A Comparison of Returns of Portfolios Formed Using Technical Analysis and Fundamental Analysis In South Africa

Research Thesis (Second Submission)

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Abstract

In a market where it has become difficult to find value, it has become very important for portfolio managers and analyst to find approaches to investing that still hold value and are less correlated with market returns. In this research project a strategy, which combines technical analysis strategies and fundamental analysis strategy was studied to find out if it is possible for an investor who uses both strategies to earn better returns than an investor who relies only on one strategy. Three technical analysis strategies were combined to form one strategy. The three strategies were also studied separately so as to see if they produce returns that are significantly better than a fundamental analysis strategy that uses Piotorski's (2002) F_score approach to invest. It was found that individual technical analysis strategies do not produce returns that are significantly better that the fundamental analysis strategy. However, it was found that a strategy that uses both fundamental analysis and technical analysis produces average returns that are better than average returns produced by any of these strategies used independently. Technical analysis strategies produced returns that showed very little correlation with an equally weighted benchmark when regressed on the CAPM. Equally weighted portfolios of the strategies showed no conclusive evidence of the presence of abnormal returns. The success rate of the technical analysis strategies was found to decline over time, which suggested that the Johannesburg Stock Exchange (JSE) is becoming weak form efficient.

Declaration

I declare that this is my own work produced for university of the Witwatersrand as a required to complete my master of management degree.
Where other people's work has been used, I have properly acknowledged and referenced accordingly.
I have not allowed anyone to copy this work.

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Chapter 1

This chapter introduces the research topic. It also provides context of the study, details research problem, research objectives, research questions, gap in the literature and structure of the report.

1.1 Introduction

The financial market is a place where investors meet borrowers. Investors surrender the current spending of their money with the expectations that the money they are investing will grow over time. As a result, investors tend to invest selectively, which is to say that they attempt to capture the assets that will yield the highest returns at the lowest possible risk. Thus, investment management firms spend sums of money doing research to find assets to invest in. The research can be done from various perspectives, including macroeconomic analysis, quantitative analysis, fundamental analysis and technical analysis.

Macroeconomic analysis involves the analysis of macro indicators such unemployment, interest rates and gross domestic product (GDP) growth to identify financial instruments' trends. Fundamental analysis considers financial statements to try to get an intrinsic value of an asset. The intrinsic value of an asset is the value at which fundamental analysts believe the asset should trade. As a result, an asset with an intrinsic value below the trading price is believed to be trading at a discount, over time, the asset will trade at its true price. Quantitative analysis involves the use of mathematics and statistical modeling to select assets for investments. Technical analysis, often called charting (Roffey, 2008), studies movement of asset prices in the past to predict future prices. Chartists believe the past repeat its self.

Fundamental and macroeconomic analysis have long established themselves in the finance industry as more scrutiny and acceptance has been given to them, while quantitative and technical analysis have trailed behind when it comes to industry wide acceptance. The reason for this lack of acceptance for technical analysis has often been the fact that it makes little reference to economics.

This thesis aims to compare the returns obtained from technical analysis strategies to those obtained using the traditional fundament analysis method of investing. The thesis will

furthermore investigate whether or not the two schools of investing can be used together to obtain higher returns. The most popular strategies in technical analysis have been used to make investment decisions. These include price patterns (double bottom strategy) and momentum indicators (moving average and volume strategies).

Fundamental analysis was used to find stocks that offer the best value (value investing) using the F Scores screening developed by Piotroski (2002). The study was conducted between January 2004 to December 2015.

1.2 Context of the Study

Eugene Fama (1970) argues that investors cannot earn extra returns by analyzing data that is already in existence, since the prices of securities reflected all the available data. From the data that Bloomberg publishes every year, which shows top performing fund managers, it has been evident that Fama's efficient market hypothesis (EMH) does not hold.

A consequence of the rejection of the EMH investment banks is that brokerage and investment firms now employ analysts to do research with the intention of trying to find opportunities that exist in the financial market. A Financial analyst performs investment research using macroeconomic, fundamental, quantitative and technical analysis.

1.2.1 Fundamental Analysis: Value investing and Growth investing

Fundamental analysis studies the economic forces of supply and demand, which causes prices to change (Murphy, 1999). The popularity of fundamental investing has grown significantly during the recent years because of an increase in evidence against efficient market hypothesis (Hancock, 2012). Fundamental investing is divided into two types: Value investing and growth investing. Value investing was first invented by Graham and Dodd in 1934 (van der Merwe, 2012), and refers to the use of historical financial statements and information to identify stocks that are perceived to be trading at a price that is below the inherent value. These stocks have low potential growth which renders them out of the favour of the general investment world, as a result, these firms are not usually followed extensively by financial and investment analysts (Chan and Lakonishok, 2004). The stocks are characterised by a high book to market ratio.

Growth investing, in contrast, is an investment approach that uses financial statements to project future earnings of firms. Subsequent to its prediction of future earnings, this approach is a speculative approach. As a result it is perceived to be more risky when compared to value investing (van der Merwe, 2012).

Fundamental analysis has gained its acceptance in the investment industry because it relates directly to factors that enable a business to exist i.e. its profitability which is shown in the income statement and its ability to continue to exists which is shown by the balance sheet. Value investing focuses on the balance sheet while growth investing focuses on the income statement. There is extensive research that shows that both approaches are profitable. This profitability has led to more advances in research to look at the company from both perspectives to find solid companies to invest in. In this paper we take a rounded approach which encompasses both investing methodologies to form the fundamental analysis approach used.

1.2.2 Technical analysis

Technical analysis is defined by John Murphy (1999) as the study of market action through the use of charts with the aim of projecting future price trends. Technical analysis is based on three premises (Murphy 1999): Market action discounts everything, prices move in patterns and history repeats.

The statement 'the market action discounts everything' means that technical analysts believe that everything that can possibly affect the price is reflected on the price. This includes market fundamentals, politics and psychology. As a result of the reflection of everything on the price, it then follows that for an investor to profit, the price should be studied.

The notion that prices move in trends is essential in technical analysis. In simple terms one can define technical analysis as the study of trends in the financial market because it is what technicians spend their time doing. They pay very little attention to the analysis the noise made by the economists and financial analysts.

Most of technical analysis and study of market action has much to do with the study of psychology, which chartists argue lead to the formation of patterns. Patterns that are used by technicians have been in existence for decades. This repetition of patterns also forms the bases of technical analysis. Chartists use different indicators to project the price movement of a

financial instrument. These indicators include chart patterns, momentum indicators and oscillators.

It is common for technical analysts to use multiple technical analysis indicators with the intent of increasing the strength of the investment case. The technical analysis field is vast. It is not possible cover all the indicators in this field. There are technical indicators that have become common. These include the moving averages in the momentum indicators, relative strength indicator in the oscillators group, head and shoulders in the price patterns and volume. There is extensive research that covers moving averages, oscillators and volume. Price patterns have not received as much attention. This study follows the practical use of technical analysis i.e. combination of indicators, including a double bottom strategy.

1.3 Research Problem

Extensive research has been done in the field of technical analysis and fundamental analysis as will be shown in the literature review. However, the research in the JSE listed companies has shied away from combining price patterns and momentum indicators. The research has focused on investigating technical analysis indicators individually. There is a study on the use of the F Score methodology on the JSE stocks but the research has not been pushed a step further to incorporate technical analysis. There is a need for this kind of research because the investment industry in South Africa has increasingly adopted technical analysis as overlay of their fundamental analysis strategies.

1.4 Research Objectives

The ultimate objective of the study is to establish whether technical analysis can be used to enhance returns achieved using fundamental analysis in the JSE. The second objective is to find out if the JSE listed stocks exhibit characteristics of weak form market efficiency.

1.5 Research Questions

This study will answer two questions: Are the returns achieved by portfolios formed using fundamental analysis higher than returns achieved by portfolios formed using technical analysis? Are the returns achieved by portfolios formed using both fundamental and technical analysis higher than returns achieved by portfolios formed using fundamental analysis?

1.6 Gap in the Literature

The increase in the number of technical analysts in investment firms in South Africa shows that investors and traders are increasingly paying more attention to technical analysis. Despite this, however, there is a limited number of studies on how technical and fundamentals analysis can be used together in the JSE. There are no studies in the South Africa that examine the effectiveness of combining double bottom strategy, moving averages and volume to make investment decisions in the JSE.

1.7 Significance of the Study

Research in the financial market continues to grow as investors continue to try to earn more returns. The poor performance of fund managers from previous years (Burton, Effinger and Bit, 2014), shows that it has become important for financial analysts to be more innovative in their approach to attempt to find assets that are heavily mispriced. The use of fundamental analysis combined with technical analysis has been growing in the South African hedge fund industry. This growth comes with added costs as charting software that technical analysts use are costly. The study will show if the costs incurred by technicians provide value for investors. This research also examines whether the JSE has weak form efficiency characteristics, based on the technical trading rules used in this study.

In the international market, especially in the developed market, technical analysis research has covered most of the technical analysis indicators. On the other hand, research in the JSE has focused mostly on momentum indicators and oscillators like moving averages and relative strength indicators. There is no research on price patterns that uses a combination of technical indicators in the JSE listed stocks. This research will bridge the gap by studying the double bottom strategy and combining the strategy with momentum indicators. It is also important to note that the research that has been conducted in JSE does not combine technical analysis and fundamental analysis in the way that is done in this paper i.e. combining different technical indicators and the F_score fundamental analysis approach. This paper will show if the use of technical analysis combined with fundamental analysis adds value for investors who use both methods combined.

Structure of the Report

The remainder of the report is structured as follows: Chapter 2 looks at the research done under the subject of market efficiency, weak form efficient market hypothesis (technical analysis), semi strong form efficient market hypothesis (fundamental analysis), and the research combining the two methods of investing. Chapter 3 presents the research methodology used in the study. It provides the data and data sources, as well as the research design. Chapter 4 presents the results of the research. Finally, Chapter 5 completes the report and acts as both a summary of the findings and the conclusion to the study.

Chapter Summary

Chapter 1 introduces the aim of the study and discusses the various methods investors use to evaluate financial instruments. This chapter also explains how the investment industry has changed over the years to incorporate technical analysis. Furthermore, the structure of the report is outlined.

Chapter 2: Literature Review

Introduction

This research project seeks to discover whether or not the efficient market hypothesis holds in the JSE listed stocks using Technical Analysis trading rules and fundamental analysis. Studies have been done in these two methods of investing (Technical and Fundamental investing) with more evidence suggesting that weak form efficiency does not hold in emerging markets while there are mixed findings in developed markets. However, very little work has been done that is publicly available that looks at the possibility of merging the two investing methods. Rather the separation of the two methods has caused the gap between the two. This chapter engages the research done under the subject of fundamental analysis. Research done within the field of technical analysis studies; and finally the research which concerns itself with combining the two methods of investing will be discussed last in this chapter.

2.1 Market Efficiency

With its roots in the 1960s, the theory of market efficiency claims that stock market prices fully reflect all available information and that when new information becomes available efficient markets adjust instantly, giving traders and investors no chance to act on this information. As a result investors cannot 'beat' the market when all costs are considered. In 1970 Eugine Fama divided market efficiency into three forms: weak, semi-strong and strong form efficient market hypothesis. Weak form claims that past stock prices and volume cannot be used to predict future prices. Semi-strong form claims that an investor who uses financial reports above using past prices can also not 'outperform' the market. The strong form posits that an investor who uses all information in the semi-strong form and information that is not public cannot earn abnormal returns. Extensive research has been done on this topic with more studies invalidating the semi-strong and strong form efficient market hypothesis; whilst scholars concerned with weak form efficiency studies are still in disagreement on whether it is valid or invalid (Titan, 2015).

To test for the efficiency of the capital markets several studies which are accepted by academics have been conducted. These include random walk tests to test for the weak form efficient market hypothesis; whilst short term market efficiency tests, such as those in event studies, test

whether or not the market adjusts instantly to new information as the efficient market hypothesis claims; and calendar tests test if there are times when the market behaves in a certain way.

2.1.1 Weak form Market Efficiency

Early studies focused on weak form market efficiency tests and were based on the random walk concept (Fama, 1970). The term random walk was first coined by Jules Regnault in the book he published in 1863 (Titan, 2015). Random walk theory claims that future prices have no relationship with the past prices. This theory has been tested extensively to prove the validity of weak form market efficient hypothesis. Among the early authors to test random walk in the stock market prices was Bachelier (1900), who studied mathematically the static nature of the market at a given time, so as to establish the probability law for the fluctuations of the prices which he claimed were influenced by infinitely large variables that no one could take into consideration. These variables included past prices and the current price. Weak form efficiency tests have gained more ground since then, however, now with more focus on emerging markets.

It is widely held that the level of market efficiency varies with the level of development of the economy. The most developed economies are supposed to have the highest market efficiency while developing markets have less efficiency. Emerson and Hall (1997) have investigated the level of efficiency across several infant markets and have reported witnessing the move from inefficiency to more efficiency as these markets evolve over time. They investigated this phenomenon in the Bulgarian market and establish that over time the market has become more efficient. Movarek and Fiorante (2014) conducted a similar test in the capital markets in the countries of Brazil, Russia, India and China (Hereafter referred to as BRIC). Their tests used daily data from September 1995 to March 2010. The aim was to determine if the efficiency was increasing. They found that these countries exhibited a trend towards increasing weak form market efficiency and the disappearance of the day of the effect.

Other authors who have contributed to the on-going research of market efficiency in emerging markets include Abrosimova, et al. (2007), Chen and Metghalchi (2012), Mobarek, et al. (2008), McGowan (2011) Poshakwele (1996). Abrosimova (2007) investigated the existence of weak form efficiency in the Russian stock market using daily, weekly and monthly Russian Trading System index, time series data, spanning the period September 1995 through May 2001. He used unit root, autocorrelation and variance to ratio to conduct the investigation. His

research showed that the monthly data showed results that were consistent with the random walk theory, while daily and weekly data studies showed evidence of short term market predictability without taking into consideration trading costs. McGowan (2011) also studied the same Russian Trading System Index in search of weak form efficiency. His study covered the period of September 1995 through the June of 2007. The results showed that the index was weak form efficient in the last 8 years of the study.

Terence, et al. (2009) studied technical trading rules using moving averages, a relative strength index, moving average convergence-divergence and momentum indicator in the Russian stock market. They discovered that these indicators were profitable in Russia for the time of September 1995 through November 2008. In line with the findings by McGowan (2011) and Movarek and Fiorante (2014), Terence et al. (2009) also found that the older the market the less beneficial these rules were.

Moberek, et al. (2008) studied the Dhaka Stock Market of Bangladesh to find out if the Bangladesh Stock Market was weak form efficient. Their study investigated the period from 1988 to 1997. Using non-parametric and parametric statistical tests they found that Dhaka market did not follow random walk, as a result invalidated weak form efficiency in that market. Poshakwale (1996) studied the Bombay Stock Exchange (BSE) in search of the weak form efficiency by studying day of the week effect. The results showed that the BSE was not weak form efficient.

Gupta and Yang (2011) studied two India stock exchanges (BSE and National Stock Exchange) to find out if these market were weak form efficient. Similar to Abrosimova (2007) methodology, Gupta and Yang (2011) study used different periods for the study: They used quarterly, monthly, weekly and daily data. Consistent with Abrosimova (2007), they showed that the longer period data showed that market was weak form efficient while daily and weekly data rejected the weak form efficiency. They also found that more profit occurred in the earlier period of the period studied and the market has become more efficient lately.

