Validity of Technical Analysis Indicators: A Case of KSE-100 Index

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Abstract

This paper examines the validity of Technical analysis on Karachi Stock Exchange by investigating the tools used in Technical analysis for the sample period of 1997 to 2014. The KSE-100 index was examined to investigate the efficiency of stock exchange by employing Wright's sign based variance ratio test. The results indicate that KSE-100 index is not efficient in its weak form. The study then compared a broad range of technical trading rules based on Simple Moving Averages, Exponential Moving Averages, with Generalized Regression Neural Network (GRNN) to find the forecasting ability of these indicators individually as well as in combination. The results indicate the predictive power over future stock price behavior. The insertion of GRNN enhances the profit generating capacity of above average return. To know that whether it is possible to beat buy-and-hold strategy, the study proposes two trading strategies based on these rules. The proposed strategies have the capability to outstrip the buy-and-hold strategy, even in the presence of transactional cost. Technical analysis is very effective for the investors in creating excess return for the sample period.

Keywords: Market Efficiency, Karachi Stock Exchange, Moving Averages, Artificial Neural Network, Technical Analysis

The concept of modern financial market is enthralling and multifaceted and thus attracting the interest of traders. Modern financial system has an important attribute of having an organized place for trading of financial assets. The detailed financial data is recorded daily in shapes of either ticker tapes or on board with chalks (Michie, 1999).

Before the dawn of efficient market hypothesis (EMH), the practitioners of financial market have already been employing some simple statistical techniques for the analysis of such data. In 1884, Dow Theory developed by Charles Dow was an attempt to analyze the board momentum of the US stock market. Similarly Bachelier (1900) employed the Random walk theory to investigate the movements in stock prices. Due to the works of the early pioneers, a new area in finance materialized. This area uses the data of previous stock prices to foretell future prices of these stocks and is known as Technical analysis today.

Pring (1991) illuminated the function of Technical analysis and Technical analysts. He argued that Technical analysis is actually a manifestation of the idea that prices follow trend and that trend depends on the investor's approach toward an assortment of political, psychological, monetary and economic forces. It is an art to discover the timing of trend reversal in advance and a trader bases his trading strategy on that trend until the evidences proves that the trend has reversed. Investors' psychology is also included in the field of Technical analysis to some extent. The area is known as behavioral finance in academics.

Baumeister and Bushman (2011) argued that in Technical analysis human behavior is incorporated in price movements and consistent over time. In other words, financial market is determined by repeated irrational factors associated with the irrational behavior of human psychology. Thus, Technical analysis is not purely technical in nature and has a very close relationship to behavioral finance as opposed to Dow Theory.

The study conducted by Khan et al. (2016) illustrated that Karachi stock exchange does not exhibit random walk. This indicates that returns follow trends and thus a rationale investor proposed their trading strategy based on these trends and thus generate abnormal return. Similarly the volatility of returns is high as evident by the high standard deviation value for the study period.

With the advancement in computer technology, it easy to use more complicated models in Technical analysis. The advantages of these models are, the abilities to tackle difficult situation like nonlinear and multivariate association among different financial variables. Complicated models like Neural Network, Chaos System and Genetic algorithm are among the models employed for the analysis. Majority of these models produced inconsistent profit generation (Allen & Karjalainen, 1999; Ready, 2002; White, 1988). These methods are not widely used as compared to the most initial and simple indicators. Moreover, the difficulties of using these new technologies network like neural network in decision related to trading is because of (a) the complex mathematical models involved, (b) the absence of any a priori hypothesis on the observed explanatory variables. The indirect consequence is that the network provides no explanation about the imprecise prediction and when will it produce better prediction, (c) similarly neural network is subjected to faulty optimization and over training.

Different varieties of analysis tools are available to investors. Traders used one or its combination to take their analysis. A combination has a better predicting ability as no single indicator has the ability identify the trend reversal (Pring, 1991). The investors use a combination of several indicators like Relative Strength Index, Moving Averages and Cumulative volume to evaluate profitability (Pruitt et al., 1992; Pruitt & White, 1988). Based on problem statement, research questions of the study are; (i) Does Karachi Stock Exchange follow random walk?, (ii)

Do the indicators used for Technical analysis have the predictive power?, and (iii) Is there any trading strategy that can outperform the buy-and-hold strategy?. Further, based on the research questions, the study has threefold objectives; (i) the study inspects the predictability of important trading rules in the perspective of Karachi stock exchange, (ii) in the presence of foreseeing ability, it is further scrutinized that which single or the combination of these rules may be applied to realize above average return, and (iii) to construct such a trading strategy, which even after considering the cost associated with the strategy outperform the buy-and-hold approach.

