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Application of the Altman Z-EM-Score and Piotroski F-Score to the Johannesburg Securities Exchange as short selling instrument.

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A research project submitted to the Gordon Institute of Business Science, University of Pretoria, in partial fulfilment of the requirements for the degree of Master of Business Administration.

7 November 2016

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ABSRACT

This research investigated the effectiveness of the Altman Z-EM-Score and the Piotroski F-Score as tools that can be used to identify stocks on the JSE that may be shorted for an abnormal return. A fundamental assumption of the efficient market hypothesis is that an abnormal return cannot be made in a market because market prices fully reflect all available information. Several studies on short selling affirmed that abnormal returns could be earned by shorting assets that are in decline. However, there has been no published work that has been done on the Johannesburg Stock Exchange (JSE) on short selling instruments. An empirical study of shares that are listed on the main board of the JSE from 2005 to 2015 was done for the purpose of this research.

The study found over the period that using the Piotroski F-Score as a short selling strategy generated an average of 6.56 percent market adjusted annual return between 2005 and 2014. Although the Altman Z-EM-Score made an average annual return that underperformed the market during the study period, however, the result was not statistically significant.

The research concluded that compared to the Altman Z-EM-Score the Piotroski F-Score is more effective as short selling instrument on the JSE.

Keywords

Piotroski F-Score, Altman Z-EM-Score, Short Selling, JSE, Fundamental Analysis

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DECLARATION

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination in any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

Akinboye Oyebode

Signature

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CHAPTER 1: INTRODUCTION TO THE RESEARCH PROBLEM

1.1 Research Title

Application of the Altman Z-EM-Score and Piotroski F-score to the Johannesburg Stock Exchange (JSE) as a short selling instrument.

1.2 Research Problem

The ability of firms to create long-term economic value is of particular importance to investors, and stock valuation models are used to determine and evaluate the current and future performance of a company (Mckinsey & Company, 2010). Consequently, investors rely extensively on stock valuation models to identify companies whose future performance would be of a positive benefit to their investment portfolios (Brzezinski & Kidambi, 2011). Modern Portfolio Theory (MPT), a theoretical framework used by investors to select and construct investment portfolios, assumes an efficient market and has as its basis the minimisation of investment risks and maximisation of the expected returns of portfolios (Fabozzi, Gupta, & Markowitz, 2002; Dunham, 2012). A major cornerstone of MPT is the assumption of an efficient market (Markowitz, 1952). The Efficient Market Hypothesis (EMH) defines an efficient market as one in which stock prices are assumed to fully reflect all available information in the market (Fama, 1970). In other words, market prices give precise signals for resource allocation.

On the other hand, risks and their management cannot be separated from all forms of economic activities. There are three types of risks that can be witnessed in markets. These can be classified as (1) operational risk, (2) credit risk and (3) market risk (Turan, Nusret, & Fousseni, 2015). Importantly, market risk is the risk that is associated with movements in market prices, changes in interest rates, foreign exchange rates, and equity and commodity prices (Turan et al., 2015). A very significant and growing market risk is the volatility in commodity prices (Power, Vedenov, Anderson, & Klose, 2013). Notably, the impact of price volatility on the real economy is the greatest in the resource driven

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economy (Power et al, 2013). This is because the volatile raw material and commodity prices touch nearly every aspect of the economy (Power et al., 2013). In addition, such economies experience pressure, due to their high dependence on commodity exports for revenues (World Economic Forum, 2014). In particular, South Africa is under a lot of pressure as its economic growth has fallen sharply on the back of lower commodity prices and on the back of China, the world's largest consumer of commodities that have seen a decline in its economic growth recently (Michaels, 2016). Short selling is a process of managing uncertainties resulting from transactions occurring in markets (Hung Wan, 2007). Furthermore, it is a very important way to hedge overall portfolio risk for asset managers. In fact, the volatility that is being experienced in the market has forced some hedge fund managers to adopt short selling as part of their investment strategy (Wagley, 2000; Mackintosh, 2007).Various fundamental analysis models can be used to identify stocks that can be shorted. These includes: the Z-score (Altman 1968), a discriminant-ratio model used to predict bankruptcy; the Zeta model (Altman, Halderman & Narayanan, 1977), a credit risk model ;the Altman emerging market Z-score (Z-EM),a derivative of the original Z-score that is intended to be used to analyse firms in emerging markets and not limited to manufacturing firms like the Z-score does; the M-score by Beneish (1999), a model designed to detect earnings manipulation; the F-score by Piotroski (2000), which is used to separate winner and loser stocks within broad portfolio of high book to market firms; the G-score by Mohanram (2005), a derivative of the F-Score (Piotroski, 2001) that is applied to low book to market firms.

1.3 Research Aim

There has always been a distinction between investment and speculation in common stock (Graham, 2005). Graham (2005) defined an investment as an “operation which upon thorough analysis promises safety of principal and an adequate return; operation not meeting these requirements are speculative” (Graham, 2005, p. 76). Hence, the investor’s view is rearward looking and is motivated by safety and acquisition of good stocks at reasonable costs. In contrast, the speculator is forward looking and is motivated by the opportunity to profit from betting on anticipated stock market movements (Graham, 2005). It has been demonstrated that it is possible to use fundamental analysis performance prediction models to earn abnormal returns (Altman E. I., 1968; Piotroski, 2000). While conventional investment strategy focuses on buying undervalued stocks to earn abnormal

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returns, it is likewise possible to earn an abnormal return by selling overvalued stocks (Abarbanell & Bushee, 1998). Notably, research has evidenced that significant volatility interaction exists between resources prices and stock market returns in emerging economies (Gomes & Chaibi, 2014). In particular, South Africa is an emerging market with strong resource-based industries and whose economic growth was resource driven in the past (OECD, 2012). Hence, further exploration of earning abnormal returns by selling overvalued stocks within the context of South Africa is required. On the other hand, academic research portrays short selling as a process that improves market efficiency and stabilises stock prices by the identifying and acting against overvalued assets (Karpoff & Lou, 2010). This research contributes to the literature by analysing the association between measures of shorting activity and abnormal returns on the Johannesburg Stock Exchange (JSE).

The aim of this research is to find the best method to identify stocks to short sell on the JSE.

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CHAPTER 2: LITREATURE REVIEW

2.1 Introduction

The aim of this research is to determine the best accounting-based fundamental analysis method of determining stocks that are suitable for short selling in emerging economies.

2.2 Asset Valuation

2.2.1 Efficient Market Hypothesis

Fama's (1970) efficient market hypothesis (EMH) proposed that markets are rational and security prices always reflect all available information in the market. Importantly, EMH suggests that the stock market captures and reflects information about company value (Shiller, 2003). Accordingly, security prices are expected to adapt continuously and quickly to new information; that may cause or result in changes in a company's value (Lim & Brooks, 2010). Fama (1970) went further to identify different forms of market efficiency. The three forms of market efficiency identified were a) weak market efficiency, b) semi-strong market efficiency and c) strong market efficiency (Fama E. F., 1970). These forms of efficiencies depend on how accurate and rapid the price adjust to new information in the market (Alajbeg, Bubas, & Šonje, 2012)

The weak form of efficiency assumes that security prices move randomly and price changes are independent of each other (Campos Dias De Sousa & Howden, 2015). In addition, only historic security price information is taken into consideration by the market (Fama, 1970; Gilson & Kraakman, 1984; Yalcin, 2016). As a result, in a weak form efficient market, abnormal returns can only be earned by fundamental analysis or by private information. In comparison, a semi-strong efficient market adapts correctly and quickly to all publicly available information, such as financial reports of companies and different press releases (Fama, 1970; Giroux, 2008; Westerlund & Narayan, 2013). Hence, abnormal returns can only be earned from private information (Kelly, 2014). Lastly, in a strong-efficient market, all relevant information including past, public and private information is reflected in the current stock prices. Consequently, then no one should be

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able to earn abnormal returns in any way, not even by private information. (Latif, Arshad, Fatima, & Farooq, 2011).

In the likelihood of the existence of one form or the other of market efficiency, security prices would ideally reflect fundamental values of companies (Chang, Yan, & Ren, 2014). Therefore, it would be impossible to generate abnormal returns using investment strategies that depend on the analysis of historical data, such as past price movements, since the information revealed would have already been priced into the value of the asset. (Schostak, 1997).

However, questions have been asked about the validity of the efficient market hypothesis. Importantly, the efficient market hypothesis may not apply in cases whereby a firm manipulates its earnings. This is due to the fact that it is possible for firms to either withhold relevant information or disclose information in a manner that is not honest and transparent (Giroux, 2008). In addition, Lee (2001) suggested that adjustment of market prices to their fundamental values is a process that requires time and effort which does not occur instantaneously. Rather, the process is an interaction between two types of investors namely information arbitrageurs and noise traders (Lee, 2001). Essentially, information arbitrageurs, are rational speculators that have rational and information-based expectations about stock returns (Schleifer & Summers, 1990). On the other hand, noise traders, are irrational traders that react to irrelevant signals and are often subjected to systematic biases (Lee, 2001). Consequently, this irrational behaviour causes mispricing on the market (Kothari, 2001). Accordingly, there is an opportunity to use the analysis of the information available in financial statements to obtain abnormal returns (Abarbanell & Bushee, 1998).

Conversely, studies on the EMH concluded that markets are inefficient (Grossman and Stiglitz 1980; Shiller 2003). Grossman and Stiglitz (1980) argued that market could not be efficient due to the existence of the cost of information in the market (Grossman & Stiglitz, 1980). Likewise, De Bondt and Thaler (1985) and Shiller (2003) opposed the validity of the EMH on the basis of excess volatility. They alluded to the fact that the actual volatility of stock prices are higher than that calculated from fundamental information and the volatility is due to an overreaction of the market to company announcements. Moreover, financial market anomalies, which are situations where stock performance deviate from the assumptions of an efficient market, has also tested the validity of the efficient market

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hypothesis (Latif, Arshad, Fatima, & Farooq, 2011). These anomalies are indicators that a market is inefficient and can be grouped into three categories: (a) calendar anomalies, (b) technical anomalies and (3) fundamental anomalies. Calendar anomalies are related to movement in security prices within a particular period (Latif et al., 2011). It contradicts the weak form of market efficiency that postulates that efficiency exists in the market based on past prices. However, the existence of monthly and seasonality effects suggests that investors can earn abnormal returns (Bourdreaux, 1995). Calendar anomalies that have been found in markets include weekend effect, turn-of-the-month effect, the January effect and year-end effect (Bourdreaux, 1995). Fundamental anomalies relate to anomalies in trading financial instruments to components of fundamental analysis and include value anomalies, low price to book and low price to earnings (Latif et al., 2011).Technical analysis combines different analysing techniques with past prices and relevant information to forecast future prices of securities. Technical anomalies are anomalies that relate to the interpretation of technical analysis (Latif et al., 2011). Although the weak form of the efficient market postulates that abnormal returns cannot be earned by technical analysis and access to past information; however, there are some technical anomalies such as the momentum effect that deviate from this assumption (Hon & Tonks, 2003; Fama & French, 2012).

2.2.2 Asset Pricing Models

Asset pricing models are the main valuation tools of the EMH. Asset pricing models link individual expected returns to aggregate expected returns either directly, as in the CAPM (Sharpe (1964), Lintner (1965), Treynor (1961) or indirectly via common state variables, as in the APT (Ross (1976).Sharpe's (1964) and Lintner's (1965) Capital Asset Pricing Model (CAPM) is an equilibrium asset pricing model that describes a linear relationship that estimates the return that is expected on an asset concerning its systematic risk, beta (Muller & Ward, 2012). In particular, CAPM divides equity risk into two components: 1) specific risk, arising from risks that are unique to individual stocks and 2) systematic risk or beta, arising from risks that relate to general market movements (Garlappi & Yan, 2011). Specific risks can be diversified away by the investor by creating a portfolio that consists of stocks that are different in nature (Joslin, Priebsch, & Singleton, 2014). As more and more different stocks are added to the portfolio, the random fluctuations that are unique to each stock offset one another. In extreme cases, the investor is left with a portfolio that has no

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specific risk and whose composition corresponds identically to that of the overall market. Such a portfolio only has a systematic risk that cannot be diversified away (Bollerslev & Todorov, 2011).

CAPM is expressed by the following equation:

$$E(R_j) = R_f + [\, E(R_m) - R_f \,] * \beta_i$$

Where:

$E(R_i)$ = The expected return on asset j

R_f = Risk-free rate

$E(R_m)$ = Return on the market portfolio

β_i = Market beta of asset i,

Beta is a measures of a portfolio's or an individual stock's systematic risk. It is defined as

$$beta = \frac{\sigma_p}{\sigma_m} \rho_{p,m}$$

Where:

σ_p = standard deviation or volatility of the return of a portfolio

σ_m = standard deviation or volatility of the return of the market.

$\rho_{p,m}$ = Correlation of portfolio and market returns.