In other studies of emerging market stock exchange weak form efficiency, Lim, et al. (2009) and Fifield and Jetty (2008) investigated the weak form efficiency of the Chinese stock market. Lim, et al. (2009) studied the Shangai and Shenzhen Stock Exchanges while Fifield and Jetty (2008) investigated the A and B shares in the Chinese Stock Markets after the Chinese government changed regulations to allow for more ownership of shares by foreign nationals. Lim et al (2009) found that over the long term both markets obeyed random walk model but in

the short term there were periods where the market rejected the weak form efficiency. Furthermore, Fifield and Jetty (2008) found that the A shares were more efficient than the B shares. The results also showed an increased speed in the diffusion of information for the B shares, which increased efficiency. They found that the efficiency heavily depended on the method used to test the efficiency. In some cases there was significant difference in the results obtained using parametric and non-parametric testing procedures.

2.1.1.1 Weak form Efficiency in the South African Stock Market

Weak form efficiency has been tested in the Johannesburg stock exchange with some researchers showing the improving efficiency of the South Africa equities market (Jefferis and Smith (2004)). Some authors found evidence of weak form inefficiency in the JSE (Cambell (2007), Jefferis and Smith (2004), Morris et al (2009). Jefferis and Smith (2005)) while some studies have validated weak form efficiency in the JSE stock (Bonga Bonga (2012), Jefferis and Smith (2004)).

Bonga Bonga (2012) used time varying Garch model to test weak form efficiency in the JSE. He then compared out of sample forecast performance of the time varying and fixed parameter Garch models in predicting stock returns. His conclusion was that the South African stock exchange has been efficient during the period studied which starts from January 2008 to December 2009 using weekly data. He estimated the models using weekly data from March 1995 to December 2007.

Jefferis and Smith (2004) divided the listed stocks in the JSE into small and large caps to study the level of efficiency. They used multiple variance ratio and tested for evolving efficiency. They used weekly data from January of 1993 to March of 2001. The large caps showed random walk existence while mid and small caps showed no evidence of weak form efficiency. Smith and Dyakova (2014) found that the JSE had periods of predictability and periods of less predictability in their study of the efficiency of the African stock exchanges. Jefferis and Smith (2005) studied the weak form market efficiency of seven African markets using the Garch approach and test evolving approach. Their study spanned from early 1990s to June 2001. They found that the South African market was efficient throughout the time studied, whilest Egypt and Morocco became weak form in the later period of the study.

2.1.1.2 Technical Analysis

The findings of studies examining profitability of various trading rules are mixed, as some researchers have found that some rules are not profitable. Among these researchers is Levy (1971) who studied five patterns. He found no evidence of the profitability of these patterns when used alone to make investment decisions. Day and Wand (2002) studied the technical analysis rules used by Broke, et al. (1992) on the Dow Jones industrial average to come to the conclusion that when transaction costs are included and nonsynchronous prices in the closing levels of the index are excluded, these rules cannot be used to trade the Dow Jones industrial average profitable. Furthermore, Fang, Qin and Jacobsen (2014) examined the profitability of technical market indicators. In their research they found little evidence of the ability of the technical market indicators to predict stock indicators.

Moreover, Taylor (2013) investigated the use of momentum based technical trading rules to examine their profitability. He found that profits evolved slowly over time and the profits were only realised when short selling was allowed. His findings also demonstrated that the profitability of these rules depended on the market conditions as these rules showed profits between the mid 1960's to the mid 1980's. Ito (1999) applied the technical trading rules examined by Brock, et al. (1992) on the United States of America's, the Canadian, Japanese, Taiwanese, Indonesian and Mexican equity indices to examine their profitability. He found that the trading rules do not have a strong forecasting power for the US market while they have strong forecasting power for the emerging markets.

The CRISMA technical trading system was introduced by Pruitt and White (1988). They examined a hybrid technical trading system which included relative strength, volume and moving averages. Their research found that technical analysis is profitable after including transaction costs and having taken into consideration the risk. These results proved that the market was not weak form efficient. As a result, CRISMA has been investigated by several researchers after it was introduced. The researchers who have taken interest in its study include Marshal, Cahan and Cahan (2006), Goodacre, Bosher and Dove (1999) and Goodacre and Speyer (2001), amongst others.

Marshal, Cahan and Cahan (2006) found that CRISMA is not consistently profitably; whilst Goodacre, Bosher and Dove (1999) and Goodacre and Speyer (2001) found that the CRISMA

trading system is profitable for United Kingdom (UK) stocks before adjustment for transaction costs and risk have been applied.

Candlestick charting is one of the most popular charts used by technicians. It is popular because it shows more price details than many of the alternatives, and this popularity has gained it interest from several researchers. Lu (2013), Lu and Shiu (2012) examined the predictive power of candlestick charting using Taiwan stocks. They found that candlestick charting produces positive returns even after including the transaction costs. Other researchers who have found candlestick charting profitable include Goo, et al. (2007), Caginalp and Laurent (1998), as well as Shiu and Lu (2011). Goo, Chen and Chang (2007) examined various candlestick patterns to determine which pattern was profitable and how many holding days would give the best returns. They found that some of the candlestick trading strategies provides value for investors and that the holding period for each strategy is different.). Orton (2009) examined the value that investors can obtain from using stars, doji and crows to select stocks. He found no evidence of value from the use of these candlestick charting methods.

Hong and Satchell (2011) derived the autocorrelation function for a general Moving Average (MA) to investigate the profitability of the MA trading rule. The results obtained showed that the MA rule has become popular because it can identify momentum and is very easy to use. Brock, Lakonishok and Lebaron (1991), on the use of the MA trading rules, also found out that the rule is profitable. On the contrary, Ready (2002) found that the apparent success of MA trading rules is a result of data snooping. Other studies done in the field of momentum investing include Rouwenhorst (1998) and Zhu and Zhou (2009). The former of these researchers found that in the medium term winners continue to outperform medium term losers, whilst the latter focused on analysing the extent to which MA is useful from an asset allocation perspective. They found that MA provides value for investors.

Furthermore, Ulku and Prodan (2013) investigated the profitability of trend following rules by testing the MACD trading rule and a 22 day MA and other MA rules to observe the sensitive of a trading rule on the returns. They studied already developed and developing markets, and found that MACD rule's profitability is insignificant, and lower than that of MA rules.

In one of the limited studies on price patterns, Lo, Harry and Wang (2000) used nonparametric kernel regression which they applied to a large number of U.S. stocks from 1962 to 1996 to

evaluate the effectiveness of technical analysis. They compared the unconditional empirical distribution of daily stock returns to the conditional distribution, conditioned on 10 technical analysis patterns which included the popular head-and-shoulders, double tops and bottoms and rectangle tops and bottoms. They found that over the 31-year sample period, several technical indicators have provided incremental information and may have some practical value.

Furthermore, Metgalchi (2012), tested various trading rules, which included: a) moving averages, b) relative strength indicators (RSI), c) Parabolic Stop And Reverse (PSAR), d) moving average convergence divergence (MACD) and, d) stochastic. He found that any combination of these results cannot contend with the buy and hold strategy. Terence, et al. (2009) using SMA, RSI, MACD and MOM found that the Brazil stock was more efficient., and concluded asa result, that these strategies were not profitable.

Technicians claim that returns can be predicted because markets do not move randomly. Lo and Mackinlay (1988) tested the random walk hypothesis for weekly stock market returns by comparing variance estimators derived from data, sampled from 1962 to 1985, at different frequencies. Their results rejected the random walk model for the entire sample period. Similarly, Reitz (2005) published a paper with the aim of explaining why technical analysis continues to be used by traders despite claims that it contains useless information. In his paper he found that the use of technical analysis enables uninformed traders to see the influence of hidden fundamentals only known by few traders.

Using variable length moving average rules, fixed length moving average rules and trading range break rules, Campbell (2007) studied the JSE all-share index from April 1988 to April 2007. His study was investigated whether or not the trading rules could yield excess returns compare to a buy and hold strategy. He found that the simple technical trading rules have predictive ability. However, he also found that these results were not statistically significant when tested using the student-t-test, as access returns above the buy and hold strategy were 4.6% per annum. This were observed across all the sub-periods tested.

2.1.2 Semi-Strong Form Market Efficiency

Early studies of semi-strong form market efficiency focused on event studies, which include stock splits, dividend and earnings' announcement, new stock issue and stock repurchasing

announcements. The first event study was conducted by Dolley in 1933, according to Basda and Oran (2014), when he studied stock splits to investigate if the price adjusted to the new level instantly based on the new information. Other early studies include FFJR (1969), Ball and Brown (1968), and Brown and Warner (1980). Since then semi-strong form efficiency tests have moved to include the profitability of fundamental analysis which focuses on a longer term market efficiency.

2.1.2.1 Fundamental Analysis

There are several models that have been developed to analyse the financial health of companies by studying financial statements. These include the F_score method developed by Piatroski (2002), the Altman bankruptcy risk check (Altman, 1968), Ohlson's bankruptcy risk check (Ohlson, 1980) and Merton's distance to failure (Merton, 1974), amongst others.

Research done by Piatroski (2002), which studied value firms using the F_scores, paved a way in which effective studying of company fundamentals can be done. Piotroski (2002) investigated the effect on investor's portfolio when firms with high book to market ratio with strong financial fundamentals are analysed using the F_score. The results show that such a portfolio produces abnormal returns of 7.5% annually over a period of 20 years (from 1976 to 1996). The study further showed that by shorting companies with low BM, abnormal returns can be increased to 23% per annum. Within the portfolio of high BM firms studied, it was shown that the benefits to financial statement analysis were concentrated in small and medium-sized firms, and companies with low share turnover.

Moreover, the F_score screening has been tested in the developed market and developing market. Mohr (2012), used the F_score to separate growth stock winners from losers in the Eurozone stock market from 1999 to 2010. He showed that fundamental analysis modelled by the F_score produces returns that outperform the market. Similar studies were conducted by Vankash, Madhu and Ganesh (2013) and Van de Merwe (2012), who studied the use of fundamental analysis to select stocks using the F_SCORE.

A Study on the JSE listed companies done by Van de Merwe (2012) using Piotroski's F_score was not conclusive. Furthermore, Iqbal, Khattak and Khattak (2013) also found that fundamental analysis could not be used to predict stock returns in Pakistan listed companies. Another study done in a developing market was conducted by Dosamantes (2013), in the

Mexican stock market (BMV), in which he aimed to establish the value relevance of accounting fundamentals in predicted future returns in stocks. His study was performed using Piotroski's F_score and Lev and Thiagarajan (1993) L- score methods. He found that the accounting fundamentals provided value relevance to investors. Moreover, he found that firms that had a high score produced abnormal returns that averaged 1.65% over a 20 year period (1991 to 2011) and excess returns of 9% over the fourteen year period between 1997 and 2011. Al-Debie and Walker (1999) also studied the variables studied by Lev and Thiagarajan (1993) in the UK market. Their findings were broadly supportive of Lev and Thiagarajan's analysis of fundamental information. They also found that gross profit, labour force, and distribution and administrative expenses were particularly significant for the UK market.

Beaver and Mcnichols (2001) examined whether property and casual insurers' stock prices completely reflect information contained in earnings, cash flows, and accruals, and development of loss reserves. They found that investors tend to underestimate the persistence of cash flows and overestimate the persistence of accruals. They also found that the market does not underestimate the persistence of development accruals. Furthermore, Dichev and Tang (2008) investigated the connection between earnings and volatility predictability. Their findings indicate that consideration of volatility enhances the predictability of both short term and long term earnings.

Furthermore, Abarbanell and Bushee (1998) examined whether or not fundamental analysis can also earn significant abnormal returns. Their study did not only show that fundamental analysis leads to excess returns of 13.2% cumulative over 12 months, but it also identified the period at which most of those returns were earned. They found that a significant portion of the returns were around the period at which firms were announcing their earnings. Furthermore, the study showed that firms that had bad news prior, performed much better than companies that were darlings of financial analysts and investors.

Dowen (2001) expanded on the work done by Abarbanell and Bushee (1998) and Lev and Thiagarajan (1993) on the understanding of the relation between past earning and other accounting data to future earnings. He added new information developed in the finance literature (dividend yield, firm size and book to market ratio) which may possibly provide indicators as to future earnings as alternatives to CAPM in explaining cross-sectional variation in returns. He found that out of the three signals, book to market ratio has the strongest relation

to future earnings. However, Fairfield and Yohn (2001) tested whether the fundamental decomposition of return on assets is useful in a forecasting context, or not. They found that disaggregating return on assets into asset turnover and profit margin does not improve forecasting accuracy while disaggregating change in return on assets into change in asset turnover and change in profit margin is useful in forecasting profitability.

Giner and Reverte (2003) analysed the predictability of financial information across France, Spain, Germany and the UK to assess if institutional and accounting differences across the countries created a difference in the predictability of financial information. The results from their study showed that there is a difference in the predictability of market data and accounting data across European countries.

Holthausen and Larcker (1992) examined the profitability of a trading strategy based on a logit model designed to predict the sign of the next twelve month excess return from accounting ratios. The strategy earned between 4.3% and 9.5% in excess returns, between the year of 1978 and 1988. Ou and Penman (1989) also performed financial statement analysis to take long and short positions. Two year holding period returns were 12.5%, but after adjusting for size they managed to earn 7.0%.

Kormendi and Lipe (1987) examined whether the magnitude effect of unexpected earnings on stock returns is positively correlated with the present value of revisions in expected future earnings, derived from a univariate time-series model. They found no evidence of excessive stock return volatility, due to reversion of earnings. Jorgensen, Li and Sadka (2012) also studied the relationship between the stock returns and earnings. They found a positive correlation between aggregate stock returns and contemporaneous earnings dispersion. and negative relation between aggregate stock returns and expected future (one year) earnings dispersion. Sandka G. and Sadka R. (2009) studied the effect of predictability on the earnings - return relation on individual firm and aggregate. They found that prices predict earnings at an aggregate level than at firm level.

Anilowski, Feng and Skinner (2006) examined whether earning guidance had an effect on the aggregate stock return through its effects on expectations about overall earnings performance and aggregate expected returns. They found that downward earnings guidance was associated with market returns within a short window, which is around its release. Following this study,

Shivakumar (2007) analysed the relationship between aggregate earnings guidance, stock market returns and the macro-economy. He found that the correlation between aggregate earnings guidance and market returns was positive for monthly data and mixed on quarterly frequency.

Bernhart and Gianneti (2008) examined the ability to predict earnings price ratio on the Standard and Poor's 500 index. They dichotomized the earnings price ratios into positive and negative, and found that the negative earnings ratio has more predictability than the positive earnings ratio. They also found that earnings-price measures have the ability to forecast both future returns and earnings growth. As a result it would be expected for an investor who focuses on the negative earnings to earn more returns than an investor who studies everything.

Using market based variables, such as volume and accounting information obtained from the financial statements, Beneish, Lee and Tarpley (2001) were able to identify extreme losers and extreme winners. Their study showed that market related variables were useful in identifying stocks that would have extreme share price movements in the next four to six months, and that accounting based fundamentals were useful in identifying winners from losers.
Ashoub and Hoshmand (2012) evaluated the ability of ratios in explaining the stocks, returns, incomes and rate of accounting return using companies listed on the Tehran Stock Exchange (TSE), between 2006 and 2009. The results from the study showed that an investor cannot obtain excess returns using accounting based information.