The study follows the following pattern. Section 2 comprises reviews of relevant literature. Section 3 consists of study methodology. Section 4 elaborates data findings and section 5 covers the conclusion and recommendation on the basis of data analysis.

Literature Review

Technical analysis is termed as a concept grounded on belief that trend is followed by assets prices. Technical analyst in an attempt to predict the future prices pattern, examined graphs, using moving averages, employ indicators based on open, close, low, high prices and volume of historical prices of the assets.

Academics like Fama (1970) elaborated that Technical analysis is exiguous and incongruous to the efficiency of market in weak form. Technical analysts argued that traders identify the opportunities in trading, though not able to envisage the future.

According to Murphy (1999) Technical analysis is a blend of many approaches and each approach has the ability to contribute to analysts' ability in predicting market. The technician constantly seeks clues in order to beat the market. The more the technician consults indicators, the more he/she may be able to choose the better clues and thus have more chances to earn abnormal returns.

Lima and Tabak (2006) tested the random walk hypothesis for the three stock markets of China, Hong Kong and Singapore. The study findings support the hypothesis for Hong Kong stock exchange and reject it for Singapore stock exchange and B shares of Chinese stock exchange.

Smith and Ryoo (2003) conducted the study to investigate the random walk hypothesis for five European developing markets like Poland, Hungary, Turkey, Greece and Portugal. The study applies multiple variance ratio tests. The results explored that four out of five markets does not follow random walk hypothesis. There is strong autocorrelation in their stock returns. One of the most important factor in investigating market efficiency is the liquidity and the result indicates that turkey stock provide more liquidity than the other four markets.

According to Rockefeller (2011) humans study behaviors, while machine study patterns. These studies are called Technical analysis. Due to the ability of fast processing of machine to repeat patterns, technology is widely used in predicting the stock prices. Different stocks behave differently. Similarly patterns and trends behave different in different occasions, so it cannot be said surely that a method successful in one case may also be successful in other.

Malkiel (2003) pointed out that the EMH losses its intellectual supremacy in twenty first century to the belief of many economists that stock prices are partially predictable. These criticisms are mainly based on the behavioral and psychological factors which traders have incorporated in their trading. Similarly, Shiller (2000) explicated that during the late 1990s, the rise in US financial markets were the results of psychological contagion. The same phenomena explained by the behavioral economists as the tendency of the investors to react this new information.

Chang et al. (2006) employed the moving average approach in Taiwan stock market and observed the excess profit as compared to the buy-and-hold strategy even after considering the transaction cost. Vasiliou et al. (2006) conducted the study by using MA and moving average convergence divergence (MACD) rules and concluded that these strategies produced above average returns as compared to B&H strategy.

The study conducted by Khan et al. (2016) investigated the predictability of moving averages individually as well as with the combination of relative strength index (RSI) and stochastic RSI on Karachi Stock Exchange data and found that the predictability of moving averages increases in the presence of these oscillators. The use of technical analysis outperformed the buy and hold strategy in generating abnormal returns.

To investigate the question that whether the tools of Technical analysis outperformed the B&H policy, Lento and Gradojevic (2007) conducted a study employing MACD, BB, TRB and filter rules on four different indexes. In order to ensure the significance of the study, the bootstrap methodology was used. A mixed result which indicates that out of the four rules, the filter, MACD and TRB rules performed well times and again. Similarly BB and filter rules are not profitable after considering the cost of transactions. Applying the Technical analysis rules enable the traders to make decision relating investment by considering the relevant information and thus enhanced its profit generating ability by adopting the combined signal approach.

To investigate the nature and strength of association between the performance of Technical analysis tools and profitability, Milionis and Papanagiotou (2013) carried out a study by decomposing the forecasting power of MA rules and to identify the portion that is attributed to the possible utilization of linear and nonlinear return dependency. For this purpose a Simulated Index was created, in whose returns there is no autocorrelation. Both the original and simulated index are noted accordingly and found both are synchronous with time but Simulated

Index has low variations. Both the indexes are tested using moving averages and found that both were very receptive to the length of the MA choice. The removal of linear dependency of the moving averages considerably reduced the efficiency of that rule.

Gencay (1996) used simple technical trading rules to investigate the linear and nonlinear price pattern in the daily Dow Jones Industrial Average Index. A single layer Feed Forward Network is employed to model the nonlinear specification in returns. Using the previous buy and sell signals, the results indicate strong evidence regarding the nonlinear predictability of the stock returns.

