three forty-eight news consists of positive news, thirty-two considered hostile, and four is neutral. The positive and negative news is checked against the error fluctuations. Whenever there is a piece of positive news regarding a stable political or economic front, the possibility of stock market predictability demonstrates a decreasing trend. The values of RMSE are high in these periods. The value of RMSE against negative news about the uncertain economic environment or any crash in the stock market shows a downward trend. There is some news which does not show any fluctuation in the return predictability pattern.

The eight data points were published during this period from January 2003 to December 2004. These data points' responses indicate eight news published during this period and showing high error terms. From January 2005 to February 2009 thirteen data points are selected to compare the response of these thirteen news with the error terms. During this time period the trend of RMSE is moving towards lower. Data points from January 2005 to February 2009 are showing low root mean square error. However, not very low peaks are visible from the plotting of root mean square values during this period. Overall, this period shows the low root mean square values, which conclude that prediction ability is high during this period, and the market is behaving inefficiently. Moreover, when these data points are contrasted with the prevailing market, economic and political conditions, it explains the reason behind these low levels of RMSE values. The major cause of market inefficiency are the crash of the stock market in 2005, the assassination of the former two times PM of Pakistan, the slower process of Pakistan steel mill (PSM) privatization, Pakistan's president Musharaf Former army chief of Pakistan resignation, 2008 elections and crash of 2008.

The second cycle of high and low RMSE starts from January 2009 to April 2016. In the first two years, from January 2009 to November 2011, high RMSE is reported. High root means square error explains the low level of predictability in the stock market, which indicates efficiency in the market during these two years. Six news have been selected for comparing the important fluctuations of the market with high RMSE values during first two years of this cycle. Moreover, from December 2011 to May 2016, the RMSE is showing low values. Seven news have been selected to compare these low values of RMSE with market fluctuations. Due to the lower values of RMSE, the level of predictability increased. When it became easy to predict a market's future movement, it is considered an inefficient market, so these remaining years show the market's inefficiency during this period

Twelve news have been selected to compare the fluctuations of stock market during the last cycle. When we relate these data points to the news published in Dawn newspaper with the values of root mean square error plotted from April 2016 to December 2018 are moving around the average value of root mean square error in figure 28. If we compare this period with Pakistan's economic and political situation at that time, it explains the mixed outcome. By critically analyzing the significant events in the Pakistan political, economic, and non-economic sectors, we can conclude that the periods in which there is any type of uncertainty, the market goes down. The graph showed in figure and the event occurring at different times elaborate that the market fluctuations are related to the degree of return predictability.

5.7 DISCUSSION ON THE RESULTS

Based on the above-reported results, we can address the objectives now with proper justification. The optimal ANN model, which is a nonlinear autoregressive neural network, presents the values of error preferences. The lower value of these errors is considered best. These values of error preferences show the predictability level of the ANN model. The periods, at which these error preference measures are low, the model is the best predictable model. Moreover, the data points at which these error preference measures are high, the model does not show the best predictability. Further, the Rolling window analysis gives a detailed insight to interpret index movement hence the market level of predictability or unpredictability.

A rolling window analysis must distribute the data set in an appropriate data split ratio. Training data must be of suitable size so that it can deal with noise and non-stationarily in data. In the case of smaller training data, the ANN estimation is not of fair value. Results from rolling window analysis are documented to detect that if there any possible seasonal patterns or not. The detection of error terms movement upward or downwards suggests a low level of predictability or high predictability, respectively. The neural network model is used to detect the predictability movement. These movements are then compared with the changing environment in the stock market and political and economic situation. By digging out the historical newspapers, the total number of news is eighty-three selected. When correlated with the order of performance measure error, this selected news handover the remarkable interpretation. The data points showing low error terms responding to the good times, and most of the good news is surrounding the market. Whenever there is positive news regarding stock market reforms or policies, the error term reports a downward movement.

The market is considered efficient compared to the points where the error performance term is small, and prediction is accessible, reflecting inefficiency. This rule can be elaborated on in two different notions. The first one is that if the small error terms move towards the broad error terms, it will represent the movement of inefficiency to efficiency, which shows the market's adaptiveness. The second notion is that moving from broad error terms to small error terms will represent efficiency to inefficiency, showing the market's inefficiency.

According to the defined rule in chapter 4 (Table 3), the periods with large measuring errors represent low predictability levels, which show efficiency. A period with small measuring error reports inefficiency in the market. From the reported results, we could conclude that some periods show low levels of predictability, and in some periods, the possibility to predict the market increased. These periods of efficiency and inefficiency validates the time-varying nature of market efficiency. These results report that in PSX, the level of predictability varies over time. It indicates that the level of PSX efficiency and inefficiency does not remain static over the entire sample period and shift from efficiency to inefficiency. This varying nature of efficiency is in line with the studies of (Lo, 2005), (Todea et al., 2009), (Kim et al., 2011), and (Verheden, 2013).

The shifting of PSX from a state of inefficiency to efficiency and then again from efficiency to inefficiency indicates the cyclical patterns of efficiency and inefficiency. Several studies indicate that the cyclical movement of market efficiency and inefficiency is related to AMH theories. AMH suggests that the market follows the process of evolution and reaches its maturity, but for a market, it is not possible to remain in that state for a long time. Some market crashes, new participants, and other conditions bring shorter periods of inefficiency in the market. These cycles of efficiency and inefficiency justify the implications of AMH, as suggested by (Kim et al., 2011), (Lo, 2012), and (Hiremath and Kumari, 2014).

The shifting of PSX from efficiency to inefficiency at the beginning of the market highlighted the essential findings. From January 2003, December 2004, the stock market is showing low levels of predictability or, in other words, is going through an efficient period. From January 2005 to February 2009, there is a possibility to predict the market more accurately. This represents that the market is passing through an inefficient market condition. According to the rule defined in Table 3(chapter 4), we can see that when the market is moving from low predictability to high predictability, the market is moving towards inefficiency. This cycle of efficiency to inefficiency justifies (Lo, 2012) implication that a newly incorporated market can be more efficient. However, it can bring inefficiencies when some dislocation comes into the market environment. As the reason behind the inefficiency from January 2005 to February 2009 is the highly uncertain political and economic environment in Pakistan during this period (Gul et al., 2013). Moreover, it was also the time of the global financial crisis, which badly affects the PSX (Ali and Afzal, 2012).

The cyclical fluctuations of market efficiency and inefficiency also justify the evolutionary approach of AMH. AMH's revolutionary approach suggests that market efficiency dynamics depend on the process of natural selection and competition among investors by entering new investors to the market and moving out of old investors from the market (Lo, 2012). The evolutionary nature of PSX validates the research findings of (Urquhart and Hudson, 2013), (Noda, 2016), and (Urquhart and McGroarty, 2016).

In the second part of the study, the cyclical shifts of market efficiency and inefficiency are correlated with the market fluctuations. The market fluctuations are determined by the stock market news published in newspapers. Research findings indicate that the shift in PSX market efficiency and inefficiency depends on the market conditions (Kim et al., 2013). The research findings of the shift in market efficiency and inefficiency due to the prevailing market conditions validate the studies of (Popovic et al., (2013) and (Urquhart and McGroarty, 2016).

From January 2009 to November 2011, high RMSE is reported. High root means square error explains the low level of predictability in the stock market, which indicates efficiency in the market during these two years (Nazir et al., 2014). Moreover, from December 2011 to May 2016, the RMSE is showing low values. These periods of economic turbulence impact the return predictability in a negative way (Rehman and Khan, 2015), Terrorist attacks are significant events to financial markets. Terrorist attacks adversely affect the Pakistani stock market, leading the market towards inefficiency for a shorter time (Aslam and Kang, 2015). Due to the lower values of RMSE, the level of predictability increased. When it became easy to predict a market's future movement, it is considered an inefficient market, so these remaining years show the market's inefficiency during this period. This cycle of efficiency to inefficiency justify the implications of (Lo, 2012).

After April 2016, the KSE-100 errors of predictability are showing mixed outcomes. The values of root mean square error plotted from April 2016 to December 2018 are moving around the average value of root mean square error in figure 20. If we compare this period with Pakistan's economic and political situation at that time, it explains the mixed outcome. This type of fluctuations of PSX predictability could not be justified according to the defined rule. Such fluctuations during this period with Pakistan's economic and political situation at that time, it explains the mixed outcome. By critically analyzing the significant events in the Pakistan political, economic, and noneconomic sectors, we can conclude that the periods in which there is any type of uncertainty, the market goes down.