Rapach and Wohar (2005) examined the in-sample and out-of-sample predictive power of financial variables such as book to market ratio, and dividend to price ratio. They found that a number of these financial variables, such as equity share, show predictive ability with respect to stock returns, with no great deal of discrepancy between in-sample and out-of-sample data. Park (2010) investigated the predictive ability of dividend to price ratio, and found that dividend-price ratio does have predictive ability. Similarly, Lettau and Ludvigson (2005) showed that dividend to price ratio has predictive ability on the stock returns; whilst Jiang and Lee (2006) examined future profitability and excess stock returns in terms of a linear combination of log book to market ratio and log dividend yield. Their results showed that book to market and dividend yield provide and an indication of the future stock returns.

2.1.2.2 Technical analysis vs. Fundamental analysis

There have not been many studies that have put together technical analysis and fundamental analysis for the purpose of attempting to investigate any correlations. Of the few studies available, the study by Lee and Swaminathan (2000), which investigates price momentum and trading volume, provides a link between momentum of stocks as determined by volume and value of companies. In the study, the Authors found that firms with high (low) turnover ratios in the past tend to show more glamour (value) characteristics, yield low (high) returns in the near future (one year) and also tend to produce negative (positive) earnings within the same period. To link these findings with technical analysis, the study shows that firms with low trading volume show characteristics associated with value stocks, while high volume stocks are associated with glamour stocks. The authors then show that trading volume gives magnitude and persistence of the price momentum.

A study done by Moosa and Li (2011), in which they used panel data and time series data obtained from traders in the Shangai Stock Exchange, showed that investors who use technical analysis determine prices better compared to fundamental analysis.

With the aim of finding out whether technical analysis and fundamental analysis are compliments or substitutes, Bettman, Sault and Schultz (2009) proposed an equity valuation model that incorporated both technical and fundamental analysis. They found that the use of these two methods of investing tends to yield superior results as compared to just using one method. Similarly, Ko, Lin, Su and Chang (2014) have recently demonstrated that a combination of fundamental analysis and technical analysis leads to an investor earning higher returns than a simple buy and hold strategy. These authors combine moving average and book to market ratio, which is a well-studied stock valuing approach. By buying high book to market ratio stocks and selling low book to market ratio stocks, the authors concluded that the use of the MA improves the timing by the investor who appreciates both methods of investing.

The latest study was done by Silva et al (2015), in which they developed a hybrid model that combines technical analysis and fundamental analysis. They used financial ratios and technical indicators to prove that an investor who utilises both methods of investing can earn better returns than an investor who only utilizes one method. In their study they show that financial ratios alone can be used to find best companies in operational terms, obtaining returns above

the market average with low variances in their returns. Technical analysis is used for timing and finding the level at which losses should be cut.

2.2 Deviation From efficient market hypothesis

Although research has shown results which invalidate the semi-strong form efficient market hypothesis, it is still observed that on average active portfolio managers still under perform their benchmarks Jiang, et al., (2013), Cahart (1997), Warmers (2000) and Fama and French (2010). This has been the argument for those economists who support efficient market hypothesis. Lo (2004) argues that this underperformance is supposed to be the case, given that the capital markets go through phases of boom and burst, and regulations have changed overtime since the 1960s. The market is constantly changing. This means a successful investor has to change with the times or else the fund manager will have periods of bad performance as their strategy goes through market conditions that are not favourable. For example, when mergers and acquisitions reduce significantly as the global economy goes through an economic circle, arbitrage strategies may become unprofitable until the time when Mergers and acquisitions return.

Most of the studies that have tested market efficiency have focused on studying the market with the assumption that the market is constant. Consequently, adaptive market hypothesis has gained ground lately as a potential way to correct this. Using first order autocorrelation, Lo (2004) shows how the market efficiency degrees changed over the period between 1871 and 2003. He concluded that the market is not always efficient but goes through times of high efficiency. A later study by Charfeddine and Khediri (2016), which studies market efficiency from May 2005 to September 2013 in Gulf Cooperation Council economies, confirms what Lo (2004) found − that is to say that the markets have varying levels of efficiency during the time tested. Ito, et al. (2012) and Lim and Books (2010) also ascertained similar evidence in the US stock market, whilst Smith and Dyakova (2014), and Jefferis and Smith (2005) found similar evidence in some African stock exchanges, including that of South Africa, the JSE.

The efficient market hypothesis assumes that all participants have access to the information when it becomes available. It also assumes market participants are highly rational which causes them to act in a rational manner when new information becomes available. However, more recent studies have shown that market participants have behavioural biases that cause

them to act out irrationally, or that they may not act in line with the expectations of the efficient market hypothesis.

2.3 Behavioural Finance impact on Market efficiency

Behavioural finance studies have identified two categories of behavioural biases that affect the behaviour of market participants, which can often lead to periods of prolonged inefficiencies in the capital markets. These categories are cognitive and emotional biases. Cognitive biases include conservatism and confirmation bias; whilstemotional biases include loss aversion bias, overconfidence bias, regret eversion and status quo bias.

Conservatism and confirmation bias has been found to cause market participants to react to new information slowly or avoid the difficulty associated with the analysis of new information. As a result of this bias, when new information becomes available stock prices can take longer to adjust to the new information.

Overconfidence bias has been found to be the potential cause of momentum in the stock market (Daniel and Titman, 1999). Daniel and Titman (1999) also found that momentum is as a result of difficulty in analysing ambiguous information; something which they found to be prevalent among market participants who show conservatism and confirmation bias. Herding, which has also been observed among mutual fund managers (Gracia, 2016), has led to the formation of patterns in the capital market.

Furthermore, Lo (2004) claims that past experience influences how individuals behave in the future which could lead to certain patterns in the price. This behaviour is consistent with emotional biases like availability bias.

Chapter Summary

This chapter summarises the work that has been done by researchers in the subjects of market efficiency: profitability of fundamental analysis, technical analysis and the use of the combinations of the methods for investing purposes. There is support for the ability of these methods to predict future prices. There are also studies that show that the capital market is weak form efficient as a result technical analysis provides no value for investors. The lack of

papers that have been published on the combined use of technical and fundamental analysis means that there are opportunities for researchers who are interested in the use of a combined approach to conduct investigations. There appears to be an overwhelming agreement among researchers that capital markets tend to become more efficient over time. The adaptive market hypothesis could cause a shift from the overwhelming acceptance of efficient market hypothesis whose existence depends heavily on the method used to test it.

Chapter 3: Research Methodology

Introduction

This chapter presents the research methodology used in the study. In particular, it provides the data and data sources, as well as the research design of the project. The chapter is organized as follows: Section 3.2 presents data, data sources and sample selection criteria. Section 3.3 presents the research design, and the chapter summary concludes the chapter.

3.1 Data and Data Sources

The aim of this study is to compare the efficacy and compatibility of technical and fundamental analysis in predicting the future share performance. The data required to conduct this study includes historical daily closing share price data, daily volume traded, and accounting ratios from the firms' financial statements. The study draws on share price and volume in technical analysis, while fundamental analysis studies makes use of accounting ratios.

The data has been obtained from Bloomberg Professional Service, which is the preferred service, because of its advanced technical analysis tools and its vast information about companies traded publicly. A 12-year period, which starts from 01 January 2004 and ends 31 December 2015, was the period of the study. Moreover, for the stock to be included in the study, it must have traded publicly for at least one year. This allows enough historical prices for technical analysis to be performed. The one-year period also means that sufficient time is available for firms' financial statements, which enables the calculations of the changes in the accounting ratios used in fundamental analysis.

3.2 Research Design

3.2.1 Selection of stocks based on their fundamental signals

To measure the efficacy of fundamental analysis in explaining share prices, the firms were selected using the F_score screening method developed by Piotroski (2002). The JSE listed firms were first ranked by book to market value. The ranked stocks were then split into five categories with the first category having the highest book to market value and the fifth category heaving the lowest book to market value. The F_scores for each firm, in each category, was

calculated and the firms in each category were ranked from highest F_score to lowest. The returns for each firm's stock were calculated in the subsequent 12 months.

The F_score was determined using equation 1 below on the 1st of January each year and performance was determined in the subsequent 12 months, quarterly. The three month period has been chosen because it was the shortest period for investment firms to report to their investors. There are nine fundamental signals used to determine the F_score. These signals are measures of firms' profitability, financial leverage, operating efficiency and liquidity. Specifically, these measures are: Return on Assets (ROA), Cash flow from operating activities (CFO), Current ratio, Assets turnover ratio, Gross margin ratio, Offering of common equity, Firm's total long term debt to total assets, Accrual and Change in ROA. Each fundamental measure was assigned a value 1 if it shows good standing or operation of the company and a measure of 0 if it does not show good standing or operation of the company.

The sum of these signals produce what Piotroski (2002) calls the F_score as shown in equation 1 below:

$$F\_Score = F\_ROA + F\_\Delta ROA + F\_CFO + F\_ACCRUAL + F\_\Delta LEVER + F\_\Delta LIQUID + F\_EQ + F\_\Delta MARGIN + F\_\Delta TURN \quad (1)$$

Where:

F_ROA	Return on assets which is a measure of firm's profitability
F_CFO	Measure of the cash flow generated from the normal operations of the firm
$F\_ACCRUAL$	Net income before extra – ordinary items less CFO scaled by the beginning of the year's total assets
$F\_\Delta LEVER$	Change firm's total long term debt to total assets
$F\_\Delta LIQUID$	Change in current ratio
F_EQ	Offering of common equity
$F\_\Delta MARGIN$	Change in gross margin ratio
$F\_\Delta TURN$	Change in assets turnover ratio

Appendix 1 explains further the F_score signals and how they are measured.

3.2.2 Selection of stocks based on technical Analysis

The study in this section looks at the profitability of the three technical indicators. These indicators are simple moving averages, which are used to determine price momentum; price patterns;double bottom;and volume. There are rules that govern the use of these indicators, as explained by Jobman (1995) and Kamich (2009) – rules that define entry levels, price targets and stop losses when the signals fail.

3.2.2.1 Moving Averages

Moving averages are by far the most common trading tool. There are many trading/investing strategies that use MAs. In this study we look at the most popular strategy following the methodology similar to that used by Ko, et al. (2013). What distinguishes this study from the one conducted by Ko, et al. (2013) is that the MA is applied to each stock not a portfolio of stocks. This is the traditional way of using MAs. This strategy compares a MA to the price of the security. In this strategy, a long position is taken on a stock at the close of the second day, when the stock closes above the moving average for two consecutive days. Furthermore, the trade is closed when the price closes below the MA two days in a row. A 10-day MA is used, which is the same MA used by Ko, et al. (2013). The longer the MA the smoother it becomes, removing volatility. Thus a longer MA is suitable for a more volatile security to reduce false signals.

3.2.2.2 Double Bottom

This pattern works on the premise that most stocks have levels where they are viewed by the market as cheap and expensive. At these levels the stocks attract more buyers (if in the cheap zone) and sellers (if in the expensive zone). To illustrate this, let us consider how most investment houses and analysts do research: They do fundamental analysis to arrive at a buy (cheap level), fair (intrinsic value) and sell level (expensive level). Unfortunately this research is not available to the public, and each analyst/investment firm has different levels, although they are often not too different from one another, which may be the reason for the observed herding of money managers by Jiang, et al. (2013); which he claims has led to the formation of patterns in the market.

Consider a stock that is trading at price Y and Investment firms A, B and C have buy (sell) recommendations at prices 0.8Y (1.3Y), 0.77Y (1.25Y) and 0.75Y (1.2Y). If the stock falls from Y to 0.9Y and continues to fall it means there are desperate sellers. If the stock falls through 0.8Y investment firm A becomes a buyer. If, however, the sellers are bigger than firm A the stock will continues to fall, below 0.77Y firm B starts buying and firm A becomes a strong buyer. If the stock starts to rise (Level 1) means firm B and A buying has overpowered the sellers and the sellers have been potentially filled, therefore, less sellers in the market. If the stock rises above 0.8Y firm A and B may reduce buying and if there are still sellers the stock will start to fall again (call this turning point level 2) back to the level (level 3) where firm A and B become dominant buyers and the stock starts to rise again. If level 3 is equal to level 1 the pattern formed is called a double bottom. In this study we use a tolerance of $\pm 0.5\%$ between level 3 and level 1. A double bottom looks like a "W". The price target for a double bottom is shown in equation 2. The pattern is considered to have failed if the price falls below the lower of the two dominant buying levels (level 1 and level 3) by firm A and B. In this study the stop loss is activated at 0.995 of the lower level 1 and level 3 for a long position.

$$PT = level\,1 + 2 * (level2 - level1) \qquad (2)$$

3.2.2.3 Volume

The rule that governs volume says that low volume is consistent with momentum behavior and high volume is consistent with changing direction (McMillan, 2007, Wang and Chin, 2004). In this study, the research undertaken by the two authors is taken one step further by identifying the points at which the trend that has been supported by low volume changes direction. Consider level 1 from the double bottom procedure: A volume investor/trader would buy (sell) if the volume is higher than the average volume traded since sellers (buyers) started to dominate buyers, causing the stock to fall (rise) on thin volume. In this study, we borrow from moving average rules (explained above) to identify the dates where sellers/buyers started dominating causing the price to move in one direction.

3.2.2.4 Combined Technical Analysis strategy

Chartists often use more than one indicator to improve the quality of the signals. In this study, the technical indicators were applied as follows: When the stock price closes above the MA two days in a row, and the double bottom pattern is just completing its formation accompanied by increased volume above volume average since the trend started, is considered a very strong buy signal. In this study we allow for a period of three days between the buy days, which is to say that, if the first strategy indicates a buy on day X, for the trade to be placed the other two strategies have to indicate a buy at or before day X+3 days. The position is closed by the first strategy that indicates a sell.

3.2.3 Technical Combined With Fundamental Analysis

So far, we have made investment decisions purely on fundamental analysis or technical analysis rules. In this section of the study, the two methods of investing are combined in way that is similar to the approach used by Ko, et al. (2013). The differences between this study and the one conducted by by Ko, et al. (2013) include the use of F_score to find good and bad value stocks, and the use of more than the one technical analysis strategy to time the entry levels. In this section the three technical investing strategies described in section 3.3.2 are used to time the entry levels based on the views developed using the F_score. For stocks with higher F_scores, only long positions are taken when technical strategies signal so and the position is closed based on the signal given by the technical analysis strategies.

3.2.4 Measuring subsequent firm performance

Investors have many options for investing. They can either put their money in an index that tracks the universe of stocks, which this study is studying, or they can just put their money in riskless assets. To be able to see if the investment approach used in this study provides any value, the two options need to be taken into account. Another important element of investing/trading is the commission costs which have been assumed to 10 basis points.