The CAPM is based on the proposition that risk and return in the market are related. It has a wide application in the estimation of the cost of capital for firms, measurement of abnormal returns and the evaluation the performance of managed portfolios (Kim, Kim, & Shin, 2012).However, research has shown that CAPM encountered severe limitations within the period of 1926 to 2004 (Fama & French, 2006).Moreover, a lot of anomalies that the CAPM could not predict has been uncovered by empirical research. Such anomalies are, book-to-market (Fama & French, 1992), short-term price continuation (Jegadeesh &

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Titman, 1993), asset growth (Yao, Yu, Zhang, & Cheng, 2011), information uncertainty and liquidity (Kim, 2010).

As a result of the inability of the CAPM to explain the cross-sectional variation in equity returns, alternatives asset pricing models has been developed (Benson & Faff, 2013). Ross, (1976) proposed the Arbitrage Pricing Model (APT), a statistical multi-factor asset pricing model, as an alternative to CAPM. Although there are myriad of factors that affect the daily variability of individual assets, however, the APT recognises that only a few systematic factors influence the long-term average returns of such assets (Cochrane, 2014). Consequently, the identification of such factors enables improved portfolio design and performance.

2.2.3 Fundamental Analysis

One of the requirements for firms that are listed on the stock market is the disclosure of their financial information on a regular basis (Ou & Penman, 1989). Although financial statements are used for multiple purposes, however, one of its primary purposes is to provide financial decision-makers with relevant information when making investment decisions (Francis & Schipper, 1999). Nevertheless, because of the large data contents of financial reports, it is important to differentiate between the relevant and irrelevant contents of financial reports when making investment decisions. Fundamental analysis is a method of identifying aspects of past financial reports that is suitable for making investment decisions (Lev & Thiagarajan, 1993; Piotroski & So, 2012). Hence, fundamental analysis uses diverse key value-drivers to measure a firm's value (Ou & Penman, 1989).

There are myriads of literature on the usefulness of the contents of a financial statement within different decisional context. Generally, these can be categorised into one of the following categories: (a) distress analysis, that is making investment decision on the basis prediction of financial distress (e.g. Beaver 1966; Altman 1968; Ohlson 1980; Beaver, McNichols, and Price 2007); (b) ratio analysis, which is a less structured approach of analysing large sets of financial data to predict stock returns (Ou and Penman 1989; Holthausen and Larcker 1992); and (c) contextual analysis, which is application of financial analysis in targeted settings as high book to market (Piotroski 2000), low book to market (Mohanram 2005), or to stocks that have extreme performance (Beneish et al., 2001).

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2.2.4 Fundamental Signals

Beaver (1966) performed a univariate analysis on the ratios of failed and non-failed firms and found that ratio analysis is useful in predicting the likelihood of corporate failure up to five years before the event occurs. Also, the cash flow to debt ratio was identified by Beaver (1966) as a key ratio in predicting bancruptcy.

The Z-score developed by Altman (1968) is a multiple discriminant analysis (MDA) models that can predict bankruptcy up to two years before actual failure. However, the model was developed with data that is limited to manufacturing companies listed on the stock exchange (Altman, 1968). Altman, Halderman and Narayanan (1977) developed the ZETA model which displays bankruptcy prediction accuracy ranging from over 96% for one period. In addition, the Z-EM model by Altman (2005) extended tests and findings to include application to non-listed firms, non- manufacturing entities, and also targeted emerging markets.

Contrary to Altman's (1968) multivariate analysis, Ohlson (1980) performed a conditional logit analysis on the financial data of one hundred and five failed companies and two thousand and fifty-eight surviving industrial companies that were listed on the stock exchange. Ohlson (1980) found that a company's capital structure, size, liquidity and financial performance are the factors that were significant in predicting business failure within a year of occurrence. Ohlson (1980) further concludes that financial ratios are useful in predicting financial distress when derived from large samples of data.

Beaver et al. (2007) investigated the effect of returns of stocks that have been delisted from the stock exchange on the returns of a portfolio. The study demonstrated that portfolio returns are sensitive to the treatment of delisting returns. If delisting returns are included the returns of a trading strategy based on earnings, cash flows and the book-to-market ratio can increase while those based on accruals decrease (Beaver et al., 2007).

Ou and Penham (1989) derived a summary measure from extensive financial statement analysis that capture equity values that are not reflected in stock prices and were able to predict future stock returns. Importantly, the evidence from the study highlighted the limitations in the approach of making inferences about accounting ratios on the basis of concurrent association with prices (Ou & Penman, 1989).

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The F-score by Piotroski (2000) is a fundamental analysis strategy used by investors to identify winner and loser stocks in a broad portfolio of high book to market firms. To this end, investors can buy stocks that are performing well and short poorly performing stocks. When this strategy was applied over the period of 1976-1966, it yielded a 23% return (Piotroski, 2000).

The G-score by (Mohanram, 2005) is a derivative of the F-Score (Piotroski, 2001) but is designed to identify winner and loser stocks amongst low book to market firms. Beneish et al. (2001) used a two-staged fundamental analysis prediction process to predict likely extreme price performers. It was determined that in comparison to market-related variables, accounting-based fundamental signals are more useful in separating extreme winners from extreme losers.

Fundamental analysis has a good performance record when used as a basis of investment strategies. However, literature has highlighted a few limitations. On the one hand, there is a view that its usefulness is limited to certain types of companies (Abarbanell & Bushee, 1998; Piotroski, 2000). That is, the fundamental analysis is most appropriate and applicable to high book-to-market stocks /value stocks, and whereas its usefulness for investments in low book-to-market firms/ glamour stocks is limited (Piotroski, 2000). However, the G score by Mohanram (2005) has proved that fundamental analysis can also be applied to glamour stocks. Moreover, investment strategies based on fundamental analysis are believed to have been most successful when applied to companies with prior bad news, implying that this has led to undervaluation and valuation pessimism (Abarbanell & Bushee, 1998).

2.2.5 Short Selling

Short selling is the process whereby an investor sells stocks that he does not own but has been borrowed for a fee from a broker or a large institutional investor (Dechow, Hutton, Meulbroek, & Sloan, 2001). The intention is to buy the stocks back at a lower price when the share price declines thus earning a profit (Dechow et al., 2001). On the other hand, if the stock price appreciates, the investor typically makes a loss (Dechow et al., 2001). Short selling as an investment strategy has been portrayed in a bad light by market regulators (Beber & Pagano, 2013). For example, most regulators reacted to the 2007–09 financial crisis by imposing bans on short selling (Beber & Pagano, 2013). However,

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evidence showed that constraints on short selling were detrimental to market liquidity, slowed price discovery and failed to support prices (Kaplan, Moskowitz, & Sensoy, 2013). In reality, short sellers could be considered as sophisticated investors that encounter far greater risks and transaction costs in the market (Israel & Moskowitz, 2013). In fact, the risks and costs that are associated with short selling necessitate that short sellers ensure perfect timing when taking positions in the market (Stambaugh, Yu, & Yuan, 2012). Moreover, Engelberg, Reed, and Ringgenberg (2012) suggested that short sellers should be more informed than other sellers because short sales are usually not undertaken for liquidity reasons. Subsequently, knowing how to highlight good candidates for short selling can enhance the returns and lower the risks involved in the process.

There is a strong relationship between the trading strategies of short-sellers and ratios of fundamentals to market prices (Dechow et al.,2001). Besides, it has been proven that low fundamental-to-price ratios are associated with temporary overpricing that is actively exploited by short-sellers (Lakonishok, Shleifer, & Vishny, 1994; Boehmer & Wu, 2013). Furthermore, to maximise their investment returns short-sellers hone the strategies they use in trading in three ways (Dechow et al., 2001). Firstly, they avoid securities for which the transactions costs are high (Dechow et al., 2001). Secondly, short-sellers enhance their trading strategies with the use of information that give a more predictive ability of future returns (Dechow et al., 2001). Lastly, they avoid the short sale of securities with low fundamental-to-price ratios when the low ratios are due to temporarily low fundamentals (Dechow et al., 2001).

2.2.6 Motivation for Short Selling

Hung Wan (2007) proposed four hypotheses to explain what motivates short selling, namely: the Trend Hypothesis, Overpricing Hypothesis, Arbitrage Hypothesis and the Taxation Hypothesis.

The Trend Hypothesis characterises some investors as trend traders (Hung Wan, 2007). They buy stocks if the past short-term prices are increasing and sell or short stocks if the past short-term prices are decreasing (Hung Wan, 2007). The weak form efficient market hypothesis suggests that all prior information is reflected in the current prices of stocks; hence future stock prices cannot be forecasted on the basis this information (Fama E. F., 1970). Nevertheless, evidence exists that demonstrates the existence of continuation of

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prices over a three- to twelve-month period and that returns of around 1% per month can be earned from the momentum strategies of buying winners and selling losers (Jegadeesh & Titman, 1993). A negative relation between short-term past returns and the short-selling level is consistent with the behaviour of momentum traders (Jegadeesh & Titman, 1993).

Overpricing Hypothesis: This postulates that short selling would be one of the choices of an investor that is in possession of inside information that shows a firm's stock is overpriced (Hung Wan, 2007). Separate studies (Shkilko, Van Ness B, & Van Ness, 2012) and (Alexander, Peterson, & Beardsley, 2014) supports this hypothesis. The Efficient Market Hypothesis (EMH) suggests that a market is efficient if there is the full reflection of information in prices (Fama E. F., 1970). The full reflection of information involves two equilibria in the same market (Gilson & Kraakman, 1984). The first equilibrium occurs if everyone has access to all relevant information, and the second is what is observed in the market (Gilson & Kraakman, 1984). If the two equilibria are identical the market is considered to be efficient (Gilson & Kraakman, 1984). It has been suggested that a short-seller will not trade unless he expects that prices will decline enough to compensate for the additional costs and risks of short selling (Diamond & Verrecchia, 1987). Dechow et al. (2001) find a strong relation between the trading strategies of short- sellers and ratios of fundamentals (such as earnings and book values) to market prices. Thus, an increase in the short sale of a stock possibly serves as a mechanism that relays private information to the market. Consequently, incorporation of such information into the share price promotes market efficiency (Gilson & Kraakman, 1984).

Arbitrage Hypothesis: This pertains to a situation whereby the stock of an acquiring company is shorted after the announcement of a merger and acquisition activity (Hung Wan, 2007). To arbitrage a price differential between the stock and convertible securities, an investor might short the stock (Dechow et al., 2001). However, the expected returns in such cases are not high (Hung Wan, 2007). This is because information about merger and acquisition activity is publicly available and the time required for incorporation of the new information into market prices is minimal (Hung Wan, 2007).

Taxation Hypothesis: this postulates that investors are motivated to engage in short selling activity because of the tax benefits that they will realise by deferring capital gain taxes achieved from shorting a stock.

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2.2.7 Short Selling Strategies

Three short selling strategies were proposed by Diether, Lee, and Werner,(2009). Firstly, short sellers exploit price differences that are brought about by short term deviation of stock prices from fundamental values (Diether et al., 2009; Karpoff & Lou, 2010). Secondly, short sellers can profit from providing liquidity when there is a buy-order imbalance in the market (Diether et al., 2009; Engelberg et al., 2012). Consequently, when the buying pressure decreases in the market and prices revert to fundamental values they can cover their position at a profit (Christophe, Ferri, & Hsieh, 2010). Lastly, short sellers can profit when they provide additional risk-bearing capacity in periods of high uncertainty (Diether et al., 2009). More specifically, short sellers gain from the reduced spread that occurs as certainty returns to the market (Hirshleifer, Teoh, & Yu, 2011) (Diether et al., 2009).

Similarly, in comparison to value and small capitalisation stocks, more short selling activity is observed in stocks with low book to market ratio (Diether et al., 2009; Hung Wan 2007). In addition, Dechow et al. (2001), showed that stocks with low fundamental to price ratios are preferred targets for short sellers.

Moreover, classification of stocks according to their sectors is another useful strategy used by investors (Lamponi, 2014).Importantly, this allows the comparison and benchmarking of stocks in the same sector against the relevant sector index (Lamponi, 2014). Duarte (2014) identified two broad categories of classification: (a) defensive stocks and, (b) cyclical stocks. Defensive stocks are stocks such as consumer products that remain stable during an economic downturn (Duarte, 2014). However, such stocks do not perform excessively well when the economy is doing well. In contrast, cyclical stocks are volatile stocks that react to a variety of market conditions and business cycles (Duarte, 2014). Muller and Ward (2013) conducted a study on the main board of the JSE that affirms the use of sector classification. The study was carried out on resource and non-resource companies and found that the commodity cycle is a significant determinant of returns on the JSE (Muller & Ward, 2013). This was ascribed to the dominant position of the resource sector on the bourse (Muller & Ward, 2013).

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2.3 Short Selling Instruments

A lot of research has been done on methods of identifying stocks that could be shorted for abnormal returns. The Altman Z EM score is a bankruptcy detection model that analyses five weighted business ratios to estimate the likelihood of financial distress. Broadly, these checks examine a company's asset, strength, profitability, solvency, efficiency and ability to generate earnings. The Z-Score is a red flag indicator that can be used as a short selling strategy. Although, the Piotroski F-Score was specifically designed to separate few winning value stocks from the majority of value stocks that lose due to their distressed nature (Fama & French, 1993). However, a bad Piotroski F-Score could be a good indicator of failure and could be shorted for abnormal returns (Piotroski, 2005; Dorantes, 2013).