The study conducted by Leigh et al. (2002) is a step towards the potential of the neural network and genetic algorithm, known as machine learning in predicting the stock market. The results developed by these Decision Support Systems (DSS) indicate the better predictability having nonlinear, connectionist model and in a more diverse situations. The results represent a superior quality of these neural network and algorithmic techniques in stock market. It indicates that Technical analysis based on pattern matching and modern computing algorithm has a better potential as compared to the traditional approaches.

Rodrıguez et al. (2000) elucidated the profit generation ability of simple technical trading strategy employing the Artificial Neural Network (ANN). In the absence of transactional cost, the strategy based on Technical analysis produces greater return in contrast to B&H policy. This ability of profit making is, in the market with both “bearish” and “stable” market position. While the trading rule loses its ability of abnormal profit generation when the market is “bullish” and thus traders with buy and hold strategy receive greater returns.

The study analyzed different indicators used for technical analysis to know the forecasting ability of these indicators alone and in combination with the Generalized Regression Neural Network, which has the capacity to cope with the non-normal data and produce better results as compared to the traditional indicators employed for technical analysis. This study opened new avenues and employed neural network for stock market predictability.

Hypotheses

Following hypotheses to be tested based of relevant literature and research objectives of the study;

H_{01}: *Karachi Stock Exchange (KSE) follows Random Walk.*

H_{02}: *Technical analysis has no foretellingability for future stock price’s patterns.*

H_{03}: *Strategy based on Technical analysis could not outperform the Buy-and-Hold Strategy.*

Research Methodology

The section demonstrates the research design and methodology employed to examine the validation of Technical analysis rules. Due to the nature of the study, the study adopted a quantitative approach and employed data was collected from the websites of Karachi stock exchange and other sources like State Bank of Pakistan and the financial daily websites. The study data is restricted to the sample period of 1997 to 2014, as the generalized regression neural network needs the open, close, low and high of daily index and the data were not complete before 1997.

Research Design

In order to examine the hypotheses of the study, following methods and procedures are used.

Sign-Based Variance Ratio Test

Wright (2000) sign based variance ratio test use signs instead of the ranks of the returns. In this case, there is a possibility to construct an exact variance ratio test, even when the conditional heteroscedasticity is present in the data. Let $\boldsymbol{u(x_t, q) = 1(x_t > q) - 0.5}$, so $\boldsymbol{u(x_t, 0)}$is $\boldsymbol{1/2}$ if $\boldsymbol{x_t}$ is positive otherwise $\boldsymbol{-1/2}$. clearly$\mathbf{S_t}$ is independently and identically distributed with a mean of zero and unit variance. Each $\mathbf{S_t}$is equal to 1 if the probability is ½ and is -1 if its probability is -1/2. Thus the variance ratio test statistic S_1 based on sign is given as:

$$\boldsymbol{S_1} = \left[\frac{\frac{1}{\mathbf{Tk}}\sum_{\mathbf{t=k+1}}^{\mathbf{T}}(\mathbf{s_t} + \mathbf{s_{t-1}} + \cdots \ldots .. + \mathbf{s_{t-k}})^{\mathbf{2}}}{\frac{1}{\mathbf{T}}\sum_{\mathbf{t=1}}^{\mathbf{T}}\mathbf{s_t^2}} - \mathbf{1}\right] \times \left[\frac{\mathbf{2(2k-1)(k-1)}}{\mathbf{3kT}}\right]^{-1/2} \ldots \ldots \ldots \ldots ..(\mathbf{1})$$

The sampling distribution of S_1 and the associated critical value are the same as found in the (Wright, 2000). S_2 is not computed in the study, because it is expected that S_2 have a lower power.

Standard Moving Average

One of the most popular indicator used for trend calculation is Standard Moving Average (SMA) (Kaufman, 2005). It is used to smooth the fluctuations in daily security prices and thus identify trends. The SMA takes the average from past closing prices over a predetermined period and is calculated as:

$$\mathbf{MA} = \frac{\mathbf{1}}{\mathbf{N}}\sum \mathbf{X} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .(\mathbf{2})$$

N is the number of days, while **X** is the price level. Although moving average of 200-day seems to be the benchmark, investors can choose themselves how long or short the time period should be.

However, while shorter time periods tend to be more responsive to price changes, longer time periods will provide more reliable estimates.

A buy position is a long position and it is generated when the short moving average exceeds the long moving average. Likewise, a "sell-signal" is generated when a short Standard Moving Averages moves below a long SMA. The main reason for using a short SMA instead of the index price level is to avoid being whip-sawed by erratic price movements. The buy and sell signal act as an indication to the investor to enter or leave the market. The position of sell is maintained till a buy signal is produced by the index. The rule is said to be effective, if buy-sell returns are above average. The process is repeated by considering the transactional cost and it refer to buy-sell net return.