AMH's revolutionary approach suggests that market efficiency dynamics depend on the process of natural selection and competition among investors by entering new investors to the market and moving out of old investors from the market. we compare this period with Pakistan's economic and political situation at that time, it explains the mixed outcome. By critically analyzing the significant events in the Pakistan political, economic, and noneconomic sectors, we can conclude that the periods in which there is any type of uncertainty, the market goes down. The graph showed in figure and the event occurring at different times elaborate that the market fluctuations are related to the degree of return predictability.The news relevant to the stock market and published on the DAWN newspaper's front pages is selected as important news. The total number of news selected is eighty-three to compare the degree of predictability and market condition. Out of eighty-three forty-eight news consists of positive news, thirty-two considered hostile, and four is neutral. The positive and negative news is checked against the error fluctuations. Whenever there is a piece of positive news regarding a stable political or economic front, the possibility of stock market predictability demonstrates a decreasing trend

According to the defined rule in chapter 4 (table 3), another explanation of this reported movement of return predictability can be drawn. The study defines if the performance measuring error moves from large measuring errors to a small measuring error. To large measuring errors, then this cyclical pattern is showing adaptiveness. From January 2003 to December 2004, the stock market shows low levels of predictability or, in other words, is going through an efficient period moving towards high predictability from January 2005 to February 2009, showing inefficiency and then again moves towards the low predictability during January 2009 to November 2011. Such movements are indicating the adaptiveness of the market. According to the defined rule, we could conclude that PSX can be better understood in light of AMH's implications. From January 2003, December 2004, the stock market is showing low levels of predictability or, in other words, is going through an efficient period. From January 2005 to February 2009, there is a possibility to predict the market more accurately. This represents that the market is passing through an inefficient marketcondition

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According to the defined rule, we could conclude that PSX can be better understood in light of AMH's implications. From January 2003 to December 2004, the stock market is showing low levels of predictability or, in other words, is going through an efficient period. From January 2005 to February 2009, there is a possibility to predict the market more accurately. This represents that the market is passing through an inefficient market condition. The second cycle of high and low RMSE starts from January 2009 to April 2016. In the first two years, from January 2009 to November 2011, high RMSE is reported. High root means square error explains the low level of predictability in the stock market, which indicates efficiency in the market during these two years. . From January 2009 to November 2011, the period with higher root means the square error is reported. New Year brings a stable political situation, which causes new hope of development for the Pakistan stock exchange (PSX). After the crash of 2008 now this is the time of market revival. The reinstatement of judges of the Supreme Court of Pakistan on 31 March 2009 brings a positive impact on the stock market.

Moreover, from December 2011 to May 2016, the RMSE is showing low values. Due to the lower values of RMSE, the level of predictability increased. When it became easy to predict a market's future movement, it is considered an inefficient market, so these remaining years show the market's inefficiency during this period. After April 2016, the KSE-100 errors of predictability are showing mixed outcomes. If we compare this period with Pakistan's economic and political situation at that time, it explains the mixed outcome. By critically analyzing the significant events in the Pakistan political, economic, and noneconomic sectors, we can conclude that the periods in which there is any type of uncertainty, the market goes down. Such mixed outcomes need further explanation and theoretical justification.

6 Conclusion

This chapter outlines the concluding remarks on how this work tries to answers the objective of the study. The study was conducted to check the validity of the adaptive market hypothesis in the context of Pakistan's equity market. The objective was to find evidence regarding the AMH implications; instead, these assumptions are better capable of explaining market behavior. The findings from this study contribute to the debate on market efficiency.

The literature review chapter begins by demonstrating how the classical school of thoughts conveys market efficiency. The concept of market efficiency states that a market is efficient in which the future stock prices are not predictable, and it is not possible to earn an abnormal return. The idea of market efficiency gain importance in 1970 when Fama defines the EMH. Numbers of studies have documented the random behavior of stock prices, which was in favor of EMH. However, the behavioral school of thoughts criticizes EMH based on findings that show the deviation of the stock market from the random walk and presented the behavioral biases which participate in the price formation process. The behavioral school of thought contradict the assumptions of EMH and concludes that investors can manipulate the stock market's behavior. They can generate abnormal returns by analyzing the patterns of stock prices using different statistical techniques. However, whatever the viewpoint, either the EMH or behavioral school of thought, there is no agreement on the topic that markets are efficient or not. To overcome the controversy and explain the time-varying market efficiency, the idea of AMH was presented by Lo (2004). AMH postulates that profit opportunities arise from time to time because of changing market dynamics.

The statistical techniques which have been used for time series analysis can be categorized into four major headings. Traditionally linear statistical measurement techniques were used for time series analysis. After the findings of nonlinear phenomena in the time series, many nonlinear statistical methods have been developed. However, now the focus is shifted towards the most robust techniques available for analyzing the time series. These methods are based on machine learning. The ANN is one of them which overcome the deficiencies of traditional linear and nonlinear statistical measurement techniques. ANNs are relatively new in finance, but as compared to traditional econometric methods, the advantages of ANNs are more distinct for approximation purposes.

Chapter three provides a detailed methodology for looking at the stock return predictability on KSE-100, from 2000 to 2018, using monthly data with NARNN under rolling window analysis. The methodology of this research work is divided into three major stages. The architecture of the neural network required little work, which is done in the first stage. The collected data set is processed for the selection of optimal parameters of the ANN model. Selected parameters are used to model the NARNN model under the rolling window frame work in the second stage. This rolling window analysis helps us to look at the time-varying fluctuations. In the third stage, the results from rolling window analysis are compared with the market fluctuations.

The selection process of the neural network's optimal architecture suggests that minimum numbers of hidden layers reduce the complexity of the network. Increasing the hidden layers from 1 to 2 and hidden nodes more than 20 caused an increase in mean square error. Input variable selection also supports the literature in favor of one lag series as the best input variable. The return generating process modeled by the optimal neural network model under rolling window analysis on monthly data enables us to look into the changing market efficiency over eighteen years time period. A sudden increase or decrease of mean square error responds to the news about significant events during this time frame. At the time of financial market crashes, some political instability or new financial reforms significantly affected the predictability by correlating the significant events to the root mean square error for returns forecasting provides a total viewpoint on market efficiency.

From the findings, it can be concluded that there are periods of accurate prediction and periods of inaccurate prediction. These findings validate AMH's concept and provide empirical evidence that the PSX equities market is efficient, as defined by AMH (Lo, 2004). These findings provide evidence of time-varying predictability, where stock returns go through periods of return predictability and non-predictability (Hiremath and Kumari, 2014). The rolling window method approach from (Ito et al., 2014, 2016) provides a more accurate measurement of time-varying market efficiency than conventional statistical inferences. The Time-varying model approach shows that the market has a changing degree of efficiency, and this varying efficiency is travelled in cyclical patterns (Svensson and Soteriou, 2017).

Interpretation of the findings in response to the Pakistan stock market's prevailing market conditions explains the importance of changing market conditions for the degree of return predictability (Kim et al., 2011). The research findings reports that during the time of financial crises and political instability the possibility to predict the market is higher. The higher return predictability during the political and economic crisis pointed towards the strong miss reaction from investors. These results suggest that investors' behavior is also context-dependent and dynamic and driven by changing market conditions. These findings are also in agreement with (Hiremath and Kumari, 2014) findings, which suggest that the possibility of return predictability increased during times of crisis.

The assumptions of AMH proposed that every individual market behaves under its economic and political environment, so every market must behave differently (Urquhart and McGoarty, 2016). This study complements the literature on the growing research in AMH by adding the study on PSX.

6.1 PRACTICAL IMPLICATION

The contribution of this research work is twofold, this work not only contributes towards the explanation of the appropriate behavior of PSX but also provide a new perspective for the portfolio managers and policymaker in decision making. The first implication of the study belongs to the observed cyclical patterns of efficiency and inefficiency. The cyclical patterns suggest that there is a possibility to predict the market on the arrival of uncertain events. If the environment shifts or the population of investors changes materially, PSX will show inefficient behavior. The investment decision should be taken because of the changing market conditions. The investment decisions should not be taken only by looking at the relative proportion of market participants. However, the decision makers should monitor the stock market as a routine activity to improve the market productivity.

It suggests that in PSX, there is always a possibility that the market will show some predictability levels based on the market condition. The possibility of the market to show some predictability at some levels enlightened the second important implication. It suggests that the relationship between risk and reward does not remain same all the time. It depends on the prevailing market condition. During the crises time period an investment management perspective would be change about the risky projects. The investment policies should be decided in light of the theories presented by AMH.

The third implication drawn from this research study is the relevance of market conditions and the changing level of predictability. It concludes that the dynamics through which one can predict the market are flexible. Moreover, this flexibility is closely related to economic and political stability. The favorable economic and political situation in an emerging economy may lead to a market to predict, become difficult, and leads the market towards efficiency. These findings suggest that appropriate investment strategies align with the changing market conditions.

6.2 LIMITATIONS

The availability of data was the first constraint faced by the researcher. Although the stock market of Pakistan was incorporated in 1947, the historical data is not reliable. The data set after the introduction of CTS in 2000 is incorporated in this research study. A nineteen year of data is incorporated into this study. However, while investigating the trends of efficiency and inefficiency in the developed markets, the very long data set has been incorporated (Urquhart and McGoarty, 2016) and Kim et al., (2011). Due to the shorter sample, the shorter moving window was decided in this study.