2.3.1 Altman Z-EM Score

The Altman Z-EM-Score is an MDA model used to predict financial distress and is based on financial ratios that can be calculated from data found on a company's annual report (Altman, 2005). Altman (2005) used the MDA model to address the predictive accuracy of the univariate model used by Beaver (1966) that considers only one ratio at a time to discriminate between failed and non-failed companies. The technique has the benefit of considering an entire profile of characteristics common to the relevant companies, as well as the interaction of properties (Betz, Oprică, Peltonen, & Sarlin, 2014). The multivariate context removes ambiguities and quantifies the weights given to specific measures (Zeytinoglu & Akarim, 2013).The Z-EM-Score is obtained from inputs into a formula derived from multiple discriminant analysis techniques. The score is subsequently modified for the sovereign yield spread of a country to determine the bond equivalent rating (Altman, 2005). Further adjustments may then be made to the Z-EM score to factor in a company’s competitive position, industry, and sensitivity to foreign exchange fluctuations.

Dichev (1998) recorded an inverse relationship between measures of financial distress that included the Altman Z and stock returns among a set of companies that faced a reasonable probability of bankruptcy. Piotoski (2000), Avramov, Chordia, Jostova, and Philipov (2013) and Friewald, Wagner, and Zechner (2014) corroborated this result. The Z-EM Score is calculated as follows:

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Z-EM = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25

Where:

X1 = Working capital / total assets

X2 = Retained earnings / total assets

X3 = Operating income / total assets

X4 = Book value of equity/ book value of debt

2.3.2 Piotroski F-Score

Piotroski's F-Score is a distress prediction model that is designed specifically for high book to market firms (Piotroski, 2000). The model takes into consideration the quality of firm earnings in predicting the risk of distress (Athanassakos, 2013). More specifically, it aggregates information contained in an array of performance measures into an overall signal that gives an indication of the overall quality of a firm's financial position (Chung, Liu, Wang, & Zykaj, 2015). This overall signal is made up of nine performance measure that evaluates three areas of a firm's financial health (Piotroski J. D., 2000). These three areas are profitability, operating efficiency and liquidity. Based on their implication for future earnings, performance measures are classified as either good or bad. For example, good performance measures are given a score of one while bad measures are given a score of zero. The aggregate Piotroski score is the sum of the nine binary performance measures. The individual components of the Piotroski's F-Score are shown below:

ROA= net income / total assets

Δ ROA = current year's ROA less prior year's ROA

CFO = cash flow from operations / total assets

Accrual =net income less cash flow from operations/total assets

Δ Margin = current year's gross margin ratio less prior year's gross margin ratio

Δ Turnover = current year's asset turnover ratio less prior year's asset turnover ratio

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Δ Leverage = current year's leverage ratio less prior year's leverage ratio

Δ Liquidity = current year's current ratio less prior year's current ratio

Eq_Offer = number of shares outstanding in the current year less the number of shares outstanding in the prior year / number of shares outstanding in the prior year.

The aggregate Piotroski's F- score is given by:

F-Score = F_ROA + F_ΔROA+ F_CFO + F_Accrual + F_Δ Margin + F_Δ Turnover

+F_Δ Leverage +F_ΔLiquidity + F_Eq_Offer (Piotroski,2000)

Given the nine underlying signals, the F-Score can range from a low of 0 to a high of 9, where a low (high) F-Score represents a firm with very few (mostly) good signals

2.3.3 Mohanram's G_Score

The G_Score, developed by Mohanram (2005) is a fundamental analysis strategy used to identify mispricing in the market. Importantly, it is an index that is made up of signals that combine traditional fundamentals such as cash flows and earnings and other measures that are deemed appropriate for growth firms (Duong, Pescetto, & Santamaria, How value–glamour investors use financial information: UK evidence of investors' confirmation bias., 2014).

There are eight fundamental signals, G1: G8, categorised into three, namely profitability, naïve extrapolation of current fundamentals and accounting conservatism (Aggarwal & Gupta, 2016). Profitability, G1: G3 is measured regarding earnings and cash flows. Naïve extrapolation, G4: G5, is measured regarding the variability in a firm's earnings. Accounting conservatism, G6: G8, is measured concerning the expenditures that may depress a company's current earnings such as R&D but may boost the future growth of the business.

By default the signals have a value of 0 and equal 1 if the following conditions are met for each signal:

G1: ROA > Ind. Median,

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G2: CFROA > Ind. Median,

G3: CFROA > ROA,

G4: VARROA< Ind. Median,

G5: VARSGR< Ind. Median,

G6: RDINT > Ind. Median,

G7: CAPINT > Ind. Median,

G8: ADINT >Ind. Median.

Where:

ROA is the ratio of Net Income and beginning of period assets,

CFROA is the ratio of cash from operations and beginning of period assets.

VARROA is the variance of ROA measured over the past 3-5 years.

VARSGR is the variance of annual sales growth measured over the past 3-5 years.

RDINT is the ratio R&D and total assets.

CAPINT is capital expenditure divided by total assets.

ADINT is advertising expenses divided by total assets.

Ind.Median is the contemporaneous industry medians of the corresponding variable

The composite G_SCORE is given by:

G_SCORE = G1 + G2+ G3 + G4 + G5 + G6 + G7 +G8

Using this composite score, the G_SCORE of a firm can range from 0 (all negative signals) to 8 (all positive signals). A high G_SCORE represent the expectation that a company will outperform the market while a low G_SCORE is a signal that a company will have poor expected future performance and therefore stock returns.

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It is important to note that though the Piotroski's F-Score and Mohanram's G Scores were tailored for value and glamour stock respectively, however, evidence suggests that they both can be employed in either context (Duong, Pescetto, & Santamaria, 2014)

2.3.4 Beneish M-Score

The M-score by Beneish et al. (2013) is a mathematical model that uses sample manipulators and industry matched firms to detect manipulation of earnings. It uses eight financial ratios to detect whether a firm has manipulated its earnings. The M-score is constructed from eight variables that are taken from a firm's financial statement. The composite score describes the degree to which earnings have been manipulated.

The composite M-score is calculated as follows:

M-score = = -4.84 +0.920 (DSRI) +0.528(GMI) + 0.404(AQI) + 0.892(SGI) + 0.115(DEPI) -0.172(SGAI) +4.679(TATA)-0.327(LVGI)

Where:

DSRI - Days' sales in receivable index

GMI - Gross margin index

AQI - Asset quality index

SGI - Sales growth index

DEPI - Depreciation index

SGAI - Sales and general and administrative expenses index

LVGI - Leverage index

TATA - Total accruals to total assets

An M-Score that is greater than-2.22 suggests that a firm had manipulated its earnings.

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2.4 Conclusion

Short selling as an investment strategy affirms and challenges the EMH. Importantly, short selling demonstrates the inefficiencies that can be exploited in the market; conversely, it also contributes valuable information to the markets such that market efficiency can be restored. Moreover, evidence exists in the literature that affirms that returns in excess of the market can be earned from short selling. Although studies have been conducted on the usefulness of Piotroski and Altman Z on the JSE, however, there has been no study on the effectiveness of the Piotroski F and Altman ZEM Scores as a tool for short selling on the JSE. Hence, further exploration of earning abnormal returns by using these tools as short selling instruments within the context of South Africa is required. The research contributes to the literature by .analysing the association between measures of shorting activity and abnormal returns on the Johannesburg Stock Exchange (JSE)

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CHAPTER 3: RESEARCH QUESTIONS AND HYPOTHESES

3.1 Introduction

The research question that underpins this research is: what is the best method to identify stocks to short sell on the JSE? More specifically, this study compares the predictive ability of the Altman Z-EM and Piotroski-F scores to determine the shares on the JSE that may be shorted. The basis of which is the detection of financial distress with an anticipated decline in stock price (Beneish, Lee, & Nichols, 2015). Therefore share and financial statement data would be used to perform statistical analyses to investigate the research question. Specifically, the research question would be studied using hypotheses in order to allow it to be tested for statistical significance. These hypotheses are set out below.

3.2 Research Questions and Hypotheses

3.2.1 Research Question 1

Is the Z-EM score is able to identify shortable stocks on the JSE?

H_0: There is no difference between the returns of stocks with low Z-EM scores (μ_{Zem}l) and the returns of high Z-EM scores (μ_{Zemh}).

H_1: Returns of stocks with low Z-EM scores (μ_{Zeml}) under-performed in comparison to the returns of high Z-EM scores (μ_{Zemh}).

$$H_0 = \mu_{Zeml} - \mu_{Zemh} = 0$$

$$H_1 = \mu_{Zeml} - \mu_{Zemh} < 0$$

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3.2.2 Research Question 2

Is the F- score able to identify shortable stocks on the JSE?

H_0: There is no difference between the returns of stocks with low F-scores (μ_{Fl}) and the returns of stocks with high F-scores (μ_{Fl}).

H_1: Returns of stocks with low F-scores (μ_{Fl}) under-performed in comparison to the returns of stocks with high F-scores (μ_{Fh}).

$$H_0 = \mu_{Fl} - \mu_{Fh} = 0$$

$$H_1 = \mu_{Fl} - \mu_{Fh} < 0$$

3.2.3 Research Question 3

Is the Z-EM-Score more efficient than Piotroski F score in identifying shortable stocks on the JSE?

H_0: There is no difference between the returns of shortable stocks identified by low Z-EM scores (μ_{Zem}l) and those identified by Piotroski F score (μ_{Fl})

H_1: The returns of shortable stocks identified by low Z-EM scores (μ_{Zeml}) out-performed the shortable stocks identified by low Piotroski F score (μ_{Fl})

$$H_0 = \mu_{Zeml} - \mu_{Fl} = 0$$

$$H_1 = \mu_{Zeml} - \mu_{Fl} > 0$$

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CHAPTER 4: RESEARCH DESIGN AND METHODOLOGY

4.1 Introduction

The aim of this research was the determination of the best risk-based fundamental analysis method of short selling in an emerging economy. Hence, the research was a quantitative, experimental study that used secondary data from the JSE from between 2005 and 2015 (Saunders & Philips, 2014). Essentially, the study assessed the causal relationships between the Altman Z-EM and Piotroski F-scores independent variables and the dependent relative returns variable (Saunders & Philips, 2014). This method was chosen because the research was aimed at the analysing the predictive power of the Altman Z-EM and F-scores in short selling. The data used in the study was numerical in nature; data was collected from financial data portals and manipulated and analysed to test the hypotheses that were formed.

4.2 Population and Sampling

4.2.1 Population

The population of relevance was made up of all the publicly listed companies on the JSE main board from January 2005 to December 2015. Restriction of the research to the main board ensured that the study focused on firms with sufficient trading history and adequate financial statements. Importantly, firms that are listed on the main board had to be duly incorporated with a proper corporate governance system in place and had to produce properly audited annual financial statements (Johannesburg Stock Exchange, 2011). The time frame from January 2005 until December 2015 is was chosen to ensure the inclusion of adequate data for the compilation of adequate sample sets. Furthermore, the period included the global financial crisis of 2007/8 with the accompanying stock market crash and the subsequent volatility in emerging markets stocks. December 2015 was chosen as the end of the period under study because it caused the time frame of the study to encompass a number of full financial years. Moreover, it is important to note that three

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years' financial statements were needed to calculate the F-scores; this has caused the time period that corresponds to data gathered for the calculation of the F-score to be somewhat extended to 2003.

4.2.2 Unit of Analysis

Creswell (2013) defines the unit of analysis as the level at which a research was performed. The units of analyses in this research were the share price and fundamental data of the companies listed on the main board of the JSE during the sample period 2005 to 2015.

4.2.3 Sampling Frame

The sampling frame was the list of the firms that appeared that appeared on the main board of the JSE from January 2005 until December 2015 which have sufficient liquidity (Banerjee & Graveline, 2013). In addition, only firms with sufficient stock price and financial statement data that were required for the calculation of the input variables were selected. Furthermore, all financial firms and firms whose financial reporting structure are structured differently from the service and industrial sectors were excluded from the data set. This approach is consistent with previous analyses of stock returns, such as Fama and French (1992) and Asness, Moskowitz, and Pedersen (2013)

4.2.4 Sampling Method and Size

Each year from 2005 to 2014, firms with adequate stock price and financial statement data with which to calculate the performance parameters of the Piotroski F and the Altman Z-EM scores were identified on the JSE. Then, each fiscal year, firms with sufficient liquidity were selected. Liquid shares are assumed to be the shares that are in the top one hundred of the JSE's listing. The required data needed for the determination of the Piotroski F-Score were extracted from financial statements of the years 2003 to 2015 and resulted in observations from the years 2005 onwards. This is because the last three years' financial statements were required to calculate the input ratios and trends on which the Piotroski F-score is based. On the other hand, the data required for the calculation of the Altman Z-EM score were extracted from financial statements of the years 2003 to 2015. The share prices that were used to calculate the returns were taken as the share prices at the year-

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end financial reporting month through the one-year holding period. The firms that make up the sample are listed in appendix 1.

