

Strathmore
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**ON THE PROFITABILITY OF TECHNICAL TRADING RULES BASED ON
ARTIFICIAL NEURAL NETWORKS:
EVIDENCE FROM THE KENYAN STOCK MARKET**

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**Submitted in partial fulfillment of the requirements for the Degree of
Bachelor of Business Science in Financial Economics at Strathmore University**

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[November, 2016]

DECLARATION

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List of Abbreviations

ANN	Artificial Neural Network
FNN	Feedforward Neural Network
PNN	Probabilistic Neural Network
NSE	Nairobi Securities Exchange

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Abstract

The aim of this study is to investigate the profitability of technical trading rules based on artificial neural networks in the Kenyan stock market. The technical trading rule is also compared to the buy-and-hold strategy to determine which strategy is more profitable. The study is carried out on the NSE 20 Index using the Excel software. A three-layered feedforward network model is used following (Rodriguez, Martel, & Rivero, 2000). The data set is divided into three sub-periods corresponding to the bear, stable and bull markets. Nine stock indices are then sampled from each sub-period and used as the inputs to the model so as to obtain the ANN forecasts. To determine the forecast accuracy, both the percentage of correct predictions and the Pesaran and Timmermann (1992) non-parametric test proportion of correctly predicted signs are used. To test for economic significance, the total return of the technical trading rule is compared to the buy-and-hold return. The results suggest that, in the absence of trading costs, the technical trading rule is always superior to the buy-and-hold strategy for both bear and stable markets. The buy-and-hold strategy, however, generates higher returns than the technical trading rule for bull markets. These findings are especially beneficial to traders since they can achieve significant trading advantages through the adoption of ANN based technical trading rules. Traders can therefore alternate between the ANN based technical trading rule and the buy-and-hold strategy, depending on whether it is a bear, bull, or stable episode, so as to maximize profits and minimize losses.

1 INTRODUCTION

1.1 Background information

For short term traders, timely decisions must be made that result in buy or sell signals so as to maintain profits. Traders have therefore sought to establish specific rules for buying and selling securities with the aim of maximizing profits and minimizing losses.

The interest in testing models of stock price behavior has led to two schools of thought: those who believe that stock prices are unpredictable, and those who take the view that stock prices are, in fact, predictable, and can be modeled in retrospect. Concerning predictability, the two approaches that have come up for predicting stock price behavior are the fundamental analysis and the technical analysis.

Technical analysis technicians believe that stock prices move in patterns that persist and are predictable to the informed investor. For example, Gencay states that technical trading analysis is based on the premise that the market's behavior patterns do not change much over time, particularly the longer-term trends. The market's way of responding to new uncertainties is usually similar to the way it handled them in the past. Therefore, the patterns in market prices are assumed to recur in the future and thus these patterns can be used for predictive purposes (Gencay & Stengos, 1997).

Evidence of predictable patterns has encouraged analysts and investors to employ technical trading strategies to execute trades. However, predictability does not necessarily imply profitability. Studies have indicated that when factors such as transaction costs and data snooping¹ are considered, there is no evidence of superior performance from technical trading rules. This is evidenced in a study conducted by Chen, Huang and Li who found that positive technical trading results in eight Asian equity markets disappear when these factors are considered (Chen, Huang, & Lai, 2009). However, taking data snooping bias into account, Hsu, Hsu and Kuan found that, in Asian emerging markets, technical trading rules perform better in young stock markets than in developed markets (Hsu, Hsu, & Kuan, 2010).

¹ Data snooping bias refers to the bias in the statistical inference that results from using information from data to guide subsequent research with the same or related data.

Studies have suggested that trading strategies guided by forecasts on the direction of price changes may be more effective and may lead to higher profits (Tilakaratne, Morris, Mammadov, & Hurst, 2007). Brock et al. found that buy signals consistently generate higher returns than sell signals and that the second moments of the distribution of buy signals are less volatile than returns following sell signals. The asymmetric nature of the returns and the volatility of the Dow series over the periods of buy and sell signals suggested the existence of non-linearities of the data generation mechanism (Brock, Lakonishok, & LeBaron, 1992). Gencay and Stengos also found predictive power of simple technical trading rules in forecasting the current evidence of nonlinear predictability in stock market returns using the past buy and sell signals of the moving average rules (Gencay & Stengos, 1997).

One of the approaches that have been tried to improve the ability of forecasting security markets using technical trading rules is the Artificial Neural Network (ANN). ANNs rely on powerful pattern recognition properties to produce short term predictions of the time series, reducing the need to specify an explicit econometric model to represent the time series (Rodriguez, Martel, & Rivero, 2000). The commonly used neural networks are the feed forward neural networks (FNNs) and probabilistic neural networks (PNNs).

1.1.1 Artificial Neural Networks

Generally, an artificial neural network is a machine that is designed to model the way in which the brain performs a particular task or function of interest. The network is usually implemented by using electronic components or is simulated in software on a digital computer (Haykim, 2009).

In econometric terms, artificial neural network models constitute a class of non-linear parametric models (Kuan & White, 1994). Non parametric models are alternatives to linear models in econometrics, and have become more easily applicable due to computational advances. The ANN models are capable of learning through trial and error, and this learning corresponds to statistical estimation of model parameters. ANNs accumulate, store and recognize patterns of knowledge based on experience, and constantly retrain as the environment of examples evolve (Kryzanowski, Galler, & Wright, 1993).

Network models and their associated learning paradigms are still far from anything close to a realistic description of how the brain actually works (Kuan & White, 1994). Nevertheless, ANNs provide a rich, powerful and interesting modeling framework with proven and potential

applications across the sciences. The pattern matching and learning capabilities allow ANNs to solve many problems that are difficult to solve by standard computational and statistical methods.

