EMPIRICAL TESTING OF THE PROFITABILITY OF TECHNICAL TRADING RULES ON GROWTH AND VALUE STOCKS LISTED AT THE NAIROBI SECURITIES EXCHANGE

By

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DECLARATION

This project is my original work and has not been presented for examination in any other university

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Joseph Kere Olwal Date

This project has been submitted for examination with my approval as a university supervisor

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Dr. J. Aduda Date

DEDICATION

It is my pleasure to dedicate this project to my wife Roselinda, and my daughters Esther and Shirley for their constant support, being there for me and their encouragement, physically and emotionally. The sacrifices each of you made were not without a course, this project is the testament of it all.

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ABSTRACT

This study looked at the applicability of the most simple and commonly used technical trading rules when applied on growth and value stocks listed at the Nairobi Securities Exchange. The period under investigation goes from 2006 to 2010.

A famous study conducted by Brock, Lakonishok and LeBaron in 1992 showed that technical analysis could indeed create abnormal profit compared to a buy and hold strategy. Later studies tested Brock et al's results in the subsequent period from 1986 and onwards and reached the conclusion that the technical trading rules in question could no longer outperform a passive investment management strategy. This study is inspired by Brock et al's 1992 study and uses simple moving average methodology to test the profitability of technical trading rules compared to buy-and-hold strategy. 5, 10 and 20 days simple moving average technical trading rules were tested using growth and value portfolios respectively. The earnings-to-price and book-to-market ratios were used to classify the stocks as growth or value stocks. The short moving average is the actual price and the long moving average varies in length from 5 to 20 days. The results are tested using the standard t-test which tests the equality of two means to test whether moving average technical trading rules outperform the buy and hold strategy.

The results show that the trading rules are able to identify periods with positive and negative returns. For both portfolios the mean return following buy signals is negative for all trading rules while it is positive following a sell signal. Furthermore, sell periods are characterized by higher volatility than buy periods. This is consistent with the leverage effect. For the growth and value strategies, the 5, 10 and 20 days simple moving average trading rules did not generate a return that is above and statistically different from the buy and hold strategy. This confirms that the NSE is weak form efficient according to Fama (1970) efficient market hypothesis.

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ABBREVIATIONS

AMEX – American Stock Exchange

B/M – Book/Market Ratio

CAPM-Capital Asset Pricing Method

DJIA-Dow Jones Industrial Average

EMH-Efficient Market Hypothesis

E/P – Earnings /Price Ratio

NYSE – New York Securities Exchange

NSE-Nairobi Securities Exchange

P/E – Price/Earnings Ratio

P/B-Price/Book Ratio

IFC-International Finance Corporation

CDS Account- Central Depository System Account

SMA 1-5-0 5 days Simple Moving Average

SMA 1-10-0 10 days Simple Moving Average

SMA 1-20-0 20 days Simple Moving Average

CHAPTER ONE

INTRODUCTION

1.1. Background of the Study

Technical analysis is a form of security analysis that uses price and volume data which is often graphically displayed in decision making. Technical analysis can be used for securities analysis in any freely traded market around the globe. A freely traded market is one in which willing buyers trade with willing sellers without external intervention or impediment. Prices are therefore the result of the interaction of supply and demand in real time. Technical analysis is used in a wide range of financial instruments including equities, bonds, commodity futures and currency futures. The underlying logic of technical analysis is supply and demand determine prices, changes in supply and demand cause changes in prices and prices can be projected with charts and other technical tools. The art of technical analysis is to identify trend changes in early stages and stay in the position you have taken until there are enough indications of a trend reversal. Technical analysis therefore rests on three premises which are market action discounts everything, prices move in trends and history repeats itself (Pring, 2002).

Technical analysis can thought of as the study of collective investor psychology or, sentiment. Prices in a freely traded market are set by human beings or their automated proxies such as computerized trading programs and price is set at the equilibrium between supply and demand at any instant in time. Various fundamental theorists have proposed that markets are efficient and rational, but technicians believe humans are often irrational and emotional and that they tend to behave similarly in similar circumstances. Human behaviour is often erratic and driven by emotion in many aspects of one’s life, so technicians conclude that it is unreasonable to believe that investing is one exception where humans always behave rationally. Technicians believe that market trends and patterns reflect this irrational human behaviour and the trends and patterns tend to repeat themselves and are therefore somewhat predictable. So, technicians rely on recognition of patterns that have occurred in the past in an attempt to project future patterns of security prices.

The primary tools used in technical analysis are charts and technical indicators. Charts are the graphical display of price and volume data, and the display may be done in a number of ways. Charts are then subjected to various analyses, including the identification of trends, patterns and cycles. Technical indicators on the other hand include a variety of measures of relative price level for example price momentum, market sentiment and funds flow. By investigating technical trading rules a hypothesis about the efficiency of the financial market in its weak form as defined by Fama (1970) is indirectly examined. If technical trading rules prove to be able to generate a statistical and economical significant better return, the efficient market hypothesis can be rejected. According to weak form of efficient market hypothesis investors cannot anticipate to generate abnormal profits by relying on information contained within past prices .Efficient market hypothesis identifies the concept that sources of predictable patterns that offer significant returns are immediately exploited by investors. By exploiting these patterns in the market, investors quickly and efficiently eliminate any predictability in the market. However, some traits of the security markets are still a puzzle. One of these is the value premium puzzle.

Studies have shown that value stocks generate a higher return than growth stocks and this is known as the value premium puzzle. The most common methods of identifying value stocks are to look at the earnings-to-price (E/P) and book-to-market (B/M) ratios. Portfolio managers often follow an overall investment philosophy by deciding which kind of stocks they want to invest in and either they can decide to invest in value stocks and hence follow a value investment approach or they can decide to use a growth stock investment approach by investing in growth stocks. The value investment strategy builds on the concept of identifying and investing in stocks which are trading at a lower price than motivated by its intrinsic value and reap a profit when the market corrects itself. Value investors are looking out for bargains where the price of a security has been beaten down unfairly. They focus on whether the market price is below the estimated economic value of the tangible assets of the company and then a real bargain can be made and the larger the gap between the market price of a stock and the market price of its tangible assets the more attractive the investment is (Hirschey & Norfsinger, 2005). The measures used to judge when a stock is selling at a discount are P/E and P/B ratios and dividend yields.

The value investors search for ratios below the historical level of the company and market average or stocks with an above average dividend yield. The company behind must be a quality firm selling at a low price compared with criteria above. Instead of comparing to other market measures value investors can compare the price of the stock to the fundamental value of the company.

Those who subscribe to growth philosophy invest in stocks which are already popular in the market place hoping their stock market values will increase further. Growth stock investors analyze the future growth potential of a firm. There are numerous ways to identify growth stocks, and different investors look at different indicators. Some look for above average growth in earnings per share and revenue while others look for growth rates at least twice the average of the company standard. The company also must have enough financial slack and thereby is able to finance future growth without additional debt. The distinctive characteristics are market expectations of future growth, low book-to-market, low cash flow-to-price, low earnings-to-price ratios and high past growth rates in sales. To find out whether growth stock is an attractive investment analysts look at the business environment with attractive characteristics such as competitive advantage in its industry.

This study used past price data from the Nairobi Securities Exchange. The NSE was constituted in 1954 as voluntary association of stock brokers registered under the Societies Act. According to Ndegwa (2006) the stock market experienced a robust activity and high returns on investment culminating in the NSE being rated by the International Finance Corporation (IFC) as the best performing market in the world with a return of 179% in dollar terms. The NSE has undergone a number changes since inception like increase in the number of listed companies, the number of CDS accounts opened and the volume of shares traded. The clearing, settlement and trading processes have been automated and are supported by robust and modern information technology infrastructure. In 2006 it implemented live trading through automatic trading systems and also a demutualization committee was set up to start process of demutualization to make it a company limited by shares. Co-operation with other exchanges in the East Africa region has led to cross listing of shares like those of Kenya Airways, Jubilee Insurance and East Africa Breweries.

1.2 Statement of the Problem

Technical analysts search the past prices of time series for recognizable patterns that have the ability to predict future price movements and earn abnormal returns. Various trading rules and indicators have been developed based on each identifiable pattern. The belief that historical data can be used to identify patterns that predict security movements violates the random walk hypothesis and weak form of market efficiency. According to efficient market theorists, technical analysis will not be able to generate abnormal returns in an efficient market. However the relatively new and emerging equity market in Kenya has not been tested to determine whether various types of technical trading rules can be used to earn abnormal returns. Nevertheless, in recent decades rigorous theoretical explanations for the widespread use technical analysis have been developed based on noisy rational expectation models (Treynor and Ferguson 1985; Brown and Jennings 1989; Grundy and McNichols 1989; Blume, Easley and O'Hara 1994), behavioural (or feedback) models (De Long et al, 1990a, 1991; Shleifer and Summers 1990), disequilibrium models (Beja and Goldman 1980), herding models (Froot, Scharfstein and Stein 1992), agency-based model(Schmidt 2002, and chaos theory (Clyde and Osler 1997). For example, Brown and Jennings (1989) demonstrated that under a noisy rational expectation model in which current prices do not fully reveal private information (signals) because of noise (unobserved current supply of a risky asset) in the current equilibrium price, historical prices (i.e. technical analysis) together with current prices help traders make more precise inferences about past and present signals than do current prices alone.

Numerous empirical studies have tested the profitability of technical trading rules in a variety of markets for the purpose of either uncovering profitable trading rules or testing market efficiency or both. Most studies have concentrated on developed markets. Alexander (1964) and Fama and Blume (1996) tested technical trading rule in the USA. Both of these studies suggest that excess returns could not be realized by making investment decisions based on the movements of certain sizes after adjusting for transaction costs. The number of influential studies that support trading rules grew in the 1990s. Some of these studies include Jegadeesh and Titmann (1993), Blume, Easley and O'Hara (1994), Chan, Jagadeesh and Lakonishok (1996), Lo and Mackinlay (1997), Grundy and Martin (1998) and Rouwenhorst (1998), Brock,LeBaron and Lakonishok (1992) and Allen and Karjalainen (1999).There have been a limited number of studies conducted in Kenya. Werah (2006) carried out a survey on the influence of behavioural factors on investor activities at the NSE and found out that investor behavior was to some extent irrational and influenced by factors such as 'herd effect', over confidence and anchoring the same factors affecting market inefficiency. Mokua (2003) tested the weekend effect and found that stock returns are equal over all week days. Okoth (2005) on the profitability of contrarian strategies found that the strategy offered profitable opportunities in the short run. Though local studies touched briefly on the efficiency of the Nairobi Stock Exchange and the behavioural effect, not much has been written about the behavior of technical trading strategies across market segments based on valuation parameters. This study will add a new perspective to the discussion by combining technical analysis with a well-known stock market anomaly; the value premium puzzle. Thuku (2009) studied the value premium and size effect and found significant value premium at 0.5% per month unlike Muhoro (2004) whose findings contradict those of Thuku (2009). Indeed there have been very few studies concerning the profitability of technical rules based on the data of any frontier stock market. The study will use the simple trading rules when applied on value and growth stocks respectively to test the efficiency of the Nairobi Stock

Exchange over the period 2006-2010 by analyzing whether it is possible to earn significantly better return than the return generated by a buy-and-hold strategy. By investigating technical trading rules a hypothesis about the efficiency of the financial market in its weak form as defined by Fama (1970) is indirectly examined. If the technical trading rules prove to be able to generate a statistical and economical significant better return, the efficient market hypothesis can be rejected. Due to this fact, the theory of efficient markets will also be covered in the study.