4.3 Research Method

4.3.1 Data Collection

Secondary data is data used for a research project that was originally collected for some other purpose (Saunders & Philips, 2014). The secondary data that was used in this research were the financial statement line items that were required to calculate the Piotroski F and the Altman Z-EM scores performance measures. The data were obtained from Thompson Reuters Eikon data base. The financial statement data were obtained from January 2005 till December 2014. In addition, monthly share price data were obtained from January 2005 till December 2015.

4.3.2 Research Instrument

A research instrument was developed in Microsoft Excel. The instrument used various data management techniques in Microsoft Excel to calculate and analyse the various inputs. This is consistent with the use of Microsoft Excel in research applications as described by Anderson, Sweeney, and Williams(2012).

4.3.3 Calculation of F-Score

The performance measures of the Piotroski screen required several financial ratios and trends that needed to be calculated from the last three years' financial statement line items. The line items extracted that were used to calculate the input ratios and trends are shown in Table 1 below.

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Table 1 F-Score Components and Fundamental Data

F-Score Components	Fundamental Data
Return on Assets (ROA)	$\frac{Net\ income\ before\ extraordinary\ items_t}{Total\ assets_{t-1}}$
Change in Return on Assets (Δ ROA)	$ROA_t - ROA_{t-1}$
Cash flow from operation (CFO)	$Cashflow\ from\ operations_t$
Cash flow from operations over assets (CFROA)	$\frac{Cashflow\ from\ operation_t}{Total\ Assets_{t-1}}$
Change in Gross Margin (Δ Margin)	$\frac{(Gross\ profit)_t}{Turnover_t} - \frac{(Gross\ Profit)_{t-1}}{Turnover_{t-1}}$
Change in Asset turnover ratio	$\frac{Long\ term\ debt_t}{Total\ Assets_{t-1}} - \frac{Long\ term\ debt_{t-1}}{Total\ Assets_{t-2}}$
Change in Leverage (Δ Leverage)	$\frac{Turnover_t}{Total\ Assets_{t-1}} - \frac{Turnover_{t-1}}{Total\ Assets_{t-2}}$
Change in Liquidity (Δ Liquidity)	$\frac{Current\ Assets_t}{Current\ Liabilities_t} - \frac{Current\ Assets_{t-1}}{Current\ Liabilitiest_{t-1}}$
Equity offer	$Outstanding\ Shares_t - Outstanding\ Shares_{t-1}$

From these ratios and trends the binary values of the nine performance measures were calculated as shown in Table 2

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Table 2 Allocation of Binary Value to F-Score Signals

F-Score Component	**Binary Value Allocation**
F_ROA	If ROA > 0 F_ROA = 1, else 0
F_CFO	If CFO > 0 F_CFO = 1, else 0
F ΔROA	If ΔROA > 0 F_ΔROA = 1, else 0
F_CFROA	If CFROA > ROA F_CFROA =1, else 0
F_ΔMargin	If ΔMargin > 0 F_ΔMargin =1,else 0
F_ΔTurnover	If ΔTurnover > 0 F_ΔTurnover
F_ΔLeverage	If ΔLeverage < 0 F_ΔLeverage = 1, else 0
F_ΔLiquidity	If ΔLiquidity > 0 F_ΔLiquidity = 1, else 0
F_Eq_Offer	If Eq_Offer < = 0 F_Eq_Offer =1, else 0

The aggregate Piotroski's F- score was given by:

F_Score = F_ROA + F_ΔROA+ F_CFO + F_CFROA + F_Δ Margin + F_Δ Turnover

+F_Δ Leverage +F_ΔLiquidity + F_Eq_Offer

4.3.4 Calculation of Z-EM Score

The fundamental data that was required to calculate the Altman Z-EM score were extracted from the financial statement line items of firms that are listed on the main board of the JSE. The line items extracted that were used to calculate the Z-EM components are shown in Table 3 below.

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Table 3 Z-EM Components and Fundamental Data

Z-EM Components	**Fundamental Data**
X1	$\frac{Current\ Assets - Current\ Liabilities}{Total\ Assets}$
X2	$\frac{Retained\ Earnings}{Total\ Assets}$
X3	$\frac{Operating\ Income}{Total\ Assets}$
X4	$\frac{Book\ Value\ of\ Equity}{Book\ Value\ of\ Debt}$

The Z-EM aggregate Score was calculated as follows:

Z-EM = 6.56X1 + 3.26X2 + 6.72X3 + 1.05X4 + 3.25

4.3.5 Portfolio Formation

The primary methodology of this research the formation of share portfolios based on a firm's aggregate F and Z-EM scores. Therefore, portfolios were formed based on a firm's aggregate F-score for each year of analysis. Firms with an F-score of 0-3 were classified as low F-score firms and firms with an F-score of 7-9 were classified as high F-score firms. This is a deviation from Piotroski (2000) which refereed to 0-1 F-score stocks as low F-score stocks and to 7-9 F-score as high F-score stocks. This approach was taken to arrive at a larger sub-sample and compensate for the shorter time frame of this research. Importantly, low F-score firms are expected to have the worst subsequent stock performance and high F-score firms are expected to have the best subsequent return performance.

Similarly, portfolios were formed based on a firm's aggregate Z-EM score for each year of analysis. Firms with a Z-EM -scores that are lower than 4.35 were classified as low Z-EM firms and firms with Z-EM -scores that are greater than 5.85 were classified as high Z-EM

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score firms. The high Z-EM portfolios were expected to outperform the low Z-EM portfolios.

An observation was uniquely identified by the combination of the firm's name and the year of portfolio formation. This resulted in several independent observations that contained the same firm but for different years of portfolio formation.

4.3.6 Calculation of Stock Returns

The firm-specific returns were measured as one-year returns earned from the firm's fiscal year-end through the entire period of analysis. The n-year annualised returns were calculated as follows:

$$\left[\frac{P_n \quad - \ P_0}{P_0}\right] * 100$$

With:

P_0 = Adjusted share price at the year of portfolio formation

P_n = Adjusted share price n years after portfolio formation

n = is the length of the buy-and- hold strategy which was chosen.

The firms' annualised returns were compared to the JSE All share index returns to give the relative returns. The relative returns were listed according to the respective Altman Z-EM and Piotroski-F scores. Finally, descriptive statistics and tests for the difference between each group for different holding periods will be conducted. It is important to highlight that the share prices used in this calculation were the adjusted share prices that reflect any distributions and corporate actions that occurred within the time period that was under analysis.

For simplicity reasons, Trading costs, slippage or taxes were not considered in this research.

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4.3.7 Empirical Tests

An observation consisted of various variables of a firm with enough financial statement information available to allow the F-score and the Z-M score to be calculated for the year of portfolio formation as well as share price at the end of the portfolio period. Variables contained in an observation were (a) the identification which is a combination of a company ticker symbol and the financial year (b) F and Z-EM scores, and (c). the annualised return.

The first research hypothesis was aimed at the determination of the effectiveness of the Z-EM score at identifying stocks that would yield underperform over an investment horizon. The average returns of one-year holding period were compared for the low and high Z-EM score portfolios. Afterwards, a t-test was performed to determine the significance of the result at a 95 % confidence level.

Similarly, the purpose of the second research hypothesis was to determine if the F score was effective at identifying stocks that would underperform over an investment horizon. The average returns of one-year holding periods were compared for the low and high F-score portfolios. Subsequently, a t-test was performed to determine the significance of the result at 95 % confidence level.

Compared to research hypotheses one and two, the goal of the third research hypothesis was to determine if the Z-EM score was more effective than the F-score at identifying stocks that would underperform over an investment horizon. The average returns of one-year period were compared for the low Z-EM and F score scores portfolios. Then, a t-test was performed to determine the significance of the result at 95 % confidence level.

4.4 Research Limitation

Although adequate care was taken to minimise and exclude possible research restrictions, however, some limitations were recognised.

While the research was designed as a causal study, there were many factors that could influence the dependent variable in order to determine causality with absolute certainty. As a result, the research could be considered as more of a predictive study rather than a

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study that could determine cause and effect between the dependent and independent variables with absolute certainty. However, the temporal relationship between the independent variables and the dependent variable strengthen the case for causality. The F and Z-EM scores preceded the portfolio returns in time by at least one year.

In addition, transaction costs and taxes have been ignored as part of this study. It was assumed that these costs would be equal for all of the portfolios. However, the inclusion of these costs could have influenced the outcome of the study.

Furthermore, the study focused on firms that are listed on the main board of the JSE and may therefore be un-representative of firms that are listed on alternative security exchanges.

Microsoft Excel was used extensively as the research tool and the impact of possible processing errors are acknowledged. Consistent application of formulas and assumptions, operating skills are crucial in ensuring error-free analysis and results. Care has been taken to make sure the data and results are error-free.

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CHAPTER 5: RESULTS

5.1 Introduction

As highlighted in chapter three, there are three research questions that were examined with hypotheses in this study. These are:

1. **Is the Z-EM-Score able to identify shortable stocks on the JSE**?

H_0: There is no difference between the returns of stocks with low Z-EM scores (μ_{Zeml}) and the returns of high Z-EM scores (μ_{Zemh}).

H_1: Returns of stocks with low Z-EM scores (μ_{Zeml}) under-performed in comparison to the returns of high Z-EM scores (μ_{Zemh}).

$$H_0 = \mu_{Zeml} - \mu_{Zemh} = 0$$

$$H_1 = \mu_{Zeml} - \mu_{Zemh} < 0$$

2. **Is the F- Score able to identify shortable stocks on the JSE?**

H_0: There is no difference between the returns of stocks with low F-scores (μ_{Fl}) and the returns of stocks with high F-scores (μ_{Fl}).

H_1: Returns of stocks with low F-scores (μ_{Fl}) under-performed in comparison to the returns of stocks with high F-scores (μ_{Fh}).

$$H_0 = \mu_{Fl} - \mu_{Fh} = 0$$

$$H_1 = \mu_{Fl} - \mu_{Fh} < 0$$

3. **Is the Z-EM score more efficient than Piotroski F score in identifying shortable stocks on the JSE?**

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H_0: There is no difference between the returns of shortable stocks identified by low Z-EM scores (μ_{Zeml}) and those identified by Piotroski F score (μ_{Fl})

H_1: The returns of shortable stocks identified by low Z-EM scores (μ_{Zeml}) out-performed the shortable stocks identified by low Piotroski F score (μ_{Fl})

$$H_0 = \mu_{Zeml} - \mu_{Fl} = 0$$

$$H_1 = \mu_{Zeml} - \mu_{Fl} > 0$$

This chapter will give an overview of the results using graphical and tabular descriptive techniques. Then the hypotheses will be examined using the data produced from the sample of firms.

5.2 Descriptive statistics

5.2.1 Characteristics of F-Score

To form one year buy-and-hold portfolios, the adjusted share prices and Piotroski F scores up to one year after portfolio formation were required. Data was obtained from 2005 until the end of 2015. Therefore, portfolios could be formed for each year from 2005 till 2014. Importantly, buy-and-hold returns consisted of ten portfolio formation years (2005 – 2014). The one-year buy-and-hold portfolio for F-scores was made up of 798 observations.

The number of observations that contain complete information for all the variables necessary to study portfolio holding periods of one year for F -scores are shown in Table 4. This sample consisted of all observations, not only high and low scores.

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Table 4 Observations per financial year with sufficient fundamental data for F-score analysis

Year	Number of Observation	Percentage of Grand Total
2005	74	9.27%
2006	82	10.28%
2007	72	9.02%
2008	76	9.52%
2009	76	9.52%
2010	80	10.03%
2011	76	9.52%
2012	85	10.65%
2013	88	11.03%
2014	89	11.15%
Grand Total	798	100.00%

On the next page, Table 5 presents the descriptive statistics of the F-Score.