Exponential Moving Average

While the SMA assign equal weights to past observations, the exponential moving average (EMA), brings the exponential value closer to the last closing price by assigning greater importance to recent data. The first value of EMA is SMA for N days while the following values of the EMA are calculated as:

$$\mathbf{EMA_t = X_{t-1} \times \alpha + (1-\alpha) \times EMA_{t-1} \qquad 0 < \alpha < 1.(3)}$$

Where X represents the last known price and$\boldsymbol{\alpha}$is the smoothing factor and is calculated as follow:

$$\boldsymbol{\alpha} = \frac{\mathbf{2}}{\mathbf{N+1}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.. (\mathbf{4})$$

Where $\mathbf{N}$ represents the number of observations included in the starting value. The trading rule for EMA is similar to the trading rule for the SMA.

Generalized Regression Neural Network (GRNN)

It is an exceptional type of artificial neural network (ANN) extensively used in financial market for forecasting. GRNN have a one way technique with parallel structure developed first by (Specht, 1991). An interval function is used to compute the learning data average weight (Heimes & Heuveln, 1998). The probability density function is used by GRNN estimator for the data representation and is based on non-linear regression function. If x represent the explanatory variable while Y be the explained variable. The conditional average value of *y* for the given value of *x* is given as:

$$\mathbf{E(y|x)} = \frac{\int_{-\infty}^{+\infty} \mathbf{yf(x,y)dy}}{\int_{-\infty}^{+\infty} \mathbf{f(x,y)dy}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots. (\mathbf{5})$$

The above equation is used only when the distribution of $\boldsymbol{f}(\boldsymbol{x},\boldsymbol{y})$ is known. Let $\boldsymbol{x_i}$ and $\boldsymbol{y_i}$represents the size of $\boldsymbol{x}$ and $\boldsymbol{y}$ respectively. Then, we have

$$\hat{\mathbf{y}}(\mathbf{x}) = \frac{\sum_{i=1}^{n} \mathbf{y_i} \mathbf{W}\,(\mathbf{x},\mathbf{x_i})}{\sum_{i=1}^{n} \mathbf{W}\,(\mathbf{x},\mathbf{x_i})} \dots\dots\dots\dots\dots\dots\dots\dots..(\mathbf{6})$$

Where $\boldsymbol{W}(\boldsymbol{x},\boldsymbol{x_i}) = \boldsymbol{e}^{-(\boldsymbol{D_i^2}/2\boldsymbol{\sigma}^2)}$symbolize the hidden layer for the first output,$\boldsymbol{D_i^2} = (\boldsymbol{x_i}-\boldsymbol{x})'(\boldsymbol{x_i}-\boldsymbol{x})$ and $\boldsymbol{\sigma}$is the given parameters and supposed to be equal to one. Where $\boldsymbol{D_i}$representsthe distance between the training and predicted points. It is obvious that smaller the value of $\boldsymbol{D_i}$results larger values for $\boldsymbol{D_i^2}/\mathbf{2}\boldsymbol{\sigma}^{\mathbf{2}}$ and vice versa.

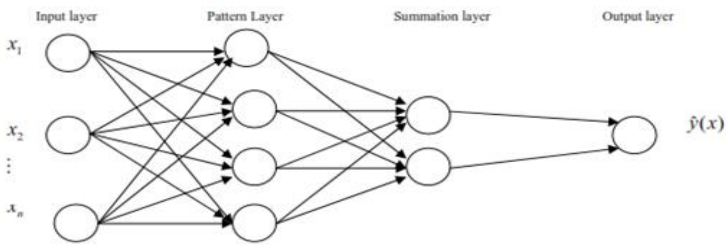


Figure 1. *Architecture of GRNN*

The Figure illustrates that GRNN architecture have four layers and same to Feed Forward Network in structure but very much different in operation. The GRNN has the ability of learning quickly and usually generate smaller error than other linear models. Similarly it generates best non-linear estimation in contrast to other neural network (Specht, 1991).