1.3. Objective of the Study

The objective of this study was to test the profitability of technical trading rules on growth and value stock listed at the Nairobi Securities Exchange.

1.4. Justification of the Study

The findings of this are likely to benefit the following;

Portfolio managers when choosing passive or active investment strategies while making investment decision. If they believe the market is efficient they will choose passive strategies, alternatively they will choose active strategies if they believe the market to inefficient.

Dealers and Brokers can use the study findings in signaling the timing of equity market entry and exit based on technical trading rules and patterns.

Academic Researchers as it builds on the research in behavioural finance suggesting that collective investor psychology impact trading decision and by analyzing past stock prices and volume in making trading decisions profitable patterns and trends can be discovered.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The following section reviews various theoretical and empirical studies on the profitability of technical trading rules. This is followed by an in depth review of the technical trading rules and value and growth stocks. The chapter concludes with a recapitulation of the literature review.

2.2 Theoretical Review

Previous empirical studies suggested that technical trading rules may generate positive profits. Various theoretical and empirical explanations have been proposed for technical trading profits. In theoretical models, technical trading profits may arise because of market ‘frictions’, such as noise in current equilibrium prices, traders’ sentiments, herding behaviour, market power or chaos. Empirical explanations focus on technical trading profits as a consequence of order flow, temporary market inefficiencies, risk premiums, market microstructure deficiencies or data snooping. Although these issues are still controversial, a thorough discussion is necessary to better understand the current state of the literature on technical analysis.

2.2.1 Noisy Rational Expectations Models

Under the standard model of market efficiency, the current equilibrium price fully reflects all available information and price adjusts instantaneously to new information. A basic assumption of the market efficiency model is that participants are rational and have homogeneous beliefs about information. Under noisy rational expectations equilibrium, the current price does not fully reveal all available information because of noise (unobserved current supply of a risky asset or information quality) in the current equilibrium price. Thus, price shows a pattern of systematic slow adjustment to new information, thereby allowing the possibility of profitable trading opportunities. Grossman and Stiglitz (1976, 1980) represent the most influential work on noisy rational expectations equilibrium models. They demonstrate that no agent in a competitive market has an incentive to collect and analyze costly information if current price reflects all available information, and as a result the competitive market breaks down. Brown and Jennings (1989) propose a two-period noisy rational expectations model in which the current price is dominated as an information source by a weighted average of past and current prices.

Noise in the current equilibrium price does not allow full revelation of all publicly available information available in price histories. Therefore, past prices together with current prices enable investors to make more accurate inferences about past and present signals than do current prices alone. As another example, Blume et al. (1994) propose an equilibrium model that emphasizes the informational role of volume. Their model assumes the source of noise is the quality of information. Blume et al. show that volume provides information about the quality of traders' information that cannot be conveyed by prices, and thus observing the price and the volume statistics together can be more informative than observing the price statistic alone. Technical analysis is valuable because current market statistics may be insufficient to reveal all information.

2.2.2 Behavioural Models

According to behavioural models there are two types of investors in a typical behavioural finance model: arbitrageurs (also called sophisticated investors or smart money traders) and noise traders (feedback traders or liquidity traders). Arbitrageurs are defined as investors who form fully rational expectations about security returns, while noise traders are investors who irrationally trade on noise as if it were information (Black, 1986). Behavioural (or feedback) models are based on two key assumptions. First, noise traders' demand for risky assets is affected by irrational beliefs or sentiments that are not fully justified by news or fundamental factors. Second, arbitrage, defined as trading by fully rational investors not subject to sentiment, is risky and limited because arbitrageurs are likely to be risk-averse (Shleifer and Summers, 1990, p. 19).

Noise traders buy when prices rise and sell when prices fall, like technical traders or 'trend chasers'. For example, when noise traders follow positive feedback strategies (buy when prices rise) this increases aggregate demand for an asset and results in a further price increase. Arbitrageurs may conclude that the asset is mispriced and above its fundamental value, and therefore sell it short. According to De Long et al. (1990a), however, this form of arbitrage is limited because it is always possible that the market will perform very well (fundamental risk) and that the asset will be even more overpriced by noise traders in the near future because they will become even more optimistic. As long as such risks are created by the unpredictability of noise traders' opinions, arbitrage by sophisticated investors will be reduced even in the absence of fundamental risk. A consequence is that sophisticated or rational investors do not fully counter the effects of the noise traders. Rather, it may be optimal for arbitrageurs to jump on the 'bandwagon' themselves. Arbitrageurs optimally buy the asset that noise traders have purchased and sell much later when price rises even higher. Therefore, although arbitrageurs ultimately force prices to return to fundamental levels, in the short run they amplify the effect of noise traders (De Long et al., 1990b). In feedback models, noise traders may be more aggressive than arbitrageurs due to overly optimistic (or overly pessimistic) views on markets, and thus bear more risk with associated higher expected returns. Despite excessive risk taking and consumption, noise traders may survive as a group in the long run and dominate the market in terms of wealth (De Long et al., 1991; Slezak, 2003). Hence, feedback models suggest that technical trading profits may be available even in the long run if technical trading strategies (buy when prices rise and sell when prices fall) are based on noise or ‘popular models’ and not on information such as news or fundamental factors (Shleifer and Summers, 1990).

2.2.3 Herding Models

Froot, Scharfstein and Stein (1992) show that herding behaviour of short-horizon traders can result in informational inefficiency. In their model, informed traders who want to buy or sell in the near future can benefit from their information only if it is subsequently impounded into the price by the trades of similarly informed speculators. This kind of positive informational spillover can be so powerful that ‘herd’ traders may even analyze information that is not closely related to the asset’s long-run value. Technical analysis is one example. Introducing a simple agent-based model for market price dynamics, Schmidt (2002) shows that if technical traders are capable of affecting market liquidity, their concerted actions can move the market price in a direction favourable to their strategy. The model assumes a constant total number of traders consisting of ‘regular’ traders and ‘technical’ traders. Price moves linearly with excess demand, which in turn is proportional to the excess number of buyers drawn from both regular and technical traders. In the absence of technical traders, price dynamics form slowly decaying oscillations around a fundamental value. However, inclusion of technical traders in the model increases the amplitude of price oscillations. The rationale behind this result is as follows. If technical traders believe price will fall, they sell, and thus excess demand decreases. As a result, price decreases and the chartist component forces regular traders to sell. This leads price to decrease further until the fundamentalist priorities of regular traders become dominant again. The opposite situation occurs if technical traders make a buy decision based on their analysis.

2.2.4. Chaos Theory

Clyde and Osler (1997) provide another theoretical foundation for technical analysis by showing that charting methods may be equivalent to non-linear forecasting methods for high dimension (or chaotic) systems. They tested this idea by applying the identification algorithm for a 'head-and-shoulders' pattern to simulated high dimension non-linear price series. They found out that technical analysis performs better on non-linear data than on random data and generates more profits than a random trading rule. Additional research by Stengos (1996) shows that very large sample sizes may be needed to produce accurate forecasts with the simplest low dimension chaotic processes, depending on the specification of the non-linear process. Hence, tests of the forecasting ability of technical trading rules on non-linear price data may be sensitive to assumptions regarding the underlying data generating process.

2.3. Review of Empirical Studies

Early empirical studies by Fama and Blume (1966) and Van Horne and Parker (1967) presented evidence supporting weak form market efficiency and the random walk theory. Fama and Blume studied 30 individual stocks listed on the Dow Jones Industrial Average (DJIA) over a six-year period. Fama and Blume found, after commissions, that only 4 of 30 securities had positive average returns. Furthermore, the rules they applied proved inferior to the buy and hold strategy before commissions for all but two securities. Van Horne and Parker analyzed 30 stocks listed on the New York Stock Exchange (NYSE) over a similar six-year period and found that no trading rule that was applied earned a return greater than the buy and hold strategy on the same index. Additionally, Jensen and Benington (1970) analyzed alternative technical trading rules over a period from 1931-1965 on NYSE stocks and found further confirmation that technical trading rules do not outperform the buy and hold strategy. Despite this, an extensive study performed by Alexander (1961) found information that supports the use of technical analysis.

Alexander's study prompted a series of studies attempting to disprove his results, and thus initiate the argument over the success of technical analysis in financial markets. Alexander researched the stock returns of the Standard and Poor Industrials and the Dow Jones Industrials from 1897-1959 and 11 filter rules from 5.0% to 50%. Although transaction costs were not accounted for in the study, all the profits found were not likely to be eliminated by commissions. As a result, the debate on whether technical analysis is a viable investment tool to find excess stock returns began in the 1960's, and the debate continues today. The benefits of using technical analysis are still debated within equity markets, but many empirical studies suggest consistent excess profitability of technical analysis above the buy and hold strategy within commodity and futures markets. Lukac, Brorsen and Irwin (1988) look at 12 futures from various exchanges including interest rates, agricultures, and currencies during the 1970's and 1980's. The study found evidence that suggested certain trading systems produced significant net returns in these markets. More recently research has taken several precautions to eliminate or diminish issues that were relevant for early empirical studies.