This study aimed to determine the efficiency of technical and fundamental analysis in terms of which of the two methods yield subsequent higher returns. The returns from common share investment are the result of capital appreciation measured by share price appreciation, and the dividends paid out by a company to its shareholders. Therefore, the performances of the companies were measured by considering their total return which includes stock price increase and dividends. It is assumed that dividends are not reinvested. Therefore, the holding period returns at the end of the 3, 6, 9, 12 months are calculated. The holding period returns are calculated as shown in Equation 3 below.

$$HPR = \frac{P_i - P_o}{P_o} + \frac{D_j}{P_0} \qquad (3)$$

Where:

P_o The price of the share at the time a position is taken

P_i The price of the share at the end of three, six, nine and twelve months from the day the position was taken

D_j Dividend paid per share

In the first part of the study, the quarterly average returns from the four technical analysis strategies were compared to the average quarterly returns from the fundamental analysis strategy. In the second part, the technical analysis strategies were then applied to the fundamentally strong stocks and the quarterly average returns from the four technical analysis strategies (applied to the fundamentally strong stocks) were compared to the average quarterly returns from the fundamental analysis strategy.

In order to test for abnormality of the returns produced by these strategies, equally weighted portfolios for each strategy were created. The returns from these portfolios were regressed on the CAPM model using the approach followed by Balatti, et al. (2017) as shown in equation 4. The market return was an equally weighted portfolio of all the stocks that were studied each year.

$$r_{jt} - r_{ft} = \alpha + \beta_{jm}(r_{mt} - r_{ft}) + \varepsilon_{jt} \quad (4)$$

Where:

$r_{jt} -$ The quarterly return of each strategy

r_{ft} Risk free rate return (US 10 year Government bond)

$\alpha -$ Alpha

β_{jm} Beta (sensitivities of portfolio j excess returns to the benchmark excess returns)

r_{mt} Market quarterly returns

ε_{jt} Unknown errors

3.2.5 Statistical significance tests

This study has three samples of results, that is: . Fundamental analysis quarterly returns, technical analysis strategies quarterly returns; and, technical analysis strategies applied to fundamentally strong stocks quarterly returns. p values were used to test the statistical significance of the difference of the means. The means compared were: mean quarterly returns of technical analysis strategies and fundamental analysis, and, mean quarterly returns of technical analysis strategies applied to fundamentally strong stocks and mean quarterly returns fundamental analysis.

3.2.6 Robustness test

Boot strapping was performed on the results obtained to create 50 samples of the data for each strategy. Several authors, including Abarbanell and Bushee (1998), and Chan and Lakonishok (2004), have shown that stocks with high book to market ratio provide value. To test the robustness of the results of this research, the F_score used for fundamental analysis was replaced by book to market value approach as the fundamental analysis strategy to which technical analysis results were compared to. To do this the stocks were ranked from high BM to low BM. The top decile of the stocks were chosen and used in the technical analysis strategies.

Chapter summary

This chapter details the data that was used for the study and its data sources. The chapter also presented and explained how technical analysis and fundamental analysis was achieved in this study. The fundamental analysis follows Piotroski's (2002) F_score analysis method, which studies stocks with high book to market ratio. Furthermore, this chapter illustrated that the performance of the firms was measured using holding period returns. Moreover, the returns of each investment approach were adjusted for risk, using the CAPM to see if there were abnormal returns. To statistically test the significance of the difference in the means, p values were chosen. Boot strapping and the use of high book to market ratio were used to test the robustness of the strategies.

Chapter 4: Results and Results Discussion

Introduction

This chapter presents a summary of results, and is structured as follows: section 4.1 presents the number of stocks studied and how these were distributed across the period under study. Section 4.2 presents the results, which compare technical analysis strategies to the fundamental analysis strategy. Section 4.3 shows results of the strategies after technically analysis strategies were used on fundamentally strong stocks. Section 4.4 presents the results of the robustness testing of the results in section 4.3 and 4.4. Section 4.5 discusses the results, and, finally, chapter summary concludes the chapter.

4.1 Distribution of stocks studied

Table 1: This table illustrates the number of stocks studied for each year and how they are spread over the period under study. From the table it can be seen that the number of stocks increases over time with the highest increase happening after the recession as more companies seem to have started disclosing more information after the recession.

Parameter	No. of Stocks studied	% of Studied
2004	34	3
2005	33	2.91
2006	38	3.35
2007	38	3.35
2008	60	5.3
2009	79	6.97
2010	120	10.59
2011	141	12.44
2012	153	13.5
2013	150	13.24
2014	146	12.89
2015	141	12.44

4.2 Profitability of Individual strategies

Table 2: The table summarises results of the technical analysis strategies applied to all the stocks studied. Column 1 shows the names of the strategies, Column 2 shows number of observations, column 3 presents quarterly mean returns of the strategies, column 4 are the p values of the strategies, and the last column presents skewness of the returns. Frequency distribution diagrams for the results in table 2 have been presented in Appendix B.

Strategy	Observations No.	Mean	P Value	STDEV	SKEW
Double Bottom	1500	0.111	0.103	19.67	0.357
Moving Average	1500	-3.203	0.000	24.702	-3.24
Volume	1500	0.582	0.180	10.49	5.017
Combined	1500	2.884	0.201	7.845	2.12
Fundamental	1500	1.762	1	31.97	1.46

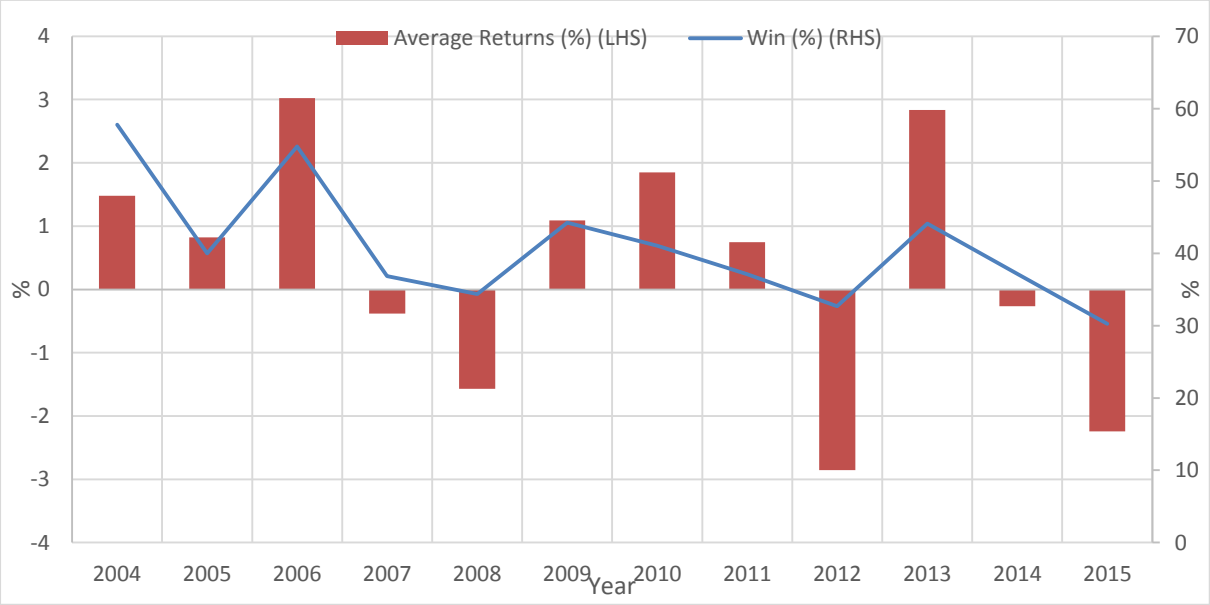

Figure 1: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades executed (Win (%)) for the double Bottom strategy. Over the entire period during which the study was done, Win (%) average was 40%. The chart shows a declining win percentage ratio while average returns per year show more positive returns. Average returns do not show any pattern during the time the study was done.

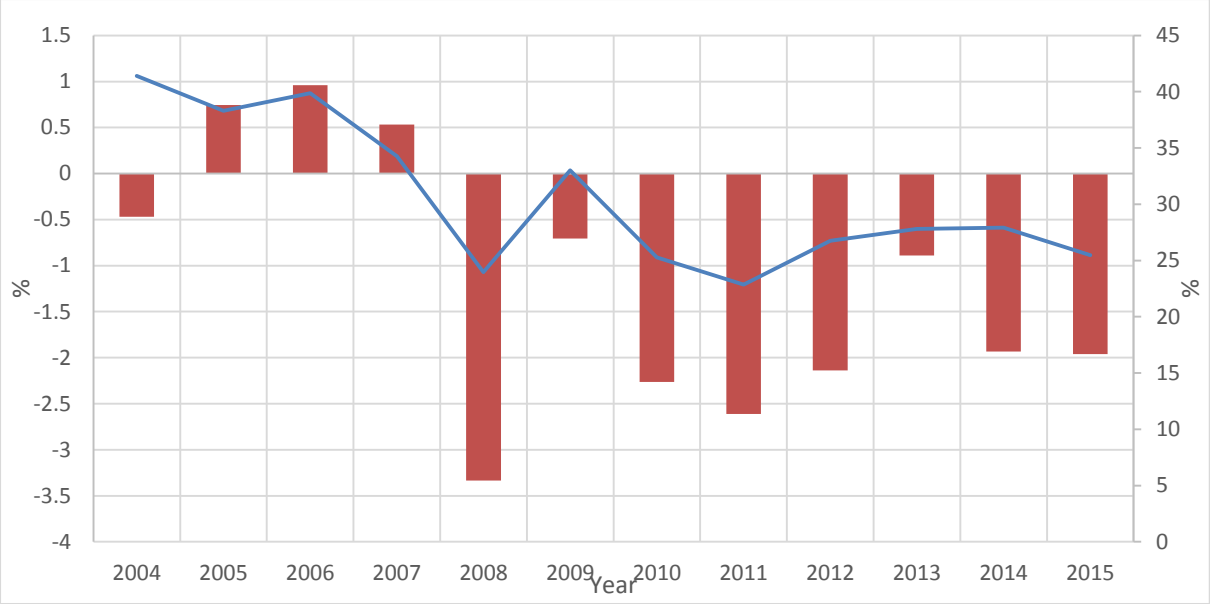

Figure 2: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the moving average strategy. Over the entire period during which the study was done Win (%) average was 30.57%. The figure shows a declining success rate of the trades executed. The strategy was only profitable until 2007.

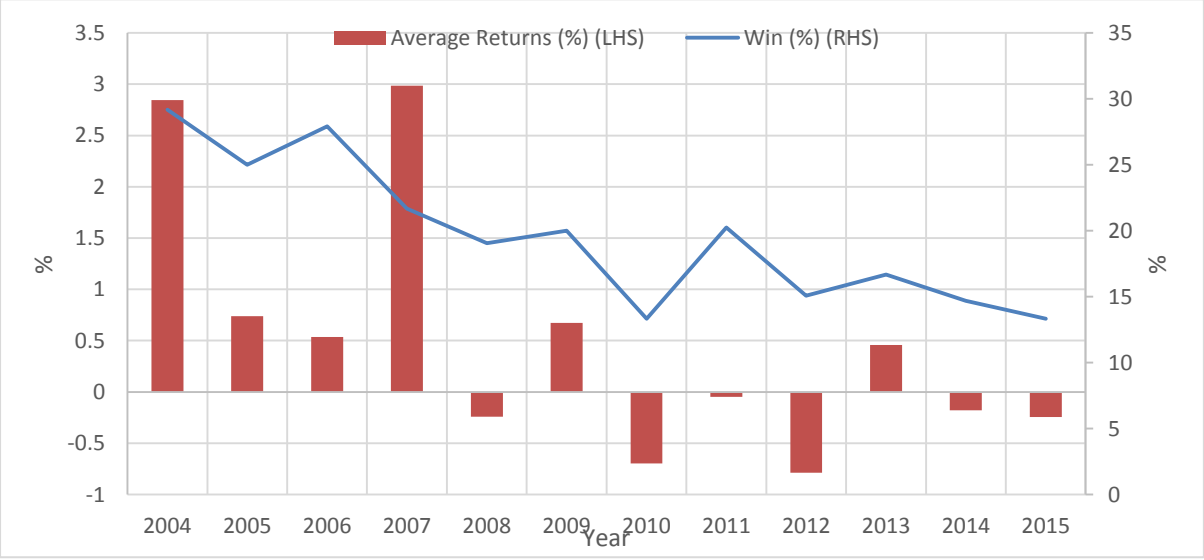

Figure 3: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the volume strategy. Over the entire period during which the study was done Win (%) average was 19.68%. Thus the Win (%) and average returns started high but had a declining trend.

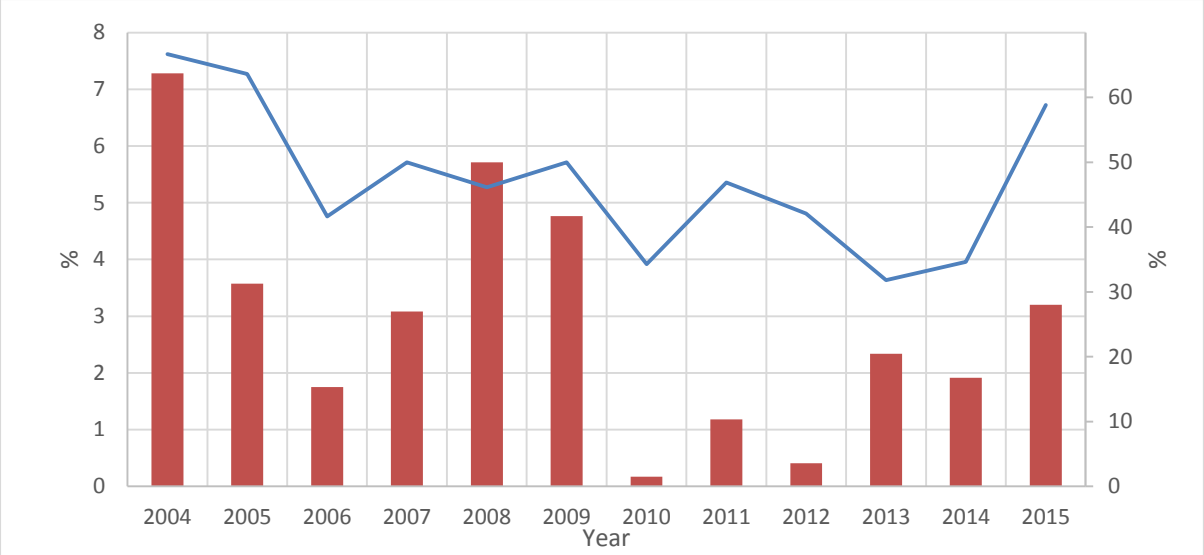

Figure 4: Reflects the average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the combined strategy. Over the entire period during which the study was done Win (%) average was 47.22%. The win (%) and average returns started high but had a declining trend with an increased observed in the last two years of the study.

Table 3: CAPM − A time series regression on the CAPM model of the quarterly returns of equally weighted portfolios of the strategies. Betas are displayed in column 2, Alphas are in column 3 and column 4 has an adjusted R-Squared of the regression. Mean squared errors are in the last column. P-values of the parameters are shown in parenthesis.

Strategy	Beta	Alpha %	Adj. R^2	MSE
Double Bottom	0.524(0.129)	-4.4(0.209)	0.032	0.029
Moving Average	0.396(0.064)	-9.8(0)	0.062	0.053
Volume	-0.407(0.561)	12.7(0.079)	-0.013	-0.014
Combined	0.112(0.582)	-2.7(0.187)	-0.013	-0.015
Fundamental	0.694(0.006)	3.1(0.224)	0.136	0.0132

4.3 Profitability of Individual strategies adjusted by Fundamental Analysis

Table 4: The table summarises results of the technical analysis strategies applied to only the fundamentally strong stocks. Column 1 shows the names of the strategies, Column 2 shows number of observations, column 3 presents quarterly mean returns of the strategies, column 4 are the p values of the strategies, and the last column presents skewness of the returns. Frequency distribution diagrams for the results in the table have been presented in Appendix C.