ANNs learn by observing data and are able to form judgments even if given fuzzy or incomplete information. An ANN operates by creating connections between many different processing elements, each similar to a single neuron in the biological brain. These neurons may be physically constructed or simulated by a digital computer. The neurons are organized in layers; input, hidden and output layer; and are tightly interconnected. Each neuron takes many input signals and produces a single output signal, based on an internal weighting system, which is sent to another neuron as input. This process continues until the final output is reached.

An artificial neural network can be linear or nonlinear. The property of nonlinearity is especially important in predicting stock prices as they tend to be nonlinear in nature. The parallel nature of the ANN enables it to process very large amounts of data efficiently and allows it to solve a problem even if some of its neurons make a mistake. The ANNs also have a built-in capability to adapt their synaptic weights to changes in the surrounding environment. These properties are beneficial to stock markets since stock prices are affected by new information.

This study applies ANNs as a technical trading rule in the stock market to determine whether ANNs are useful in predicting stock prices, and if ANNs are profitable. The study determines profitability by comparing the ANN-based strategy to that of a buy-and-hold.

1.2 Problem statement

In as much as efforts have been made to predict stock prices using non-parametric technical trading rules, the profitability of these rules should be significant so as to encourage their adoption. Previous studies on the subject have identified the profitability of technical trading rules based on ANNs. Rodriguez et al., for example, identify Artificial Neural Networks as a technical trading rule, and pit it against the buy-and-hold strategy in the Madrid stock market to investigate the profitability of a simple technical trading rule based on ANNs (Rodriguez, Martel, & Rivero, 2000). The results suggest that in the absence of trading costs, the technical trading rule is always superior to the buy-and-hold strategy for both bear and stable markets, while the buy-and-hold strategy generates higher returns as compared to the ANNs in bull markets. However, these previous studies are based on stock markets in developed countries. The profitability of ANNs in developing countries is yet to be explored. In Africa, the stock markets are still relatively

underdeveloped and inefficient. Traders still rely on traditional investment strategies such as the buy-and-hold to execute trades, while ANN-based strategies remain a foreign concept. The contribution of this paper is to extend the study by Rodriguez et al. to the Kenyan stock market so as to identify whether using ANNs as a technical trading rule is still profitable when compared to the buy-and-hold strategy. No similar research has been carried out in the region.

1.3 Research questions

- Is the use of technical trading strategies using neural networks profitable in the Nairobi Securities Exchange?
- Is the use of technical trading strategies using ANNs more profitable than the buy-and-hold trading strategy?

1.4 Research objectives

- To investigate the profitability of trading strategies using artificial neural networks in the Nairobi Securities Exchange.
- To compare the technical trading strategies using ANN with the buy-and-hold trading strategy and determine which is more profitable.

1.5 Significance of the research

The Kenyan stock market is relatively young and underdeveloped, hence the interest in investigating whether a technical trading strategy based on ANNs is profitable in such a market. This research may be beneficial to the stock market players, especially in emerging markets where inefficiencies have been found to provide significant trading advantages. Technical analysts may be able to take advantage of stock prices' predictability and secure higher excess returns based on ANNs' predictions of whether to buy or sell. If ANNs prove to be more profitable than the buy-and-hold, then analysts may be more inclined to use ANNs as a trading strategy as compared to the buy-and-hold strategy.

2 LITERATURE REVIEW

Technical trading rules have been widely studied by academicians all over the world. This has been as a response to predictive patterns observed in stock markets attributed to market inefficiencies. The literature reviewed in this paper constitute research on the predictability and profitability of technical trading rules based on non-parametric models, with a focus on ANN-based trading strategies. The literature is subdivided into two sections and arranged in chronological order.

2.1 On predictability

This section highlights the contribution of various authors on the predictive abilities of non-parametric technical trading rules. It supports the existence of non-linearities in stock returns, and emphasizes the involvement of ANNs in predicting these stock returns.

(Brock, Lakonishok, & LeBaron, 1992) Brock et al. explored the moving average-oscillator and the trading-range break, by utilizing the Dow Jones Index from 1897 to 1986. The authors combined both the bootstrapping methodology and the use of technical analysis in the study. In the first method, buy and sell signals were generated by two moving averages, a long period and a short period. In the second method, signals were generated as stock prices hit new highs and lows. Returns from an artificial Dow series were generated and the trading rules were applied to the series. These rules were evaluated by their ability to forecast future price changes. Comparisons were made between returns from these simulated series and the actual Dow Jones series. The study revealed that technical analysis helps in predicting stock price changes. The results also show that the returns during buy periods are larger and less volatile than returns during sell periods.

(Gencay R. , 1997b) Gencay uses the daily Dow Jones Industrial Average Index from 1897 to 1988 to examine the linear and nonlinear predictability of stock market returns with simple technical trading rules. The nonlinear specification of returns is modeled by single layer feedforward networks and is used as the conditional mean estimator. The forecast gains originate from the utilization of the past buy and sell signals as inputs in the feedforward network specifications. To measure its performance against linear specifications, popular linear null models such as AR and GARCH-M models are also studied. The results indicate strong evidence of nonlinear predictability of stock market returns found by using the past buy and sell signals of the moving average rules.

(Gencay & Stengos, 1997) Gencay examines the linear and nonlinear predictability of stock market returns with simple technical trading rules by using the nearest neighbors and the feedforward network regressions. The sample used is daily Dow Jones Industrial Average Index from 1963 to 1988. Gencay uses the moving average rule to investigate the predictive power of simple technical trading rules in forecasting the current returns. The test regressions contain the past buy and sell signals of the technical trading rules used in the moving average rule as regressors to forecast the current returns. The random walk model is studied as the benchmark model to measure the performance of the test regressions, and the simple GARCH model is used as the linear parametric conditional mean estimator. Non parametric regressions are used to capture any possible nonlinearities in the conditional means. The results obtained from the study indicate that there is evidence of nonlinear predictability in stock market returns by using past returns and buy and sell signals of the moving average rules. Also, the forecasts generated by the nonparametric models dominate the parametric ones. The nonparametric models that use past buy-sell signals are more accurate than those that use past returns.