These issues included, but were not limited to: data snooping and the non-allocation of transaction costs. In an effort to mitigate these issues Brock, Lakonishok, and LeBaron (1992) used a large data series (1897-1986) and reported results for all rules that were evaluated. The Brock et. al. study indicated that some technical trading rules have an ability to forecast price changes in the Dow Jones Industrial Average. For statistical inferences, Brock et. al. performed their tests using a statistical bootstrapping methodology inspired by Efron (1979) and Jensen and Bennington (1970). Stock prices are studied frequently in financial research, and are therefore susceptible to data snooping. Brock et. al. opened the door for further arguments in support of technical analysis as a powerful forecasting tool, especially in markets that may be considered less "efficient." Bessembinder and Chan (1995), Ito (1999), and Ratner and Leal (1999) researched similar technical trading strategies as Brock et. al. in a variety of foreign markets in Latin America and Asia. The studies each found significantly higher profits using technical trading strategies than using the buy and hold strategy in countries such as Malaysia, Thailand, Taiwan, Indonesia, Mexico and the Philippines. Sullivan, Timmerman and White (1999), dug further into technical analysis by utilizing certain strategies to address the issue of data-snooping. Data-snooping occurs when data sets are reused for inference or model selection. Given this, the success of the results obtained may be due to chance rather than the merit of the actual strategy. Sullivan et al employed

White's Reality Check bootstrap methodology to filter the data in a way not previously done. Sullivan et al explain it in this way "data-snooping need not be a consequence of a particular researcher's efforts… as time progresses, the rules that happen to perform well historically receive more attention, and are considered serious contenders by the investment community, and unsuccessful trading rules tend to be forgotten…If enough trading rules are considered over time, some rules are bound by pure luck to produce superior performance1." Sullivan, Timmerman and White (1999) implemented over 8000 technical trading strategies to the same data set used by Brock et. al.(1992). Sullivan, Timmerman and White (1999) sought to find that certain trading strategies outperform the benchmark buy-and-hold strategy after controlling for data-snooping. Although the Reality Check bootstrap methodology allowed for Sullivan, Timmerman and White (1999) to differentiate themselves from previous researchers, the bootstrap methodology is not unique to technical analysis academic literature.

Perhaps one of the most recognized studies on the subject of technical analysis was the work conducted by Andrew Lo and Craig MacKinlay beginning in 1988. The research argued against famous research by Fama (1970) that dictated that prices fully reflect all available information. Lo and MacKinlay produced arguments for the creation of the concept of relative efficiency. Relative efficiency dictates that instead of comparing markets and their inefficiencies to a "frictionless-ideal" market, professionals should consider the varying degrees of efficiencies that currently exist within markets. Research conducted by Kwon and Kish (2002) and Hudson et al. (1996) indicate that gains obtained by investors from technical trading are squandered as technological advancements improve informational and general efficiency of equity markets. Thus, this study will expand upon the results found that demonstrate how informational and general market efficiency impact the profitability of technical analysis trading rules.

Recently, academic literature on technical analysis has ventured to include examinations of behavioral finance in an effort to derail efficient market hypothesis further. West (1988) examined theories that there exist disparate differences in the volatility of stock prices as compared to volatility of fundamentals or expected returns. West suggests that it may be necessary to consider non-standard models focusing on sociological or psychological mechanisms such as momentum in stock prices. Momentum and concepts behind herd mentality are prominent in many tools used by technical analysts including moving averages and trading range breakouts. Scharfstein and Stein (1990) summarize arguments for the presence of momentum in equity markets: The consensus among professional money managers was that price levels were too high – the market was, in their opinion, more likely to go down than up. However, few money managers were eager to sell their equity holdings. If the market did continue to go up, they were afraid of being perceived as lone fools for missing out on the ride. On the other hand, in the more likely event of a market decline, there would be comfort in numbers – how bad could they look if everybody else had suffered the same fate? Money managers that use momentum strategies to invest are evidence that bolster arguments inconsistent with efficient market hypothesis because these strategies challenge the validity of the random walk hypothesis. Lakonishok, Shliefer, and Vishny (1992) find evidence of pension fund managers either buying or selling in herds, with slightly stronger evidence that they herd around small stocks. Stock market efficiency, in essence, demonstrates that the price of a stock should at all times reflect the collective market beliefs about the value of its underlying assets. Any change in value should immediately be portrayed in the stock price of the asset via new information. If this informational efficiency is in place then any historical changes in price cannot be used to predict future changes in the price.

Bekaert and Harvey (1997) suggest emerging capital markets exhibit both higher volatility and higher persistence in stock returns as compared with developed markets. This evidence pokes holes in efficient market hypothesis and demonstrates the possibility of at least some market inefficiency that could offer opportunities for abnormal returns to investors. Emerging capital markets are arguably more likely to demonstrate these characteristics given their low level of liquidity, non-synchronous trading biases and general market thinness which provide significant evidence of the possibility for market inefficiencies. Other research such as Barkoulas et. al. (2000) suggests that investors in emerging capital markets react slower and more gradually to information as compared with developed markets leading to learning effects. Emerging capital markets exhibit unique characteristics that help investors implement diversification within their portfolio.

2.4 Technical Trading Rules

Markets are formed by human actions and people tend to make the same mistakes. Since human nature is more or less constant, the mistakes or emotional swings keep recurring which technical analysts exploit and there are no limitations of the number of trading rules you can make use of. Below, the most important issues within the area of technical trading are described. Chartists do not only focus on prices when making decisions but also include several other indicators, which will be described in this part. The study will use simple trading rules which will also be described in this part.

2.4.1 Dow Theory

Charles Dow, one of the founders of The Wall Street Journal and its first editor, developed Dow Theory in the late 1890s. Dow was the first to create a stock market average, which he published on July 3rd, 1884. It was not until after Dow's death, however, that his theory was formulated. His successor as editor, William Hamilton, published more than 250 stock-market predictions using theories proposed by Dow. Dow's technical basis for stock market forecasts came to be known as Dow Theory and was articulated in the book 'The Stock Market Barometer', published in 1922. Dow Theory is therefore a natural starting point in the study of technical analysis. Dow Theory tries to identify long-term trends in stock market prices. Six of the most important and basic tenets of the theory are: averages discounts everything, that a market has three trends, major trends have three phases, averages must confirm each other, volume must confirm the trend and a trend is assumed to be in effect until it gives definite signals that it has reversed.

2.4.2 Market Cycle Model and Elliot Wave Theory

The business cycle is a well-known phenomenon in the economy. Economists believe that the economy moves in a rhythmic cycle from boom to recession. Among technical analysts there is a widespread belief that stock markets also move in rhythmic cycles from boom to recession and back to boom again or, in other words, they believe that there is a tendency for prices to rotate from market peak to market trough in a rhythmic cycle. Some of the factors that cause this cyclical movement are the underlying political and economic forces and crowd behavior among humans. It can take months or even years for crowd behavior to rise to the level of irrational exuberance, decline to despondent pessimism and back to irrational exuberance again. One of the best-known market cycle models is The Elliot Wave Pattern, named after Ralph Nelson Elliot.

He believed that crowd behavior, trends and reversals occur in recognizable patterns. The basic principle of the Elliot Wave Theory is that stock prices are governed by the Fibonacci numbers (1, 2, 3, 5, 8, 13, 21, 34, 55….) and the upside market moves in five waves and three on the downside. Within these waves there can, however, be minor waves and these also show the same patterns as the major wave with five waves on the upside and three on the downside. As it was the case in Dow Theory, the waves can be divided in accordance with their size. The major wave decides the major or primary trend of the market and the minor waves the minor trend.

2.4.3 Simple Trading Rules

2.4.3.1 Moving Average

Probably the most versatile and used trading rule is the moving average trading rule and belongs to category of indicators called trend-following indicators. These indicators are meant to smooth the price pattern of indices or stocks making it easier to identify beginnings and end of trends and identify the underlying trend. The popularity of moving average is because buy and sell signals can easily be computed into a computer. Technicians may disagree whether a price pattern is a head-and-shoulder pattern while moving averages is a mathematical calculated pattern leaving no issues open for debate. Moving average is a technique where the data of a certain stock or an index is averaged over a time period. There are no specific demands to the length of the time period, but it has to fit the trading issue. Normally, however, the closing price is used, but there is no rule that says you cannot use other prices such as highs, lows or maybe even a combination of more prices.

2.4.3.1.1 Simple Moving Average

The most commonly used type of average is the simple moving average. If a 20-day average is needed, the price of each day for the last 20 days is added and then divided by 20. To make it a moving average, the oldest observation is subtracted and a new is added. To find out what length the average should have, logic sense must be applied. If you need weekly data a 4-week data may seem reasonable. If monthly data is needed a 12-month moving average is more useful. The simple moving average has, however, two major drawbacks. The first is the fact that it only covers the period under observation. It totally excludes earlier data, which might contain useful information. The second criticism is that each observation is given equal weight. The oldest observation is in other words regarded just as important as the newest. Some analysts argue that more recent observations should be given more weight in the average. To correct for this, the linearly weighted moving average and exponential moving average have been created.

2.4.3.1.2 The Linearly Weighted Moving Average

The easiest way to correct for the second of the above-mentioned problem is to use the linear weighted average. By using this average more recent observations are given more weight than old ones. If a 5 day moving average is used, the observation on the fifth day is multiplied by five; the observation on the fourth day is multiplied by four etc. The total is added up and divided by the sum of the multipliers. In this little example, the sum of the observations is divided by 15 (5+4+3+2+1=15). The linear weighted moving average method does, however, not help with the so-called drop-off effect. To correct for both problems, analysts must turn to the exponentially smoothed moving average.

2.4.3.1.3 The Exponential Moving Average

The exponential moving average is also a weighted average assigning more weight to recent observations. The oldest price observations are never removed from the data but the further back they are, the less weight they are given in the calculations. The formula for the exponential moving average is:(2-1) (1) 1 − = × − × t t EMA α price α EMA where ά = 2/(N+1). Advocates of the exponential moving average argue that this kind of moving average is relatively easy to maintain by hand day by day. The only data needed is the previous day's exponential moving average data and today's closing data.

2.4.3.1.4 One Moving Average

The moving average is just a line on a piece of paper or a computer screen and is not by itself a signal that can be used for making buy or sell decisions. To make signals out of the average, analysts benchmark either one or more against the actual price or each other. The simplest way to generate a signal is by using one moving average and compares it to the actual price. The idea behind this is that in an uptrend, the moving average tends to lag the price action and trails below the prices. If the actual price moves above the moving average a buy signal is generated and conversely, if the price moves below the average a sell signal is generated.