	FA Adjusted Strategy vs FA				
Strategy	Observatio	Mean	P Value	STDEV	SKEW
Double Bottom	1500	4.17	0.007	26.83	1.872
Moving Average	1500	-1.64	0.000	20.53	0.0684
Volume	1500	-0.056	0.419	7.19	3.05
Combined	1500	2.69	0.100	8.783	2.656
Fundamental Analysis	1500	1.762	1	31.97	1.46

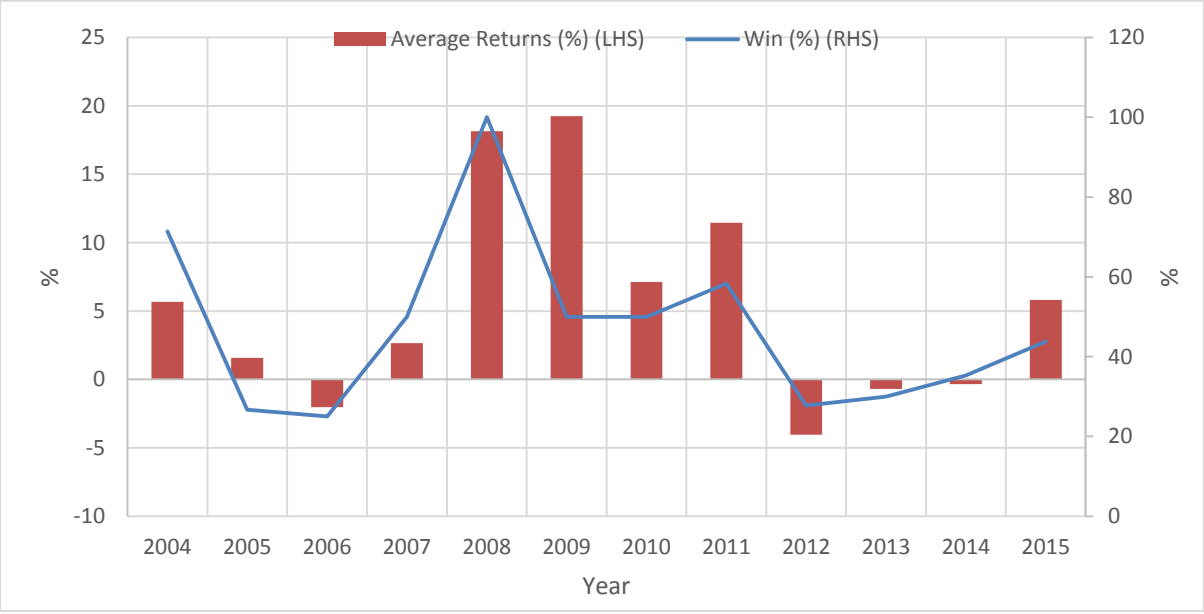

Figure 5: average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the double Bottom strategy. Over the entire period during which the study was done Win (%) average was 47.35. The chart shows no trend for both win (%) and average returns (%).

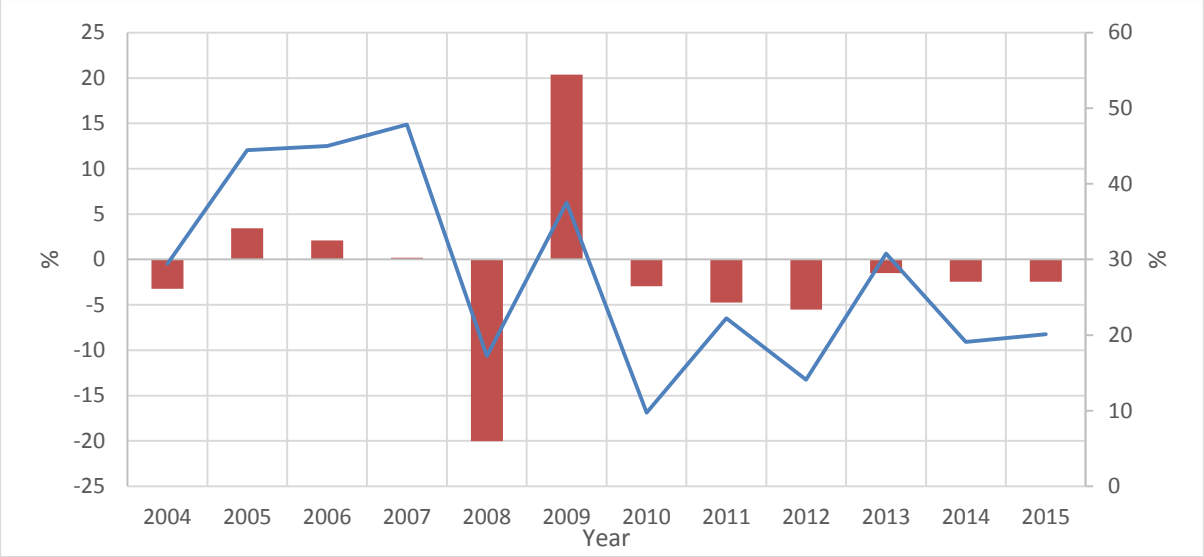

Figure 6: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the moving average strategy. Over the entire period during which the study was done Win (%) average was 28.12%. low Win (%) and consistently negative returns throughout the period under study, with the exception of 2009.

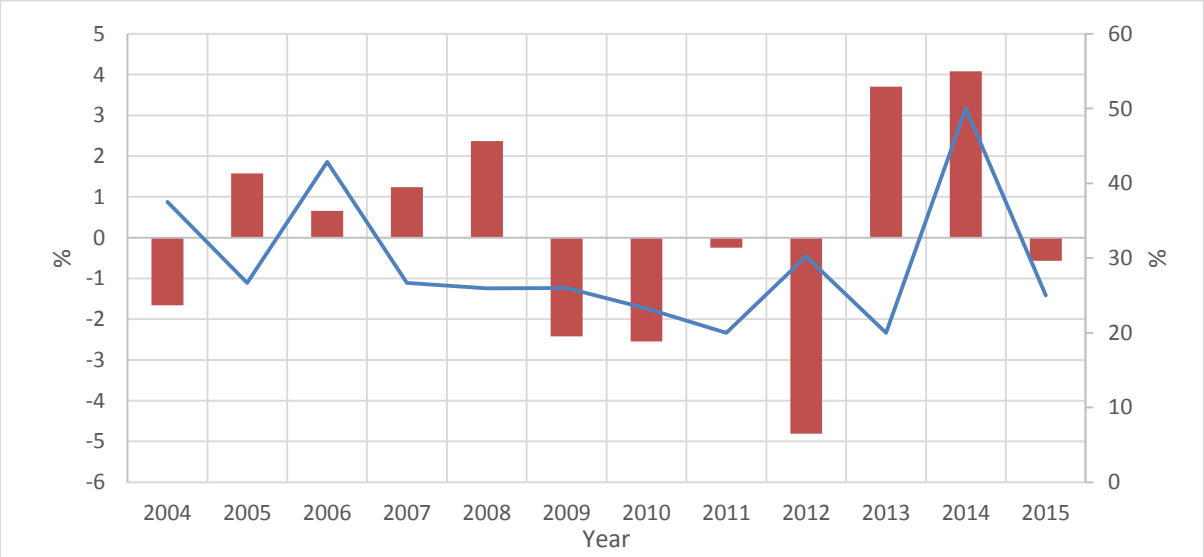

Figure 7: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the volume strategy. Over the entire period during which the study was conducted, Win (%) average was 29.51%. The figure shows that the strategy produces low win (%). The average returns were mixed with 6 positive years and 6 negative years.

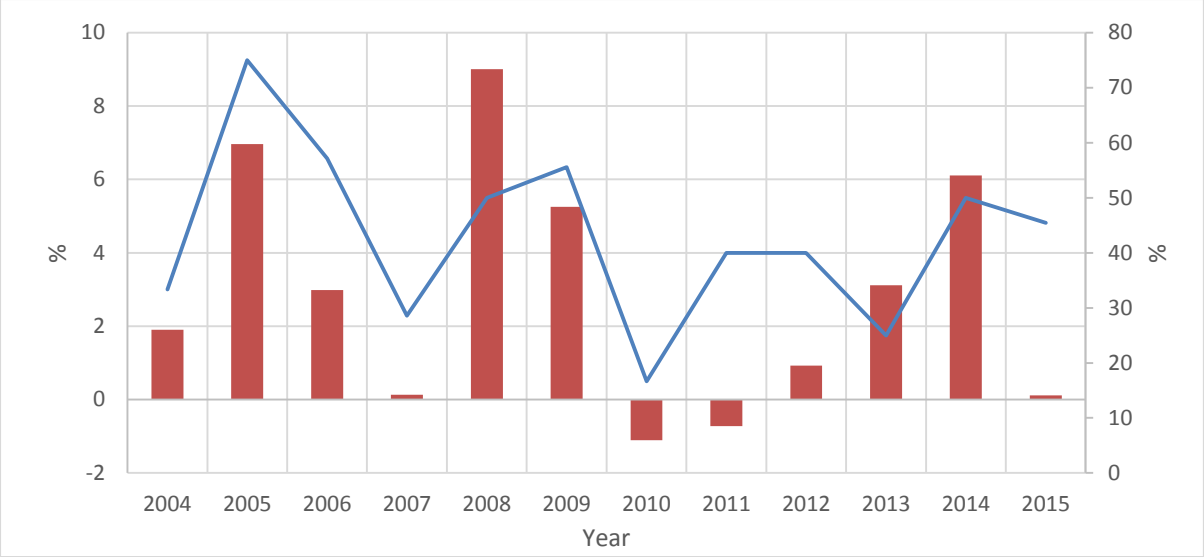

Figure 8: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the combined strategy. Over the entire period during which the study was conducted, Win (%) average was 43.06%. The chart shows limited negative returns and win (%) that has declined over time.

Table 5: CAPM: A time series regression on the CAPM model of the quarterly returns of equally weighted portfolios of the strategies. Betas are displayed in column 2, Alphas are in column 3 and column 4 has adjusted R-Squared of the regression; the mean square error in the last column; and P-values of the parameters are shown in parenthesis.

Strategy	Beta	Alpha	Adj. R^2	MSE
Double Bottom	-0.039(0.911)	1.3(0.712)	-0.02	0.044
Moving Average	-0.305(0.189)	1.7(0.478)	0.02	0.019
Volume	-0.178(0.436)	3.0(0.2)	-0.01	0.019
Combined	-0.261(0.239)	-0.500(0.814)	0.01	0.018
Fundamental	0.697(0.006)	3.1(0.224)	0.14	0.022

4.4 Robustness

Table 6: The table summarises results of the technical analysis strategies applied to only the fundamentally strong stocks. Column 2 shows number of observations, column 3 presents means of the strategies, column 4 are the p values of the means and the last column presents skewness of the data. Frequency distribution diagrams for the results in the table have been presented in Appendix D.

	FA Adjusted Strategy vs FA				
Strategy	Observations	Mean	P Value	STDEV	SKEW
Double Bottom	1500	4.715	0.036	26.83	1.872
Moving Average	1500	-4.458	0.000	38.785	-0.256
Volume	1500	1.062	0.058	8.531	3.372
Combined	1500	3.194	0.000	8.782	2.758
Fundamental Analysis	1500	1.128	1	2.51	-1.609

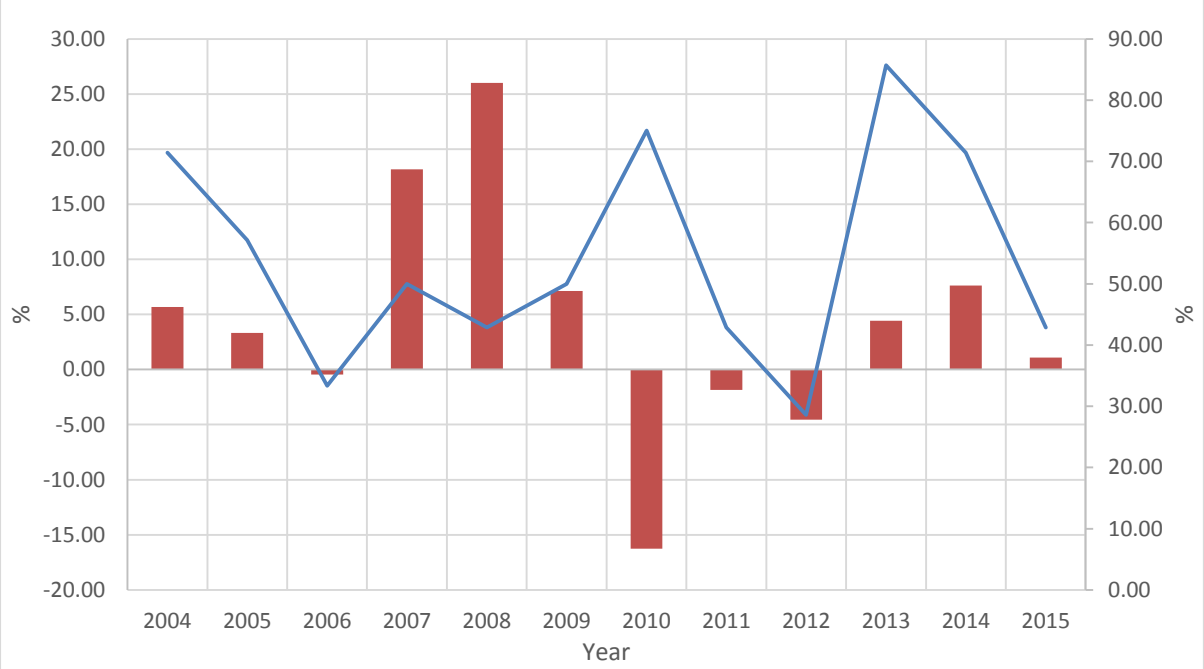

Figure 9: average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the double Bottom strategy. Over the entire period during which the study was done Win (%) average was 54.27. The figure shows that both Win (%) and average returns had high volatility.