The second limitation of the study relates to the analysis of market dynamics and adaptive market hypothesis implications. For comparing the market movements with the prevailing market conditions this study focuses on the qualitative analysis. The selected news and their comparison with movement of stock market can be subjective opinion biased.

Comparing the political and economic situation with the response of the optimal model was a difficult task. To collect published news relevant to the stock market from old newspapers, only one data source is selected. Again this was due to the non-availability of any digital source for old news.

6.3 FUTURE DIRECTIONS

AMH's true spirit can be better explained when some psychological factors can also be incorporated into the research design. Changing patterns of return predictability can be explained by the psychology of old and new investors. The behavior of the Pakistan stock market needs further evaluation concerning persistent anomalies in the market. Different researchers document anomalies in the Pakistan stock market in recent years (Quayyouma et al., 2017). These anomalies and their persistence can be clarified under the assumptions of adaptive market hypothesis presented by Lo (2004, 2005, and 2012).

6.4 CONCLUDING REMARKS

The concluding remarks on the thesis can declare that Pakistan's stock market is having an evolving nature of efficiency, as proposed by Lo (2005, 2012). It reveals that for PSX, it is not possible to be efficient over the entire sample period. The concept of market efficiency in PSX is moved from a static nature of efficiency to dynamic efficiency. The PXSX is showing cyclical patterns of efficiency and inefficiency. It suggests that the PSX has periods of accurate and inaccurate predictions. The recurring patterns of return predictability confirm that the risk and reward do not remain constant in a market. Rapid changes in volatility cause investors to take some safety measures. Moreover, investors shifted their investments from risky assets to safe assets. In highly uncertain situations, the positive association between risk and reward does not remain the same.

In financial time series analysis, when modelling returns without any preliminary processing on data, the artificial neural network model shows the potential research area. The ANN is one of the new statistical techniques which overcome the deficiencies of traditional linear and nonlinear statistical measurement techniques. ANNs are relatively new in finance, but as compared to traditional econometric methods, the advantages of ANNs are more distinct for approximation purposes.

To model, the return predictability patterns and the changing level of predictability over varying time frames can be analyzed under the rolling window framework. By using such a framework, one can examine the market efficiency as proposed by AMH.

The assumptions of AMH proposed that every individual market behaves under its economic and political environment and every market must behave differently. This study complements the literature on the growing research in AMH by adding the study on PSX. The cyclical patterns suggest that there is a possibility to predict the market on the arrival of uncertain events. The results from rolling window analysis the root mean square error for returns forecasting by correlating the significant events of the market provides a total viewpoint on market efficiency. Comparison with the market fluctuations concludes that at the time of financial market crashes, some political instability or new financial reforms significantly affected the predictability If the environment shifts or the population of investors changes materially, PSX will show inefficient behavior. These findings suggest that in PSX the investment strategies should be align with the assumptions of AMH to get maximum benefits from the market.

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Appendices

Appendix A

Author	Subject Under Examination	Empirical data	Test implemented	findings /remarks
		Asian Markets		
Arusha V. Cooray and G. Wickramasigh (2007)	The efficiency of emerging stock markets: empirical evidence from the South Asian region	fIndia,Sri Lanka, Pakistan and Bangladesh, January 1996 to January 2005	Augmented Dickey Fuller (ADF-1979, 1981), the Phillips-Perron (PP-1988), the Dicky-Fuller Generalized Least Square (DF-GLS-1996) and Elliot-Rothenberg-Stock (ERS – 1996) tests	Weak form efficiency is supported by the classical unit root tests. However, it is not strongly supported for Bangladesh under the DF-GLS and ERS tests.
NisarandHanif (2012)	Testing Weak Form of Efficient Market Hypothesis: Empirical Evidence from South-Asia	14 Years (1997-2011)	Runs test, serial correlation, unit root and variance ratio test.	None of the four major stock markets of south-Asia follows Random walk and hence not all these markets are the weak form of efficient market.
Mishra et, al. (2014)	The Random-Walk Hypothesis on the Indian Stock Market	monthly data for the period January 1995 – December 2013 (19 years)	traditional unit root tests Lee and Strazicich (2003) LM unit root test Narayan and Popp (2010) unit root test Narayan and Liu (2013) GARCH unit root test	Our results point to the need to consider heteroskedasticity when testing for a random walk with high frequency financial data. When we do this, we find that the Indian stock indices are mean reverting.
Gupta and Yang (2011)	Testing Weak form Efficiency in the Indian Capital Market	1997 to 2011.	ADF, PP and KPSS	Markets do not show characteristics of random walk and as such are not efficient in the weak form.

Kasilingam Lingaraja1 , Murugesan Selvam1 andVinayagamoorthiVasanth (2014)	The Stock Market Efficiency of Emerging Markets: Evidence from Asian Region	Eight Asian Emerging market indices. For ten years from 01-01-2004 to 31-12-2013	(GARCH, Autocorrelation and Runs Test	Significant evidences of market efficiency and randomness distribution in these emerging Asian markets.
AmnaTahir (2011)	Capital Market Efficiency: Evidence from Pakistan	twenty companies from the Karachi stock exchange	unit root test, runs test and autoregressive integrated moving average (ARIMA)	KSE is inefficient in the weak form.
		Middle Eastern emerging markets		
MarashdehandShrestha (2008)	Efficiency in Emerging Markets - Evidence from the Emirates Securities Market	August 2003 to 13 April 2008	ADF and PP Unit Root Test, Perron (1997) Unit Root	Emirates stock market index has a unit root and follows a random walk. This is consistent with the weak-form of the efficient market hypothesis
BatoolAsiri and HamadAlzeera (2013)	Is the Saudi Stock Market Efficient? A case of weak-form efficiency	All share index and sectoral indices for daily closing prices, between October 15, 2006 and November 15, 2012	Unit root Dickey-Fuller test, Pearson Correlation test, Durbin-Watson test and Wald-Wolfowitz runs-test	The four tests confirmed the weak-form market efficiency in the Saudi stock market for All share prices and 11 individual sectors.
		African Markets		

MlamboandBiekpe (2007)	The efficient market hypothesis: Evidence from ten African stock markets	02 Jan 97 - 30 Dec 02	results from the Box-Ljung, ACF and PACF are used here to show the prevalence of higher order serial correlation for Africanstock markets.	
Maria Rosa Borges (2010)	Efficient market hypothesis in European stock markets	stock market indexes of UK, France, Germany, Spain, Greece and Portugal, from January 1993 to December 2007.	runs test, and joint variance ratio tests, which are performed using daily and weekly data for the period 1993–2007 and for a subset, 2003–2007	Mixed evidence found, The hypothesis is rejected on daily data for Portugal and Greece, France and UK data rejects EMH, due to the presence of mean reversion in weekly data, and stronger in recent years. market being the Taken together, the tests for Germany and Spain do not allow the rejection of EMH, this last most efficient.
Ananzeh (2014)	Testing the Weak Form of Efficient Market Hypothesis: Empirical Evidence from Jordan	Jan 2000 to Dec 2013	Autocorrelation Function Test (ACF) Unit Root Tests Run Test	The results of serial correlation reject the presence of random walks in daily returns of the ASE Index. In addition, the runs tests conclude that the ASE at the weak form is inefficient. The unit root tests also conclude the weak-form inefficiency in stock return series for ASE.

Appendix B

Author	Subject Under Examination	Empirical data	Test implemented	findings /remarks
Tim Verheyden, Filip Van den Bossche and Lieven De Moor (2013)	Towards a new framework on efficient markets: A rolling variance ratio test of the adaptive markets hypothesis	Historical prices of the three major U.S. stock markets (Dow Jones Industrial Average (DJIA), Standard and Poor's-500 (SandP-500) and NASDAQ) and the largest Belgian stock market (BEL-20)	Rolling Variance Ratio test using daily data and rolling windows of length 6 months and 1 year.	peaks in p-values represent periods with a relatively high degree of weak form market efficiency and the time between the different peaks can be characterized by a relatively low degree of efficiency. Study confirms the dynamic character of weak form market efficiency, and the opposite pattern was found with long periods of relatively low degrees of efficiency being disturbed by short periods of relatively higher degrees of efficiency in times of market mania.
Andrew W. Lo (2005)	Reconciling efficient markets with behavioral finance: The adaptive Markets hypothesis	monthly returns of the SandP Composite Index from January 1871 to April 2003	computing the rolling first-order autocorrelation	Based on evolutionary principles, the Adaptive Markets Hypothesis implies that the degree of market efficiency is related to environmental factors characterizing market ecology such as the number of competitors in the market, the magnitude of profit opportunities available, and the adaptability of the market participants.
AlexandruTodea , Maria ulici, and SimonaSilaghi (2009)	Adaptive markets hypothesis: evidence from Asia-pacific Financial markets	period under study being 1997-2008	investigate the profitability of the moving average strategy on six Asian capital markets considering the episodic character of linear and/or nonlinear dependencies,	Profitability of moving average strategies is not constant in time; it is episodic showing when sub-periods of linear and non-linear correlation appear. Efficiency varies in a cyclical fashion over time and these statistical features are in line with Adaptive Markets Hypothesis (AMH) of Lo (2004, 2005).