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Table 5 Descriptive Statistics of F-Score

F-Score	
Mean	5.224311
Standard Error	0.052558
Median	5
Mode	5
Standard Deviation	1.484698
Sample Variance	2.204327
Kurtosis	-0.29499
Skewness	-0.00855
Range	8
Minimum	1
Maximum	9
Sum	4169
Count	798
Largest(1)	9
Smallest(1)	1
Confidence Level (95.0%)	0.103168

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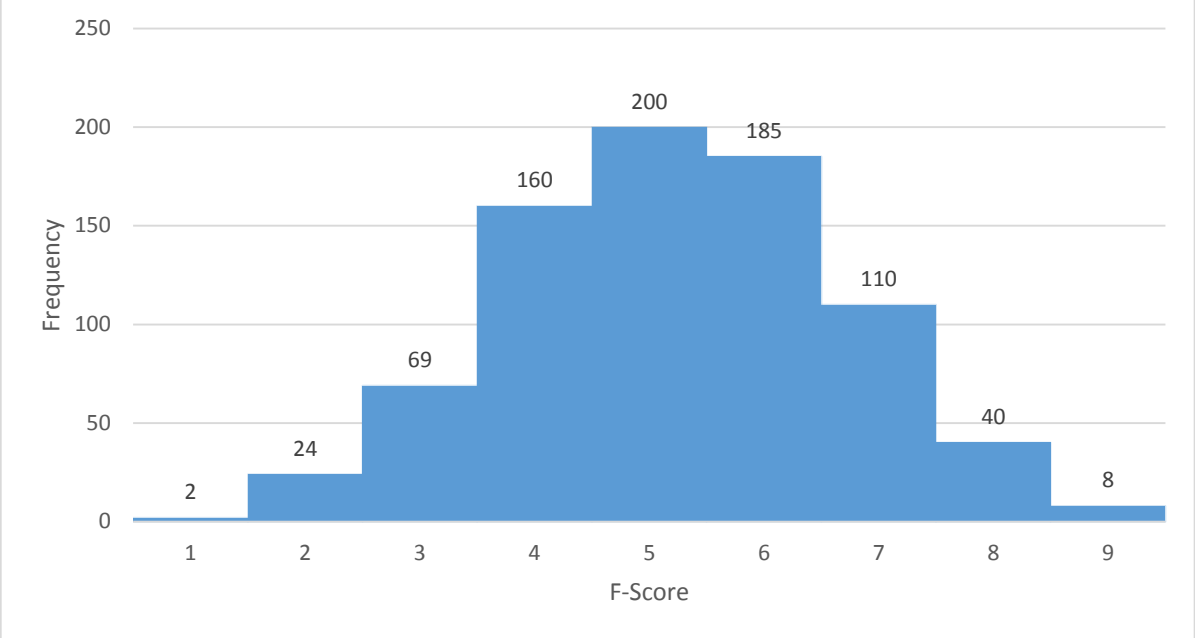
Figure 1 shows the frequency distribution of the F-scores over the entire period of analysis from 2005 till 2014.

Figure 1 Histogram of F-score distribution over the entire period of analysis



The F-score frequency distribution is bell-shaped, relatively symmetrical and unimodal. The fact that the distribution was unimodal is a strong indication that only one distribution is present (Berenson, Levine, Szabat, & Krehbiel, 2012). This distribution highlights the fact that most probably only one mechanism is responsible for the F-score distribution despite the fact that the period under study spans periods of economic downturns and expansions. The median and mode were five which were slightly more than the middle of the range of possible F-scores (4.5). Very few firms have F-scores below 2.

Remarkably, there were no companies with an F-score of zero which is most probably due to the frequent occurrence of the non-issuance of equity (which would cause F_Eq_Offer to be one). And in cases whereby equity was issued (which would cause F_Eq_Offer to be

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zero), there was at least one other performance measure that scored a one instead of a zero which would cause the combined F-score of that observation to be larger than zero.

5.2.2 Characteristics of Z-EM -Score

To form one year buy-and-hold portfolios, the adjusted share prices and Altman Z-EM scores up to one year after portfolio formation were required. Data was obtained from 2005 until the end of 2015. Therefore, portfolios could be formed for each year from 2005 till 2014. Importantly, buy-and-hold returns consisted of ten portfolio formation years (2005 – 2014). The one-year buy-and-hold portfolio for Z-EM scores contained 820 observations.

The number of observations that include complete information for all the variables necessary to study portfolio holding periods of one year for Z-EM scores is shown in Table 6. This sample was all-inclusive, in other words, the sample consisted of all observations, not only high and low scores.

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Table 6 Observations of Z-EM scores per financial year

Year	Number of Observation	Percentage of Grand Total
2005	76	9.27%
2006	82	10.00%
2007	75	9.15%
2008	77	9.39%
2009	79	9.63%
2010	83	10.12%
2011	81	9.88%
2012	89	10.85%
2013	89	10.85%
2014	89	10.85%
Grand Total	**820**	**100.00%**

The descriptive statistics and frequency distribution for the Z-EM score are shown in Table 7 and figure 2 respectively. The Z-EM score has a mean and mode of 7.55 and 6.82 respectively and has a wider range when compared to the F-Score. In addition, the Z-EM Score frequency distribution is bell-shaped, relatively symmetrical and unimodal.

The Z-EM-Scores calculated over the period indicated that 9.88% of the companies obtained a score that is below 4.35 and is likely to fail within two years. Furthermore, 67.56% of the company analysed obtained a score that is above 5.85 and unlikely to fail there was uncertainty as to whether 22.56% of the companies would fail or not.

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Table 7 Descriptive statistics of Z-EM score

Z-EM-Score	
Mean	7.552071
Standard Error	0.186641
Median	6.61
Mode	6.82
Standard Deviation	5.344586
Sample Variance	28.5646
Kurtosis	147.9865
Skewness	10.26161
Range	96.93
Minimum	-0.1
Maximum	96.83
Sum	6192.698
Count	820
Largest(1)	96.83
Smallest(1)	-0.1
Confidence Level (95.0%)	0.366351

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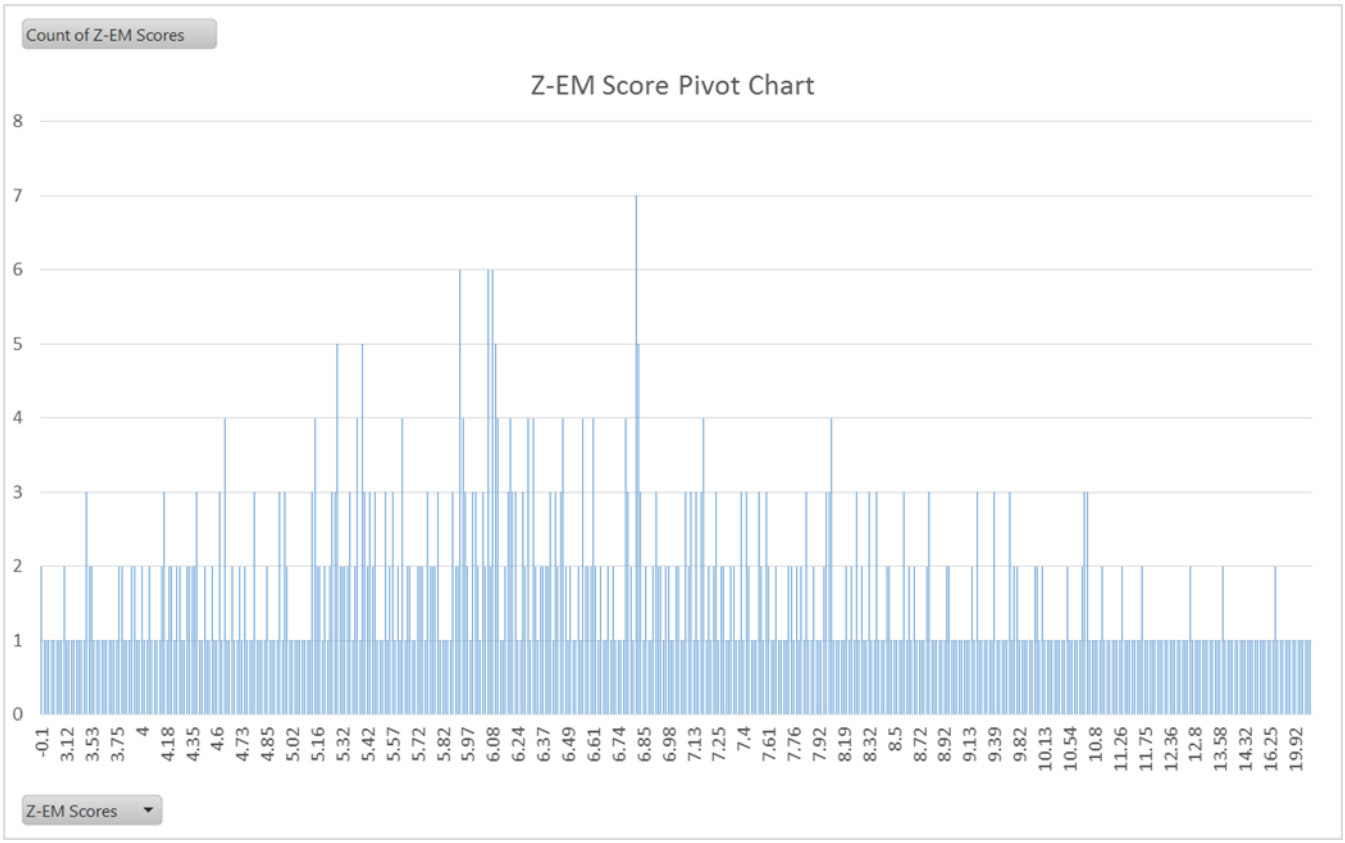
Figure 2 Frequency distribution of Z-EM Scores



5.2.3 F-Score Return Characteristics

The classification of the one-year buy-and –hold raw and market-adjusted returns for the F-Scores into percentiles are shown in table 8. Importantly, the table indicates the percentage of firms in the complete sample with positive raw and market adjusted returns over the holding period. In addition, table 9 and table 10 shows the descriptive statistics of the one-year buy-and –hold raw and market-adjusted returns for the F-Scores.

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The mean raw returns out-performed the market adjusted returns over the holding period with a majority of the firms earning a negative market-adjusted return over the period under consideration. Consequently, a strategy that would eliminate the negative return observations will significantly improve the mean return performance.

Table 8 Division of F-Score Buy -and-Hold Returns into Percentiles

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	% Positive
Raw Return	13.48%	-25.42%	-6.22%	12.09%	30.75%	52.02%	66.79%
Market Adjusted Return	1.31%	-35.03%	-19.14%	-1.04%	18.62%	39.51%	48.75%

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Table 9 Descriptive Statistics of F-Score one-year buy and-hold Raw Returns

Raw Return	
Mean	0.134763
Standard Error	0.011744
Median	0.120894
Mode	0
Standard Deviation	0.331752
Sample Variance	0.110059
Kurtosis	2.367296
Skewness	0.739798
Range	2.519613
Minimum	-0.89584
Maximum	1.623777
Sum	107.5409
Count	798
Largest(1)	1.623777
Smallest(1)	-0.89584
Confidence Level(95.0%)	0.023053

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Table 10 Descriptive Statistics of F-Score One-year buy-and-hold Market Adjusted Return

Market Adjusted Return	
Mean	0.013093
Standard Error	0.011318
Median	-0.01042
Mode	0.260003
Standard Deviation	0.31971
Sample Variance	0.102215
Kurtosis	2.214683
Skewness	0.681919
Range	2.449915
Minimum	-0.98587
Maximum	1.464041
Sum	10.44825
Count	798
Largest(1)	1.464041
Smallest(1)	-0.98587
Confidence Level(95.0%)	0.022216

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5.2.4 Z-EM Score Return Characteristic

The classification of the one-year buy-and –hold raw and market-adjusted returns for the Z-EM-Scores into percentiles are shown in table 11. The table shows the percentage of firms in the all-inclusive sample with positive raw and market adjusted returns over the holding period. In addition tables 12 and 13 shows the descriptive statistics of the one-year buy-and –hold raw and market-adjusted returns for the ZEM-Scores.

Similar to the F-Score the mean raw returns out-performed the market adjusted returns over the holding period with a majority of the firms earning a negative market-adjusted return over the period under consideration.

Table 11 Division of ZEM-Score Buy -and-Hold Returns into Percentiles

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	% Positive
Raw Return	13.49%	-25.28%	-6.08%	12.17%	30.53%	51.89%	66.71%
Market Adjusted Return	1.33%	-34.73%	-18.46%	-1.04%	18.52%	39.06%	48.66%

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Table 12 Descriptive Statistics of Z-EM Score One-year buy-and -hold Raw Return

Raw Return	
Mean	0.134946
Standard Error	0.011522
Median	0.121741
Mode	0
Standard Deviation	0.329941
Sample Variance	0.108861
Range	2.519613
Maximum	1.623777
Sum	110.6559
Count	820
Smallest(1)	-0.89584
Confidence Level(95.0%)	0.022616

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Table 13 Descriptive Statistics of Z-EM-Score One-year buy-and-hold Market Adjusted Return

Market Adjusted Return	
Mean	0.013292
Standard Error	0.01108
Median	-0.01042
Mode	0.260003
Standard Deviation	0.317296
Sample Variance	0.100677
Range	2.449915
Maximum	1.464041
Sum	10.89918
Count	820
Smallest(1)	-0.98587
Confidence Level (95.0%)	0.021749

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5.3 Research Hypothesis 1

To test the research question if the Altman Z-EM Score can identify stocks that can be shorted on the JSE, it was hypothesised that the mean returns of the stocks with low Z-EM scores (μ_{Zeml}) and the high Z-EM scores (μ_{Zemh}) are not different from each other. Therefore, the alternate hypothesis is that there is a significant difference between the mean returns of the two groups. Table 14 shows the characteristics of the low and high Z-EM Score market adjusted returns per year.

Table 14 Characteristics of Low and High Z-EM Market Adjusted Returns

Year	High ZEM score Market adjusted Return	Low ZEM Score Market adjusted return	Number of observations(high/low
2005	-2.70%	-33.09%	53 / 8
2006	23.06%	2.70%	55 / 6
2007	12.59%	-2.92%	48 / 9
2008	-17.39%	-15.07%	48 / 11
2009	-4.58%	-3.28%	50 / 6
2010	10.34%	-4.94%	62 / 7
2011	-8.79%	-3.94%	58 / 7
2012	0.70%	-9.92%	63 / 7
2013	-2.51%	18.10%	62 / 8
2014	-2.83%	1.92%	54 / 13

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Table 15 below presents the classification of the low and high Z-EM-Scores into percentiles.