(Walczak, 1999) Walczak noted that because of the possible inefficiency in emerging capital markets, various indicators external to the emerging capital market may provide a significant trading advantage. Walczak focuses on the Singapore market, which preliminary analysis suggested to be efficient but which Walczak found to possess some form of inefficiencies, and evaluates the claim that emerging equity markets are affected by external signals and attempts to exploit any trading advantage imparted by these signals. This is done using artificial neural networks. To identify emerging market inefficiency factors using neural networks, Walczak determined information that may indicate the presence of a non-random walk market behavior and provide a significant trading advantage to an investor. The evidence shows that the Singapore market suffers from at least one form of inefficiency and that this inefficiency can be exploited. Also, the evidence emphasizes that neural networks provide a mechanism for both evaluating the presence of an inefficient market and exploiting that inefficiency. The neural network technique as applied to trading on market indices in the emerging Singapore market is compared with the Dow Jones market index. Results indicated that external market signals can significantly improve forecasting on the Singapore DBS50 index but have little effect on forecasts of the established Dow Jones Industrial Average Index. This demonstrated the efficacy of using neural network models to capitalize on discovered market inefficiencies.

From the above studies, it can be noted that capital markets may suffer from market inefficiencies, and that these inefficiencies result in the predictability of stock markets. This predictability may be exploited by traders to provide significant trading advantages. ANNs are observed to be effective in capturing the inefficiencies. The ANNs are used to model the nonparametric trading rules so as to obtain buy and sell signals. The forecasts that use buy and sell signals are found to be more accurate than those that use past returns. However, the previous studies fail to account for whether the technical trading strategies are profitable. This issue is highlighted in the next section.

2.2 On profitability

Having established the predictive abilities of technical trading rules, this section highlights the contribution of various authors on the profitability of these rules. The technical trading rules are based on non-parametric models and are pitted against simple strategies such as the buy-and-hold. Profitability is then decided based on the strategy that gives the best results.

(Gencay R. , 1998) Gencay investigated the profitability of simple technical trading rules based on non-parametric models of a feedforward design against a simple buy-and-hold strategy on the security and its distance from the ideal net profit. The sign predictions used to provide information for market timing were the Henriksson and Merton (1981) test and the Pesaran and Timmermann (1992) test, and the results from the sign prediction tests indicated statistical significance. The data used was from the Dow Jones Average Index and was studied in five subsamples to study the sensitivity of the results to sample variation. The results suggested that non-parametric models with technical trading strategies provide significant profits when tested against a simple buy-and-hold strategy.

(Qi, 1999) Min Qi examines the predictability of S&P 500 index returns using a linear regression model and nonlinear NN forecast models with monthly observation on nine financial and economic variables. The aim of the research was to gauge the usefulness of alternative linear and nonlinear models in stock return prediction using financial and economic variables, with particular attention to nonlinear NN's forecast. Qi uses a three-layered ANN and subjects both the linear and nonlinear model to the same tests using the sample used by Pesaran and Timmermann (1995). In regards to artificial NNs, Qi states that given the numerous empirical findings that stock returns are linearly predictable using some financial and economic variables, an NN with these input variables is ideal. The nonlinear NN model not only fits the data better than the linear model in

sample, but also provides fairly accurate forecasts out of sample. Regarding profitability, assuming no short-selling or leverage, and holding transaction costs constant through time, the results suggested that the portfolio based on the recursive nonlinear NN forecasts earns higher risk-adjusted returns than the portfolio based on the recursive linear forecasts. Both the two portfolios outperform the buy-and-hold market-index portfolio primarily during the volatile markets periods. Qi concludes that there is clear evidence of nonlinear predictability of U.S. stock market returns using financial and economic variables, and adds that the complexity of NN models and the loss of interpretation and statistical inference seems to be compensated with more accurate forecasts and higher profitability.

(Rodriguez, Martel, & Rivero, 2000) Rodriguez et al. investigated the profitability of a simple technical trading rule based on Artificial Neural Networks in the Madrid Stock Market. The ANN's predictions were transformed into a simple trading strategy and the profitability was evaluated against a simple buy-and-hold strategy. This simple trading strategy was in the form of an econometric model of a feedforward neural network. The data used corresponded to a bear sub period, a stable sub period and a bull sub period. To evaluate the accuracy of the ANN predictors' forecasts, Rodriguez et al. computed the percentage of correct predictions and the Pesaran and Timmermann's (1992) non parametric test proportion of correctly predicted signs. To evaluate profitability, Rodriguez et al. compared the total return from the ANN to the buy-and-hold returns. The results showed that in the absence of trading costs, the technical trading rule was superior to the buy-and-hold strategy for both bear and stable markets; and that the buy-and-hold strategy was superior in the bull market.

From the above papers on profitability, it can be noted that in the absence of transaction costs, ANNs are indeed profitable. Nonlinear NN models fit data more precisely, are often better predictors, and are more profitable than their linear counterparts. Moreover, both the linear and nonlinear models consistently outperform the simple buy-and-hold strategy during volatile market periods.

One of the misgivings of the above studies, apart from (Gencay R. , 1998), is that the studies fail to factor in transaction costs yet transaction costs are a major market friction. The presence of transaction costs may lead to insignificant profits hence rendering ANNs ineffective as a technical trading rule. Another misgiving is that the studies only highlight the impact of technical trading

strategies on developed capital markets while their impact on developing capital markets is left unexplored. The current study seeks to focus on the latter by investigating the profitability of technical trading rules in developing capital markets.

The paper by (Rodriguez, Martel, & Rivero, 2000) contributes to the current research as it acts as an anchor to the study. The aim of this research is to replicate (Rodriguez, Martel, & Rivero, 2000) in the Kenyan stock market and test whether trading strategies based on ANNs are profitable as compared to the buy-and-hold strategy. The fact that the Kenyan stock market is a relatively underdeveloped market in an emerging economy is an area of interest since market inefficiencies are more prevalent in such markets and would therefore result in significantly higher trading advantages if exploited.