2.4.3.1.5 Two Moving Averages

An effective and common method is to use two moving averages simultaneously. The averages are of different lengths with the shortest of them used instead of the actual price and the longest to identify the underlying trend. There are numerous combinations of averages that can be used, but some very common combinations are the 5- and 20-day averages and 10- and 40-day averages. For a signal to be given the shorter average must cross the longer average. If the shorter moving average crosses from below a buy signal is given and if it crosses from above a sell signal is given. The use of two moving averages lags the signal a little bit, but the advantage is that it produces fewer whipsaws than by the use of only one moving average. Another way to make use of a two moving average method is to create an oscillator. The oscillator is the mathematical difference between the short and long moving average. It measures whether a market is overbought or oversold. When a security lies too far above the longer moving average it is overbought and technicians believe that the price will fall. Another way of interpreting the oscillator is to look at crossovers on the zero line. If it crosses from below, a buy signal is given and vice-versa.

2.4.3.1.6 Three Moving Averages

To make even fewer mistakes, technicians make use of three moving averages. The analogy is, if two averages resulted in fewer false signals than one, three must result in fewer than two. Technicians choose the length of the three moving averages in different ways. Probably the most used way is to use cycle length as a deciding factor. The first moving average is a 5-day moving average representing a week. The second is a 21-day average representing a month and finally a 63-day moving average for a quarter. Another way is to use harmonic numbers. If this strategy is used, you simply multiply the next longer average with a factor of two. This means that if the first moving average is a 10-day average the next moving average will be a 20-day moving average and so forth. Lastly, some also make use of the Fibonacci numbers described earlier. A popular three moving average system based on these numbers is a 5-, 13- and 34-day moving average. The trading rules with three moving averages are similar to those under one and two moving averages. The general principle is that the longer moving average must cross the shorter to generate a signal. A sell signal is generated when the e.g. 5-day average crosses the 21- day average and the 21-day average crosses the 63-day average from above. With three averages there is an in-between. The period from the fastest moving average crosses the medium until the medium average crosses the slowest moving average is a period with no clear signals. With three moving averages there is a period in-between where you are out of the market. The first sign of a reversal of a trend is that the fastest moving average crosses the medium average. As soon as this happens the position is liquidated and a position out of the market is taken.

2.4.3.2 Trading Range Breakout

As described earlier, technical analysis builds on the belief that price moves in trends. A trend can move in three directions, sideways, upwards and downwards. To be able to use these trends and easier react on them, technicians often draw trend lines. Trend lines can be drawn from either the lows in an uptrend and highs in a downtrend or through some key closes. The time issue is very important when using trend lines. If you have a very short time horizon, a 10-year trend line is of very little use. Similar a two-week trend line will trigger too many signals for a trader with a five-year time horizon. The technique of drawing trend lines is subjective. This means that no formula can be used to help you draw the line; you must simply draw what you think you see. The fact that it is a subjective technique makes it hard to use for buy and sell signals. If the price crosses the trend line from either below or above it should be a signal. To help making better decisions some analysts use bands around the line. Typically these bands are 1% or 3% bands. The idea is, in case of a 1% band, that the security must trade more than 1% above or below the line before action is taken. If the band approach is taken the signals that are generated must be used as mechanical signals; if the price reaches the 1% or 3% level action is required without any extra hesitation. Another way to use trend lines is to draw what is referred to as channels. Basically, two trend lines are drawn; one up or downtrend line and a return line also called channel line. To be able to draw a channel in an uptrend, two bottoms with an intervening high followed by another high at a level higher than the intervening high is needed. In a channel four possible kind of signals are generated, two in uptrend and two in a downtrend. If the price in an uptrend does not reach the uptrend line analysts believe that the price accelerates and a steeper trend has begun. If the price, however, fails to reach the return line it may be a signal of a reversal of the trend. The signals in a downtrend are of course similar to those in an uptrend just the opposite way. A signal is generated where the last peak fails to reach the return line. Hereafter, the price crosses the uptrend line and analysts believe that a trend reversal has occurred.

2.4.3.2.1 Support and Resistance

When the price of a stock keeps bouncing back and forth between two price levels and no clear trend can be observed, analysts make use of support and resistance levels. The support level refers to the troughs of a price curve. After a certain period of declining prices, the price will hit the support level. At that point the buying pressure is sufficiently strong to overcome the selling pressure and the price will begin to rise again. The previous trough normally defines the support level. Conversely, after a period with rising prices, the resistance level is reached. At this level selling pressure overcomes buying pressure and prices will start to fall again. As with support level a previous peak defines the resistance level. In the range between support and resistance there is so to say a war between buyers and sellers. At one point, however, one of the sides will win and the support or resistance level is broken. At this point the trend reveals itself. If the trend is an uptrend the price will cross the resistance level while in a downtrend the support level is crossed. When one of the lines is crossed the roles of them are reversed. This means that if the support level is crossed from above it becomes the new resistance level and if the original resistance level is broken it becomes the new support level. The reason for this is that investors have the price in mind. Investors want to get out of losing trades at break-even. Similarly, traders seek to increase winning positions by buying more stocks at or near the support level. Another psychological aspect of support and resistance levels is the role of round numbers as support and resistance. Round numbers has a tendency to stop advances or declines. Investors tend to see round numbers such as 50, 100, 1.000 10.000 etc. as price objectives and act accordingly. Hence, round numbers often act as psychological support or resistance levels.

2.4.3.3 Other Technical Indicators

While price is the most used signal for technical analysts other indicators are also used. Some of these indicators are used for confirming the signal generated but they can also be used as a primary signal.

2.4.3.3.1 Volume

Volume is often used as a confirmation of the trend .Volume has, however, the potential to provide useful information. When investors are uncertain of the future they normally do nothing. This means that when volume decreases a reversal can be underway. Therefore, volume can give indications of the future direction of prices by measuring the level of confidence among buyers and sellers. Most of the time volume is, however, used as a secondary indicator in connection with price movements as described above.

2.4.3.3.2 Money flows

Another way of measuring conviction among buyers and sellers is to look at the money flows. Money flow is the relative buying and selling pressure on stock prices and is measured on a daily basis. Technical analysts try to figure out what the “smart money” is doing. Investors talk about uptick and downtick trades where an uptick trade is a trade at a higher price than the previous day and vice versa. To get the money flow of a stock or a portfolio, the share price is multiplied by the number of shares traded. The net gain or net loss is then the money flow. Hence, positive money flow figures are a sign of a bullish market the opposite is true for bear market.

2.4.3.3.3 Market Breadth

In a bull market it is not necessarily all stocks that are rising in price. Neither stocks nor markets rise or fall in straight lines. Some fluctuations will always occur and some stocks will go against the major trend. Identifying the major trend can be done by calculating the market breadth. The market breadth measures how many stocks are increasing in price relative to the number of stocks decreasing in price. One of the most used ways to determine the market breadth is probably the advance/decline ratio. Technical analysts consider this ratio as a good indication of the overall direction of the market and can be determined by dividing the number of stocks rising in price by the number of stocks declining in price. If the ratio is above 1 the market is considered bullish and if the ratio is below 1 it is bearish. Another way to measure the breadth of the market is to use the advance/decline line. This method is very similar to the advance/decline ratio, but differs in the way that it uses the ongoing sum of the difference between rising and declining stocks. For the breadth to be healthy the line has to rise indicating that there are more positive price movements than negative. Normally, the overall market and the advance/decline line moves together but at times a so-called divergence emerges. This occurs when the overall market continues to move higher while the advance/decline line drops. Technicians see this as a warning of a pending reversal of the trend.

Only the basic foundation of what is known as technical analysis has been touched upon in preceding section. One should bear in mind that there are innumerable ways of combining trend-following systems and thus, an exhaustive description of technical analysis is almost impossible and also not of interest in this study.

2.5 Growth and Value Stocks

2.5.1 Value Stocks

The general idea in the value investment approach is to identify securities that are temporarily undervalued or unpopular for various reasons. Value investors are, so to speak, looking out for bargains where the price of a security has been beaten down unfairly. They focus on whether the market price is below the estimated economic value of the tangible and intangible assets of the company. To measure the economic value investors look at easily measurable tangible assets such as plants, equipment, real estate and common stock or financial holdings in subsidiaries etc. When value investors find a stock where the current market price is below a conservative estimate of the tangible assets a real bargain can be made and the larger the gap between the market price of a stock and the market of its tangible assets the more attractive the investment is

(Hirschey & Nofsinger, 2005). Value investors look at certain measures when judging whether a stock is selling at a discount. The most common used measures are P/E and P/B ratios and dividend yields. They search for ratios below the historical level of the company and market average or stocks with an above-average dividend yield. However, one must be aware that a bargain is not always the low price stocks. The fact that a stock is cheap does not automatically mean that it is a good deal. The company behind must be a quality firm selling at a low price compared with the above-mentioned criteria, not a bad company selling at a low price. Instead of comparing to other market measures value investors can compare the price of the stock to the fundamental value of the company. If the stock price is thought to be below the fundamental value the stock is undervalued and a good deal can be made. The price can go below the fundamental value if an entire industry falls into disfavor. The companies that only experience this temporarily can become undervalued. As before it is important to identify those companies that are cheaply priced compared to their fundamental value and be aware of the fact that some companies are simply bad companies on the brink of bankruptcy or with a poor business model and hence priced correctly at a low level (Hirschey & Nofsinger,2005). Generally, when identifying value stocks investors look for the following characteristics: ample cash reserves, free cash flow to fund necessary investment, conservative dividend payout policy , conservative financial structure, conservative issuance of common stock to managers and other employees, low P/B ratio relative to the market and the history of the company , low P/CF ratio relative to the market and the history of the company, low P/E ratio relative to the market.(Hirschey & Nofsinger, 2005). The strategy involves buying stocks currently out of favor and selling stocks that are popular. To master this, value investors must be in full control and avoid being influenced by psychological biases.

2.5.2 Growth Stocks

Whereas value investors focus on the present situation and price of the stock compared to the market, growth stock investors analyze the future growth potential of a firm. There are numerous ways to identify growth stocks, and different investors look at different indicators. Some look for above-average growth in earnings per share and revenues while others look for growth rates at least twice the average of the standard company. In general however, growth stock investors look at whether a company has sufficient internal financial slack and thereby is able to finance future growth without borrowing additional funds. Investors also look at the business environment of the company either niche or fast growing industry. Growth stocks also have some distinct characteristics just as value stocks have. These characteristics are markets expectations of future growth, low book-to-market ratio, low cash flow-to-price ratio, low earnings-to-price ratio, high past growth rates in sales (Lakonishok, Shleifer and Vishny, 1994). These characteristics must however, be carefully studied before using them as criteria for dividing stocks into certain categories. A low book-to-market ratio can simply describe a company with a lot of intangible assets that are not reflected in the book value. Another problem with the book-to-market measure is that it can reflect a company with high temporary profits but without high growth opportunities like Oil companies when oil prices rise. Also, one should be aware of looking at past growth rates since these measures often are imperfect and does not always have implications for future growth. Besides looking at stock specific measures, growth stock investors also look at the business environment in which the company operates. To find out whether a growth stock is an attractive investment analysts often look for the following characteristics competitive advantage, highly talented and well-paid employees, low overall labor costs, leading within innovation, product development and ability to spot new markets and/or market segments, nonsensitive to changes in regulation and conservative capital structure and steadily growing earnings per share. ROA should also be attractive (Hirschey & Nofsinger, 2005). It is clear that to sustain a high growth rate competition must be minimized and to do that companies must have a competitive advantage over other companies in the business sector. This competitive advantage can come from the sources mentioned above.