Gourishankar S Hiremath and JyotiKumari (2014)	Stock returns predictability and the adaptive market hypothesis in emerging markets: evidence from India	Sensex data is from January 1991 to March 2013, while Nifty data spans from January 1994 to March 2013.	Linear Tests: Autocorrelation Test, Runs Test, Variance ratio test and Multiple variance ratio test Nonlinear test: Mcleod Li test, Arch LM test and BDS test	linear tests show a cyclical pattern suggesting that the Indian stock market switched between periods of efficiency and inefficiency. In contrast, the results from nonlinear tests reveal a strong evidence of nonlinearity in returns throughout the sample period with a sign of tapering magnitude of nonlinear dependence in the recent period. The findings suggest that Indian stock market is moving towards efficiency.
SašaPopović, Ana Mugoša and AndrijaĐurović (2013)	Adaptive markets hypothesis: Empirical evidence from montenegro equity market	market value weighted index MONEX20, over 2004-2011	first order serial autocorrelation coefficients	The evidence was found that all three factors, observation period, time horizon represented by rolling window sizes and data aggregation level, impact degree of weak form Montenegro equity market efficiency which has serious consequences on profit opportunities over time on this market
MajidMirzaeeGhazani and Mansour KhaliliAraghi (2013)	Evaluation of the adaptive market hypothesis as an evolutionary perspective on market efficiency: Evidence from the Tehran stock exchange	Daily returns of Tehran stock exchange (TSE) from 1999 to 2013	linear (automatic variance ratio and automatic portmanteau) and nonlinear (generalized spectral and McLeod–Li)	tests represent the oscillatory manner of returns about dependency and independency which corresponds with the adaptive market hypothesis.
Kian-Ping Lim and Robert D. Brooks (2006)	The evolving and relative efficiencies of stock Markets: empirical evidence from rolling Bicorrelation test statistics	Using all the country indices constructed by MSCI that covered both developed and emerging stock markets,	Portmanteau bicorrelation test statistic	Results reveal that the degree of market efficiency varies through time in a cyclical fashion over time. These statistical features are in line with the Adaptive Markets Hypothesis of Lo (2004, 2005, 2006).

JianZhou and Jin Man Lee (2013)	Adaptive market hypothesis: evidence from the REIT market		automatic variance ratio test of Choi (1999), and the automatic portmanteau test of Escanciano and Lobato (2009)	The degree of REIT return predictability is found to be time varying return predictability is indeed influenced by market conditions.

Appendix C

Table 13. ***MSE First lag, all combinations, node 1 to node 50.***

Comb/H.N	**1N**	**2 N**	**3 N**	**4 N**	**5 N**	**6 N**	**7 N**	**8 N**
.6,.2,.2	0.006161	0.005994	0.006259	0.006324	0.006254	0.006169	0.006432	0.027282
.65, .15, .2	0.006177	0.005994	0.006403	0.006377	0.006405	0.006169	0.006606	0.027282
.65,.2,.15	0.006161	0.005994	0.006294	0.006377	0.006254	0.006169	0.00651	0.027282
.7,.2,.1	0.006161	0.005994	0.006294	0.006377	0.006405	0.006169	0.006606	0.027282
.7,.15,.15	0.00619	0.005994	0.006403	0.006377	0.006405	0.006169	0.006606	0.027282
.7,.1,.2	0.006205	0.005995	0.006605	0.006377	0.006624	0.006169	0.006606	0.027282
.75,.2,.05	0.006177	0.005994	0.006337	0.006377	0.006405	0.006169	0.006606	0.027282
.75,.15,.1	0.006198	0.005994	0.006403	0.006377	0.006405	0.006169	0.006606	0.027282
.75,.1,.15	0.006224	0.005995	0.00673	0.006377	0.006624	0.00617	0.006606	0.027282
.75,.05,.2	0.006271	0.005995	0.006921	0.007137	0.007602	0.006224	0.006952	0.027282
.8,.05,.15	0.006296	0.005995	0.007177	0.007785	0.007602	0.006278	0.006952	0.037126
.8,.1,.1	0.006244	0.005995	0.00673	0.006652	0.00695	0.006199	0.006606	0.027282
.8,.15,.05	0.006198	0.005994	0.006479	0.006377	0.006624	0.006169	0.006606	0.027282
.85,.05,.1	0.006352	0.005995	0.007664	0.00914	0.008626	0.006278	0.007065	0.038818
.85,.1,.05	0.006244	0.005996	0.00673	0.006652	0.00695	0.006224	0.006723	0.027282
.9,.05,.05	0.006448	0.005995	0.008692	0.012879	0.008626	0.006429	0.007065	0.064883
Comb/H.N	**15 N**	**20 N**	**25 N**	**30 N**	**35 N**	**40 N**	**45 N**	**50 N**
.6,.2,.2	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.65, .15, .2	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.65,.2,.15	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.7,.2,.1	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.7,.15,.15	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.7,.1,.2	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.75,.2,.05	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.75,.15,.1	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.75,.1,.15	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.75,.05,.2	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	0.742216	2.881206
.8,.05,.15	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	0.742216	2.881206
.8,.1,.1	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	0.742216	2.881206
.8,.15,.05	0.723845	0.378652	1.245405	0.246324	2.952993	0.847585	0.742216	2.881206
.85,.05,.1	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	1.635757	2.881206
.85,.1,.05	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	0.742216	2.881206
.9,.05,.05	0.723845	0.378652	1.372937	0.246324	2.952993	0.847585	1.635757	2.881206

Table 14. ***MAE First lag, all combinations, node 1 to node 50***

Comb/H.N	1N	2 N	3 N	4 N	5 N	6 N	7 N	8 N
.6,.2,.2	0.061256173	0.054907	0.047857	0.066578	0.06176	0.049423	0.054249	0.126062
.65, .15, .2	0.061525958	0.054907	0.046452	0.06767	0.063989	0.049423	0.053272	0.126062
.65,.2,.15	0.061256173	0.054907	0.047337	0.06767	0.06176	0.049423	0.053821	0.126062
.7,.2,.1	0.061256173	0.054907	0.047337	0.06767	0.063989	0.049423	0.053272	0.126062
.7,.15,.15	0.061662246	0.054907	0.046452	0.06767	0.063989	0.049423	0.053272	0.126062
.7,.1,.2	0.062214362	0.054883	0.045456	0.06767	0.067079	0.049423	0.053272	0.126062
.75,.2,.05	0.061525958	0.054907	0.046943	0.06767	0.063989	0.049423	0.053272	0.126062
.75,.15,.1	0.062049093	0.054907	0.046452	0.06767	0.063989	0.049423	0.053272	0.126062
.75,.1,.15	0.062612358	0.054883	0.045012	0.06767	0.067079	0.049295	0.053272	0.126062
.75,.05,.2	0.063372329	0.054944	0.044725	0.077736	0.075998	0.048136	0.052174	0.126062
.8,.05,.15	0.063579125	0.054944	0.044092	0.084715	0.075998	0.047157	0.052174	0.161407
.8,.1,.1	0.062987936	0.054883	0.045012	0.072325	0.070363	0.048526	0.053272	0.126062
.8,.15,.05	0.062049093	0.054907	0.045937	0.06767	0.067079	0.049423	0.053272	0.126062
.85,.05,.1	0.064056989	0.054944	0.04442	0.094498	0.083139	0.047157	0.053661	0.168969
.85,.1,.05	0.062987936	0.054989	0.045012	0.072325	0.070363	0.048136	0.052778	0.126062
.9,.05,.05	0.064922473	0.05498	0.046451	0.113215	0.083139	0.046173	0.053661	0.22362
Comb/H.N	**15 N**	**20 N**	**25 N**	**30 N**	**35 N**	**40 N**	**45 N**	**50 N**
.6,.2,.2	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.65, .15, .2	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.65,.2,.15	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.7,.2,.1	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.7,.15,.15	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.7,.1,.2	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.75,.2,.05	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.75,.15,.1	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.75,.1,.15	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.75,.05,.2	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	0.812611	1.576939
.8,.05,.15	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	0.812611	1.576939
.8,.1,.1	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	0.812611	1.576939
.8,.15,.05	0.829691328	0.508335	0.939938	0.406824	1.694217	0.781006	0.812611	1.576939
.85,.05,.1	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	1.26587	1.576939
.85,.1,.05	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	0.812611	1.576939
.9,.05,.05	0.829691328	0.508335	1.088587	0.406824	1.694217	0.781006	1.26587	1.576939