Table 15 Division of Z-EM-Score One-year Market Adjusted Returns divided into Percentiles

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	% Positive
Low-ZEM	-5.03%	-36.58%	-21.59%	-3.15%	12.16%	21.39%	42%
High-ZEM	0.96%	-35.13%	-20.18%	-1.34%	19.46%	39.02%	48.46%

In order to perform the appropriate independent samples t-test, the assumption of homogeneity of variance between the two means should be tested. Table 16 shows the output of this test in Microsoft Excel. From the table, the probability is 0.162194854. This is a one tail p-value associated with the test for equality of variance. As a rule of thumb, if this value less than 0.05 it can be assumed that the variances are not equal and the t-test that assumes unequal variances can be done. Likewise, if this value is greater than 0.05 it can be assumed that variances are equal the t-test that assumes equal variances can be performed.

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Table 16 Z-EM Returns Homogeneity of Variance Test

F-Test Two-Sample for Variances

	LOW Z-EM Score Market Adjusted Returns	*High Z-EM Score Market Adjusted Returns*
Mean	-0.05025284	0.009618051
Variance	0.088935634	0.106260004
Observations	81	553
df	80	552
F	0.836962452	
P(F<=f) one-tail	0.162194854	
F Critical one-tail	0.743398828	

Table 17 shows the output of the t-test assuming equality of variance for the two samples at a confidence interval of 95%. From the table, it can be observed that the mean of low Z-EM Score market adjusted returns is -0.05025284 and a mean of 0.009618051 for the high Z-EM Score Market adjusted returns; with a variance of 0.088935634 for the low Z-EM Scores and 0.106260004 for the high Z-EM Score. Furthermore, the mean of the low Z-EM score market adjusted return is negative while the mean of the high Z-EM Score market adjusted return is positive; this suggest that there is a difference in the mean returns. However, in order to determine the statistical significance of this result, the p-value of the

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one tail test was compared to 0.05. As a rule of thumb if the value is larger than 0.05 there is no significant difference, and if it is smaller than 0.05, there is a significant difference.

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Table 17 Z-EM Returns t-Test

t-Test: Two-Sample Assuming Equal Variances

	LOW Z-EM Score Market Adjusted Returns	*High Z-EM Score Market Adjusted Returns*
Mean	-0.05025284	0.009618051
Variance	0.088935634	0.106260004
Observations	81	553
Pooled Variance	0.104067046	
Hypothesized Mean Difference	0	
df	632	
t Stat	-1.55998189	
P(T<=t) one-tail	0.059632372	
t Critical one-tail	1.647268214	
P(T<=t) two-tail	0.119264744	
t Critical two-tail	1.963724655	

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In this case the, the value is 0.059632372 and therefore indicative that there is no significant difference between the market adjusted returns of the low and high Z-EM Scores. Hence, we fail to reject the null hypothesis.

5.4 Research Hypothesis 2

To test the hypothesis that the Piotroski F-Score can identify stocks that can be shorted on the JSE, a hypothesis was formed that the mean returns of the stocks with low F-scores (μ_{Fl}) and the high F-scores (μ_{Fh}) are not different from each other. Therefore, the alternate hypothesis is that there is a significant difference between the mean returns of the two groups. Table 19 shows the characteristics of the market adjusted returns of the low and high F-Score per year.

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Table 18 Characteristics of Low and High F-Score Market Adjusted Returns

Year	High F-Score Market adjusted Return	Low F-Score Market adjusted return	Number of observations(high/low)
2005	-17.60%	-37.26%	22 / 5
2006	32.11%	42.83%	18 / 7
2007	18.69%	-9.89%	16 / 5
2008	-23.94%	-20.05	15 / 13
2009	10.44%	-7.54%	9 / 10
2010	6.39%	-6.95%	15 / 7
2011	1.50%	-7.14%	22 / 10
2012	-3.91%	-10.91%	14 / 9
2013	-6.93%	-0.04%	13 /16
2014	-2.21%	-10.19%	14 / 13

Table 19 presents the low and high F-Score market adjusted returns classified into percentiles.

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Table 19 Division of F-Score One-year Market Adjusted Returns divided into Percentiles

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	% Positive
Low-F	-6.56%	-44.69%	-28.31%	-9.97%	14.53%	34.10%	36.84%
High-F	1.12%	-39.44%	-23.59%	-5.16%	17.94%	41.03%	51.27%

Table 20 presents the output of the test for homogeneity of variance in Microsoft Excel. From the table the highlighted probability is 0.34098858.

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Table 20 F-Score Returns Homogeneity of Variance Test

F-Test Two-Sample for Variances

	Low F-Score Market Adjusted Returns	*High F-Score Score Market Adjusted Returns*
Mean	-0.065618526	0.011249333
Variance	0.118884768	0.110552904
Observations	95	158
df	94	157
F	1.075365395	
P(F<=f) one-tail	0.34098858	
F Critical one-tail	1.347045507	

As this value is greater than 0.05 it can be assumed that the variances are equal and the t-test that assumes equal variances can be performed.

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Table 21 F-Score Returns t-Test

t-Test: Two-Sample Assuming Equal Variances

	Low F-Score Market Adjusted Returns	*High F-Score Market Adjusted Returns*
Mean	-0.065618526	0.011249333
Variance	0.118884768	0.110552904
Observations	95	158
Pooled Variance	0.113673204	
Hypothesized Mean Difference	0	
df	251	
t Stat	-1.756086164	
P(T<=t) one-tail	0.040146655	
t Critical one-tail	1.650947025	
P(T<=t) two-tail	0.080293309	
t Critical two-tail	1.969460227	

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Table 21 shows the output of the t-test assuming equality of variance for the two samples at a confidence interval of 95%. From the table, it can be observed that the mean of low F-Score market adjusted returns is -0.065618526 and a mean of 0.011249333 for the high F-Score Market adjusted returns; with a variance of 0.118884768 for the low F- Scores and 0.110552904 for the high F- Score. Furthermore, the mean of the low F-Score market adjusted return is negative while the mean of the high F-Score market adjusted return is positive; this suggest that there is a difference in the mean returns. However, in order to determine the statistical significance of this result, the p-value of the one tail test was compared to 0.05.

In this case the, the value is 0.040146655 and therefore indicative that there is a significant difference between the market adjusted returns of the low and high F-Scores. Hence, the alternate hypothesis is accepted, and the null hypothesis is rejected.

5.5 Research Hypothesis 3

A hypothesis was formed that the mean returns of the stocks with low Z-EM scores (μ_{Zem}l) and low F-scores (μ_{Fl}) are not different from each other. This hypothesis was formed to test whether the Altman Z-EM Score is more efficient than the Piotroski F-Score in the identification of stocks on the JSE that can be acquired for the purpose of short selling. Therefore, the alternate hypothesis is that there is a significant difference between the mean returns of the two groups.

Table 22 shows the comparison of the characteristics of the low Z-EM-Score and low F-Score market adjusted returns per year.

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Table 22 Characteristics of The Low Z-EM and F-scores Market Adjusted Returns

Year	Low ZEM Score Market adjusted return	Low F-Score Market adjusted return	Number of observations(Z-EM/F)
2005	-33.09%	-37.26%	8 / 5
2006	2.70%	42.83%	6 / 7
2007	-2.92%	-9.89%	9 / 5
2008	-15.07%	-20.05	11 / 13
2009	-3.28%	-7.54%	6 / 10
2010	-4.94%	-6.95%	7 / 7
2011	-3.94%	-7.14%	7 / 10
2012	-9.92%	-10.91%	7 / 9
2013	18.10%	-0.04%	8 / 16
2014	1.92%	-10.19%	13 / 13

Table 23 shows the comparison of the percentile classification of the low Z-EM-Scores and low F-scores.

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Table 23 Division of The Low Z-EM and F-Scores One-year Market Adjusted Returns into Percentiles

Return	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	% Negative
Low-ZEM	-5.03%	-36.58%	-21.59%	-3.15%	12.16%	21.39%	58%
Low F	-6.56%	-44.69%	-28.31%	-9.97%	14.53%	34.10%	63.16%

Table 24 shows the output of the test for homogeneity of variance in Microsoft Excel. From the table the highlighted probability is 0.091422942.

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Table 24 Low Scores Returns Homogeneity of Variance Test

F-Test Two-Sample for Variances

	Low F-Score	*Low Z-EM Score*
Mean	-0.065618526	-0.05025284
Variance	0.118884768	0.088935634
Observations	95	81
df	94	80
F	1.336750667	
P(F<=f) one-tail	0.091422942	
F Critical one-tail	1.431543953	

As this value is greater than 0.05 it can be assumed that the variances are equal and the t-test that assumes equal variances can be performed.

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Table 25 Low Scores Returns t-Test

t-Test: Two-Sample Assuming Equal Variances

	Low F-Score	*Low Z-EM Score*
Mean	-0.065618526	-0.05025284
Variance	0.118884768	0.088935634
Observations	95	81
Pooled Variance	0.105115051	
Hypothesized Mean Difference	0	
df	174	
t Stat	-0.313377259	
P(T<=t) one-tail	0.377184697	
t Critical one-tail	1.653658017	
P(T<=t) two-tail	0.754369394	
t Critical two-tail	1.97369144	

Table 25 presents the output of the t-test assuming equality of variance for the two samples at a confidence interval of 95%. From the table, it is observed that the mean of

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low F- Score market adjusted returns is -0.065618526 and a mean of -0.05025284 for the low Z-EM Score Market adjusted returns; with a variance of 0.118884768 for the low F-Scores and 0.088935634for the low Z-EM Score. In order to determine the statistical significance of this result, the p-value of the one tail test was compared to 0.05.

In this case the, the value is 0.377184697 and therefore indicative that there is no significant difference between the market adjusted returns of the low and high Z-EM Scores. Hence, the alternate hypothesis is rejected, and we fail to reject the null hypothesis.

5.6 Summary

The objective of this research was the determination of the best fundamental analysis tools that can be used to identify stocks on the main board of the JSE that can be shorted for abnormal returns. The Altman Z–EM and the Piotroski F scores were selected, and their effectiveness in the identification of stocks that can be shorted on the JSE was investigated. Independent samples t-tests were performed between the portfolio of firms on either end of the Altman ZEM and Piotroski F scores spectrums..

On the one hand, the results showed that the returns from the portfolio of firms with low Z-EM scores did not differ significantly from the returns of the portfolio of companies with high Z-EM scores. On the other hand, the returns of the portfolio of firms with low F scores underperformed the market and differed significantly from the returns of the high F-Score portfolio. These results are discussed in chapter 6.

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CHAPTER 6: DISCUSION OF RESULTS

6.1 Introduction

The primary purpose of this study was to determine the best method to identify stocks to short sell on the JSE. The process involved the use of the Altman Z-EM Score and the Piotroski F-Score as screening tools in the formation of a portfolio of shares that are to be shorted over an investment period of one year.

Since Hung Wan (2007) postulated the overpricing hypothesis, studies by Shkilko et al. (2012) and Alexander et al. (2014) concurred that that short selling would be one of the choices of an investor that is in possession of inside information that shows a firm's stock is overpriced. Although, different short selling strategies were proposed in the literature, however, Diether et al. (2009) and Karpoff & Lou (2010) purposed that short sellers exploit price differences that are brought about by short term deviation of stock prices from fundamental values. Essentially, fundamental analysis is one of the methods of predicting potential price deviations from fundamental values. The Altman Z-EM and Piotroski F scores are two of the fundamental analysis models that have been used in literature to detect the fundamental signals of firms. However, nothing in the literature was found that rigorously tested the effectiveness of these models as a short selling instrument on the JSE using the scientific method of hypothesis testing.

Hypothesis one investigated the effectiveness of The Altman Z-EM Score in the identification of shares that can be shorted on the JSE. Likewise, Hypothesis two examined the effectiveness of the Piotroski F- Score in the identification of shares that can be shorted on the JSE. Finally, Hypothesis three examined whether the Altman Z-EM - Score is more effective than the Piotroski F-Score in the identification of shares that can be shorted on the JSE.

6.2 Research Hypothesis 1

This research specifically investigated a possible short selling strategy that could be used to earn abnormal returns on the JSE. One of the short selling instrument considered in this

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study is the Altman Z-EM-Score. To determine the effectiveness of this tool in the identification of stocks that could be shorted on the JSE, a test of the difference between the returns of two portfolios that were created based on the Altman Z-EM- Scores of the firms in the portfolios were tested for statistical significance. These two portfolios were, low Z-EM Score portfolio that is made up of businesses with Z-EM-Score that is below 4.35 and high score portfolio consisting of firms with Z-EM-Score above 5.85. The Low F-score portfolio consisted of 81 samples and the High F-Score portfolio consisted of 533 samples. These relatively large samples ensured the accuracy of the statistical comparison method used.