3 METHODOLOGY

3.1 Research design

3.1.1 The model

The ANN model used for this study is a three-layered, 9-4-1 feedforward network. The FFN follows (Rodriguez, Martel, & Rivero, 2000), and shall be in the form,

$$y_t = G\left(a_0 + \sum_{j=1}^4 a_j F\left(b_{0j} + \sum_{i=1}^9 b_{ji} r_{t-i}\right)\right)$$

This specification follows (Gencay R., 1999) and considers nine inputs. There is one hidden layer with four units and one output layer with a single neuron (y_t). F and G are transformation functions: where the hidden transfer function F is a logarithmic function and the output transfer function G is a hyperbolic tangent function. a_j is the weight of the connection from the j^{th} hidden layer unit to the output layer; b_{ji} is the weight of the connection from the i^{th} input unit to the j^{th} hidden layer unit. r_{t-i} denotes the returns at time $t - i$.

The hidden transfer function F is a logarithmic function due to the fact that logarithmic functions scale down variables thereby reducing the impact of outliers. Moreover, it has been found that differencing using the logarithmic function increases the number of correct predictions.

The output transfer function G is defined as a hyperbolic tangent function as a standard backpropagation configuration. Error backpropagation is the most common method used to train ANNs. The backpropagation algorithm trains a feed-forward neural network by comparing the output response to the sample input pattern and its known output. The error value is calculated and based on the error the connection weights are adjusted. The aim of error backpropagation is to minimize the sum of squared errors of the system by moving down the gradient error curve. Furthermore, according to (Refenes, Zapranis, & Francis, 1994), the hyperbolic tangent function is consistent with faster training times. The hyperbolic tangent function is defined as:

$$\tanh(z) = \frac{\sinh(z)}{\cosh(z)} = \frac{e^z - e^{-z}}{e^z + e^{-z}} = \frac{e^{2z} - 1}{e^{2z} + 1}$$

The final output (y_t) will be a value in the (-1, +1) interval; where a value greater than 0 will be used as a buy signal, while a value less than 0 is interpreted as a sell signal.

3.1.2 How it works

In the input layer, the data is assigned a weight b_{ji} based on an internal weighting system. The weighted sum of all inputs receives a biased term b_{0j} and produces a single output signal. This signal is then transformed by the hidden transfer function F and is sent to the hidden layer as input. The transformation is assigned another randomized weight in the hidden layer. The weighted sum of the inputs is then assigned a biased term a_0 and the output transfer function G translates the signal, using a hyperbolic tangent function, to produce the final output (y_t). A negative sign is interpreted as a sell signal while a positive sign is interpreted as a buy signal.

For each sub-period, the ANN produces forecasts 250 days ahead, long enough to reduce the effects of data snooping. These forecasts are then analyzed to test for economic significance.

3.1.3 Justification

The choice of a nonlinear ANN econometric model is due to the fact that stock returns are nonlinear in nature. The model specified in this study embodies an econometric form as described by (Kuan & White, 1994). In ANNs, learning corresponds to statistical estimates of model parameters.

3.2 Population and sampling

The population used is the Kenyan stock market indices. Specifically, the study shall use the NSE 20 index as a sample representation of the Kenyan stock market. The NSE 20 is used due to the availability of data. The data shall be divided into three sub-periods each corresponding to a downward trend, stable episode, and upward trend. This is because stock market prices tend to have alternating periods of rising and falling prices generally referred to as bull and bear markets respectively. The three sub-samples shall be used to generate forecasts of stock returns based on ANNs. The forecast horizon shall be approximately one year of daily observations. The last 250 observations in each sub-period shall therefore be reserved for out-of-sample forecast comparisons.

3.3 Data collection

3.3.1 Data types and sources

Secondary data on stock indices shall be used to carry out the research. Stock indices are quantitative data. The data frequency used is daily since stock positions are opened and closed on a daily basis so as to facilitate trade.

The source of the historical daily stock indices is the Nairobi Securities Exchange online platform while the forecasts shall be generated on Excel.

3.3.2 Data collection methods and instruments

The historical daily stock indices data shall be extracted from the NSE website through its online platform. The NSE provides a portal through which historical data can be accessed at a fee. The forecasts needed for the out-of-sample forecast comparisons shall be generated on Excel using the econometric model. The Excel software is used due to ease of use and suitability.

3.4 Data analysis

3.4.1 Forecast accuracy

The forecast accuracy of the final output y_t is evaluated by calculating the percentage of correct predictions and by using the Pesaran and Timmerman (1992) non-parametric test proportion of correctly predicted signs.

The Pesaran and Timmermann (1992) non-parametric test examines the ability of a forecast to correctly predict the direction of change in the variable. The focus is on the sign of the predictability and the nonparametric test is based on the number of correctly predicted signs in the forecast series. The assumptions put forward are that the distributions are continuous, independent and invariant over time. It is important to ensure that the sign predictions of the trading strategy are correct since the signals are the basis for buy or sell decisions. A positive sign indicates a buy signal while a negative sign indicates a sell signal. An incorrect sign may therefore prove fatal as it may lead the investor in making wrong trading decisions that may result in significant, and potentially disastrous, losses (Pesaran & Timmermann, 1992).