Table 15. ***RMSE First lag, all combinations, node 1 to node 50***

Comb/H.N	**1N**	**2 N**	**3 N**	**4 N**	**5 N**	**6 N**	**7 N**	**8 N**
.6,.2,.2	0.0871429	0.0777065	0.0681314	0.0948506	0.08744	0.0723339	0.0804678	0.158522
.65, .15, .2	0.0875724	0.0777065	0.0662375	0.0962138	0.090858	0.0723339	0.0794958	0.158522
.65,.2,.15	0.0871429	0.0777065	0.0674325	0.0962138	0.08744	0.0723339	0.080145	0.158522
.7,.2,.1	0.0871429	0.0777065	0.0674325	0.0962138	0.090858	0.0723339	0.0794958	0.158522
.7,.15,.15	0.0878294	0.0777065	0.0662375	0.0962138	0.090858	0.0723339	0.0794958	0.158522
.7,.1,.2	0.0884779	0.0777322	0.0649009	0.0962138	0.095236	0.0723339	0.0794958	0.158522
.75,.2,.05	0.0875724	0.0777065	0.0668866	0.0962138	0.090858	0.0723339	0.0794958	0.158522
.75,.15,.1	0.0882553	0.0777065	0.0662375	0.0962138	0.090858	0.0723339	0.0794958	0.158522
.75,.1,.15	0.0889562	0.0777322	0.0641353	0.0962138	0.0952367	0.0722395	0.0794958	0.158522
.75,.05,.2	0.0900455	0.077754	0.0633395	0.1086797	0.1079713	0.0709004	0.0775824	0.158522
.8,.05,.15	0.0904711	0.077754	0.0622665	0.1174934	0.1079713	0.069538	0.0775824	0.1845742
.8,.1,.1	0.0894551	0.0777322	0.0641353	0.1020115	0.1000195	0.0713379	0.0794958	0.158522
.8,.15,.05	0.0882553	0.0777065	0.0655928	0.0962138	0.0952367	0.0723339	0.0794958	0.158522
.85,.05,.1	0.0913187	0.077754	0.0623123	0.1300981	0.1176686	0.069538	0.0784604	0.1906585
.85,.1,.05	0.0894551	0.0777359	0.0641353	0.1020115	0.1000195	0.0709004	0.0788605	0.158522
.9,.05,.05	0.0925586	0.0777839	0.063988	0.1543938	0.1176686	0.0679255	0.0784604	0.2442362
Comb/H.N	**15 N**	**20 N**	**25 N**	**30 N**	**35 N**	**40 N**	**45 N**	**50 N**
.6,.2,.2	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.65, .15, .2	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.65,.2,.15	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.7,.2,.1	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.7,.15,.15	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.7,.1,.2	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.75,.2,.05	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.75,.15,.1	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.75,.1,.15	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.75,.05,.2	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.8,.05,.15	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.8,.1,.1	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.8,.15,.05	0.8540058	0.6168502	1.1183273	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.85,.05,.1	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	1.2830719	1.6956986
.85,.1,.05	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	0.8662499	1.6956986
.9,.05,.05	0.8540058	0.6168502	1.1651408	0.4948634	1.7217955	0.9181224	1.2830719	1.6956986

Appendix D

Table 16. ***MAE second lag, all combinations, node 1 to node 50***

Combinations	N1	N2	N3	N4	N5	N6	N7	N8
.6,.2,.2	0.054378	0.056502	0.056865	0.056112	0.055401	0.056656	0.059987	0.053798
.65, .15, .2	0.054523	0.05694	0.057102	0.056356	0.055987	0.056572	0.061093	0.053812
.65,.2,.15	0.054388	0.056616	0.056865	0.056112	0.055401	0.056572	0.061093	0.053798
.7,.2,.1	0.054523	0.056792	0.056865	0.056112	0.05564	0.056572	0.061093	0.053798
.7,.15,.15	0.054523	0.05694	0.057737	0.056465	0.055987	0.056669	0.061093	0.054453
.7,.1,.2	0.054478	0.05721	0.058401	0.056636	0.055987	0.056853	0.061159	0.054083
.75,.2,.05	0.054523	0.05694	0.057115	0.056162	0.055987	0.056572	0.061093	0.053812
.75,.15,.1	0.05452	0.05721	0.057737	0.056394	0.055987	0.056741	0.061093	0.054083
.75,.1,.15	0.054558	0.057519	0.058401	0.056885	0.056254	0.056853	0.061159	0.054083
.75,.05,.2	0.054558	0.058435	0.0594	0.057544	0.059248	0.057352	0.064016	0.054605
.8,.05,.15	0.054805	0.059024	0.060067	0.058934	0.061869	0.057898	0.064016	0.055544
.8,.1,.1	0.054558	0.057519	0.0594	0.057544	0.056956	0.057352	0.062643	0.054112
.8,.15,.05	0.05452	0.05721	0.058401	0.056394	0.055987	0.056853	0.061093	0.054083
.85,.05,.1	0.054805	0.059987	0.060067	0.058934	0.066506	0.05927	0.066411	0.055544
.85,.1,.05	0.054558	0.057958	0.0594	0.057544	0.057702	0.057352	0.062643	0.054605
.9,.05,.05	0.05548	0.063522	0.062485	0.062316	0.075003	0.075592	0.066411	0.065995
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.65, .15, .2	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.65,.2,.15	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.7,.2,.1	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.7,.15,.15	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.7,.1,.2	0.279651	0.701463	0.951789	0.241123	0.482688	0.577066	0.830559	1.704034
.75,.2,.05	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.75,.15,.1	0.279651	0.701463	0.951789	0.290447	0.482688	0.577066	0.830559	1.704034
.75,.1,.15	0.285453	0.701463	0.951789	0.246117	0.482688	0.577066	0.830559	1.704034
.75,.05,.2	0.301595	0.701463	0.951789	0.289895	0.482688	0.577066	0.830559	1.704034
.8,.05,.15	0.316065	0.701463	0.951789	0.289895	0.482688	0.577066	0.830559	1.704034
.8,.1,.1	0.285453	0.701463	0.951789	0.246117	0.482688	0.577066	0.830559	1.704034
.8,.15,.05	0.279651	0.701463	0.951789	0.241123	0.482688	0.577066	0.830559	1.704034
.85,.05,.1	0.316485	0.701463	0.951789	0.289895	0.482688	0.577066	0.830559	1.704034
.85,.1,.05	0.292135	0.701463	0.951789	0.289895	0.482688	0.577066	0.830559	1.704034
.9,.05,.05	0.316485	0.701463	0.951789	0.289895	0.482688	0.577066	0.830559	1.704034

Table 17. ***MSE second lag, all combinations, node 1 to node 50***

Comb/H.N	N1	N2	N3	N4	N5	N6	N7	N8
.6,.2,.2	0.005967	0.006048	0.005915	0.006095	0.006468	0.006025	0.007624	0.006357
.65, .15, .2	0.005992	0.006108	0.005967	0.006142	0.006642	0.006057	0.007975	0.006418
.65,.2,.15	0.005993	0.006074	0.005915	0.006095	0.006468	0.006057	0.007975	0.006357
.7,.2,.1	0.005992	0.00609	0.005915	0.006095	0.006545	0.006057	0.007975	0.006357
.7,.15,.15	0.005992	0.006108	0.006014	0.006147	0.006642	0.00609	0.007975	0.0065
.7,.1,.2	0.006005	0.006147	0.00611	0.006232	0.006642	0.006185	0.007995	0.006552
.75,.2,.05	0.005992	0.006108	0.005956	0.006111	0.006642	0.006057	0.007975	0.006418
.75,.15,.1	0.005994	0.006147	0.006014	0.006174	0.006642	0.00611	0.007975	0.006552
.75,.1,.15	0.006006	0.006206	0.00611	0.006318	0.006824	0.006185	0.007995	0.006552
.75,.05,.2	0.006006	0.006334	0.006198	0.006423	0.007823	0.006356	0.009643	0.006752
.8,.05,.15	0.006037	0.006427	0.006316	0.006707	0.008517	0.006528	0.009643	0.006953
.8,.1,.1	0.006006	0.006206	0.006198	0.006423	0.007053	0.006356	0.008718	0.00658
.8,.15,.05	0.005994	0.006147	0.00611	0.006174	0.006642	0.006185	0.007975	0.006552
.85,.05,.1	0.006037	0.00657	0.006316	0.006707	0.009608	0.006914	0.010317	0.006953
.85,.1,.05	0.006006	0.006257	0.006198	0.006423	0.007334	0.006356	0.008718	0.006752
.9,.05,.05	0.006115	0.007005	0.006616	0.007335	0.011785	0.010619	0.010317	0.008374
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.65, .15, .2	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.65,.2,.15	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.7,.2,.1	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.7,.15,.15	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.7,.1,.2	0.111933	0.659711	1.016302	0.094116	0.446183	0.455728	0.970648	3.041179
.75,.2,.05	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.75,.15,.1	0.111933	0.659711	1.016302	0.130965	0.446183	0.455728	0.970648	3.041179
.75,.1,.15	0.105688	0.659711	1.016302	0.095888	0.446183	0.455728	0.970648	3.041179
.75,.05,.2	0.112588	0.659711	1.016302	0.13304	0.446183	0.455728	0.970648	3.041179
.8,.05,.15	0.120199	0.659711	1.016302	0.13304	0.446183	0.455728	0.970648	3.041179
.8,.1,.1	0.105688	0.659711	1.016302	0.095888	0.446183	0.455728	0.970648	3.041179
.8,.15,.05	0.111933	0.659711	1.016302	0.094116	0.446183	0.455728	0.970648	3.041179
.85,.05,.1	0.123577	0.659711	1.016302	0.13304	0.446183	0.455728	0.970648	3.041179
.85,.1,.05	0.105896	0.659711	1.016302	0.13304	0.446183	0.455728	0.970648	3.041179
.9,.05,.05	0.123577	0.659711	1.016302	0.13304	0.446183	0.455728	0.970648	3.041179