The Altman Z-EM Score was chosen for this study because it was designed for firmss operating in emerging markets, and unlike the Altman Z-Score is not restricted to manufacturing companies (Altman, 2005). The results of the Altman Z-EM Scores calculated over the 10-year period shows that an average of 8 companies per year were expected to fail. Also, an average of 55 companies per year were unlikely to fail. These findings are consistent with the results of a previous study done on emerging markets (Altman, 2005)

Table 14 and 15 presents evidence on how an investment strategy of shorting low Z-EM-Score stocks and buying high Z-EM-Score stock performed in the 2005-2014 investment horizon. Over the ten-year horizon, the low Z-EM-Score stocks showed an average market-adjusted mean returns of -5.03% per year. Importantly, the low Z-EM-Score portfolio predominantly underperforms the market by realising a negative market adjusted mean returns in seven out of ten years. However, contrary to Dichev (1998), Avramov et al. (2012) and Friewald et al. (2014), the conclusion drawn from the independent samples t-test of the return data for this portfolio showed that the -5.03% return is not significant at the 95% confidence level. Hence, the data supports the rejection of the alternate hypothesis and the failure to reject the null hypothesis. The conclusion drawn is that there is no significant difference between the means of the market adjusted returns of the low and high Z-EM portfolios

Consistent with Altman (2005) and Li (2012), amongst the components of the Z-EM-Scores, the ratio of the equity to total liabilities of the companies listed on the JSE appeared to be the most significant contributor to their Z-EM scores. Furthermore, similar to the findings of the Altman Z-Score study (1968), the reduction in the ratio of the

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operating profit and total assets had the greatest impact on the Z-EM scores over the period. Moreover, the reduction in the ratio of the working capital and total assets is also a substantial contributing factor.

The predictive accuracy of the Z-EM-Score was appraised by making a comparison between the constituents of the low Z-EM-Score portfolio and the real corporate failures that had occurred on the JSE over the study period. Within the sample used for this study, there were two bankruptcies. Out of these bankruptcies, the Altman Z-EM Score only successfully predicted corporate failure for one of the companies in the two years preceding corporate failure. As a result, the Altman Z-EM Score appears to have a large type 2 error, in that it has predicted a substantial number of corporate failures that have as yet not occurred. This finding is contrary to Altman (2005) who found that the Z-EM score to be a robust predictor of business failure in the two years preceding actual failure. Nevertheless, there is a likelihood of the companies that identified as likely to fail in the year 2016 may still enter into bankruptcy after the outcome of this study and thereby confirm the efficacy of the low Z-EM score.

6.3 Research Hypothesis 2

The effectiveness of the Piotroski F-score in the identification of stocks that could be shorted on the JSE was determined by testing if there was a statistically significant difference between the returns of two portfolios chosen in such a way that eliminated all sources of variation except for the effect of Piotroski F-Score. These two portfolios were the low F-Score portfolio that comprise of companies with F-Score of 0-3 and the high score portfolio that is made up of businesses with F-Score of 7-9 for each portfolio forming year. Further to the above, the Low F-score portfolio comprised of 95 samples, and the High F-Score portfolio consisted of 158 samples. These relatively large samples ensured the accuracy of the statistical comparison method used.

Table 19 shows the one-year buy-and-hold returns for the portfolio of low and high F-Scores and with the proportion of firms in the portfolio with positive raw and market-adjusted returns over the investment period. Importantly the table shows a positive relationship between the F-Score and subsequent returns. This relationship is consistent with Piotroski (2000) and Piotroski et al. (2012). The high F-Score firms outperform low F-

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Score firms in the one-year period that followed portfolio formation (mean market-adjusted returns of 0.12% versus -6.56%, respectively). However, notwithstanding the strong performance of this portfolio, a majority of the firms earn negative market-adjusted returns over the year window.

Furthermore, Table 18 and 19 shows evidence on how an investment strategy of shorting low F-score stocks and buying high F-score stock performed in the 2005-2014 investment horizon. Over the ten-year horizon, the low F-Score stocks showed an average market-adjusted mean returns of -6.56% per year. Importantly, the low F-Score portfolio predominantly underperforms the market by realising negative market adjusted mean returns in nine out of ten years. Furthermore, the conclusion drawn from the independent samples t-test of the return data for this portfolio showed that the -6.56% return is significant at the 95% confidence level. Hence, the data supports the rejection of the null hypothesis and the acceptance of the alternate hypothesis that postulates that the there is a significance difference between the mean returns of the two portfolios. Furthermore, consistent with Piotroski (2000) and Asness et al. (2013), buying high F-Score stocks yielded an average market-adjusted mean return of 1.12% per year. Importantly, the market-adjusted return for the high F-score stocks is positive for five out of the ten years under consideration. Essentially, when compared to the low F-Score, the high F-Score was less successful as a buy and hold strategy. The inference drawn from these results was that the Piotroski F-Score was successful in the selection of stocks that could be shorted on the JSE. However, this result could also be viewed in the context of the market conditions that existed during the period that was under investigation.

The period that encompasses the investigation was made up of both bull and bear market conditions. During this time, the JSE All Share index had a compound growth rate of 12.25% (rounded) per annum. This figure reflects only the adjusted share price increases of the JSE's All Share index. Importantly, an effort was made to include delisted firms in the calculation of the mean returns; this was to ensure that the results do not suffer from survivorship bias. Importantly, de-listings brings about investment losses and is probably the reason why the mean return of the one-year buy-and-hold strategy is not higher (Beaver, Mcnichols, & Price, 2007). However, a concern still exists on the likely existence of survivorship bias, especially given the small number of observations in the low F-Score portfolios compared to the high F-Score portfolio. To the extent that there exists a set of firms with weak fundamentals that did not survive, these missing low F-Score observations

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would have generated substantial negative returns. The omission of these companies from the study would dampen the loss experienced by the current low F-Score portfolio.

Moreover, the return improvements extend beyond the mean performance of both portfolios. Consistent with Piotroski (2000), Table 19 show that the 10th percentile, 25th percentile, median, 75th percentile and 90th percentile returns of the high F-Score portfolio are greater than the corresponding returns of the low F-Score portfolio. Similarly, the proportion of positive returns in the high F-Score portfolio, 51.27%, is higher than the low F-Score portfolio (36.84%).

6.4 Research Hypothesis 3

It was hypothesised that the mean returns of the stocks with low Z-EM scores (μ_{Zeml}) and low F-scores (μ_{Fl}) are not different from each other. This hypothesis was formed to test whether the Altman Z-EM Score is more efficient than the Piotroski F-Score in the identification of stocks on the JSE that can be shorted. Therefore, the alternate hypothesis is that there is a significant difference between the mean returns of the two groups. This hypothesis was based on Engelberg et al. (2012) who observed that because short-sale earnings cannot be used for consumption, short sales are usually not undertaken for liquidity reasons, which means that short sellers should be more informed than other sellers. Hence, short-sellers would be able to enhance their trading strategies with the use of a strategy that gives a more predictive ability of future returns

Essentially, a test of the statistically significant difference between the market adjusted returns of the low Z-EM-Score and the low F-Score was done. The Low Z-EM-Score portfolio was made up of 82 samples, and the low F-Score portfolio consisted of 95 samples. Table 22 shows the comparison of the characteristics of the low Z-EM-Score and low F- Score market adjusted returns per year. From this table, it is observed that the low-Z-EM portfolio a negative market adjusted returns in seven out of ten years of observation. In comparison, the low F-Score portfolio predominantly underperforms the market by realising negative market adjusted mean returns in nine out of ten years. Furthermore, Table 23 presents one-year buy-and-hold returns for the low Z-EM-Score and low F-Score portfolio divided into percentiles along with the percentage of firms in the portfolio with negative market-adjusted returns over the one-year investment horizon. Over the ten-year

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horizon, the low F-Score stocks showed an average market-adjusted mean return of -6.56% per year. On the other hand, the low Z-EM-Score stocks showed an average market-adjusted mean return of -5.03% per year. Moreover, a majority of the firms with low F-Score and low Z-EM-Score earn a negative market adjusted return (63.16% and 58% respectively). However, compared to the low Z-EM-Score portfolio a higher proportion of the low F-score portfolio firms earned a negative market adjusted return over the holding period.

The inference drawn from the results highlighted in the preceding paragraphs is that the low Altman Z-EM-Score is not as effective as the low Piotroski F-Score in the identification of short selling candidates on the JSE. However, in order to determine the statistical significance of these results, a t-test was performed on the difference between the mean returns of both portfolios. Table 25 presents the output of the independent samples t-test of the return data for this portfolio showed that the mean return difference between the two portfolios is not significant at the 95% confidence level.

This outcome could be attributed to the nature of the two models. In particular, the construction of the F-Score is significantly different from multivariate discriminant models such as the Z-EM-Score. Ohlson (1980) attributed the limited predictive ability of multivariate discriminant models to their use of a matched sample approach to differentiate treatment firms. Although the components of the Z-EM-Score are similar to the components of the F-Score, the latter does not anchor to specific values in the companies' fundamentals. Rather, the F-Score focuses on the directions in which the fundamentals of a company are moving and whether general financial health conditions are met.

6.5 Conclusion

Short selling is an investment strategy that involves high levels of risks and necessitates that short sellers ensure perfect timing when taking positions in the market (Stambaugh, Yu, & Yuan, 2012). Therefore, knowing how to highlight good candidates for short selling can enhance the returns and lower the risks involved in the process.

This chapter discussed the results of the hypotheses that were investigated with the aim of determining if the Altman Z-EM-Score and the Piotroski F-Score could be used as a short selling instrument on the JSE. The basis of short selling as an investment strategy is the

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formation of a portfolio of shares selected on the JSE with the aid of the Altman Z-EM and Piotroski F scores. The three main aspect of this investment strategy that was investigated were (a) the effectiveness of Altman Z-EM-Score as a short selling instrument on the JSE, (b) the effectiveness of Piotroski F-Score as a short selling instrument on the JSE, and (c) the determination of the most effective short selling instrument between the Altman Z-EM-Score and the Piotroski F-Score on the JSE.

Overall, the results obtained from the study were mixed. Although the mean returns of the low Altman Z-EM –Scores portfolio underperform the market in seven out of the ten years that were under analysis, however the result was deemed to be statistically insignificant. On the other hand, the mean returns of the low Piotroski F-Score portfolio underperformed the market in nine out of the ten years of observation and the result was statistically significant at the 95% confidence level. Moreover, a majority of the companies in this portfolio earned negative returns over the period of study. Therefore, compared to the Altman Z-EM-Score the Piotroski F-Score is a more appropriate short selling instrument that can be applied to the JSE.

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CHAPTER 7: CONCLUSION AND RECOMENDATION

7.1 7.1 Conclusion and Limitations

This research study sought to investigate the effectiveness of Altman Z-EM Score and Piotroski F-Score, accounting-based fundamental analysis models, in the identification of stocks that can be shorted on the JSE. This was achieved by the evaluation of whether the use of these fundamental analysis models as short selling instruments could have been able to yield abnormal returns when applied to the main board of the JSE between 2005 and 2014. Although these two models have different information content, however, the negative and positive fundamental signals were given equal importance in this study. In addition, based on the research questions, three hypotheses were made and analysed through the empirical results of this research.

Although, the mean market-adjusted returns for the low Altman Z-EM-Score portfolio was -5.03% per year over the ten-year investment horizon and underperformed the market in seven out of these ten years, however, the results was not statistically significant. Therefore, the null hypothesis for research question one was confirmed.

The alternate hypothesis for research question two was confirmed as the low Piotroski F-Score portfolio generated average market-adjusted returns of -6.56% with the portfolio predominantly underperforming the market by realising negative market adjusted mean returns in nine out of the ten years that was investigated.

The null hypothesis for research question three was confirmed for the third research question. Over the ten-year investment horizon, the low Z-EM-Score portfolio earned an average market-adjusted mean return of -5.03% per year when compared to the low F-Score portfolio that yielded an average market-adjusted mean return of -6.56% over the same period. Although a majority of the firms with low F-Score and low Z-EM-Score earn a negative market adjusted, however, compared to the low Z-EM-Score portfolio, a higher proportion of the low F-score portfolio firms made a negative market adjusted return over the holding period return (63.16% vs. 58%).

Finally, we can conclude that use of the Altman Z-EM and the Piotroski F-Score models on the sample as short selling tools have been beneficial for rendering above market returns.

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However, the Piotroski –Score has been the only model out of the two models that gave a significant result.

This study has been able to shed some light into the association between short selling instruments of shorting and abnormal returns on the JSE. Moreover it represents a starting point for further investigation into short selling on the JSE.

7.2 Limitations

However, while the data offers striking evidence for the usefulness of a strategy that shorts low F-Score companies, the number of stocks in the portfolio per year is a potential reason for criticism. In fact, within the low F-Score portfolio, the number of stocks range from a minimum of 5 to a maximum of 16. It can be argued that this relatively low sample size could make the strategy susceptible in a practical set-up.

Another limitation of this study is the likelihood of the existence of data-snooping bias that could have an adverse effect on the out-of-sample predictive ability of the strategy. Moreover, transaction costs and taxes have been ignored as part of this study. There is a likelihood that the inclusion of these costs could have had a significant influence on the outcome of the research.