The Pesaran and Timmermann (1992) test denotes the series of interest as y_t , and the forecast as X_t , and is given by:

$$Sn = \frac{\hat{P} - \hat{P}_*}{[\hat{V}(\hat{P}) - \hat{V}(\hat{P}_*)]^{0.5}}$$

Where;

$$\hat{P} = n^{-1} \sum_{t=1}^n I(y_t X_t)$$

$$\hat{P}_* = \hat{P}_y \hat{P}_x + (1 - \hat{P}_y)(1 - \hat{P}_x)$$

$$\hat{V}(\hat{P}) = n^{-1} \hat{P}_*(1 - \hat{P}_*)$$

$$\hat{V}(\hat{P}_*) = n^{-1} (2\hat{P}_y - 1)^2 \hat{P}_x (1 - \hat{P}_x) + n^{-1} (2\hat{P}_x - 1)^2 \hat{P}_y (1 - \hat{P}_y) + 4n^{-2} \hat{P}_y \hat{P}_x (1 - \hat{P}_y)(1 - \hat{P}_x)$$

$$\hat{P}_y = n^{-1} \sum_{t=1}^n I(y_t)$$

$$\hat{P}_x = n^{-1} \sum_{t=1}^n I(X_t)$$

$$I(.) = \begin{cases} 1, & . > 0 \\ 0, & otherwise \end{cases}$$

The notation \hat{V} denotes the variance, \hat{P} the proportion of times that the sign of y_t is predicted correctly, while \hat{P}_* is the estimator of the expectations of \hat{P} obtained under the null hypothesis that y_t and X_t are distributed symmetrically around the mean. The test is normally distributed with $N \sim (0,1)$. The test is evaluated at the 1% and 5% levels of significance.

3.4.2 Economic significance

To evaluate the economic significance of the technical trading strategy, the profitability measures considered are the total return, ideal profit and the Sharpe ratio.

The total return is given by:

$$R_T = \sum_{t=1}^n y_t r_t$$

Where $r_t = \log\left(\frac{p_t}{p_{t-1}}\right)$ is defined as the continuously compounded gross return of the stock at time t . y_t is the buy or sell signal of the ANN output: positive returns are executed as buy signals with a value of +1 and negative returns are executed as sell signals with a value of -1. n is the number of observations.

The total return of the ANN is compared to the return on a simple buy-and-hold strategy (R_b). For the buy-and-hold strategy, the returns are given by:

$$R_b = \log\left(\frac{p_{t+\rho}}{p_t}\right)$$

Where ρ represents the holding period yield, and p_t and $p_{t+\rho}$ are the prices of the security at time t and $t + \rho$ respectively. Log returns are used due to the continuous nature of stock prices.

The ideal profit measures the returns on the trading system against a perfect predictor and is calculated by:

$$R_i = \frac{\sum_{t=n+1}^{n+\rho+1} \hat{y}_t r_t}{\sum_{t=n+1}^{n+\rho+1} |r_t|}$$

$R_i=1$ if \hat{y}_t takes the correct trading position for all observations in the sample. If all the trading positions are wrong, then the value of this measure is $R_i = -1$. An $R_i = 0$ value is considered a benchmark to evaluate the performance of an investment strategy.

The Sharpe ratio is the mean return of the trading strategy divided by its standard deviation. It is expressed as:

$$S_R = \frac{\mu_{R_T}}{\sigma_{R_T}}$$

The higher the Sharpe ratio, the higher the return and the lower the volatility.

The results of the analysis for both the buy-and-hold and the technical trading rule are then tabulated and compared across the three sub-periods to determine profitability.

4 RESULTS AND ANALYSIS

4.1 ANN based technical trading strategy

This section discusses the procedure of analyzing a technical trading strategy based on ANNs. The technical trading rule is based on (Rodriguez, Martel, & Rivero, 2000) and is used to maximize the total returns of an investment strategy. The data series is the daily NSE 20 stock indices from 4th February 1991 to 2nd February 2015. Below is a graph representing the General Index of the NSE 20 stocks, which showed alternating episodes of generally rising or generally falling stock prices.