Table 18. ***RMSE second lag, all combinations, node 1 to node 50***

Comb/H.N	N1	N2	N3	N4	N5	N6	N7	N8
.6,.2,.2	0.076488	0.08083	0.080475	0.080454	0.077759	0.082688	0.088633	0.077956
.65, .15, .2	0.076459	0.081464	0.081179	0.080789	0.078423	0.082599	0.090661	0.078178
.65,.2,.15	0.076623	0.081223	0.080475	0.080454	0.077759	0.082599	0.090661	0.077956
.7,.2,.1	0.076459	0.08133	0.080475	0.080454	0.078038	0.082599	0.090661	0.077956
.7,.15,.15	0.076459	0.081464	0.081882	0.080832	0.078423	0.082692	0.090661	0.078558
.7,.1,.2	0.076506	0.081892	0.082999	0.08141	0.078423	0.082857	0.09079	0.078278
.75,.2,.05	0.076459	0.081464	0.081087	0.080561	0.078423	0.082599	0.090661	0.078178
.75,.15,.1	0.076462	0.081892	0.081882	0.080975	0.078423	0.082748	0.090661	0.078278
.75,.1,.15	0.076467	0.08255	0.082999	0.082025	0.07906	0.082857	0.09079	0.078278
.75,.05,.2	0.076467	0.083644	0.08384	0.08268	0.083312	0.083106	0.099939	0.078579
.8,.05,.15	0.076552	0.084454	0.085112	0.084488	0.086542	0.083577	0.099939	0.079257
.8,.1,.1	0.076467	0.08255	0.08384	0.08268	0.079995	0.083106	0.094729	0.078404
.8,.15,.05	0.076462	0.081892	0.082999	0.080975	0.078423	0.082857	0.090661	0.078278
.85,.05,.1	0.076552	0.085593	0.085112	0.084488	0.091624	0.084625	0.103356	0.079257
.85,.1,.05	0.076467	0.082927	0.08384	0.08268	0.081217	0.083106	0.094729	0.078579
.9,.05,.05	0.07698	0.087791	0.08744	0.088327	0.101376	0.100363	0.103356	0.086524
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.65, .15, .2	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.65,.2,.15	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.7,.2,.1	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.7,.15,.15	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.7,.1,.2	0.329589	0.809611	1.010588	0.306386	0.666941	0.675425	0.990145	1.742632
.75,.2,.05	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.75,.15,.1	0.329589	0.809611	1.010588	0.365689	0.666941	0.675425	0.990145	1.742632
.75,.1,.15	0.318707	0.809611	1.010588	0.306988	0.666941	0.675425	0.990145	1.742632
.75,.05,.2	0.330477	0.809611	1.010588	0.365818	0.666941	0.675425	0.990145	1.742632
.8,.05,.15	0.34309	0.809611	1.010588	0.365818	0.666941	0.675425	0.990145	1.742632
.8,.1,.1	0.318707	0.809611	1.010588	0.306988	0.666941	0.675425	0.990145	1.742632
.8,.15,.05	0.329589	0.809611	1.010588	0.306386	0.666941	0.675425	0.990145	1.742632
.85,.05,.1	0.34911	0.809611	1.010588	0.365818	0.666941	0.675425	0.990145	1.742632
.85,.1,.05	0.321971	0.809611	1.010588	0.365818	0.666941	0.675425	0.990145	1.742632
.9,.05,.05	0.34911	0.809611	1.010588	0.365818	0.666941	0.675425	0.990145	1.742632

Appendix E

Table 19. ***MAE Third lag, all combinations, node 1 to node 50***

Comb/H.N	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
.6,.2,.2	0.054669	0.054437	0.056051	0.05701	0.058562	0.057546	0.056589	0.058761
.65, .15, .2	0.054619	0.054382	0.05625	0.057311	0.059052	0.05844	0.056893	0.058761
.65,.2,.15	0.054669	0.054398	0.05625	0.05701	0.058937	0.057546	0.056755	0.058761
.7,.2,.1	0.054662	0.054398	0.05625	0.05701	0.059052	0.057899	0.056755	0.058761
.7,.15,.15	0.054908	0.054382	0.056251	0.057311	0.059479	0.05844	0.057637	0.059378
.7,.1,.2	0.054908	0.054351	0.056633	0.057993	0.060585	0.059318	0.060389	0.061487
.75,.2,.05	0.054662	0.054398	0.05625	0.05701	0.059052	0.057899	0.056755	0.058761
.75,.15,.1	0.054908	0.054382	0.056592	0.057311	0.059794	0.05844	0.058441	0.060377
.75,.1,.15	0.054653	0.054342	0.056341	0.059034	0.060585	0.060836	0.060389	0.061487
.75,.05,.2	0.054653	0.054306	0.056341	0.059663	0.139705	0.062971	0.060389	0.064075
.8,.05,.15	0.054653	0.054306	0.056341	0.060677	0.20269	0.066844	0.061987	0.068047
.8,.1,.1	0.054653	0.054342	0.056341	0.05956	0.06358	0.060836	0.060389	0.061487
.8,.15,.05	0.054908	0.054393	0.056592	0.057993	0.059794	0.05844	0.05943	0.060377
.85,.05,.1	0.054631	0.054306	0.05654	0.061837	0.183543	0.075935	0.061987	0.075188
.85,.1,.05	0.054653	0.054323	0.056341	0.05956	0.06358	0.060836	0.060389	0.064075
.9,.05,.05	0.054787	0.054307	0.056749	0.061837	0.185814	0.075935	0.063406	0.088947
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.199802	0.468765	0.580372	0.637838	0.867537	0.621314	1.062798	1.423815
.65, .15, .2	0.201265	0.468765	0.580372	0.637838	0.867537	0.621129	1.062798	1.423815
.65,.2,.15	0.199802	0.468765	0.580372	0.637838	0.867537	0.621314	1.062798	1.423815
.7,.2,.1	0.199802	0.468765	0.580372	0.637838	0.867537	0.621314	1.062798	1.423815
.7,.15,.15	0.200755	0.468765	0.580372	0.637838	0.867537	0.621129	1.062798	1.423815
.7,.1,.2	0.205665	0.468765	0.540769	0.637838	0.867537	0.668962	1.062798	1.423815
.75,.2,.05	0.199802	0.468765	0.580372	0.637838	0.867537	0.621314	1.062798	1.423815
.75,.15,.1	0.20367	0.468765	0.580372	0.637838	0.867537	0.621129	1.062798	1.423815
.75,.1,.15	0.204142	0.468765	0.540769	0.637838	0.867537	0.668962	1.062798	1.423815
.75,.05,.2	0.218021	0.468765	0.582101	0.637838	0.867537	0.700224	1.062798	1.423815

.8,.05,.15	0.218021	0.498967	0.582101	0.637838	0.867537	0.700224	1.062798	1.423815
.8,.1,.1	0.204954	0.468765	0.490234	0.637838	0.867537	0.668962	1.062798	1.423815
.8,.15,.05	0.205665	0.468765	0.540769	0.637838	0.867537	0.646995	1.062798	1.423815
.85,.05,.1	0.219139	0.498967	0.609232	0.721485	0.867537	0.713537	1.062798	1.423815
.85,.1,.05	0.211244	0.468765	0.490234	0.637838	0.867537	0.700224	1.062798	1.423815
.9,.05,.05	0.219896	0.498967	0.609232	0.721485	0.988712	0.718482	1.062798	1.423815