The Welch t-statistic

In order to measure the predictability of different trading rules, Welch's t-test is employed. The assumptions for the test are that sample size and the population variances are not same. The statistic can be calculated as:

$$\mathbf{t} = \frac{\bar{\mathbf{X}}_1 - \bar{\mathbf{X}}_2}{\mathbf{S}_{\bar{\mathbf{X}}_1-\bar{\mathbf{X}}_2}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots...(\mathbf{7})$$

Where

$$\mathbf{S}_{\bar{\mathbf{X}}_1-\bar{\mathbf{X}}_2} = \left(\frac{\mathbf{S_1^2}}{\mathbf{n_1}} + \frac{\mathbf{S_2^2}}{\mathbf{n_2}}\right)^{\mathbf{1/2}} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots.(\mathbf{8})$$

Where $\bar{\mathbf{X}}$is the daily mean return, S is the standard deviation and n is the sample size.

Sharpe Ratio

In order to estimate the performance ability of the proposed strategies, different in rewards and risks, Sharpe ratio is employed. It is the ratio of generating abnormal return relative to their risk. A strategy having high rewards with respect to risk is the best strategy and is defined as:

$$\mathbf{SR} = \frac{\mathbf{E(R - R_f)}}{\boldsymbol{\sigma}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots.\ldots(\mathbf{9})$$

In the equation "R" is the investment's return, where risk free rate is presented by $\mathbf{R_f}$ and $\boldsymbol{\sigma}$the standard deviation represents investment risk. In this study "R" represents the average daily return generated by the proposed strategies. In TS_1, on buy day, the investor trade in stock market while on sell day trade in the money market. Similarly in TS_2, in order to double its investment, the investor borrows from money market and in the market on buy day while in the money market on sell day.

Findings

Summary Statistic

Table 1 illustrates the summary statistics of KSE-100 index daily returns for the sample period and calculated as the natural log of the closing index. The average daily returns are 0.000698 having a standard error of 0.000251. This standard error indicates that the mean is significant for the entire sample and indicates larger variations in the returns. Similarly the skewness having a value of -0.3465, cascades in the range of -0.5 to 0.5, which indicates that returns have a normal distribution. Similarly distribution is leptokurtic in nature as evident by kurtosis value of 5.69.

Table 1. *Descriptive statistics of returns*

Descriptions	Statistics
Mean	0.000698
Standard Error	0.000251
Median	0.001243
Standard Deviation	0.016149
Kurtosis	5.690001
Skewness	-0.3465
Count	4155

Wright Signs Test

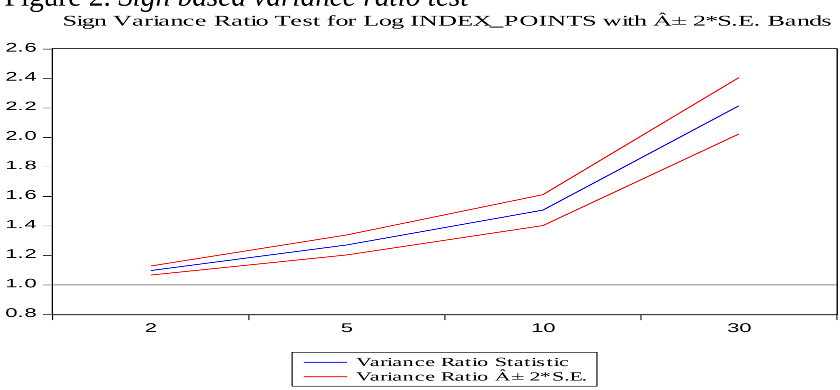
Table 2 demonstrates the Wright signs test results for the sample data having period of 2, 5, 10 and 30 to resembles the Wright work. For joint test the Wald chi-square have a value of 209.74 with the p-value of 0.0000, demonstrates strongly rejection of first hypothesis for the entire period. The null hypothesis is similarly rejected for individual period, evidenced by the z-values and its associated probabilities.

The graphical presentation of Table 2 is presented in Figure 2. The index point variance ratio statistics are plotted for different levels. The variance ratio of 1 is taken as the benchmark. As the variance ratio statistic does not intersect the benchmark line at any level, indicating the rejection of null hypothesis at different periods. The findings of the above variance ratio tests strongly reject the hypothesis of random walk, elucidate that Karachi stock exchange is not efficient in its weak form. The inefficiency indicates that the Technical analysis can be employed to beat the market.