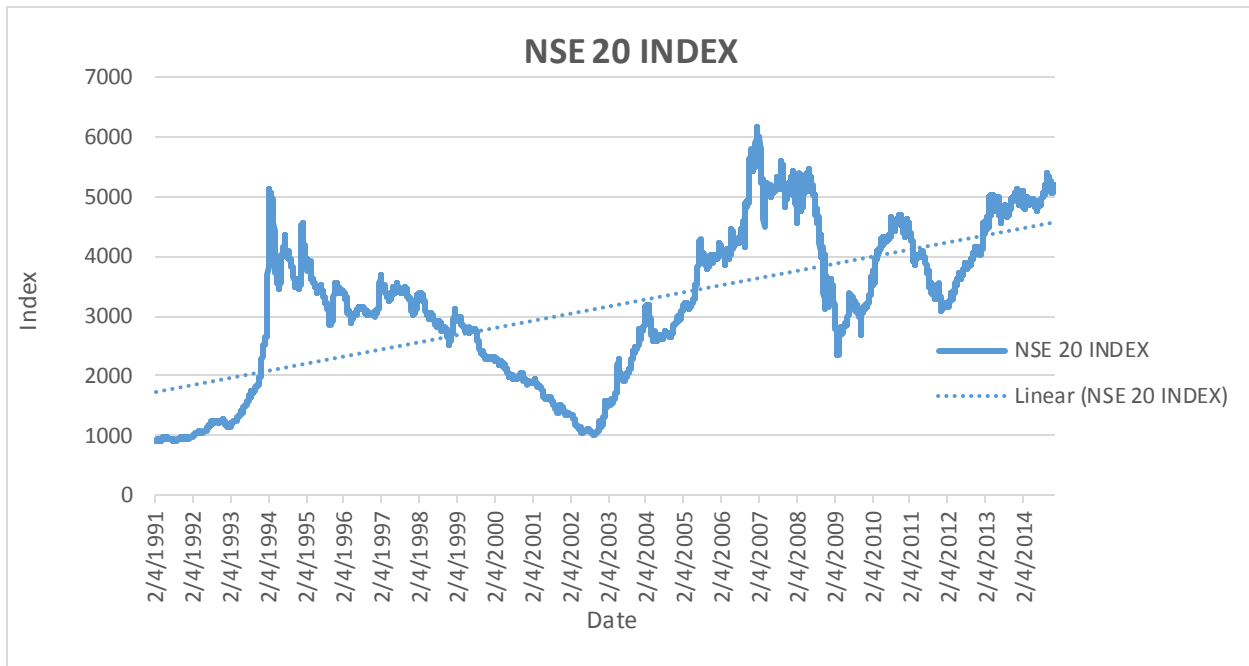


Figure 1. The general index of the NSE 20 stock exchange

The data set is studied in three subsamples: sub-period 1 corresponds to the bear market, sub-period 2 corresponds to the stable market and sub-period 3 corresponds to the bull market. For selection purposes, the bear (bull) run is signaled by a 20%, or more, rise (drop) in stock prices over a period of two months. Thus, the samples chosen to examine the performance of the ANN in the three different sub-periods are: (1) 1/26/2011 to 2/14/2012, (2) 5/16/2013 to 8/4/2014 and (3) 2/28/2012 to 5/23/2013. For each subsample, the ANN uses nine observations to produce forecasts 250 days ahead (a year of price data in daily frequency).

Using Excel, the returns of the stock indices are computed using the natural logarithmic function due to the linear relationship observed for logarithmic returns in time series data. The first nine returns in each sub-period are then used as the in-sample observations for r_{t-i} . The weights, b_{ji} and a_j , in each sub-period, are calculated as a function of random numbers between 1 and 100. For each weight, the random numbers are weighted with their sum in each hidden layer unit. The weights are initially set as random numbers due to the fact that ANNs use iterative processes to train the network such that the weights will finally converging to some useful set of values. The bias units, b_{0j} and a_0 , are extra neurons added to each pre-output layer that store the value of 1. Bias units are not connected to any previous layer and hence do not represent any true activity and are not influenced by the values in the previous layer. The bias units, however, still have outgoing connections and contribute to the output of the ANN. In this study, the biases are treated just like any other weight and hence initialized to some random value that will end up converging to some useful set of values. Furthermore, when multiplied by 1, the bias will still result in an arbitrary number.

Following (Rodriguez, Martel, & Rivero, 2000), the nine inputs r_{t-i} are multiplied with the weights b_{ji} and summed using the SUMPRODUCT function. The bias units b_{01} to b_{04} are initialized as weighted random values between 1 and 100, and added to the values obtained using the SUMPRODUCT function. The weighted sum of all inputs and a bias term is then transformed by the hidden transfer function F , a logarithmic function, to produce output signals in the hidden layer. The output signals produced are multiplied by the connection weights a_1 to a_4 and summed. The bias term a_0 is initialized with a value of 1 purely based on assumption. The weighted sum of the hidden layer inputs and the bias a_0 produce an output signal (y_t) through the output transfer function G which is a hyperbolic tangent function. The final output is found to be between the (-1, +1) interval. This process is then repeated to produce 250 forecasts of returns in each sub-period.

The error is calculated as the difference between the actual returns and the projected returns of the out-of-sample observations. Solver is used to minimize the squared errors in the model. This is achieved by changing the weights and the bias units to find the optimal weights and bias that give a minimum squared error for the model. The change in the values of the weights and bias result in a change in the values of the projected returns, such that the values of the projected returns are much closer to the values of the actual returns. This can be observed in the graphs below:

Sub-period 1

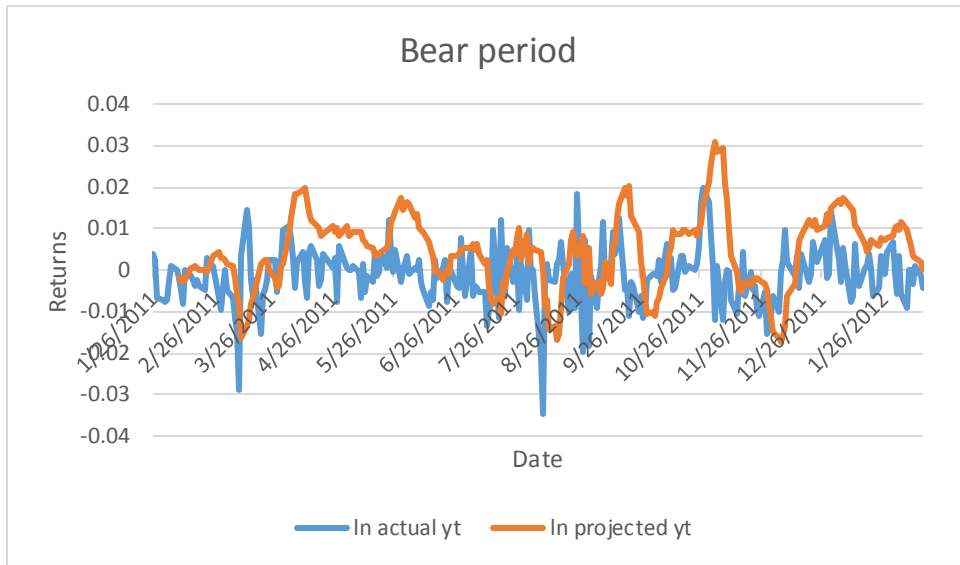


Figure 2. Graph showing the projected and actual returns in sub-period 1

Sub-period 2

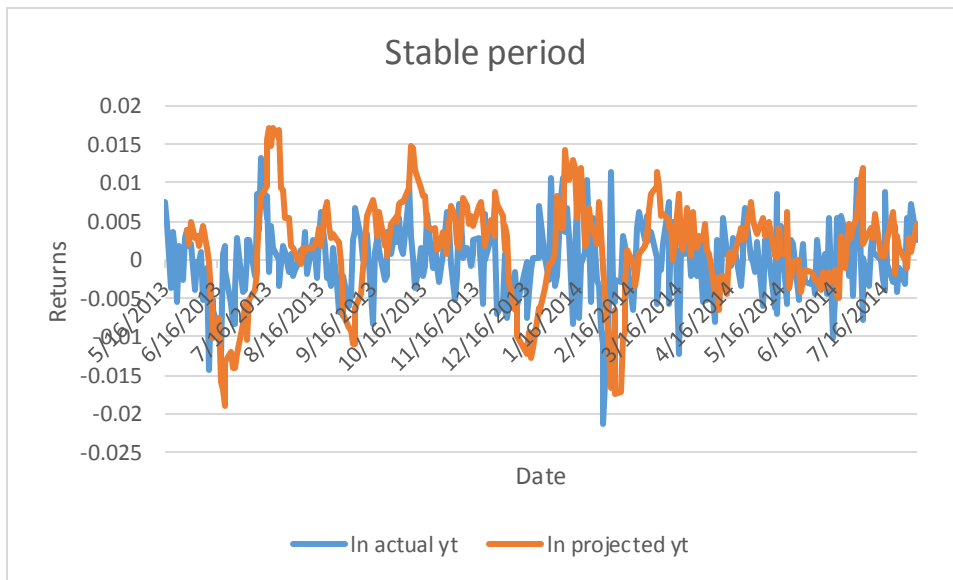


Figure 3. Graph showing the projected and actual returns in sub-period 2

Sub-period 3

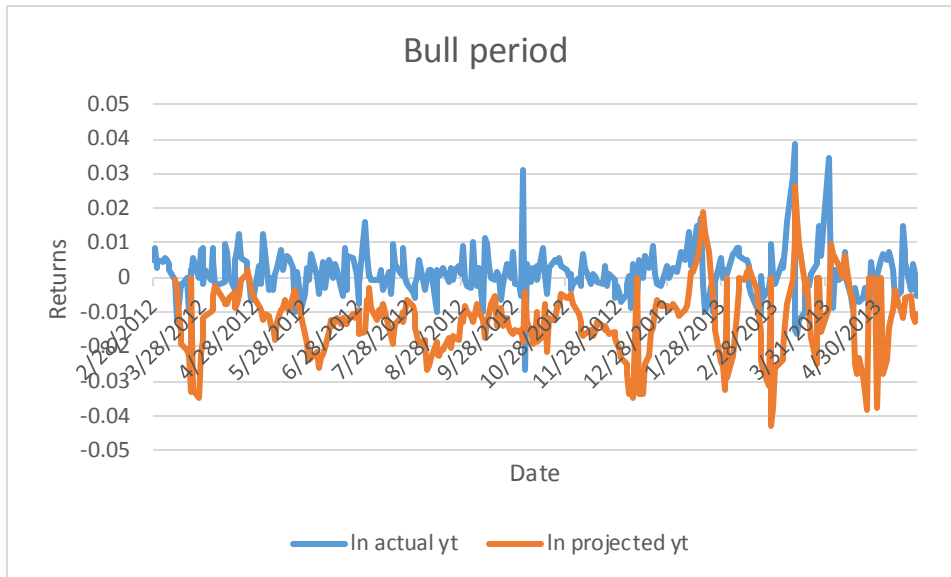


Figure 4. Graph showing the projected and actual returns in sub-period 3

4.2 Forecast accuracy

Sign predictions provide valuable information for market timing (Gencay R. , 1998). To evaluate the forecast accuracy of the ANN predictors, the percentage of correct predictions and the Pesaran and Timmermann’s 1992 non-parametric test proportion of correctly predicted signs are used in each sub-period. The results of the tests are as follows:

Table 1. Percentage of correct predictions

	Sub-period 1 (Bear market)	Sub-period 2 (Stable market)	Sub-period 3 (Bull market)
No. of correctly predicted signs	125	149	106
No. of incorrectly predicted signs	125	101	144
Total	250	250	250 ²
Percentage of correctly predicted signs	50%	60%	42%

² The total number of predicted signs were less than 250 due to errors (#NUM!) observed in the projections. The errors were replaced with nil values as sign predictions so as to provide results. The nil values were therefore counted as incorrect predictions.

Table 2. Pesaran and Timmermann's (1992) non-parametric test proportion of correctly predicted signs

	Sub-period 1 (Bear market)	Sub-period 2 (Stable market)	Sub-period 3 (Bull market) ³
S_n	1.013287	2.884592	-0.17349
Mean error	-0.00561	-0.00157	0.014325
Mean Squared Error	0.000146	0.000061	0.000317

As the limiting distribution of the Pesaran and Timmermann's (1992) test is $N(0,1)$, its one-sided critical values at the 1% and 5% levels are 2.33 and 1.645 respectively.

4.3 Economic significance

To assess the economic significance of the ANN predictors as a simple technical trading strategy, the total return, returns on a simple buy-and-hold strategy, ideal profit and the Sharpe ratio are considered for each sub-period. The analysis yields the following results:

Table 3. Economic significance tests

	Sub-period 1 (Bear market)	Sub-period 2 (Stable market)	Sub-period 3 (Bull market) ⁴
Total return (ANN)	0.075633	0.267843	-0.25966
Buy-and-hold returns	-0.32492	-0.01863	0.344084
Ideal profit	0.058136	0.288221	-0.23572
Sharpe ratio	0.0424	0.227652	-0.1691

³ The (#NUM!) errors in the return forecasts for sub-period 3 (bull market) were replaced with nil values when conducting the Pesaran and Timmermann 1992 test proportion of correctly predicted signs so as to obtain the results. The nil values were therefore counted as incorrect predictions.

⁴ The results for economic significance in the bull market were also influenced by the (#NUM!) errors in the return forecasts.