Table 20. ***MSE Third lag, all combinations, node 1 to node 50***

Comb/H.N	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
.6,.2,.2	0.0058286	0.005952	0.005933	0.006224	0.006617	0.006003	0.006251	0.006241
.65, .15, .2	0.0058337	0.005965	0.005931	0.006287	0.006686	0.006147	0.00634	0.006241
.65,.2,.15	0.0058286	0.005959	0.005931	0.006224	0.006609	0.006003	0.006288	0.006241
.7,.2,.1	0.0058300	0.005959	0.005931	0.006224	0.006686	0.006066	0.006288	0.006241
.7,.15,.15	0.0058429	0.005965	0.005938	0.006287	0.006858	0.006147	0.006482	0.006346
.7,.1,.2	0.0058429	0.005986	0.005963	0.006386	0.007209	0.006257	0.007047	0.00668
.75,.2,.05	0.0058300	0.005959	0.005931	0.006224	0.006686	0.006066	0.006288	0.006241
.75,.15,.1	0.0058429	0.005965	0.005961	0.006287	0.006905	0.006147	0.00664	0.00651
.75,.1,.15	0.0058345	0.00599	0.005967	0.006525	0.007209	0.006507	0.007047	0.00668
.75,.05,.2	0.0058345	0.006012	0.005967	0.006661	0.031431	0.006943	0.007047	0.007092
.8,.05,.15	0.0058345	0.006015	0.005967	0.006853	0.049739	0.007713	0.007372	0.007762
.8,.1,.1	0.0058345	0.00599	0.005967	0.006649	0.00808	0.006507	0.007047	0.00668
.8,.15,.05	0.0058429	0.005973	0.005961	0.006386	0.006905	0.006147	0.006809	0.00651
.85,.05,.1	0.0058390	0.006015	0.006052	0.007163	0.047621	0.00951	0.007372	0.009038
.85,.1,.05	0.0058345	0.006001	0.005967	0.006649	0.00808	0.006507	0.007047	0.007092
.9,.05,.05	0.0059006	0.006018	0.006104	0.007163	0.046312	0.00951	0.007682	0.012413
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.0504994	0.331953	0.410982	0.615499	1.19533	0.429711	1.217883	2.49921
.65, .15, .2	0.0545579	0.331953	0.410982	0.615499	1.19533	0.419552	1.217883	2.49921
.65,.2,.15	0.0504994	0.331953	0.410982	0.615499	1.19533	0.429711	1.217883	2.49921

.7,.2,.1	0.0504994	0.331953	0.410982	0.615499	1.19533	0.429711	1.217883	2.49921
.7,.15,.15	0.0520769	0.331953	0.410982	0.615499	1.19533	0.419552	1.217883	2.49921
.7,.1,.2	0.0523838	0.331953	0.398533	0.615499	1.19533	0.477945	1.217883	2.49921
.75,.2,.05	0.0504994	0.331953	0.410982	0.615499	1.19533	0.429711	1.217883	2.49921
.75,.15,.1	0.0530952	0.331953	0.410982	0.615499	1.19533	0.419552	1.217883	2.49921
.75,.1,.15	0.0531972	0.331953	0.398533	0.615499	1.19533	0.477945	1.217883	2.49921
.75,.05,.2	0.0581257	0.331953	0.450161	0.615499	1.19533	0.526198	1.217883	2.49921
.8,.05,.15	0.0581257	0.389923	0.450161	0.615499	1.19533	0.526198	1.217883	2.49921
.8,.1,.1	0.0529605	0.331953	0.354532	0.615499	1.19533	0.477945	1.217883	2.49921
.8,.15,.05	0.0523838	0.331953	0.398533	0.615499	1.19533	0.448215	1.217883	2.49921
.85,.05,.1	0.0593797	0.389923	0.497301	0.735919	1.19533	0.547401	1.217883	2.49921
.85,.1,.05	0.0551965	0.331953	0.354532	0.615499	1.19533	0.526198	1.217883	2.49921
.9,.05,.05	0.0592828	0.389923	0.497301	0.735919	1.305545	0.550356	1.217883	2.49921

Table 21. ***RMSE Third lag, all combinations, node 1 to node 50***

Comb/H.N	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
.6,.2,.2	0.078692	0.077616	0.07873	0.079196	0.081837	0.082009	0.081951	0.084031
.65, .15, .2	0.078763	0.077618	0.078708	0.079542	0.082142	0.083106	0.082582	0.084031
.65,.2,.15	0.078692	0.077629	0.078708	0.079196	0.081917	0.082009	0.08219	0.084031
.7,.2,.1	0.078715	0.077629	0.078708	0.079196	0.082142	0.082537	0.08219	0.084031
.7,.15,.15	0.078777	0.077618	0.078783	0.079542	0.082684	0.083106	0.083788	0.084896
.7,.1,.2	0.078777	0.077671	0.078958	0.080269	0.084078	0.083757	0.087859	0.087568
.75,.2,.05	0.078715	0.077629	0.078708	0.079196	0.082142	0.082537	0.08219	0.084031
.75,.15,.1	0.078777	0.077618	0.078947	0.079542	0.082917	0.083106	0.084939	0.086199
.75,.1,.15	0.07879	0.077587	0.079033	0.081136	0.084078	0.085188	0.087859	0.087568
.75,.05,.2	0.07879	0.077603	0.079033	0.081899	0.176237	0.087636	0.087859	0.090254
.8,.05,.15	0.07879	0.077564	0.079033	0.082995	0.222392	0.09185	0.090443	0.094965
.8,.1,.1	0.07879	0.077587	0.079033	0.081832	0.087906	0.085188	0.087859	0.087568
.8,.15,.05	0.078777	0.077556	0.078947	0.080269	0.082917	0.083106	0.086181	0.086199
.85,.05,.1	0.078846	0.077564	0.079622	0.084757	0.218313	0.101089	0.090443	0.102392
.85,.1,.05	0.07879	0.077604	0.079033	0.081832	0.087906	0.085188	0.087859	0.090254
.9,.05,.05	0.079304	0.077547	0.079964	0.084757	0.21555	0.101089	0.092693	0.119395
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.224166	0.581126	0.649279	0.780372	1.076284	0.658626	1.105486	1.583643
.65, .15, .2	0.236535	0.581126	0.649279	0.780372	1.076284	0.652432	1.105486	1.583643

.65,.2,.15	0.224166	0.581126	0.649279	0.780372	1.076284	0.658626	1.105486	1.583643
.7,.2,.1	0.224166	0.581126	0.649279	0.780372	1.076284	0.658626	1.105486	1.583643
.7,.15,.15	0.22791	0.581126	0.649279	0.780372	1.076284	0.652432	1.105486	1.583643
.7,.1,.2	0.226902	0.581126	0.628242	0.780372	1.076284	0.694743	1.105486	1.583643
.75,.2,.05	0.224166	0.581126	0.649279	0.780372	1.076284	0.658626	1.105486	1.583643
.75,.15,.1	0.229767	0.581126	0.649279	0.780372	1.076284	0.652432	1.105486	1.583643
.75,.1,.15	0.22998	0.581126	0.628242	0.780372	1.076284	0.694743	1.105486	1.583643
.75,.05,.2	0.238733	0.581126	0.668724	0.780372	1.076284	0.727426	1.105486	1.583643
.8,.05,.15	0.238733	0.63271	0.668724	0.780372	1.076284	0.727426	1.105486	1.583643
.8,.1,.1	0.230094	0.581126	0.594439	0.780372	1.076284	0.694743	1.105486	1.583643
.8,.15,.05	0.226902	0.581126	0.628242	0.780372	1.076284	0.672239	1.105486	1.583643
.85,.05,.1	0.240567	0.63271	0.702359	0.853942	1.076284	0.741446	1.105486	1.583643
.85,.1,.05	0.233305	0.581126	0.594439	0.780372	1.076284	0.727426	1.105486	1.583643
.9,.05,.05	0.240675	0.63271	0.702359	0.853942	1.141387	0.743971	1.105486	1.583643