2.5.3 Value vs. Growth Stocks

Since Graham and Dodd in 1934 came up with the idea of dividing stocks into categories based on the above-mentioned measures in their famous book “Security Analysis”, researches have investigated whether one of the strategies is superior to the other. Most have come up with the result that a value strategy outperforms a growth strategy. A famous study by Fama & French (1992) showed that the ratio of book value to market value of equity and company size were the main explanatory variables for cross-sectional stock returns. Their empirical tests, which used data from NYSE, AMEX and NASDAQ, showed beta β had no effect on average stock returns but returns were more a result of size and book-to-market ratio. When sorted by book-to-market ratio growth stocks yielded an average monthly return on .30% while value stocks had a return on 1.83%. Fama and French also tested on stocks sorted by earnings-to-price ratio and came up with the same result. Growth stocks yielded a monthly average of 1.04% and value stocks yielded 1.72%. The fact that the beta’s of the portfolios was merely the same led to the conclusion that other variables explained the difference in return better than the capital asset pricing model (CAPM) did. Another famous study conducted by Lakonishok, Shleifer & Vishny (1994) came to the same conclusion as Fama & French. They tested four different strategies, dividing stocks into the growth or value category based on book-to-market ratio, cash flow-to-price ratio, earnings-to-price ratio or growth in sales.

The test was based on yearly returns and for all the four categories value stocks clearly outperformed growth stocks. The difference in the average annual five-year return per year was 10.5%, 11%, 7.6% and 6.8% respectively. One might argue that testing on the same data and period can lead to the problem of data snooping. To test whether the value premium is only an American phenomenon Fama & French (1998) tested on thirteen major markets. They found that in twelve of the thirteen markets value stocks outperformed growth stocks. Italy stands out as the only country where growth stocks outperform value stocks. While almost all researches agree that value stocks earn higher return than growth stocks there are divergent opinions about why this is the case. As fathers of the efficient market hypothesis Fama & French (1996) argue that the higher return must be the result of increased risk compared to growth stocks. Thus, according to Fama and French value stocks are fundamentally riskier than growth stocks and the value premium is compensation for bearing more risk. The competing explanation considers behavioral finance as the important reason for the higher return on value stocks. Lakonishok, Shleifer & Vishny (1994) argue that investors tend to get overly excited with stocks that have performed well in the past and thus the stocks become overpriced. On the other hand investors overreact to stocks that have performed poorly in the past and thus oversell them resulting in these stocks to become under priced. The reason for these overreactions can be numerous. Maybe investors extrapolate past earnings growth to far into the future. Lakonishok et al. found evidence of a systematical pattern of expectation errors among investors. The expectations of future growth appear to be tied on past growth rates only despite the fact that future growth rates are highly mean reverting.

To put excessive weight on recent past history instead of a rational prior is a common psychological error not just in stock markets but in everyday life as well. Another reason for the over- and under pricing problem can be that investors assume a trend in the stock price or that they simply overreact to good or bad news. It is not only individual investors who tend to have a bias toward stocks with high historical growth. Also institutional investors seem to prefer “good” companies with steady earnings and dividend growth. The reason for this can be that it is easier to justify investments in stocks that have a good track record and hence a better story. Sponsors may wrongly believe that growth stocks are a safer investment than value stocks because of the perceived lower risk of running into financial distress problems. Also career concerns of money managers may tilt them towards investing in growth stocks. While a value strategy can take 3 to 5 years to pay off, growth stocks can earn a high abnormal profit within few months, which is something that many individuals look for. It can be concluded that there is relatively large agreement that value stocks outperform growth stocks when measured in returns.

2.6 Summary of Literature Review

A considerable body of research in the predictability of asset returns has occupied the attention of practitioners and academicians for many years now. Regarding technical analysis, however, the early studies of filter rules by Alexander (1964) and Fama and Blume (1966) contained strong conclusions that discounted the status of technical analysis in the mainstream finance research. However, in the 1980s, a remarkable "come back" in studies of predictability motivated researchers to reconsider technical analysis as well. The renewed motivations in predictability studies followed Banz (1981), Reinganum (1983), Keim(1983) and others who noticed that efficient market hypothesis anomalies such as size, weekend effect, momentum effect, turn-of-the-year and book-to-market could not be explained by the Capital Asset Pricing Model (CAPM). In the recent past, studies of technical analysis have been extended to more forms of markets and more speculative assets.

The testing procedures used in studies have also been widened, particularly in the recent past, to include more candidate prices (e. g. intra-daily and high frequency tick data) and they have also considered a wider spectrum of trading systems ranging from simple moving averages to sophisticated genetic algorithms and neural networks. Empirical evidence from many recent studies has shown that returns are predictable from the current price, past prices and other variables like volume and open interest. These studies provide a strong challenge to the efficient market hypothesis. It can also be concluded that there is relatively large agreement about value stocks outperforming growth stocks when measured in returns. When the discussion is turned towards the explanation of the value premium the agreement stops. For technical rules only the basic foundation of what is known as technical analysis has been touched upon in preceding section. One should bear in mind that there are innumerable ways of combining trend-following systems and thus, an exhaustive description of technical analysis is almost impossible and also not of interest in this study. Often empirical studies are criticized for finding patterns ex-post and thus, the way of making stock market analysis is not valid when investors make decisions ex-ante.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1. Introduction

The review of literature has produced a recurring theme emphasizing the profitability of technical trading rules. This chapter therefore sets out various stages and phases that were be followed in completing the study. Methodology involves a blue print for the collection, processing, measurement and analysis of data. This section shows the plan, scheme and structure conceived to help the researcher in answering the research question. It shows how the research was carried out, therefore this section identifies the steps taken to collect process and analyze data. The chapter comprises the following sub-sections research design, population and sample design, data collection methods, data analysis and data validity and reliability techniques.

3.2. Research Design

The study tested the profitability of simple technical trading rule as applied to value and growth stock listed at the Nairobi Stock Exchange. The profitability of the daily closing prices of both value and growth stock were be compared using technical trading rules. By investigating whether past market action data can be studied to detect profitable trends the study used a descriptive research approach. A good description provokes the 'why' questions of explanatory research i.e. in this study what is causing the excess returns.

3.3. Population and Sampling Technique

The study included all 58 companies listed at the Nairobi Stock Exchange during the period of the study. The justification being since the study categorized the listed companies into value and growth stock it is important all companies were taken into consideration besides all the data to be used in the study were extracted from one NSE database. Also the number of listed companies is small and it possible to access and review the entire NSE data for the period of the study. All the companies listed at the NSE in the period 2006 - 2010 were be included in the study. This study period also captured the impact economic growth from 2006 – 2007 and decline experience thereafter before recovery set in from 2009.

3.4. Data Collection

The secondary method of data collection was used in the study. This study used trading data from the Nairobi Stock exchange hence the secondary data was collected. The trading data used was taken from all the 55 companies listed at the exchange in the period of the study. The data collected included the daily trading prices and financial results data at the end of each trading day. Also to construct portfolios of value and growth stock the study used fundamental data such earnings, stock price, book value and market value since the portfolios were formed using E/P and B/M ratios.

3.5. Data Analysis

In order to test buy and hold strategies versus technical trading rules analysis approach when using different investment strategies, two portfolios were formed for each of 5 years studied. The first portfolio was formed based on earnings and book value information from 1st January 2006. The portfolios were rebalanced each year and the annual rebalancing is meant to create pure value and growth portfolio Thuku (2009). The last portfolio was formed on 5th Jan 2010 and ends the last trading day for 2010. Portfolios were made up all of common stocks listed the Nairobi

Stock Exchange based on the selection criteria. The stocks were divided into quintiles of 30% ,40% , 30% based on earning-to-price ratios. The quintile containing stocks with highest E/P ratio were value stock and those with lowest E/P ratios were classified as growth stocks. To make the portfolios more pure they were divided into quintiles of 30%, 40%, 30% based on the book-market ratio. Stocks with higher B/M ratios were classified as value portfolio and lower B/M ratio stocks were classified as growth portfolio. The price of each portfolio
was calculated using geometric mean of all stock to de-emphasize relative price changes.

The study used arithmetic return to calculate the as indicated below;

$R_t = p_t/p_{t-1}$ where p_t is the current price and p_{t-1} is the price at the end of the previous period

The return for each trading rule was given by the formula defined by Allen & Karjalainen (1999).

$$r = \sum r_t I_b(t) + \sum r_f(t) I_s(t)$$

where r_t is the daily continuously compounded return, $I_b(t)$ is an indicator variable equal to one if the day is a buy day and zero if the rule indicates a sell day, $r_f(t)$ denotes the risk free rate on day t and I (t) s is the indicator variable with value of one on sell days and zero on buy days.
The buy and hold return is given by;

$$R_{bh} = \sum r_t$$

In empirical analysis the study investigated whether technical trading rules were able to outperform the buy-and-hold strategy without correcting for transaction costs. Unlike Allen & Karjalainen (1999) who used transaction cost 0.25% this study did not consider transaction costs. For technical trading rules 3 moving averages were used in the study. The time span of the moving averages was chosen in accordance with rebalancing of the portfolio which takes place every year of the study. Short average was 1 day and long average had intervals of 5, 10 and 20 days. If the short average was below the long average line the risk free asset was held. The main question in this study was whether or not a strategy based on technical trading rules in this case moving average trading rules was able to outperform a buy-and-hold strategy. Two hypothesis tested in this study are

Null Hypothesis 1

H_0 : The returns generated by technical trading rules are zero

H_1 : The returns generated by technical trading rules are not equal to zero

Null Hypothesis 2

H_0 : The mean returns generated by technical trading rules equals the returns derived by the buy and hold strategy.