Table 2. *Wright sign based variance ratio test*

Joint Tests		Value	Df	Probability
Max $\|\boldsymbol{Z}\|$ (at period 30)		14.18323	4155	0.0000
Wald (chi-Square)		209.7398	4	0.0000
Individual Tests				
Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.097473	0.015514	6.283035	0.0000
5	1.271095	0.033989	7.976025	0.0000
10	1.507485	0.052380	9.688494	0.0000
30	2.769598	0.124767	14.18323	0.0000

Figure 2. *Sign based variance ratio test*



For buy-and-hold strategy, the average daily return for the study period was 0.0598% with a standard deviation 1.615% and trading days of 4155. The t-statistic for the buy-and-hold strategy, using the one sample t-test is 1.32

$$\boldsymbol{t} = \frac{\mathbf{0.0598\% - 0}}{\mathbf{1.615\%/\sqrt{4155}}} = \mathbf{1.32}$$

Compared with the critical value of 1.96 at the 5% significance level, the average daily return for the buy-and-hold strategy is not significantly larger than zero. This implies that a buy-and-hold strategy have not provided positive significant average daily returns in sample period.

Knowing that KSE-100 did not follow a random walk, the study seeks evidence that Technical analysis could have been used to predict recurring price patterns. For the purpose, the study employed different trading rules like simple moving averages, exponential moving average and the combination of these averages with Generalized Regression Neural Network. The returns generated by these indicators are compared with the buy and hold return for the same time frame.

Table 3. *Multiple SMAs and EMAs returns*

Rules	Mean (Buy)	Mean (Sell)	Buy-Sell	StDev (Buy)	StDev (Sell)	N (Buy)	N (Sell)
Panel 1							
SMA (25-100)	0.2919%	-0.1919%	0.4837%	1.355%	1.831%	2175	1846
	(1.04)	(-0.50)	(1.37)				
SMA (25-150)	0.2869%	-0.1789%	0.4658%	1.341%	1.836%	2131	1839
	(0.87)	(-1.17)	(1.90)				
SMA (25-200)	0.2971%	-0.1759%	0.4730%	1.368%	1.813%	2079	1842
	(2.90)	(-4.16)	(9.13)				
SMA (50-100)	0.2068%	-0.0776%	0.2844%	1.392%	1.803%	2084	1937
	(0.78)	(-1.89)	(0.56)				
SMA (50-150)	0.1994%	-0.0746%	0.2740%	1.454%	1.751%	2112	1860
	(1.30)	(-1.83)	(1.32)				
SMA (50-200)	0.2094%	-0.0616%	0.2710%	1.495%	1.708%	1976	1945
	(1.22)	(-1.59)	(5.28)				
Panel 2							
SMA (25-100)	0.4852%	-0.4342%	0.9194%	1.270%	1.822%	2209	1814
	(1.95)	(-1.14)	(1.16)				
SMA (25-150)	0.4620%	-0.0042	0.8771%	1.285%	1.819%	2201	1771
	(1.87)	(-0.60)	(1.14)				
SMA (25-200)	0.4560%	-0.4026%	0.8586%	1.279%	1.838%	2179	1743
	(16.64)	(-9.14)	(16.56)				
SMA (50-100)	0.3971%	-0.3115%	0.7086%	1.312%	1.828%	2169	1853
	(1.09)	(-0.31)	(1.95)				
SMA (50-150)	0.3706%	-0.2867%	0.6573%	0.153%	0.179%	2196	1812
	(12.97)	(-6.70)	(12.73)				
SMA (50-200)	0.3670%	-0.2846%	0.6516%	1.328%	1.837%	2161	1761
	(12.85)	(-6.50)	(12.46)				

Mean (Buy and Mean (Sell) are the mean average daily returns for buy and sell days respectively. StDev (Buy) and StDev (Sell) are the standard deviation and N (Buy) and N (Sell) the number of trading days for buy and sell days respectively. Numbers in parenthesis are the Welch-t-statistic. In column 2 and 3, the Welch t-statistic measure the difference between average daily return on buy day to average buy-and-hold returns. In column 4, the Welch t-statistic measure the difference between average daily return on buy days and average daily sell day returns.

Table 3 reports results of multiple Simple Moving Averages and Exponential Moving Averages. Panel1 indicates moving average having short duration of 25 and 50 days with the long averages with values of 100, 150 and 200 days respectively. Similarly panel2 repeat the same practice for exponential moving averages with the same short and long periods. In case of SMA, the results are not very good. On buy day all trading rules generates positive profit while on sell day it generates negative mean daily return and the buy-sell days return are positive. Although the results are positive for buy days and negative for sell days, but in most of the cases, the coefficients are statistically insignificant for both buy and sell days. Only SMA (25-200) and SMA (50-200) have the appropriate sign on buy and sell days as well as significant as obvious from the t-statistic value of 9.13 and 5.28 for buy-sell days. The findings give an approving support that KSE-100 index follow trends, however the correlation does not indicates strong enough support about the stock predictions. In panel 2 the results are better as compared to SMA approach. The EMA results illustrate the positive daily average return on buy days while negative on sell day transactions. The output indicates that EMA (25-200), EMA (50-150) and EMA (50-200) produced statistically significant return on buy-sell transactions as evidenced by the high t-statistic value of 16.75, 12.73 and 2.46 respectively. The results indicate that some of the combinations have the ability of forecasting the stock index in generating the above average return. The results illustrates that the performance of EMA is comparatively superior to that of simple moving average approach.