Appendix F

Table 22. ***MAE Fourth lag, all combinations, node 1 to node 50***

Comb/H.N	N1	N2	N3	N4	N5	N6	N7	N8
.6,.2,.2	0.057157	0.054214	0.0562	0.055326	0.058232	0.115494	0.058591	0.05819
.65, .15, .2	0.058377	0.054414	0.056511	0.055541	0.061725	0.115494	0.058665	0.05819
.65,.2,.15	0.057157	0.054214	0.05638	0.055326	0.058988	0.115494	0.058665	0.05819
.7,.2,.1	0.057611	0.054414	0.05638	0.055326	0.058988	0.115494	0.058665	0.05819
.7,.15,.15	0.058377	0.054414	0.056511	0.055541	0.061725	0.115494	0.059644	0.05819
.7,.1,.2	0.059228	0.05423	0.056783	0.056545	0.061725	0.115494	0.060514	0.058985
.75,.2,.05	0.057611	0.054414	0.056464	0.055541	0.060397	0.115494	0.058665	0.05819
.75,.15,.1	0.058377	0.05423	0.056783	0.055947	0.061725	0.115494	0.059644	0.05819
.75,.1,.15	0.060674	0.05423	0.057072	0.057034	0.061725	0.115494	0.060514	0.058985
.75,.05,.2	0.062393	0.05423	0.057129	0.05762	0.065291	0.115494	0.064299	0.066614
.8,.05,.15	0.065692	0.05423	0.057168	0.05955	0.065291	0.115494	0.067869	0.066614
.8,.1,.1	0.060674	0.05423	0.057028	0.056929	0.064487	0.115494	0.061484	0.060648
.8,.15,.05	0.060674	0.05423	0.057028	0.056929	0.064487	0.115494	0.061484	0.060648
.85,.05,.1	0.065692	0.054213	0.057576	0.062758	0.072342	0.115494	0.074754	0.066614
.85,.1,.05	0.065692	0.054213	0.057576	0.062758	0.072342	0.115494	0.074754	0.066614
.9,.05,.05	0.080691	0.05426	0.05773	0.070536	0.074113	0.115494	0.087013	0.074282
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.102747	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.65, .15, .2	0.102747	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.65,.2,.15	0.102747	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.7,.2,.1	0.102747	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.7,.15,.15	0.102424	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.7,.1,.2	0.151292	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.75,.2,.05	0.102747	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.75,.15,.1	0.140097	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.75,.1,.15	0.27045	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.75,.05,.2	0.561619	1.219957	1.289769	0.366853	1.670416	0.811481	0.867512	0.791798
.8,.05,.15	0.496885	1.219957	1.289769	0.366853	1.670416	0.811481	0.867512	0.791798
.8,.1,.1	0.41269	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.8,.15,.05	0.41269	1.219957	1.289769	0.366853	1.670416	0.811481	0.592856	0.791798
.85,.05,.1	0.546193	1.219957	1.289769	0.366853	1.670416	0.811481	0.867512	0.791798
.85,.1,.05	0.546193	1.219957	1.289769	0.366853	1.670416	0.811481	0.867512	0.791798
.9,.05,.05	0.556824	1.219957	1.289769	0.366853	1.670416	1.194813	0.867512	0.791798

Table 23. ***MSE Fourth lag, all combinations, node 1 to node 50***

Comb/H.N	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
.6,.2,.2	0.006015	0.005794	0.005739	0.005811	0.007094	0.017698	0.006331	0.006863
.65, .15, .2	0.006152	0.005799	0.005756	0.0 0583	0.007981	0.017698	0.006387	0.006863
.65,.2,.15	0.006015	0.005794	0.005741	0.005811	0.007242	0.017698	0.006387	0.006863
.7,.2,.1	0.006067	0.005799	0.005741	0.005811	0.007242	0.017698	0.006387	0.006863
.7,.15,.15	0.006152	0.005799	0.005756	0.005835	0.007981	0.017698	0.006486	0.006863
.7,.1,.2	0.006266	0.005795	0.005776	0.005862	0.007981	0.017698	0.006669	0.007089
.75,.2,.05	0.006067	0.005799	0.005749	0.005835	0.007525	0.017698	0.006387	0.006863
.75,.15,.1	0.006152	0.005795	0.005776	0.005835	0.007981	0.017698	0.006486	0.006863
.75,.1,.15	0.006468	0.005795	0.0058	0.005893	0.007981	0.017698	0.006669	0.007089
.75,.05,.2	0.006741	0.005795	0.005829	0.005975	0.008906	0.017698	0.007244	0.009037
.8,.05,.15	0.007279	0.005795	0.005852	0.006178	0.008906	0.017698	0.008039	0.009037
.8,.1,.1	0.006468	0.005795	0.005803	0.005914	0.008745	0.017698	0.00685	0.00749
.8,.15,.05	0.006468	0.005795	0.005803	0.005914	0.008745	0.017698	0.00685	0.00749
.85,.05,.1	0.007279	0.005795	0.005863	0.006548	0.010037	0.017698	0.009421	0.009037
.85,.1,.05	0.007279	0.005795	0.005863	0.006548	0.010037	0.017698	0.009421	0.009037
.9,.05,.05	0.01007	0.005795	0.005874	0.007576	0.010386	0.017698	0.01261	0.011044
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.014621	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.65, .15, .2	0.014621	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.65,.2,.15	0.014621	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.7,.2,.1	0.014621	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.7,.15,.15	0.014065	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.7,.1,.2	0.033791	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.75,.2,.05	0.014621	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.75,.15,.1	0.02846	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.75,.1,.15	0.104695	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.75,.05,.2	0.516058	1.834031	1.803853	0.229674	3.025237	0.912237	0.826242	0.928968
.8,.05,.15	0.323342	1.834031	1.803853	0.229674	3.025237	0.912237	0.826242	0.928968
.8,.1,.1	0.223122	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.8,.15,.05	0.223122	1.834031	1.803853	0.229674	3.025237	0.912237	0.551473	0.928968
.85,.05,.1	0.391787	1.834031	1.803853	0.229674	3.025237	0.912237	0.826242	0.928968
.85,.1,.05	0.391787	1.834031	1.803853	0.229674	3.025237	0.912237	0.826242	0.928968
.9,.05,.05	0.421516	1.834031	1.803853	0.229674	3.025237	1.819833	0.826242	0.928968

Table 24. ***RMSE Fourth lag, all combinations, node 1 to node 50***

Comb/H.N	**N1**	**N2**	**N3**	**N4**	**N5**	**N6**	**N7**	**N8**
.6,.2,.2	0.078881	0.077755	0.080605	0.077593	0.081087	0.132182	0.083044	0.082383
.65, .15, .2	0.080061	0.07777	0.080993	0.077945	0.085759	0.132182	0.083439	0.082383
.65,.2,.15	0.078881	0.077755	0.080699	0.077593	0.081796	0.132182	0.083439	0.082383
.7,.2,.1	0.079361	0.07777	0.080699	0.077593	0.081796	0.132182	0.083439	0.082383
.7,.15,.15	0.080061	0.07777	0.080993	0.077945	0.085759	0.132182	0.084693	0.082383
.7,.1,.2	0.081031	0.077755	0.08124	0.078455	0.085759	0.132182	0.085809	0.083516
.75,.2,.05	0.079361	0.07777	0.080882	0.077945	0.083213	0.132182	0.083439	0.082383
.75,.15,.1	0.080061	0.077755	0.08124	0.078031	0.085759	0.132182	0.084693	0.082383
.75,.1,.15	0.082619	0.077755	0.081532	0.078835	0.085759	0.132182	0.085809	0.083516
.75,.05,.2	0.084571	0.077755	0.082224	0.079838	0.09076	0.132182	0.090362	0.092941
.8,.05,.15	0.088195	0.077755	0.08237	0.081885	0.09076	0.132182	0.095644	0.092941
.8,.1,.1	0.082619	0.077755	0.081765	0.079116	0.089927	0.132182	0.087268	0.085545
.8,.15,.05	0.082619	0.077755	0.081765	0.079116	0.089927	0.132182	0.087268	0.085545
.85,.05,.1	0.088195	0.077765	0.082595	0.085051	0.096161	0.132182	0.103502	0.092941
.85,.1,.05	0.088195	0.077765	0.082595	0.085051	0.096161	0.132182	0.103502	0.092941
.9,.05,.05	0.10324	0.077763	0.082669	0.092433	0.097842	0.132182	0.118835	0.102265
Comb/H.N	**N15**	**N20**	**N25**	**N30**	**N35**	**N40**	**N45**	**N50**
.6,.2,.2	0.132588	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.65, .15, .2	0.132588	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.65,.2,.15	0.132588	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.7,.2,.1	0.132588	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.7,.15,.15	0.130603	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.7,.1,.2	0.192835	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.75,.2,.05	0.132588	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.75,.15,.1	0.178954	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.75,.1,.15	0.331235	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.75,.05,.2	0.719118	1.367142	1.341733	0.476854	1.738251	0.9577	0.91157	0.967878
.8,.05,.15	0.576865	1.367142	1.341733	0.476854	1.738251	0.9577	0.91157	0.967878
.8,.1,.1	0.474361	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.8,.15,.05	0.474361	1.367142	1.341733	0.476854	1.738251	0.9577	0.742921	0.967878
.85,.05,.1	0.636563	1.367142	1.341733	0.476854	1.738251	0.9577	0.91157	0.967878
.85,.1,.05	0.636563	1.367142	1.341733	0.476854	1.738251	0.9577	0.91157	0.967878
.9,.05,.05	0.656375	1.367142	1.341733	0.476854	1.738251	1.355673	0.91157	0.967878