H_1 : The mean returns generated by technical trading rules is not equal to the returns derived by the buy and hold strategy.

To test this question many academic articles use t-test which test the equality of two means hence $H_0{:}\mu=\mu_0$, $H_1{:}\mu\neq\mu_0$ where μ_0 is the population mean, in this case the buy-and-hold mean return and μ is the sample mean, the mean return generated by the moving average trading rule with significance level of 5% for a two-tailed test 2.5% each tail of the test.. Rejection means profitable of trading rule is confirmed. The following descriptive statistics were calculated and used in the study i.e mean, median, standard deviation of returns.

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSIONS

4.1 Introduction

The purpose of this study was to test the profitability of technical trading rules when applied to growth and value stock listed at the Nairobi Securities Exchange. This chapter deals with findings data analysis and interpretation of the findings of the study. The study used secondary data and the data used in this study was collected from the NSE database. Data analysis was done using Excel 2003 and SPSS Version 7 and it involve the calculation descriptive statistics. The study was therefore guided by the general objective which was to test the profitability of technical trading in relation to value premium. The research focused on past price data and used simple moving average. The result of the data analysis has been presented using tables.

4.2 Data Analysis and Results of the Study

Firstly, the results from the growth portfolio are presented. Secondly, the value portfolio is analyzed. Thirdly, a short discussion of the differences of the two portfolios is conducted.

4.2.1 Growth Portfolio

Table 4.1

Trading Rule	Observations	N(Buy)	N(Sell)	Mean Buy Return	Mean Sell Return	Total
SMA 1-5-0	1202	594	608	-0.17	0.18	0.0074
SMA1-10-0	1202	609	588	-0.18	0.18	0.005
SMA1-20-0	1202	595	591	-0.12	0.13	0.0053

Tables 4.1 reports the buy and sell signals produced by the trading rules and from the table it is possible to identify positive and negative. During the 'buy periods' all the simple moving average rules produce a negative mean annual return of -0.17, -0.18 and -0.12 while the 'sell periods' are characterized by positive mean annual return of 0.18, 0.18 and 0.13. The sell days exceed the buy days in trading rule SMA 1-5-0 and in the other trading rule SMA 1-10-0 and SMA 1-20-0 the buy days exceed the sell day. This is consistent with a downward sloping trend in the NSE in the period under review.

Table 4.2

Trading Rule	t (Buy)	Standard Dev (Buy	t (Sell)	Standard Dev(Sell)
SMA 1-5-0	-2.717	0.0127	3.246	0.011
SMA 1-10-0	-4.040	0.0088	5.026	0.0074
SMA 1-20-0	-4.044	0.00614	5.159	0.005

Table 4.2 above presents the results of the tests which test the hypothesis that the returns generated by the trading rules are zero. All the buy days have negative t-statistic indicating returns less than zero while sell days have significant positive returns and hence t-statistics. Thus the null hypothesis 1 is rejected as the buy days return are less than zero and sell day returns are greater than zero.

Notice also that volatility is higher during the buy days. This is consistent with a well known characteristic of asset returns named the leverage effect, which states that the volatility associated with negative returns is greater than for volatility associated with positive returns.

Table 4.3

Pairs	Mean	Standard Deviation	T	df	Sig(2 tailed)
Buy and Hold SMA1-5-0	0.00002	0.032	0.022	1201	0.982
Buy and Hold SMA1-10-0	0.00002	0.031	0.021	1196	0.983
Buy and Hold SMA1-20-0	0.000008	0.030	0.009	1185	0.992

The result indicated in Table 4.3 represents the t-statistic ratio that tests the mean returns generated by technical trading rules equal to the returns derived by the buy and hold strategy. This tests if the return obtained by using technical trading rules is significantly different from the return obtained by a buy and hold strategy,

The t-statistic for difference of means between trading rules SMA 1-5-0, SMA 1-10-0 and SMA 1-20-0 are 0.022, 0.021 and 0.009 respectively. The means of difference are 0.00002, 0.00002 and 0.000008 respectively. The results in Table 4.3 indicated the difference between technical trading rules return and buy and hold strategy are insignificant.

Table 4.4

Trading Rule	Daily mean return	Standard Deviation	t-Statistic
SMA 1-5-0	0.00003076	0.012	0.022
SMA 1-10-0	0.00002105	0.008	0.021
SMA 1-20-0	0.00002226	0.006	0.009
Buy and Hold Strategy	0.00006714	0.0297	0.079

The results from using simple moving average as trading rule generate return that is below the buy and hold strategy. The returns produced by the strategies are below the one for buy and hold though the difference is insignificant as the t-statistics in Table 4.4 indicate above. The best performing trading rule is SMA 1-5-0 with a mean daily return of 0.00003076 or annual mean return of 0.74% compared to buy and hold at 1.629% annual mean return.

The standard deviation is much lower for the technical trading rules compared to buy and hold strategy. SMA 1-5-0, SMA 1-10-0 and SMA 1-20-0 the standard deviations are 0.012, 0.0083 and 0.006 respectively. This is due to the nature of technical trading investment strategy where one moves out of the market and invests in a risk free asset during sell signals period and in this study sell period dominates. When following buy and hold strategy the investor is in the market at all times and therefore bears more risk. The fact that the risk differs from each investment strategy causes it to make good sense to compare returns on a risk-adjusted basis. This study considers risk incorporation in profitability analysis an area for further research.

4.2.2 Value Portfolio

Table 4.5

Trading Rule	Observations	N(Buy)	N(Sell)	Mean Buy Return	Mean Sell Return	Total
SMA 1-5-0	1202	583	619	-0.18	0.45	0.2705
SMA1-10-0	1202	573	623	-0.21	0.48	0.2707
SMA1-20-0	1202	545	641	-0.09	0.35	0.2542

The results for the value portfolio are very similar to results obtained in the growth portfolio. Here the number of ‘sell days’ exceeds ‘buy days’ which is consistent with a downward sloping trend in the market. In the period under study NSE was mostly a bear market. The trend however appears to be less downward for value portfolio than for growth portfolio. The number of sell days as indicated in Table 4.5 is consistently greater than was the case of the growth portfolio as shown in 4.2.1 above.

For the value portfolio ‘sell days’ exceeds ‘buy days’ for all the technical trading rules. This depicts a steeper trend that can also be seen in the size of the ‘sell return’ which is consistently higher than ‘sell return’ in the growth portfolio SMA 1-5-0,SMA 1-10- 0 and SMA 1-20-0 the comparative return for value versus growth are) 0.18 vs 0.45, 0.18 vs 0.48 and 0.13 vs 0.35 respectively.

Table 4.6

Trading Rule	t (Buy)	Standard Dev (Buy	t (Sell)	Standard Dev(Sell)
SMA 1-5-0	-2.549	0.0144	5.143	0.0175
SMA 1-10-0	-4.828	0.0089	7.753	0.0123
SMA 1-20-0	-3.518	0.0057	8.923	0.0027

As the results in Table 4.6 indicate it is important to mention that the higher return is not the result of higher risk, though the volatility of the value portfolio is higher the difference can account fully for the result value premium.

Table 4.6 above presents the results of the tests which test the hypothesis that the returns generated by the trading rules are zero. All the buy days have negative t-statistic ie -2.549, -4.828 and -3.518 respectively for SMA 1-5-0, SMA 1-10-0 and SMA 1-20-0 indicating returns that are less than zero while sell days have significant positive returns for the simple moving average for 5, 10 and 20 days ie 5.143, 7.753 and 8.923 respectively. Thus the null hypothesis 1 is rejected as the sells days are significantly positive above zero while buy day returns are negative and significantly below zero.

Table 4.7

Trading Rule	Daily mean return	Standard Deviation	t-Statistic
SMA 1-5-0	0.00112533	0.0163	0.017
SMA 1-10-0	0.00112942	0.0112	0.023
SMA 1-20-0	0.001071	0.0071	0.093
Buy and Hold Strategy	0.00113581	0.0373	1.059

Table 4.8

Pairs	Mean	Standard Deviation	t	df	Sig(2 tailed)
Buy and Hold SMA1-5-0	0.00002	0.0408	0.017	1201	0.986
Buy and Hold SMA1-10-0	0.00003	0.0391	0.023	1196	0.981
Buy and Hold SMA1-20-0	0.0001	0.0374	0.093	1185	0.926

The results of Table 4.7 and Table 4.8 test the hypothesis the mean returns generated by technical trading rules equal to the returns derived by the buy and hold strategy.

As with growth portfolio, the t-statistic for difference of means between the technical trading rules and buy and hold strategy SMA 1-5-0, SMA 1-10-0 and SMA 1-20-0 are 0.017, 0.023 and 0.093 respectively. The means of difference are 0.00002, 0.00003 and 0.0001 respectively. The results in Table 4.3 indicated the difference between technical trading rules return and buy and hold strategy are insignificant. This implies that the forecast ability of simple moving averages is statistically insignificant.

4.3 The Value Premium

The results presented in this section confirm the value premium discussed in chapter 2. In this study the difference between the two portfolios is outspoken. The value portfolio generates a yearly mean return of 27.55% while the growth portfolio only earns 1.63% on an average yearly basis. The three trading strategies post lower average annual returns of 0.74%, 0.5% and 0.53% respectively. Though, the standard deviation is higher on the value portfolio at 3.73% compared to growth portfolio at 2.97% the higher return cannot be explained by an increase in risk. Consequently, it seems as if the value premium is present in the data examined.

The portfolio Average Annual Return and Standard Deviation as set out in Table 4.3

Table 4.9

Portfolio	Value Portfolio	Growth Portfolio
Average Annual Return	27.55%	1.63%
Standard deviation	3.73%	2.97%

Table 4.9 depicts the variance in the return between the growth and value portfolio strategies. The difference between 27.55% -1.63% = 25.92 cannot be due to the 0.76% increase in risk.

4.4 Summary and Interpretation of Findings

The objective of the study was to test the profitability of technical trading rule on growth and value stock listed at the NSE. The study covered the period between the year 2006 and 2010 inclusive. The study used daily price data from the NSE and also the NSE handbook for the period under study. To classify stock into growth and value portfolios the study used used E/P and B/M ratio Lakonishok, Shleifer and Vishny (1994), Hirschey and Nofsinger (2005). To qualify to be included in the portfolio the companies had to have 5 full years of data for period as per Appendix 3. Two portfolios were formed at the beginning of the study and rebalanced annually for the five years to classify stock. The study used simple moving averages of 5, 10 and 20 days as the technical rules for the study. The study then tested two null hypotheses i.e.