Table 4. *Statistical results for multiple SMAs, GRNN*

Rules	Mean (Buy)	Mean (Sell)	Buy-Sell	StDev (Buy)	StDev (Sell)	N (Buy)	N (Sell)
Panel 1							
SMA (25-100), GRNN	0.2179%	-0.0476%	0.2655%	1.074%	1.120%	2178	1843
	(7.86)	(-3.56)	(7.27)				
SMA (25-150), GRNN	0.1532%	-0.3543%	0.5075%	1.239%	1.714%	2307	1663
	(11.50)	(-1.98)	(11.37)				
SMA (25-200), GRNN	0.5188%	-0.1092%	0.6280%	1.471%	1.354%	2175	1746
	(5.27)	(-5.11)	(5.90)				
Average	0.2966%	-0.1704%	0.4670%	1.261%	1.396%	2220	1751
Panel 2							

SMA (50-100), GRNN	0.3123%	-0.1971%	0.5094%	1.423%	1.562%	2517	1504
	(5.01)	(-5.13)	(11.07)				
SMA (50-150), GRNN	0.2079%	-0.1723%	0.3802%	1.510%	1.674%	2391	1580
	(4.10)	(-4.72)	(5.13)				
SMA (50-200), GRNN	0.1959%	-0.2039%	0.3998%	1.296%	1.315%	2465	1456
	(9.24)	(-2.55)	(9.31)				
Average	0.2387%	-0.1911%	0.4298%	1.409%	1.517%	2458	1513

Mean (Buy and Mean (Sell) are the mean average daily returns for buy and sell days respectively. StDev (Buy) and StDev (Sell) are the standard deviation and N (Buy) and N (Sell) the number of trading days for buy and sell days respectively. Numbers in parenthesis are the Welch-t-statistic. In column 2 and 3, the Welch t-statistic measure the difference between average daily return on buy day to average buy-and-hold returns. In column 4, the Welch t-statistic measure the difference between average daily return on buy days and average daily sell day returns.

The combination of generalized regression neural network with simple moving average is shown in Table 4. A buy signal is generated when the value generated by GRNN is larger than that of SMA value for the same period. In the same way if the value of closing price of the period t+1 generated by GRNN is smaller than that of the SMA for the same period, a sell signal is generated. No buy and sell signal is generated for all other cases.

The table illustrate that the buy day average daily return are positive and significant for all the combinations of SMA with GRNN. Similarly the return for sell day is negative and significant for all the combinations. The returns for buy-sell are also highly statistically significant as evident by t-value and its significance level. The standard deviation of sell day is greater than the buy day, implies that investor react more to the loss as compared to gain. This implies that investors at large are risk averse.

The results indicate that neural network can be equally employed for the prediction of stock prices and thus generate better results as compare to its counterpart. This is due to the handling of nonlinear distribution of stock prices.

Table 5 summarizes the output of the two proposed strategies (TS_1) and (TS_2). The first strategy involves the traders to trade in the stock market on buy day while in money market on sell day. The second strategy comprises borrowing from money market for doubling its equity market's investment. The investor trades in stock market on buy days contrasting with sell days when the investor may be in money market.

The returns are calculated by deducting the average buy-and-hold return from the average daily return generated by these trading rules. The average daily returns for the different trading rules with their t-value are given in the table. Two rules i.e. SMA (50-200) and SMA

(25-200), GRNN generates statistically significant return for the first strategy. Most of trading rules produce insignificant return, so break even trading cost are reported for the two rules generating abnormal returns. Results indicate the necessity of leverage for trading. In order to beat the buy and hold strategy, the investor must take higher risk associated with borrowing from money market and thus increase its investment. All trading rules except EMA (25-200) generate abnormal return and thus beat the buy-and-hold strategy. The returns are significant while ignoring the transactional cost associated with the rules. According to KSE rules book: “Trading fees will be levied at the rate of 0.005% of the securities’ trading value, or as may be prescribed by the Board from time to time (Page.92)”. Similarly, higher risk adjusted returns for second strategy verified also by the Sharpe ratio. The finding suggests to reject the hypothesis that buy and hold strategy could by beaten by the Technical analysis. Thus, the validity of Technical analysis is confirmed for the sample period and has a significant impact on Karachi Stock Exchange for the study period.