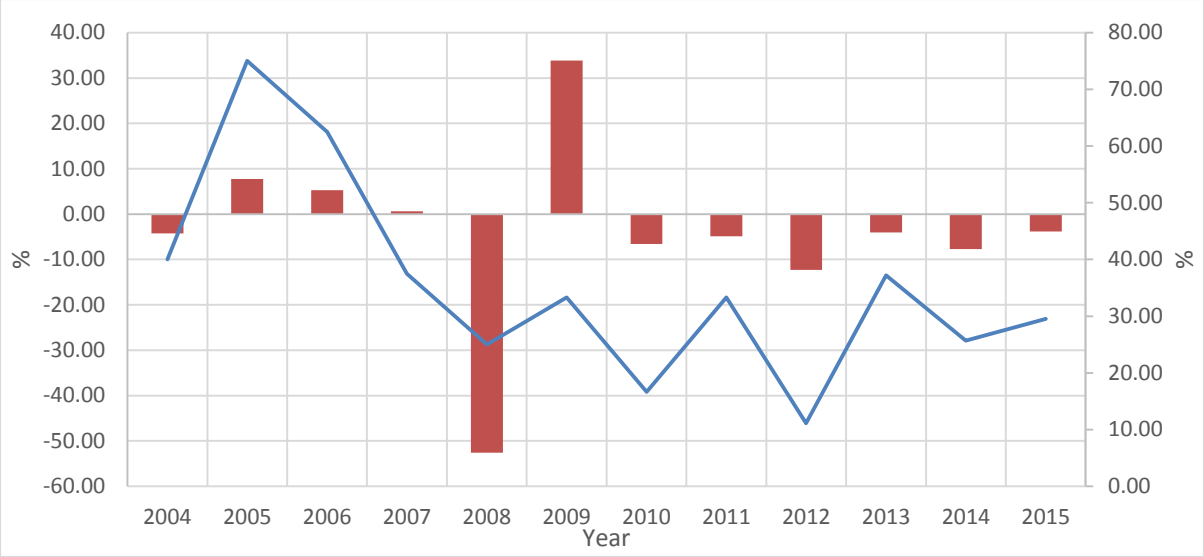

Figure 10: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the moving average strategy. Over the entire period during which the study was done Win (%) average was 42%. Figure 10 shows declining Win (%) and consistently low, or negative, average returns throughout the period studied.

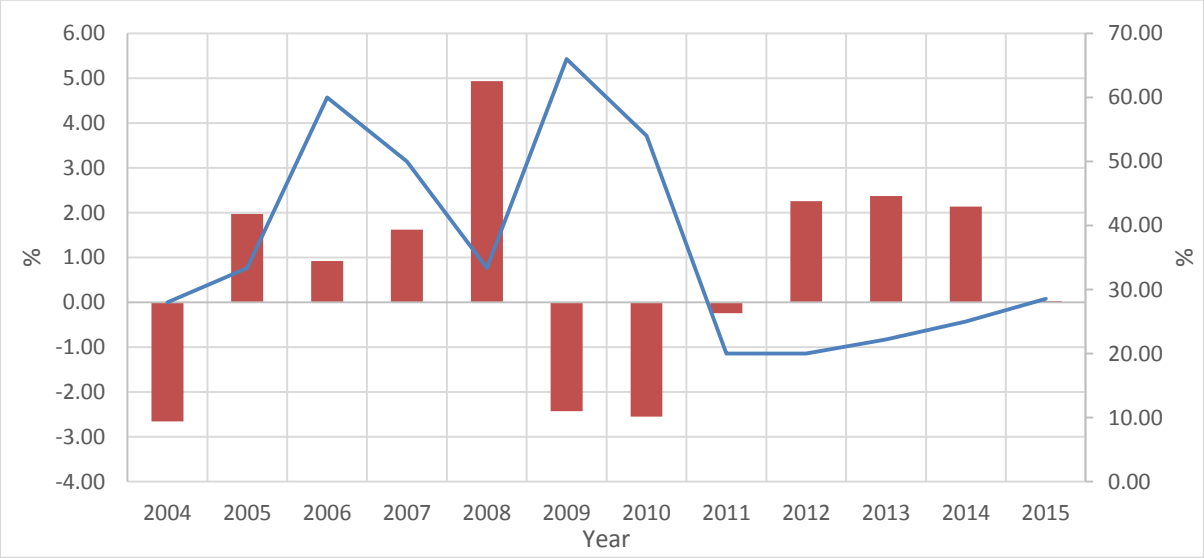

Figure 11: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the volume strategy. Over the entire period during which the study was done Win (%) average was 38%. The chart shows more positive average returns but high volatility in Win (%) which declined over time.

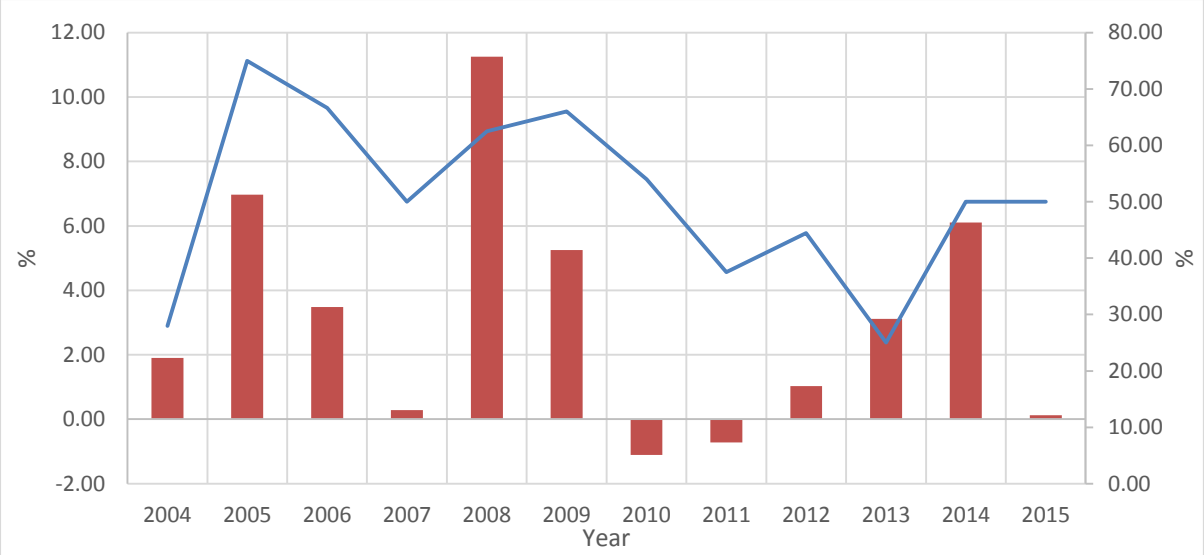

Figure 4: Figure 4: Average quarterly returns (Average Returns (%)) and percentage of trades executed that were positive out of the total trades (Win (%)) for the combined strategy. Over the entire period during which the study was done Win (%) average was 50.75%. The chart shows the strategy produced mostly positive average returns at a declining win rate.

Table 7: CAPM: A time series regression on the CAPM model of the quarterly returns of equally weighted portfolios of the strategies. Betas are displayed in column 2, Alphas are in column 3 and column 4 has adjusted R-Squared of the regression; the mean square error in the last column; and the P-values of the parameters are shown in parenthesis.

Strategy	Beta	Alpha	Adj. R^2	MSE
Double Bottom	0.489(0.243)	-2.4(0.57)	0.01	0.064
Moving Average	0.667(0.017)	9.3(0.001)	0.10	0.031
Volume	0.094(0.748)	0.2(0.957)	-0.02	0.031
Combined	0.194(0.114)	-2.1(0.089)	0.03	0.005
Fundamental	1.247(0)	-0.8(0.357)	0.84	0.002

4.5 Results Discussion

4.5.1 Research question 1: Does the analysis of historical financial statements give an investor an edge over an investor who uses technical analysis tools?

The research aimed to answer two questions. The first question asked was whether or not an investor who uses technical analysis can outperform an investor who uses fundamental analysis, on the JSE. From Table 2 it can be observed that all technical analysis strategies except the strategy that is the combination of the three strategies underperform fundamental analysis strategy. The moving average strategy produced results that have a mean difference from the fundamental analysis mean that was significant at a 100% significance level. This meant we could be 100% certain that the strategy was guaranteed to lose money, when used on JSE listed equities. The other strategies had means that were different from the fundamental analysis mean but also had very high p values, which suggested that the difference in the means was statistically insignificant which is consistent with the prior study by Campbell (2007). All technical analysis strategies had lower standard deviations. The reason for the good performance of the combined strategy was its use of the volume strategy to execute stop losses which tended to have tighter stop losses while most closing positions were closed by the moving average strategy which tended to have huge gains when the strategy had found a successful investment.

The study was taken a step further by performing a regression of the equally weighted portfolios quarterly returns of the strategies on the equally weighted benchmark index quarterly returns. This was done to check if the strategies produced excess returns. From Table 3 it can be observed that fundamental analysis had the highest beta followed by double bottom strategy which was followed by volume strategy then MA strategy. The combined strategy had the lowest beta which was also not very different from zero based on its p value. The fact that the beta for fundamental analysis was very close to 1 suggests that there was no skill in this strategy while the combined strategy's beta of 0.125 and average returns greater than fundamental analysis suggests that this strategy could hold some value if an investor can find a suitable asset allocation. The adjusted R squared was very small suggesting that there was barely any linear relationship between the returns of the strategies and the returns of the market. This is good for portfolio managers, like hedge fund managers, whose mandates often require them to produce returns that have no correlation with market. With the exception of the volume strategy,

technical analysis strategies produced returns that were not abnormal using the equal weighted asset allocation. Asset allocation with technical analysis strategies tends to be more challenging because it is not certain when the next investment opportunity will occur. This was consistent with the findings of Terence, et al. (2009), in the Brazil Stock Exchange.

From Figure 1 to Figure 4 it was observed that the technical strategies had a declining success rate. The MA strategies had the highest decline in success rate and profits disappeared in 2007. This disappearance of profitability of the strategy is consistent with observations of increasing efficiency of the stock markets around the globe, over time, as more investors gain access to the market. This was observed by Emerson and Hall (1997), Jefferis and Smith (2004), McGowan (2011), Gupta and Yang (2011) , and finally Movarek and Fiorante (2014)

4.5.2 Research question 2: is it possible to combine fundamental analysis technical analysis to earn higher returns?

Table 4 and 5 contain results data that illustrates the value added by combining fundamental analysis and technical analysis. Table 4 illustrates that applying technical analysis rules to stocks that have strong fundamental data improves the returns of technical analysis strategies, with the exception, however, of the moving average strategy. There are a few interesting things about these returns. Firstly, it was noticed that the average returns increased and the p values decreased when compared to the results in Table 2. This meant the difference in the means between the technical analysis strategies combined with fundamental analysis and fundamental analysis strategy were more significant when compared to technical analysis strategies without fundamental analysis use. Secondly, it was found that the standard deviations for the technical strategies increase slightly towards the standard deviation of the fundamental analysis strategy. This shows that the stocks that had better fundamental data were more volatile than the total list of the stocks used for the results in Table 2. It is well known that value in the stock market is often found in the smaller cap stocks, because they are not widely followed by analysts. These small cap stocks tend to be more volatile and tend to be less efficient. This was the case in this study. The skewness of the returns of the returns also increases with exception of the combined strategy which remains greater than zero but decreases. These results were consistent with the observations by Jefferis and Smith (2004), who found that small cap stocks showed less market efficiency.

After only including stocks with stronger fundamental data there was an improvement in the equally weighted portfolios returns, after adjusting for risk. All technical strategies except the combined strategy produced abnormal returns consistent with Campbell (2007). As shown in Table 5, the p values for the beta and the alphas in the CAPM regression suggests that the betas and alphas were insignificant, which is also consistent with Campbell (2007). The R squared also illustrates that the relationship between the buy and hold benchmark and the technical analysis strategies is minimal. This comes as no surprise given that technical analysis is a more active portfolio management strategy, that is to say, the returns tend to differ significantly from the equity benchmarks. By adjusting asset allocation a portfolio manager can adjust these returns to track the benchmark a lot closer.

Even after applying technical trading rules on fundamentally strong firms, the observations by Emerson and Hall (1997), Jefferis and Smith (2004), McGowan (2011), Gupta and Yang (2011) and Movarek and Fiorante (2014) were still observed, as it appeared that the technical trading rules produced less winning trades as time progressed. This is observed in Figures 5 − 8. However, the success rate was more volatile as there were fewer stocks observed after filtering for fundamentally strong firms. The success rate was higher overall when compared to technical strategies used without fundamental analysis.

4.5.3 Robustness

In this section, the robustness of the profitability of the technical analysis combined with fundamental analysis strategy is examined. Table 6 and 7 show the results of technical analysis strategies' returns performed on the top decile of stocks, arranged from the highest book to market ratio. From the results in Table 6 it can be observed that the double bottom and the combined strategy used on stocks with high BM ration outperformed the average return of stocks with just high BM ratio as observed by Campbell (2007). The p value for the combined strategy shows very high confidence in this outperformance, almost 100% guaranteed while the double bottom strategy has confidence of 96.4% which is also very high. These results are not very different from those obtained using the F_Score approach. The last column of Table 6 shows that with the exception of the moving average strategy, the returns of the technical analysis strategies are spread towards the write i.e. skewed to the right of the median which similar to the F_score approach skewness.

The regression on the CAPM model produces beta and alphas values with very high p values which suggest that the beta values are not very in accurate. The adjusted R squared also show that the returns from technical strategies even when applied to the on high BM stocks do not have a linear relationship with the benchmark. This was consistant with results obtained using the F_Score approach. None of the technical analysis strategies produced abnormal returns using equal weighted asset allocation.

Consistent with the findings in section 4.6.2, observations by Emerson and Hall (1997), Jefferis and Smith (2004), McGowan (2011), Gupta and Yang (2011) and Movarek and Fiorante (2014), it appeared that the technical trading rules produced less winning trades as time progressed which implied that these strategies were becoming less effective as time progressed. This is observed in Figure 9 to Figure 12. The success rate was more volatile as there were fewer stocks observed after filtering for fundamentally strong firms. The success rate was overall higher than those observed in section 4.6.1 to 4.6.2.

Chapter Summary

This chapter delineates a summary of the results. The results show that on average, with the exception of the MA strategy, and taking into account the strength of the financial statements data, an investor can improve the returns by utilising both technical analysis and fundamental analysis. These results are confirmed when the F_score approach is replaced by the high book to market ratio approach. Furthermore, after testing to see if the returns are abnormal, we found that only fundamental analysis shows the existence of abnormal returns.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

In this research project the use of three technical analysis strategies (double bottom, moving average, and volume) and fundamental analysis in investing in the stock market were investigated. This was the first technical analysis study on the JSE and one of the very few technical studies that combined more than one technical strategy, as is usual in practice. The study was also the first that combined F_Score fundamental analysis approach with technical analysis strategies. These technical analysis strategies were then applied to stocks that were fundamentally strong; selected using the F_score stock selection methodology; and high book to market selection methodology to check robustness. It was found that the technical strategies on their own had average returns that were lower than the average returns of stocks selected using the F_score methodology with the exception of the combined which reported significant average returns at a probability less than 80%. This is in contrast to the findings by Moosa and Li (2011) where they showed technical analysis was superior to fundamental analysis. When fundamental analysis was used to select stocks for the application of technical analysis strategies, there was an improvement in the returns. Only the MA and volume strategies reported less returns than fundamental analysis, which was found to be in contrast to the findings by Ko, et al. (2014), who demonstrated that the MA strategy improves fundamental analysis returns. Rather, with the exception of the MA and volume strategies, our findings confirm the findings of Betterman, et al. (2009) and Silva, et al. (2015) who proved that a strategy that uses technical analysis produces superior results to a strategy that does not use technical analysis. These results were also observed when the fundamental analysis strategy was changed to high BM stock selection approach.

It was, furthermore, observed that technical trading rules produced lower successful trades as a percentage of total trades. This observation suggested that the South African stock market was becoming more weak form efficient overtime. The results were thus consistent with the findings by Emerson and Hall (1997), Jefferis and Smith (2004), McGowan (2011), Gupta and Yang (2011), and Movarek and Fiorante (2014).