Null Hypothesis1

H_0 : The returns generated by technical trading rules are zero.

H_1 : The returns generated by technical trading rules are not equal to zero.

Null Hypothesis 2

H_0 : The mean returns generated by technical trading rules equals the return derived by the buy and hold strategy.

H_1 : The mean returns generated by technical trading rules is not equal to the return derived by the buy and hold strategy.

As indicated in chapter 4 the two null hypotheses were tested using at-statistic test in the study and the first null hypothesis was rejected and though no statistically significant difference in return greater than zero was found. The null hypothesis 2 was also subjected to a two-tailed t-test at 5% and the result was insignificant statistically. The outcome of the study therefore confirms

Fama's (1970) weak form efficiency of the efficient market hypothesis for the NSE. The study by investigating technical trading rules a hypothesis about the efficiency of the financial market in its weak form as defined by Fama (1970) is indirectly examined Besseminder and Chan (1995). If technical trading rules prove to be able to generate a statistical and economical significant better return then weak form efficient market hypothesis is rejected. In the study test turn out insignificant and the weak form efficient market hypothesis is accepted.

According to Joy and Jones (1986) there may not be a one-to-one relationship between the market efficiency and technical analysis. The findings of this study do not provide conclusive evidence that the since the returns of the technical trading rules have been found to be insignificant then the NSE is weak form efficient and past price data and market statistics cannot generate excess returns and predict future trends.

The results reached in chapter 4 are in line some earlier studies. They confirm what was concluded by Alexander (1964) and Fama and Blume (1966) though Alexander had to introduce transaction costs and use filter rules to reach the same conclusion of insignificant statistical and economical profitability of technical trading rules. Fama and Blume (1966) share the same view that the market neglected any information from past prices in setting current prices.

The study also looked into the value premium puzzle. The value premium puzzle has challenged the efficient market hypothesis. It was concluded in section 4.3 of this study that the return generated by the value portfolio was higher and statistically different different from return generated by the growth portfolio. The absolute difference is return between value and growth portfolio is 25.92% which could not be explained by increase in standard deviation of 0.76%. If one accepts CAPM, the finding violates the EMH. The behavioural explanation is that investors are overconfident in their ability to project high earnings growth and hence overpay for growth stocks. Advocates of the EMH, however have another explanation. Fama and French (1993) argue that the value premium is the result of the CAPM fails to capture a risk factor that is priced into the market.

In the EMH debate this argument is referred to as the joint hypothesis problem. The hypothesis states that a test for market efficiency must be based on an asset pricing model. If the findings are against the efficient market it can be because of two things: either the market is indeed inefficient or the asset pricing model underlying is incorrect. The size of the absolute difference in return between value and growth portfolio at 25.92% leads the study to believe that a puzzle is indeed present and cannot be explained by increased risk but behavioural explanation is supported. In behavioural explanation it is believed that investors overestimate future growth rates of growth stocks relative to value stocks Debondt and Thaller (1983). Thus the fact that valuation parameters seemingly have predictive power of returns is a violation of the EMH.

It can be argued that even though the financial markets might be inefficient to some degree it is very difficult to exploit this Brighan and Daves (2004). Using technical trading rules on past prices and market statistics therefore can yield excess returns as the shows in analysis in chapter 4. History shows once one anomaly is discovered it is quickly arbitraged away. This applies to the use also to the use of technical trading rules.

CHAPTER FIVE

Summary, Conclusions and Recommendations

5.1 Summary

The objective of the study was to establish the profitability of technical trading rule using simple technical trading compared to buy and hold strategy in relation to growth and value strategy for firms listed at the NSE. The data used in the study was taken from the 58 listed companies trading data and the NSE handbook for the year 2006 – 2010. The study used only the companies whose financial year ends were December 31st and considered companies that had trading data for five years since 2006. The study used E/P and B/M ratio to classify and form portfolios of value and growth stocks reducing the number of companies analyzed to 26 companies. The results presented in chapter 4 indicate that technical trading rules cannot be used to predict stock prices at the NSE. This result is consistent to the weak efficiency of the efficient market hypothesis Fama (1970), Fama and Blume (1966) and Alexander (1961). In this chapter the conclusions derived from the results are presented. In addition the limitations of the study and recommendations for further study are highlighted.

Since the formulation of the EMH many attempts have been made to dismiss it. A popular test of market efficiency has been to test whether the use of technical trading rules enables investors to systematically earn excess return. If this is indeed the case then the market is considered as inefficient. The study conducted by Brock, Lakonishok and LeBaron (1992) inspired this study but findings of this study contradicts their result.

5.2 Conclusions

The findings of the study suggest that investors at the NSE cannot use analysis of past price data and market activity using technical trading rules to predict future stock prices changes. The results of the study show a significant under performance of the technical trading returns compared to the buy and hold strategies. The result confirms that the NSE is weak form efficient according to the efficient market hypothesis Fama (1970). Thus past price and market activity data cannot be used to predict future price changes.

The findings are contrary to the findings by Brock, Lakonishok, Lebaron (1992) who found significant profit opportunities even after adjusting for transactions costs. Their result challenged the efficient market hypothesis of the weak-form efficient market. The implication of the study being that the use of technical trading rules to predict stock prices at the NSE will not yield positive returns and shows that stock prices do follow a random walk.

Another finding of the study is the confirmation of the value premium puzzle. Thus the return generated by the value portfolio was higher and statistically different from the return generated by the growth portfolio. The behavioral explanation is that investors are overconfident in their ability to project higher earnings growth and hence over pay for growth stocks Shiller (2003).

The result of the study shows that the trading rules are able to identify periods with positive and negative returns. For both portfolio the mean sell return is positive while the buy returns are negative. Further the buy periods are characterized by high volatility due the leverage effect on negative return and low volatility in positive return periods.

5.3 Recommendations

The study found out that the difference between using technical trading rules and buy and hold strategy is very insignificant and therefore based on results I can recommend to investment firms using the technical trading rules to predict future prices patterns that their efforts will yield excess return over the buy and hold strategy. Investment firms should employ other strategies to earn returns.

Regulators can employ technical trading rules to test the weak form efficiency of the NSE. The results of the study confirm the weak form efficiency of the NSE for the period under study of 2006 -2010.

The central bank can study price trends to discern if there is predictability in past prices. The exchange rate predictability on foreign exchange markets can be compared during periods with and without market intervention by the central bank using simple moving average a type of technical trading rule to study patterns in past price behavior. Acccording to Dooley and Shaffer (1983) they said central bank intervention would introduce noticeable trends into the evolutions of exchange rates and create opportunities for alert private market participants to profit from speculating against the central bank.

The study did find that there are statistical insignificant excess returns on the use of technical trading rules in the NSE. The study can thus help market regulators in understanding market price behavior through looking at the evidence of positive technical trading profits. Negative returns will show efficiency of the market Chang and Olser (1999).

5.4 Limitations of the Study

In empirical analysis of technical trading only moving average rules were used. This was due to the fact that it is possible to use these rules mathematically and they are easily testable due to the clear buy and sell signals they produced. Other rules like pennants are complex to test.

The number of stocks studied was small and this was due to the fact that the study had to consider the prevailing market conditions and hence only those stock whose financial year end were 31st December were considered.

Unlike similar studies the period of the study was relatively short and this may explain why some results were not consistent to the results in the developed markets Brock, Lakinoshok, LeBaron (1992) study covered the period 1896 – 1986 using DJIA data where technical trading rules generated significant positive returns.

The study did not consider the stock return assumptions that could bias the results of the study. Stock returns are characterized by certain properties that are not in accordance with the assumptions behind t-test. This leaves the question open whether the seemingly worse performance of the trading rules is simply caused by the use of a test that does not capture the effect of the specific properties of the data.

The risk of non-synchronous trading due to low liquidity for certain stocks trading at the NSE which may cause first order serial correlation as confirmed by the study of Alexander (1961)

The study did not consider the effect of the transaction costs. Investors face costs when buying and selling stocks. Not considering these costs will bias the results in favour of technical trading rules due to frequent investment analysis Alexander (1966).

5.5 Suggestions for further Studies

Further research can done using the various technical trading methodologies like the bootstrap methodology, charts, fixed length moving average, trading range break out and patterns and relative strength index. This study will explore the use of other technical trading rules and investigate their profitability. This would widen the scope of investment industry understanding of technical trading rules and make more efficient.

Similar study can employ a band around the long term moving average and a buy and sell signal is initiated only when a short-term moving average exceeds (falls below) the long term moving average by for example at least one percent band. This is to eliminate ‘whiplash’ signals as highlighted by Brock et al (1992) particularly when short term and long term moving averages are very close.

The technical trading rules tested in the study should also be conducted on the NSE Index as well as on individual stocks without a portfolio. With similar objective as the one used in the study, this would help establish the existence of profitability of technical trading rule and establish if NSE is weak form efficient.

The study therefore finds technical trading rules to have insignificant and limited ability to predict future stock prices using past price data. This also confirm Fama (1970) weak form efficiency of the efficient market hypothesis in which he said that investors cannot earn excess profits by analyzing on the past price and market activity data. The NSE is therefore weak form efficient.

REFERENCES

Banz, Rolf. (1981): The Relationship Between Return and Market Value of Common Stocks. Journal of Financial Economics, vol. 9, March, pp. 3-18.

Bartholdy, Jan (2001): Earnings-Price Effects? Only If You Use a Magnifying Glass SSRN; ID271889, 2001.

Bhardwaj, Ravinder K. & Brooks, Leroy D. (1992): The January Anomaly: Effects of Low Share Price, Transaction Costs, and Bid-Ask Bias. Journal of Finance, vol. 47, no. 2, pp. 553-575.

Brigham,E.F and Daves, P.R. 2004 Intermediate Financial Management. 8thedition. Mason,OH: South-Western College.

Brock, W., Lakonishok, J and LeBaron, B. 1992 Simple Technical Trading Rules and the Stochastic Properties of Stock Returns, Journal of Finance 47 (5): 1731-1764.

Chang, Kevin P.H. and Osler, Carol. 1999: 'Methodical Madness: Technical Analysis and irrationality of exchange rate forecasts'. Economic Journal 109 No.458

De Bondt, Werner F. M. & Thaler, Richard (1990): Do Security Analysts Overreact? American Economic Review, vol. 80, no. 2, pp. 52-57

De Long, J. B., Shleifer, A., Summers, L. H. & Waldmann, R. J. (1990): Noise Trader Risk in Financial Markets. Journal of Political Economy, vol.98, pp.703-738.