Table 5. *Statistical results successful trading rules, Strategy 1 and 2*

		TS1					*TS2*				
Rules	*Trades*	*Mdiff*	*SDDiff*	*SD*	*BE/TC*	*SR*	*Mdiff*	*SDDiff*	*SD*	*BE/TC*	*SR*
SMA (25-200)	120	0.004	1.22	1.24	..	0.239	1.18	2.24	2.14	2.23	0.14
		(0.04)					(5.76)				
SMA (50-200)	121	0.59	1.12	1.46	0.3	0.16	2.92	2.26	2.95	0.43	0.092
		(5.76)					(16.71)				
EMA (25-200)	139	0.35	1.96	1.98	..	0.234	0.05	2.31	1.86	..	0.155
		(1.95)					(0.28)				
EMA (50-150)	122	0.42	2.39	2.05	..	0.199	2.83	2.79	3.14	0.15	0.155
		(1.90)					(11.21)				
EMA (50-200)	121	0.43	2.44	2.02	..	0.21	2.86	2.29	3.1	0.42	0.146
		(1.93)					(11.69)				
SMA (25-100), GRNN	200	1.08	2.14	2.12	..	0.12	2.01	2.74	2.82	0.15	0.12
		(1.74)					(3.75)				.
SMA (25-150), GRNN	188	0.98	1.78	1.89	..	0.21	1.77	1.75	1.87	0.32	0.21
		(0.97)					(6.97)				
SMA (25-200), GRNN	214	1.01	1.28	1.71	0.1	0.172	1.05	1.25	1.7	0.21	0.172
		(3.76)					(4.16)				

SMA (50-100), GRNN	218	1.27	1.94	2.01	..	0.22	2.21	2.09	2.11	0.17	0.22
		(1.72)					(11.72)				
SMA (50-150), GRNN	166	0.98	2.06	2.16	..	0.097	1.9	2	2.07	0.21	0.097
		(1.81)					(2.81)				
SMA (50-200), GRNN	237	1.51	1.65	1.71	..	0.173	2.51	1.67	1.92	0.2	0.173
		(0.92)					(5.92)				

MDiff is the average daily return when average daily buy-and-hold returns are subtracted from *TS2*'s average daily returns. *SDDiff* is the standard deviation when daily buy-and-hold returns are subtracted from TS2's average daily returns. *SDDiff* is used for t-statistic, *SD* is the standard deviation for *TS2*. *BE/TC* is the break even trading cost for the given strategy. *SR* is the sharpie ratio realized return during the given time period for the given risk. Numbers in bracket represents the t-value of different trading rules.

Conclusions

The study was an attempt to inspect the effect of Technical analysis on Karachi stock exchange. Different trading rules were tested to evaluate its ability of generating abnormal return for the study period.

The sign based variance ratio test developed by (Wright, 2000) were employed to test the first objective of the study. The study did not provide support for my first hypothesis, that KSE-100 index follow random walk and are consistent with the previous studies (Gustafsson, 2012). The study confirms the finding of previous studies and found statistically significant autocorrelation among the stock returns.

The study employed the Generalized Regression Neural Network (GRNN) technique in combination with moving averages to test the efficacy of techniques for prices prediction. The study found that daily mean buy day returns were positive and significant in comparison to the average daily sell day returns. The price prediction increases especially when the GRNN technique was applied with these averages. The artificial neural network have better in dealing with the non-linear behavior of the stock prices and thus better in prediction. The findings are sufficient to reject my second null hypothesis that technical trading rules did not have predictive power for future price movements. The study further contradicts the study reported by Metghalchi et al. (2005) and Gustafsson (2012) to reject the successfulness of trading rules.

The study adopted two different trading strategies used by Metghalchi et al. (2005) supposed to outperform the buy and hold strategy. To test these strategies, the results concluded that the findings are not encouraging for first strategy, while second strategy produces significant abnormal returns. Leverage is necessary in contrast to buy-and-hold strategy in generating greater return. The findings illustrate that the investors can earn larger returns with the same level of risk in buy-and-hold strategy and thus beat B&H strategy in generating returns.

The study is limited to Karachi stock exchange especially to its KSE-100 index and may be equally applicable to the other indexes like KSE-30 index and KSE all share index. It is also recommended to carry out the study on commodity market. Further studies may apply other aspects of moving averages to thoroughly investigate different pattern like adaptive moving averages (AMA) and moving averages conversion diversion (MACD).

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