It was also found that the equally weighted portfolios of technical analysis strategies had very low beta and adjusted R squares when their returns were regressed on the CAPM. The beta and the alpha values were less accurate as they recorded p values that were very high. Therefore,

the abnormality of the returns of the technical analysis strategies was inconclusive. These findings were similar to those observed by Campbell (2007).

5.1 Recommendations

The results obtained in the study are promising. The next interesting step would be to find an appropriate asset allocation for the strategies investigated in this study, because, as was illustrated, some of the technical analysis strategies and fundamental analysis had, on average, positive returns per trade placed. With a good asset allocation strategy, an investor could be able to find abnormal returns.

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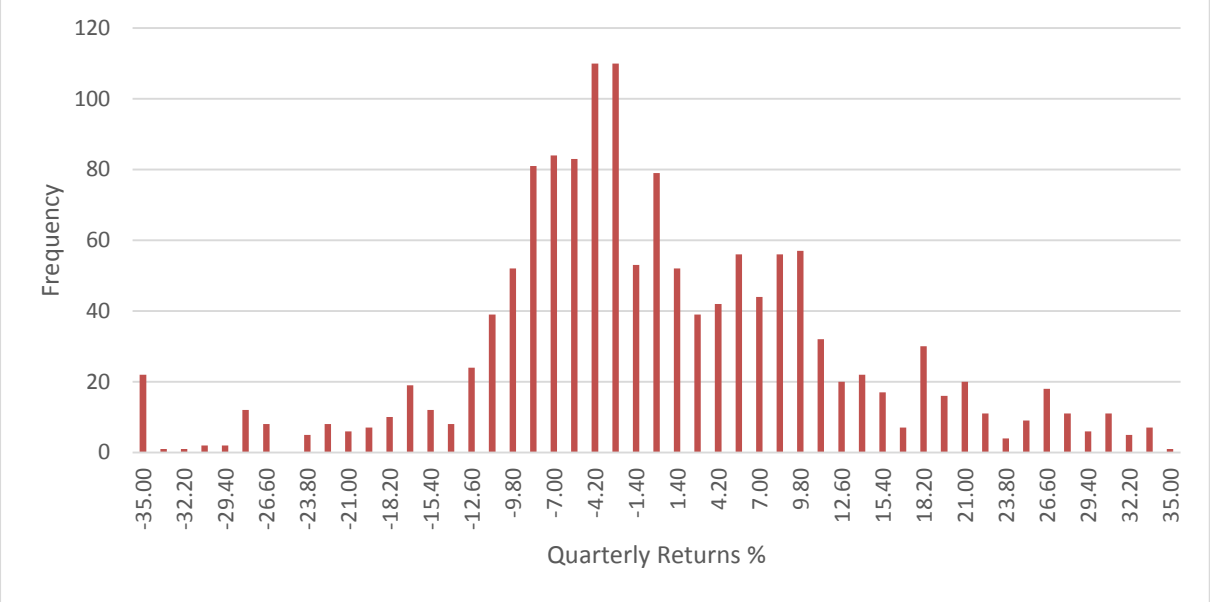
Appendix A: Construction of the F_score from the signals

$$F\_Score = F\_ROA + F\_\Delta ROA + F\_CFO + F\_ACCRUAL + F\_\Delta LEVER + F\_\Delta LIQUID + F\_EQ + F\_\Delta MARGIN + F\_\Delta TURN \quad (1A)$$

Signal	**Measurement**
ΔLEVER	This is measured as a change in the firm's total long term debt to total assets. A zero is assigned to F_ΔLEVER if ΔLEVER is positive and one is assigned if ΔLEVER is negative.
ΔLiquid	This is a change in current ratio from the previous year's current ratio. F_ ΔLiquid is assigned a one if there is an increase in the current ratio and a zero is assigned to a decrease in this ratio.
EQ – Offer	A zero is assigned to F_EQ if a company issue common shares and a one if it did not within the previous year.
ΔMARGIN	A change in the gross margin ratio from the previous measured period. A positive change is assigned a one while a negative change is assigned a zero
ΔTURN	ΔTURN is the change in asset turnover ratio from the previously measured period. An increase in this ratio is assumed to be an increase in operating efficiency, hence a positive change is assigned a one, otherwise a zero.
ROA	ROA is defined as net income before extra – ordinary items divided by total assets. If ROA of a firm is positive, it is assigned a

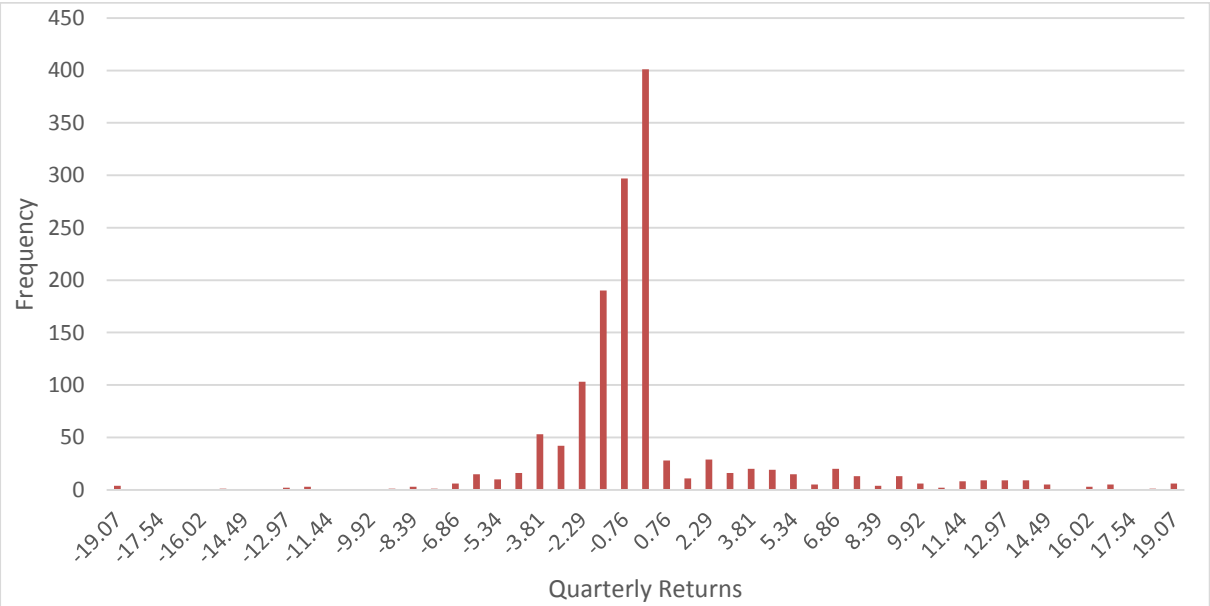
	value of 1 and 0 otherwise. The same applies to F_ΔROA in the model.
CFO	Cash flow from operations. F_CFO is assigned a value 1 if CFO is positive and 0 if CFO is negative.
ACCRUAL	ACCRUAL is defined as net income before extra – ordinary items less CFO scaled by the beginning of the year's total assets. F_ACCRUAL is assigned one if CFO>ROA and zero if CFO<ROA.

Appendix B: Individual Strategies: Frequency distribution of quarterly returns (%)



Mean	Median	STDEV	Skew
0.11117	-1.02045	19.67153	0.357411

Figure B1: Frequency distribution diagram for the double bottom strategy.

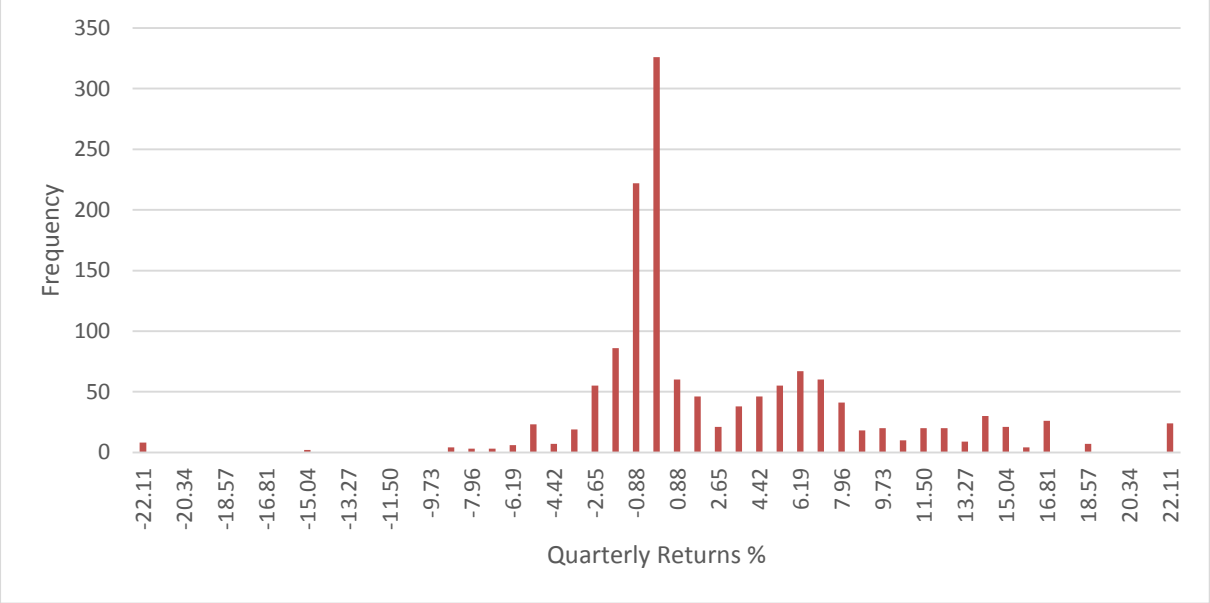


Mean	Median	STDEV	Skew
0.582286	-1.14	10.49	5.01

Figure B2: Frequency distribution diagram for the volume strategy.

Mean	Median	STDEV	Skew
-3.20276	-1.15045	24.70717	-3.24474

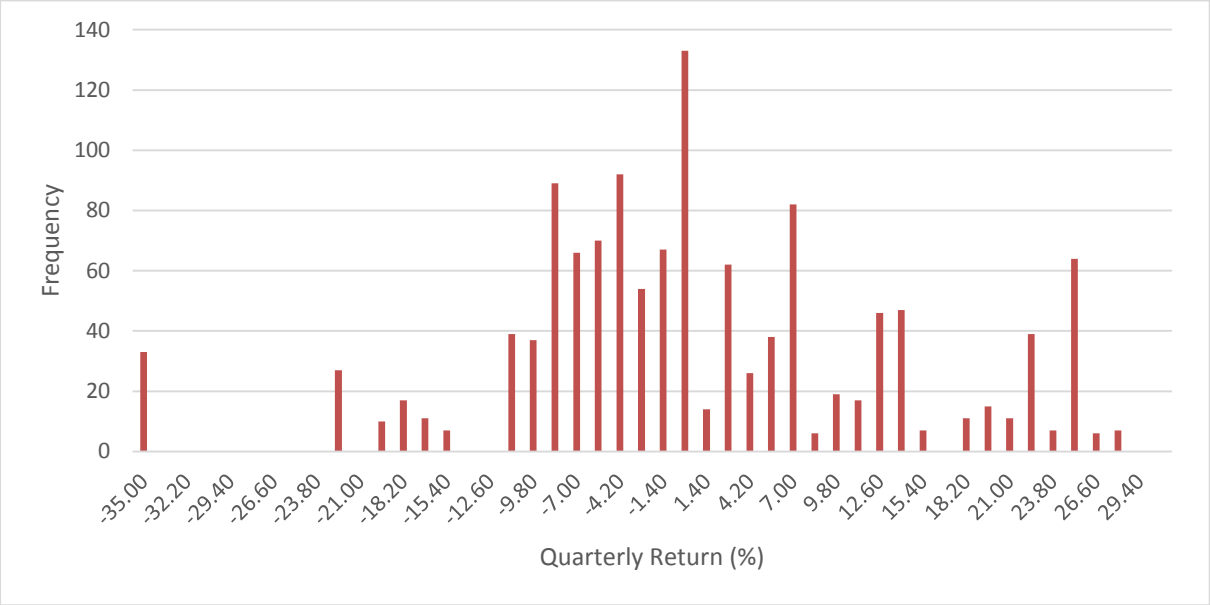
Figure B3: Frequency distribution diagram for the moving average strategy



Mean	Median	STDEV	Skew
2.88	-0.23	7.84	2.12

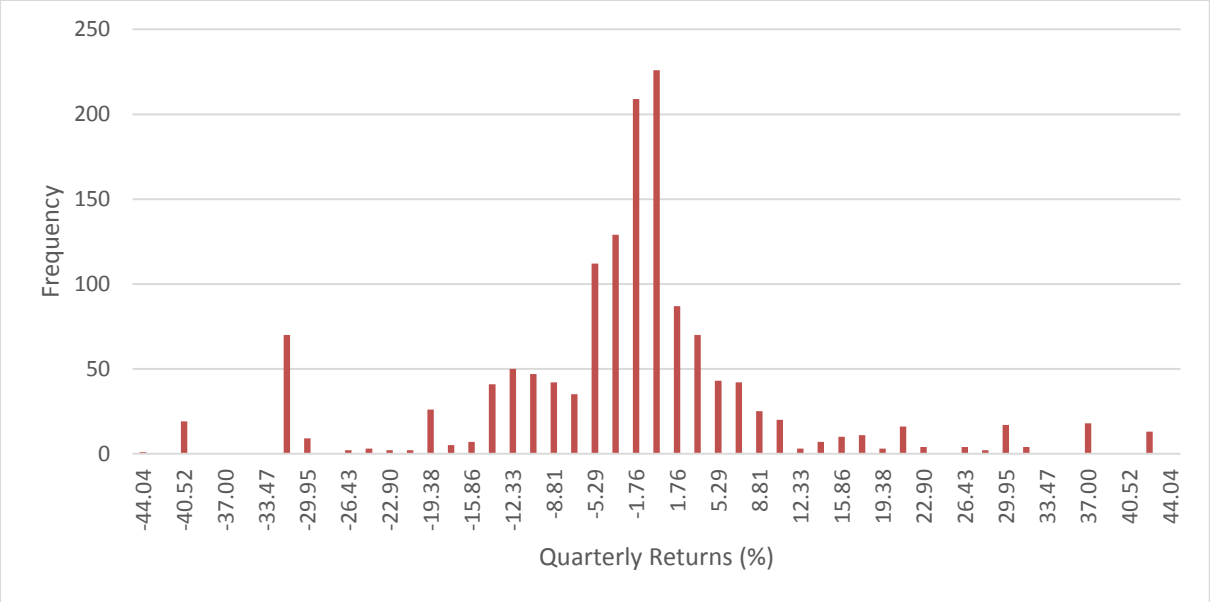
Figure B4: Frequency distribution diagram for the combined strategy.