DeBondt,W.F.M. and Thaller, R. 1983 Does the stock market overreact? The Journal of Finance, 40(3): 793-805

Fama, E.F. 1970 Efficient Market: A Review of Theory and Empirical Work. The Journal of Finance 25 : 383-417.

Fama, E. and French, K. 1998 Value Vs Growth. The International Evidence; Journal of Finance, 53: 1975 – 1999.

Grossman, Sanford J., Stiglitz, Joseph E. (1980): On the Impossibility of Informationally Efficient Markets. American Economic Review, vol. 70, pp. 393-408.

Hirschey, David and Nofsinger, John (2005): Investments: Analysis and Behavior. McGraw-Hill/Irwin

Joy, O. Maurice and Jones, Charles P.(1986): "Should We Believe the Tests of Market Efficiency", Journal of Portfolio Management (Summer) pp. 49-54.

Lakonishok, Josef, Shleifer, Andrei & Vishny, Robert W. (1994): Contrarian Investment, Extrapolation and Risk. The Journal of Finance, vol. 49, no. 5, December, pp. 1541-1578.

Mokua E.M. 2003 "An Empirical study on the weekend effect on stocks at the NSE. Unpublished MBA Project of the University of Nairobi.

Muhoro F.W.2004: Value Vs Growth Stocks at the NSE. Unpublished MBA Project of the University of Nairobi.

Ndegwa G.W.(2006) Factors affecting the development of emerging markets: A case of the NSE. Unpublished MBA Project of the University of Nairobi.

Okoth EA 2005. Testing whether contrarian investment strategy offers a profitable opportunity at the NSE. Unpublished MBA Project of the University of Nairobi.

Pring, Martin (2002): Introduction to Technical Analysis.10th Printing, New York, McGraw-Hill

Reilly, K.F and Brown, C.K. 2007 Investment Analysis and Portfolio Management; 8th edition. South-Western, a division of Thompson Learning.

Shiller, Robert J. (2003): From Efficient Markets Theory to Behavioral Finance. Journal of Economic Perspective, vol. 17, no. 1, winter, pp. 83-104

Sullivan, Ryan, Timmerman, Allan & White, Halbert *(1999)*: *Data-Snooping,* Technical Trading Rule Performance, and the Bootstrap. The Journal of Finance, vol.54, no. 5, October, pp.1647-1691.

Sweeney, Richard J. (1988): Some New Filter Rule Tests: Methods and Results. Journal of Financial and Quantitative Analysis, vol. 233, no. 3, pp. 285-300.

Thuku S.W.(2009) Value premium and the effect of size: Evidence from the Nairobi Stock Exchange. Unplished MBA project of the University of Nairobi.

West, Kenneth D. (1987): A Specification Test for Speculative Bubbles. Quarterly Journal of Economics, vol. 102, pp. 553-580.

Werah A.O: A Survey of the influence of behavioural factors on investor activities at the NSE. Unpublished MBA Project of the University of Nairobi

West, Kenneth D. *(1988b)*: *Bubbles, Fads and Stock Price Volatility Tests: A Partial Evaluation*. The Journal of Finance, vol. 43, pp.639-660.

APPENDIX 1

List of Companies Listed at the Nairobi Securities Exchange

1. Eaagads Ltd
2. Kapchorua Tea Company Ltd
3. Kakuzi
4. Limuru Tea Company Ltd
5. Rea Vipingo Plantations Ltd
6. Sasini Ltd
7. Williamson Tea Kenya Ltd
8. Express Ltd
9. Kenya Airways Ltd
10. Nation Media Group
11. Standard Group Ltd
12. TPS Eastern Africa (Serena) Ltd
13. ScanGroup Ltd
14. Uchumi Supermarket Ltd
15. Hutchings Beimer Ltd
16. Access Kenya Ltd
17. Safaricom Ltd
18. Car and General Kenya Ltd
19. CMC Holdings Ltd
20. Sameer Africa Ltd
21. Marshalls (EA) Ltd
22. Barclays Bank Ltd
23. CFC Stanbic Holdings Ltd
24. Diamond Trust Bank Kenya Ltd
25. Housing Finance Company Ltd
26. Kenya Commercial Bank Ltd
27. National Bank of Kenya Ltd
28. NIC Bank Ltd

29. Standard Chartered Bank Ltd
30. Equity Bank Ltd
31. The Co-operative Bank of Kenya Ltd
32. Jubilee Holdings Ltd
33. Pan Africa Insurance Holdings Ltd
34. Kenya Re-Insurance Corporation Ltd
35. CFC Stanbic Holdings Ltd
36. City Trust Ltd
37. Olympia Capital Holdings Ltd
38. Centum Investment Company Ltd
39. B.O.C Kenya Ltd
40. British American Tobacco Kenya Ltd
41. Carbacid Investment Ltd
42. East African Breweries Ltd
43. Mumias Sugar Company Ltd
44. Unga Group Ltd
45. Eveready East Africa Ltd
46. A.Baumann Company Ltd
47. Athi River Mining
48. Bamburi Cement Ltd
49. Crown Berger Ltd
50. E.A. Cables Ltd
51. E.A. Portland Cement Ltd
52. KenolKobil Ltd
53. Total Kenya Ltd
54. Kengen Ltd
55. Kenya Power & Lighting Company Ltd

APPENDIX 2

NSE Listed Companies with 5 Years Continuous Data

1. Kakuzi Ltd
2. Nation Media Group Ltd
3. Standard Group Ltd
4. TPS Serena
5. Barclays Bank of Kenya Ltd
6. CFC Bank Ltd
7. Diamonf Trust Bank of Kenya Ltd
8. Housing Finance
9. Centum Investment Ltd
10. Jubilee Insurance
11. Kenya Commercial Bank Ltd
12. National Bank of Kenya Ltd
13. NIC Bank Ltd
14. Pan African Insurance
15. Standard Chartered Bank of Kenya Ltd
16. Athi River Mining Ltd
17. Bamburi Cement Ltd
18. BAT Tobacco Kenya Ltd
19. Crown Berger Ltd
20. Olympia Capital Ltd
21. East Africa Cables Ltd
22. East Africa Portland Ltd
23. Sameer Africa Ltd
24. Total Kenya Ltd
25. Express Kenya Ltd
26. Limuru Tea

APPENDIX 3

Portfolio 1 – 2006

Value			**Growth**	
Name of the company	**E/P**		**Name of the company**	**E/P**
Sameer Africa Ltd	-0.003		Nation Media Group	0.035
Kakuzi Ltd	0.161		E A Portland Ltd	0.035
Centum Investment Ltd	0.111		Athi River Mining Ltd	0.034
Express Kenya Ltd	0.085		Bamburi Cement Ltd	0.034
Total Kenya Ltd	0.081		EA Cables Ltd	0.029
Olympia Capital Ltd	0.072		Limuru Tea	0.023
CFC Bank Ltd	0.068		Pan Africa Insurance	0.021
Crown Berger Ltd	0.061		Housing Finance	0.018

Portfolio 2 – 2007

Value			**Growth**	
Name of the company	**E/P**		**Name of the company**	**E/P**
Kakuzi Ltd	0.27		CFC Bank Ltd	0.046
National Bank of Kenya Ltd	0.12		Athi River Mining Ltd	0.046
BAT Tobacco Kenya Ltd	0.1		Barclays Bank of Kenya Ltd	0.046
Express Kenya Ltd	0.093		Pan Africa Insurance	0.042
Total Kenya Ltd	0.089		NIC Bank Ltd	0.040
EA Portland Ltd	0.077		Sameer Africa Ltd	0.035
Centum Investment Ltd	0.076		Housing Finance	0.014
Standard Group Ltd	0.069		Limuru Tea	0.006

Portfolio 3 – 2008

Value			**Growth**	
Name of the company	**E/P**		**Name of the company**	**E/P**
Limuru Tea	-0.015		CFC Bank Ltd	0.047
Kakuzi	-0.078		Bamburi Cement Ltd	0.042
Jubilee Insurance	0.183		Crown Berger Ltd	0.041
Olympia Capital Ltd	0.145		Housing Finance	0.037
Express Kenya Ltd	0.121		Sameer Africa	0.034
National Bank of Kenya	0.104		Standard Group Ltd	0.028
Pan Africa Insurance	0.092		Barclays Bank of Kenya Ltd	0.009
Centum Investment Ltd	0.081		TPS Serena	0.004

Portfolio 4 – 2009

Value			**Growth**	
Name of the company	**E/P**		**Name of the company**	**E/P**
Kakuzi Ltd	0.725		EA Cables Ltd	0.072
EA Portland Ltd	0.291		Nation Media Group Ltd	0.066
Olympia Capital Ltd	0.205		Pan Africa Insurance	0.064
National Bank of Kenya Ltd	0.188		Athi River Mining Ltd	0.059
Jubilee Insurance	0.177		Housing Finance	0.057
Crown Berger Ltd	0.152		Centum Investment Ltd	0.056
Bamburi Cement Ltd	0.123		Express Kenya Ltd	0.053
Diamond Trust Bank Kenya Ltd	0.119		CFC Bank Ltd	0.003

Portfolio 5 – 2010

Value			**Growth**	
Name of the company	**E/P**		**Name of the company**	**E/P**
EA Portland Ltd	-0.028		BAT Tobacco Kenya Ltd	0.065
Express Kenya Ltd	-0.102		Housing Finance	0.062
Kakuzi Ltd	0.244		Athi River Mining Ltd	0.059
Limuru Tea	0.208		Nation Media Group Ltd	0.059
Jubilee Insurance	0.202		EA Cables Ltd	0.056
Pan Africa Insurance	0.187		TPS Serena	0.051
National Bank of Kenya Ltd	0.186		Olympia Capital Ltd	0.027
Total Kenya Ltd	0.182		Sameer Africa Ltd	0.027

APPENDIX 4

Growth Portfolio Performance Summary

	Buy and Hold Strategy	SMA 1-5-0	SMA 1-10-0	SMA 1-20-0
Mean Daily Return	0.006714%	0.0031%	0.0021%	0.0022%
Mean Yearly Return	1.627%	0.74%	0.5%	0.53%
Standard Deviation	2.971%	1.12%	0.826%	0.571%

Value Portfolio Performance Summary

	Buy and Hold Strategy	SMA 1-5-0	SMA 1-10-0	SMA 1-20-0
Mean Daily Return	0.114%	0.113%	0.129%	0.107%
Mean Yearly Return	27.555%	27.030%	27.016%	25.394%
Standard Deviation	3.727%	1.631%	1.121%	0.706%