5 DISCUSSION

This chapter contains a discussion of the results obtained from the analysis. A comparison is drawn between the ANN-based trading strategy and the buy-and-hold strategy in the three sub-periods to identify which of the two strategies is more profitable. Linkages to previous studies are then provided. The results are summarized in the Table below:

Table 4. Out-of-sample tests

Tests	Sub-period 1 (Bear market)	Sub-period 2 (Stable market)	Sub-period 3 (Bull market)
Sign predictions	50%	60%	42%
Pesaran & Timmermann	1.013287	2.884592	-0.17349
Total return (ANN)	0.075633	0.267843	-0.25966
Ideal profit ratio	0.058136	0.288221	-0.23572
Sharpe ratio	0.0424	0.227652	-0.1691
Buy-and-hold return	-0.32492	-0.01863	0.344084

5.1 Forecast accuracy

From the results reported in *Table 4*, the percentage of correctly predicted signs for all sub-periods range between 40%-60%, with the stable market having the highest percentage of correctly predicted signs. The Pesaran and Timmermann (1992) test is seen to be significant in sub-period 2 at both the 1% and 5% significance levels, but insignificant in both sub-period 1 and sub-period 3. Overall, the results imply that ANNs are useful in predicting stock market returns especially in the bear and stable markets where ANNs are seen to have a 50%-60% degree of accuracy.

5.2 Economic significance

Regarding returns, technical trading rules based on ANNs dominate the buy-and-hold investment strategy in both sub-period 1 and sub-period 2; whereas the buy-and-hold dominates in sub-period 3. Both sub-period 1 and sub-period 2 are observed to yield positive returns for technical trading rules based on ANNs while sub-period 3 yields negative returns. The buy-and-hold strategy yields positive returns only in sub-period 3.

The ideal profit ratio is highest in sub-period 2 (stable market) and is greater than the benchmark value of zero in both sub-period 1 and sub-period 2. However, the ideal profit takes a negative value in sub-period 3 (bull market) with a 23% deviation from the benchmark. This implies that the ANNs are profitable when used in the bear and stable markets, but not profitable when used in the bull market.

The risk/return ratios indicated by the Sharpe ratio are consistent with the observed values of returns⁵. The Sharpe ratio is highest in the stable market in accordance with the high returns observed in this market. The bear market also has a positive Sharpe ratio while the bull market has a negative Sharpe ratio that corresponds to its negative returns. The ANN based technical trading rule is therefore found to generate higher returns, evidenced by the higher Sharpe ratio, in the bear and stable markets; and is therefore profitable in these markets.

5.3 Linkages to previous literature

The results were found to be consistent with the observations of (Rodriguez, Martel, & Rivero, 2000) who found that technical trading strategies based on ANNs are superior to the buy-and-hold strategy in both the bear and stable markets. In the bull market, previous literature found the buy-and-hold strategy to be superior to the ANN-based technical trading rule. The current study supports Rodriguez et al. by observing that the ANN-based technical trading rule, when applied to the NSE, is more profitable than the buy-and-hold strategy in both the bear and the stable markets. The buy-and-hold strategy, on the other hand, is more profitable than the ANN-based technical trading rule when applied in the bull market. However, there is a slight deviation in the observations in this study as compared to the findings of Rodriguez et al. where the bear market is concerned. Rodriguez et al. found the ANN-based strategy to have the highest profitability in the bear market evidenced by the high percentage of correctly predicted signs, high total returns, high Sharpe ratio and high ideal profit ratio as compared to the bull and stable markets. The current study, however, finds that the stable market possesses the highest profitability among the three sub-periods. This deviation may be attributed to the sample periods observed, the volatility in the markets at the time period, or the inefficiencies specific to the Kenyan market.

⁵ The higher the Sharpe ratio, the higher the return and the lower the volatility.

5.4 Limitations of the study

A major limitation of the study was that the logarithmic transformation function used as the hidden transfer function F resulted in (#NUM!) errors in some forecast values for the bull market. This was as a result of the impossibility of obtaining logarithms for negative values. The errors in the bull market were therefore replaced with nil values when conducting tests on the forecast accuracy and economic significance. These nil values were counted as incorrect predictions and therefore influenced the results obtained. The results for the bull market may therefore be understated. In spite of this limitation, the results obtained are still significant since the parallel nature of ANNs allow it to solve a problem even if some of its neurons make a mistake.

6 CONCLUSION

The current study investigated the profitability of technical trading rules based on artificial neural networks and compared it to the buy-and-hold strategy in three different sub-periods. The study was carried out in the Kenyan stock market, specifically on the NSE 20 stock indices, and the sub-periods encompassed the bear market, the bull market and the stable market. Excel was used to carry out the analysis, and a comparison of the sub-periods results was drawn to establish the profitability of the two trading strategies.

The findings suggest that in the absence of transaction costs, the technical trading strategy based on ANNs is more superior and more profitable than the buy-and-hold strategy in both the bear and stable markets. This is especially so in the stable market, where the results suggest the highest levels of forecast accuracy and the highest economic significance for the ANNs. Conversely, the buy-and-hold strategy is more superior to the ANN-based technical trading rule in the bull market, where the buy-and-hold is found to yield positive returns as compared to the negative ANN returns.

6.1 Recommendations

The findings from this study are highly beneficial to traders, especially those trading in Kenyan markets, as they provide a means to maximize profits and minimize losses. Traders should, therefore, take advantage of the ANN-based technical trading rules in the stable and bear markets so as to secure timely buy-and-sell decisions that result in trading profits. The traders can then revert to the buy-and-hold strategy in the presence of bull markets so as to cash in on the positive returns.

6.2 Further areas of research

The current study can be extended to individual stocks as opposed to market indices so as to determine the profitability of ANNs in predicting stock returns for individual firms. This may be particularly useful since individual investors do not invest in the market as a whole, but rather in a portfolio of assets. The profitability of the individual assets may then be aggregated to establish the profitability of a portfolio of assets.

The current study may also be improved by factoring in transaction costs to the returns obtained from ANN-based technical trading rules. The inclusion of transaction costs may result in insignificant or no profits thereby rendering ANNs inefficient.

The transformation functions may also be changed to functions other than the logarithmic or the hyperbolic tangent. This may result in a reduction in forecasting errors and an increase in the forecast accuracy of the model.

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