Appendix C: The Hybrid Approach: Frequency distribution of quarterly returns (%)



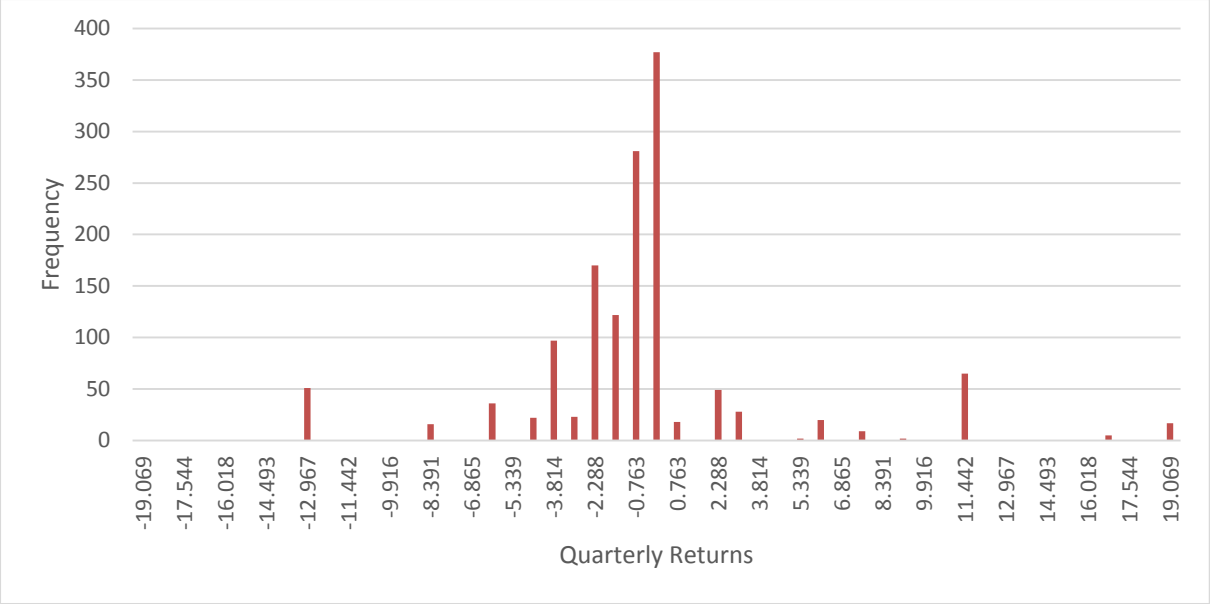
Mean	Median	STDEV	Skew
4.71	-0.65	26.83	1.87

Figure C1: Frequency distribution diagram for the double bottom strategy.



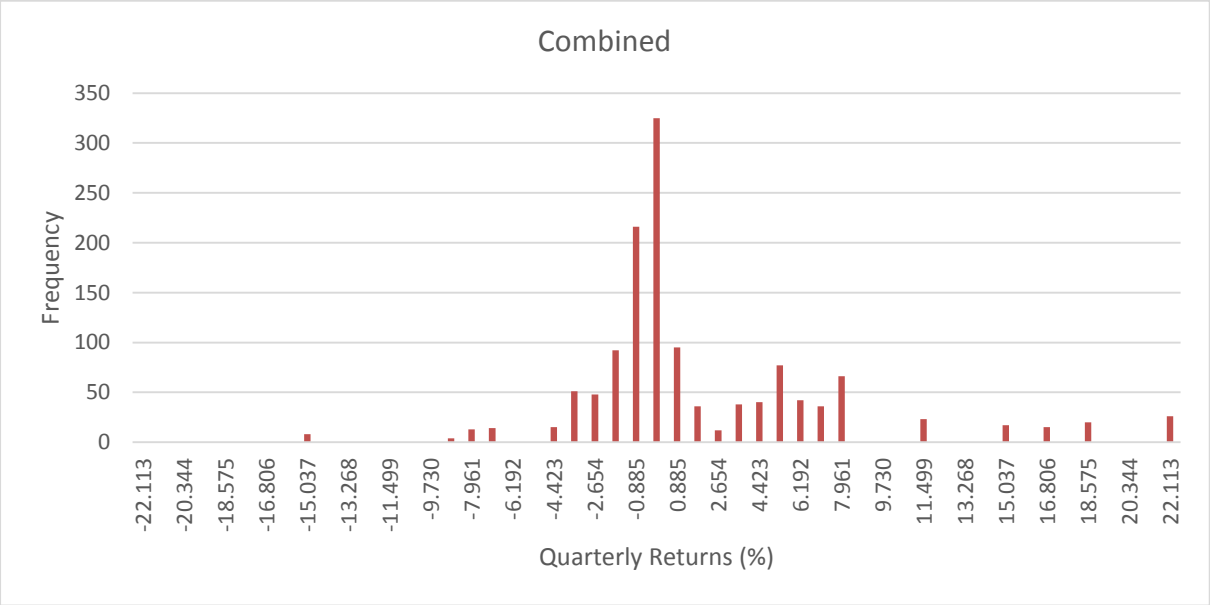
Mean	Median	STDEV	Skew
-1.64	-2.48	20.53	4.28

Figure C2: Frequency distribution diagram for the moving average strategy.



Mean	Median	STDEV	Skew
-0.06	-1.00	7.19	3.05

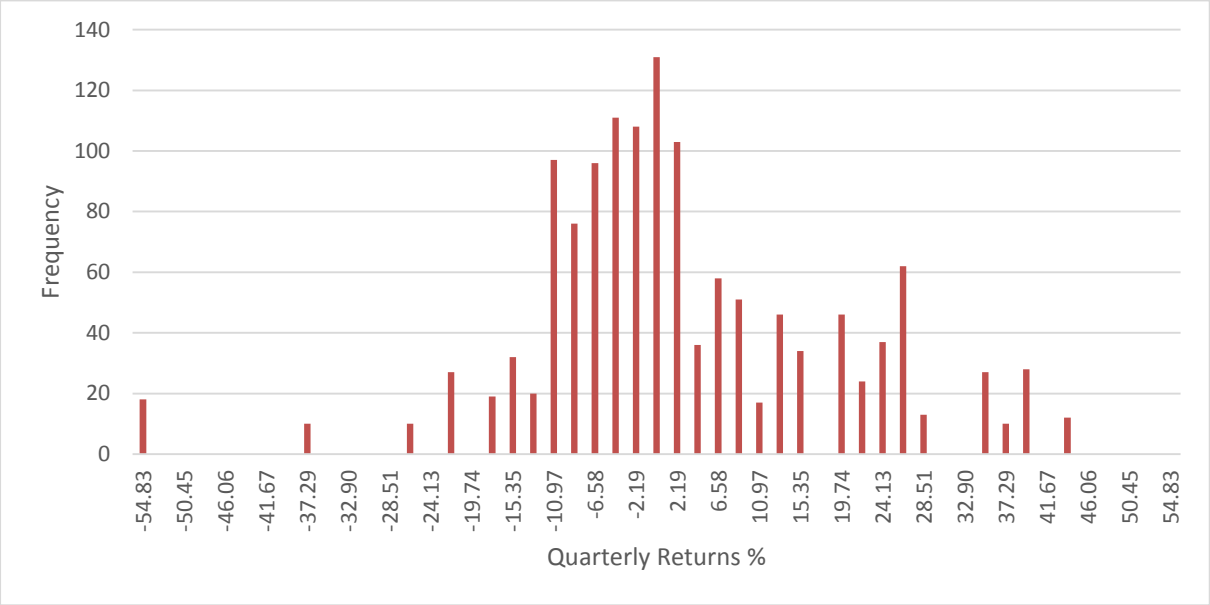
Figure C3: Frequency distribution diagram for the volume strategy.



Mean	Median	STDEV	Skew
2.69	-0.32	8.15	2.66

Figure C4: Frequency distribution diagram for the combined strategy.

Appendix D: Hybrid Approach (High Book to Market Ratio): Frequency distribution of quarterly returns (%)

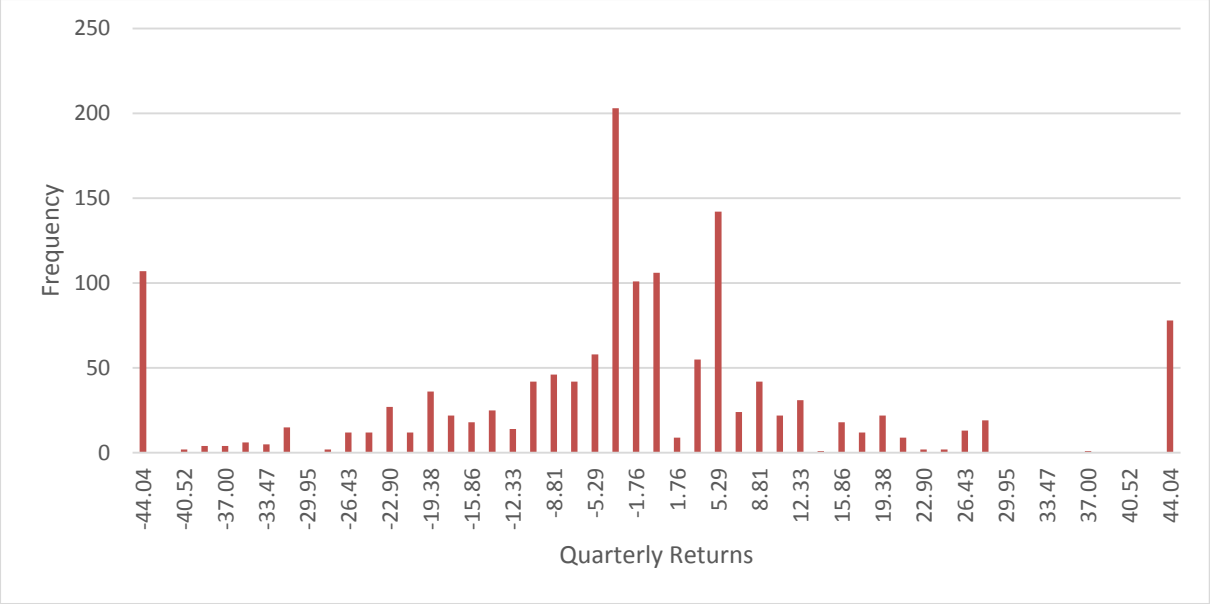


Mean	Median	STDEV	Skew
4.714991	-0.65391	26.8265	1.871842

Figure D1: Frequency distribution diagram for the double bottom strategy.

Mean	Median	STDEV	Skew
1.061799	-0.97586	8.53144	3.372178

Figure D2: Frequency distribution diagram for the volume strategy.



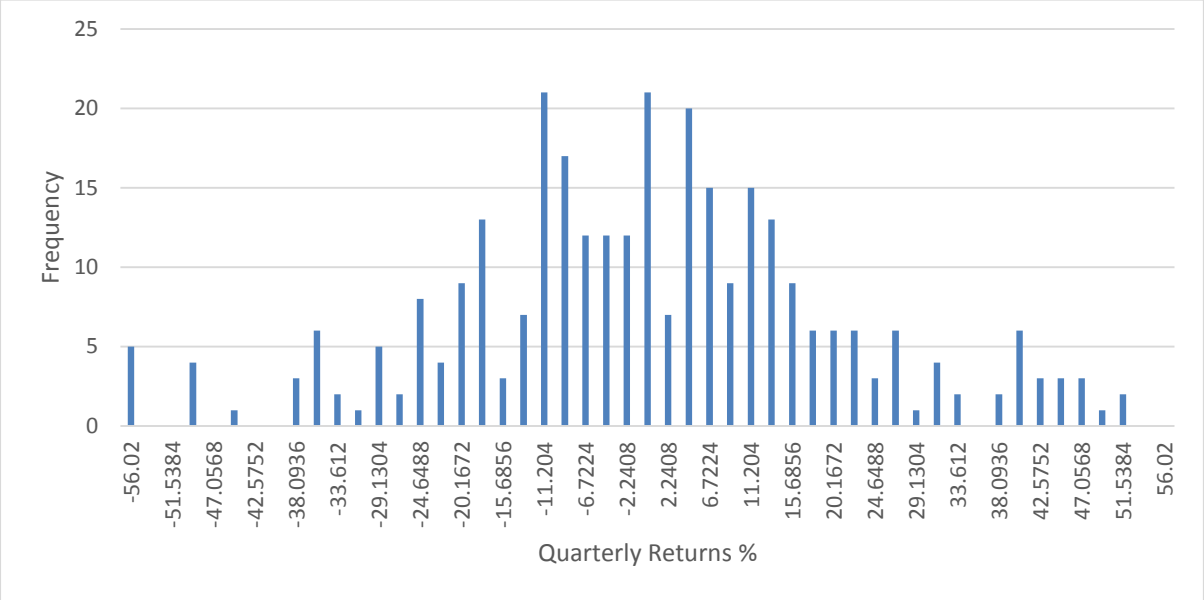
Mean	Median	STDEV	Skew
-4.45806	-3.59848	38.78557	0.068371

Figure C3: Frequency distribution diagram for the moving average strategy.

Mean	Median	STDEV	Skew
3.194534	-0.17299	8.782559	2.758275

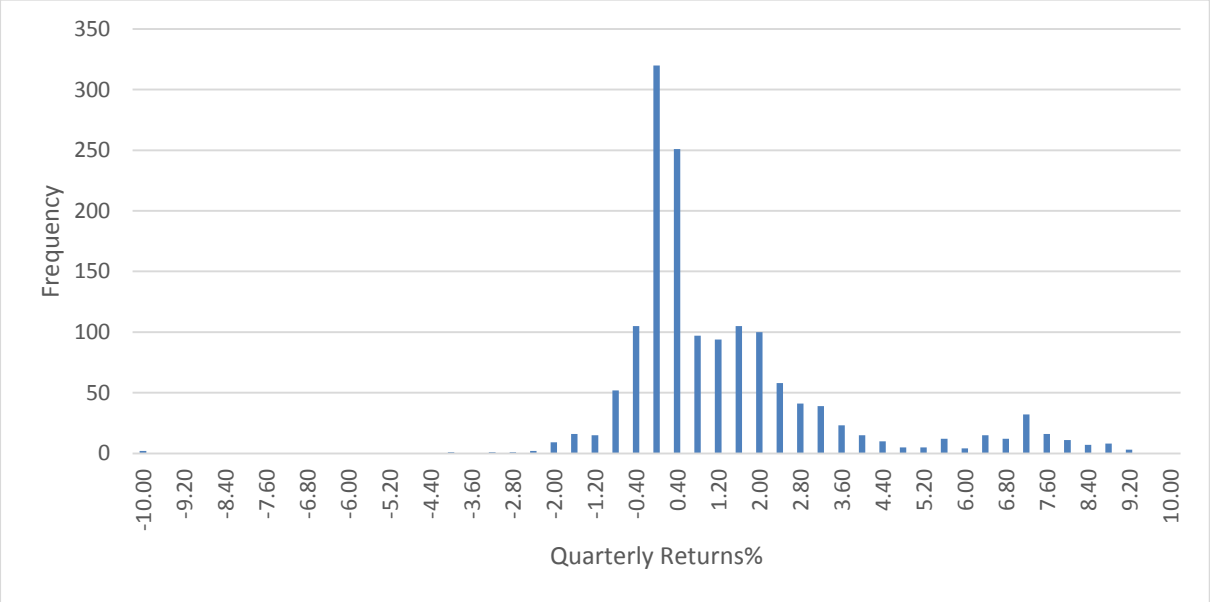
Figure C4: Frequency distribution diagram for the combined strategy.

Appendix E: Fundamental Analysis Frequency distribution of quarterly returns (%)



Mean	Median	STDEV	Skew
1.128	0.308	2.51	-1.608

Figure E1: F_Score quarterly results frequency distribution



Mean	Median	STDEV	Skew
1.128	0.308	2.51	-1.608

Figure E2: High Book to Market ratio quarterly returns frequency distributions