7.3 Recommendations

This research demonstrated that the market adjusted returns from the low Piotroski F-Score portfolio underperformed the high Piotroski F-Score portfolio and the market. In addition, the low Piotroski F-Score portfolio underperformed the low Altman Z-EM-Score portfolio over a 10-year investment period. Hence, the Piotroski F-Score proved to be effective in separating winners from losers stocks from the population of stocks that were explored

Therefore, based on the research findings and the literature, investors that are seeking to pursue short selling as an investment strategy on the JSE should use the Piotroski F-Score in combination with historical information to eliminate firms with poor prospects from a portfolio of liquid shares on the JSE.

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7.4 Future Research

In this study, the firms analysed consisted mostly of top 40 and mid-cap firms that were chosen based on their market capitalization at the prior fiscal year-end. It would be valuable to assess if size effect has any influence on the above market returns earned using these fundamental analysis strategies. Further studies should be done to determine whether the excess returns earned are concentrated in large or small firms and the effectiveness of these strategies across all size categories. Another area that could be explored for further research is the application of these investment strategies to the Alternate Exchange (AltX) which is the secondary securities exchange to the JSE. Kelly (2014) suggested that the likelihood of finding and exploiting mis-priced securities reduces as analysts compete against each other in their effort to take advantage of over- and under-valued securities. In comparison to the JSE, the AltX is not heavily covered by the investment community and it would be valuable to explore if the ability to earn above market returns is driven by the limitation of the information available for the firms listed on the AltX.

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REFERENCES

Abarbanell, J. S., & Bushee, B. J. (1998). Abnormal returns to a fundamental analysis strategy. *The Accounting Review, 73*(1), 19-45.

Aggarwal, N., & Gupta, M. (2016). Returns from financial statement analysis among low book-to-market stocks: Evidence from India. *The IUP Journal of Applied Finance, 22*(2), 47-61.

Alajbeg, D., Bubas, Z., & Šonje, V. (2012). The efficient market hypothesis: Problems with interpretations of empirical tests. *Financial Theory and Practice, 36*(1), 53-72.

Alexander, G. J., Peterson, M. A., & Beardsley, X. W. (2014). The puzzling behavior of short sellers around earnings announcements. *Journal of Financial Intermediation, 23*(2), 255-278.

Altman, E. I. (1968). Financial Ratios,Discrimant Analysis And The Prediction of Corporate Bankruptcy. *The Journal of Finance, 23*(4), 589-609.

Altman, E. I. (2005). An emerging market credit scoring system. *Emerging Market Review, 6*, 311-323.

Altman, E. I., Haldeman, R. G., & Narayanan, P. (1977). Zeta tm analysis a new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance, 1*(1), 29-54.

Anderson, D., Sweeney, D., & Williams, T. (2012). *Modern business statistics with Microsoft Excel.* Cengage Learning.

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. *The Journal of Finance, 68*(3), 929-985.

Athanassakos, G. (2013). Separating winners from losers among value and growth stocks in Canada another step in the value investing process. *Journal of Applied Research in Accounting and Finance , 8*(1), 17-40.

© University of Pretoria

Avramov, D., Chordia, T., Jostova, G., & Philipov, A. (2013). Anomalies and financial distress. *Journal of Financial Economics, 108*(1), 139-159.

Banerjee, S., & Graveline, J. J. (2013). The Cost of Short-Selling Liquid Securities. *The Journal of Finance, 68*(2), 637-664.

Beaver, W. H. (1966). Financial ratios as predictors of failure. *Journal of Accounting Research, 4*, 71-111. doi:10.2307/2490171

Beaver, W., Mcnichols, M., & Price, R. (2007). Delisting returns and their effect on accounting-based market anomalies. *Journal of Accounting and Economics, 43*(2-3), 341-368.

Beber, A., & Pagano, M. (2013). Short-selling bans around the world: Evidence from the 2007-09 crisis. *The Journal of Finance, 68*(1), 343-381.

Beneish, M. D., Lee, C. M., & Nichols, D. C. (2013). Earnings manipulation and expected returns. *Financial Analysts Journal, 69*(2), 57-80.

Beneish, M. D., Lee, C. M., & Nichols, D. C. (2015). In short supply: Short-sellers and stock returns. *Journal of Accounting and Economics, 60*(2), 33-57.

Beneish, M. D., Lee, C. M., & Tarpley, R. L. (2001). Contextual fundamental analysis Through the prediction of extreme returns. *Review of Accounting Studies, 6*, 165-169.

Benson, K., & Faff, R. (2013). β. *ABACUS, 49*(Supplement), 24-31.

Berenson, M., Levine, D., Szabat, K. A., & Krehbiel, T. C. (2012). *Basic business statistics: Concepts and applications.* Australia: Pearson Higher Education.

Betz, F., Oprică, S., Peltonen, T. A., & Sarlin, P. (2014). Predicting distress in European banks. *Journal of Banking & Finance, 45*, 225-241.

Boehmer, E., & Wu, J. J. (2013). Short selling and the price discovery process. *Review of Financial Studie, 26*(2), 287-322.

© University of Pretoria

Bollerslev, T., & Todorov, V. (2011). Tails,fears and risk premia. *The journal of Finance, 66*(6), 2165-2211.

Bourdreaux, D. O. (1995). The monthly effect in international stock markets: Evidence and implications. *Journal of Financial and Strategic Decisions, 8*(1), 15-20.

Brzezinski, A., & Kidambi, V. (2011). Portfolio consideration in investing. *The Journal of Investing, 20*(2), 124-137.

Campos Dias De Sousa, R. E., & Howden, D. (2015). The efficient market conjecture. *The Quarterly Journal of Austrian Economics, 18*(4), 387-408.

Chang, E. C., Yan, L., & Ren, J. (2014). Short-selling, margin-trading, and price efficiency: Evidence from the Chinese market. *Journal of Banking and Finance, 48*(11), 411-424.

Christophe, S. E., Ferri, M. G., & Hsieh, J. (2010). Informed trading before analyst downgrades: Evidence from short sellers. *Journal of Financial Economics, 95*(1), 85-106.

Chung, C. Y., Liu, C., Wang, K., & Zykaj, B. B. (2015). Institutional monitoring: Evidence from the F-Score. *Journal of Business Finance and Accounting, 42*(7-8), 885-914.

Cochrane, J. H. (2014). A mean-variance benchmark for intertemporal Portfolio Theory. *The Journal of Finance, 69*(1), 1-49.

Creswell, J. W. (2013). *Research design: Qualitative, quantitative, and mixed methods approaches.* New York: Sage publications.

De Bondt, W., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance, 40*(3), 793-805.

Dechow, P. M., Hutton, A. P., Meulbroek, L., & Sloan, R. G. (2001). Short-sellers, fundamental analysis and stock returns. *Journal of Financial Economics, 61*(1), 77-106.

Diamond, D. W., & Verrecchia, R. E. (1987). Constraints on short-selling and asset prices adjustment to private information . *Journal of Financial Economics, 18*, 277-312.

© University of Pretoria

Dichev, I. (1998). Is the Risk of Bankruptcy a Systematic Risk? *Journal of Finance, 53*(3), 1131-1147.

Diether, K. B., Lee, K. H., & Werner, I. M. (2009). Short-sale strategies and return predictability. *Review of financial Studies, 22*(2), 575-607.

Dorantes, C. A. (2013). The relevance of using accounting fundamentals in the Mexican stock market. *Journal of Economics,Finance & Administrative Science, 18*(Special Issue), 2-10.

Duarte, J. (2014). Cyclical,defensive and value stocks. In J. Duarte, *The everything investing in your 20s and 30s book: Learn how to manage your money and start investing for your future--now* (pp. 64-65). Avon: Adams Media.

Dunham, L. M. (2012). Managerial hedging ability and firm risk. *Journal of Economic and Finance, 36*, 882-899.

Duong, C., Pescetto, G., & Santamaria, D. (2014). How value–glamour investors use financial information: UK evidence of investors' confirmation bias. *The European Journal of Finance, 20*(6), 524-549.

Duong, C., Pescetto, G., & Santamaria, D. (2014). How value–glamour investors use financial information: UK evidence of investors' confirmation bias. *The European Journal of Finance, 20*(6), 524-549.

Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics, 105*(2), 260-278.

Engelberg, J. E., Reed, A. V., & Ringgenberg, M. C. (2012). How are shorts informed?: Short sellers, news, and information processing. *Journal of Financial Economics, 105(2)*(2), 260-278.

Fabozzi, F. J., Gupta, F., & Markowitz, H. M. (2002). The Legacy of Mordern Portfolio Theory. *Journal of Investing, 11*(3), 7-22.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Emperical Work. *Journal of Finance, 25*(2), 383-417.

© University of Pretoria

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *The Journal of Finance, 47*(2), 427-465.

Fama, E. F., & French, K. R. (2006). The value premium and the CAPM. *The Journal of Finance, 61*(5), 2163-2185.

Fama, E. F., & French, K. R. (2012). Size, value, and momentum in international stock returns. *Journal of Financial Economics, 105*(3), 457-472.

Francis, J., & Schipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research, 37*(2), 319-352.

Friewald, N., Wagner, C., & Zechner, J. (2014). The Cross-Section of Credit Risk Premia and Equity Returns. *The Journal of Finance, 69*(6), 2419-2469.

Garlappi, L., & Yan, H. (2011). Financial distress and cross section of equity returns. *The Journal of Finance, 66*(3), 789-822.

Gilson, R. J., & Kraakman, R. H. (1984). The mechanism of market efficiency. *Virginia Law Review, 70*(4), 549-644.

Gilson, R. J., & Kraakman, R. H. (1984). The Mechanisms of Market Efficiency. *Virginia Law Review, 70*(4), 549-644.

Giroux, G. (2008). What went wrong? Accounting fraud and lessons from the recent scandals. *Social research, 75*(4), 1205-1238.

Giroux, G. (2008). What went wrong? Accounting fraud and lessons from the recent scandals. *Social Research, 70*(4), 1205-138.

Gomes, M., & Chaibi, A. (2014). Volatility spillovers between oil prices and stock returns: A focus on frontier markets. *The Journal of Applied Business Research, 30*(2).

Graham, B. (2005). Investment Vs. Speculation. *Better Investing, 59*(9), 76.

Grossman, S. J., & Stiglitz, J. E. (1980). On the impossibility of informationally efficient markets. *The American Economic Review, 70*(3), 393-408.

© University of Pretoria

Hirshleifer, D., Teoh, S. H., & Yu, J. J. (2011). Short arbitrage, return asymmetry, and the accrual anomaly. *Review of Financial Studies, 24*(7), 2429-2461.

Hon, M. T., & Tonks, I. (2003). Momentum in the UK stock market. *Journal of Multinational Financial Management, 13*(1), 43-70. doi:10.1016/S1042-444X(02)00022-1

Hung Wan, K. (2007). What determines the level of short-selling activity? *Financial Management, 36*(4), 123-141.

Israel, R., & Moskowitz, T. J. (2013). The role of shorting, firm size, and time on market anomalies. *Journal of Financial Economics, 108*(2), 275-301.

Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and losers. *The Journal of Finance, 48*(1), 65-91.

Johannesburg Stock Exchange. (2011). *JSE Limited Listing Requirements.* Johannesburg: LexisNexis.

Joslin, S., Priebsch, M., & Singleton, K. J. (2014). Risk premiums in dynamic term structure models with unspanned macro risks. *The Journal of Finance, 69*(3), 1197-1233.

Kaplan, S. N., Moskowitz, T. J., & Sensoy, B. A. (2013). The effects of stock lending on security prices: An experiment. *The Journal of Finance, 68*(5), 1891-1936.

Karpoff, J. M., & Lou, X. (2010). Short sellers and financial misconduct. *The Journal of Finance, 65*(5), 1879-1913.

Kelly, P. J. (2014). Information efficiency and firm-specific return variation. *The Quarterly Journal of Finance, 4*(04), 1450018.

Kim, D. (2010). Information uncertaintly risk and the seasonality in international stock markets. *Asia-Pacific Gournal of Financial Studies, 39*(2), 229-259.

Kim, S.-H., Kim, D., & Shin, H.-S. (2012). Evaluating asset pricing models in the korean stock market. *Pacifi-Basin Finance Journal, 20*(2), 198-227.

© University of Pretoria

Kothari, S. P. (2001). Capital Markets Research in Acounting. *Journal of Accounting and Economics, 31*(1-3), 105-231.

Lakonishok, J., Shleifer, A., & Vishny, R. W. (1994). Contrarian investment,extrapolation and risk. *The Journal of Finance, 49*(5), 1541-1578.

Lamponi, D. (2014). Is industry classification useful to predict U.S. stock price co-movements? *The Journal of Wealth Management, 17*(1), 71-77.

Latif, M., Arshad, S., Fatima, M., & Farooq, S. (2011). Market Efficiency, Market Anomalies, Causes, Evidences, and Some Behavioural Aspects of Market Anomalies. *Research Journal of Finance and Accounting, 2*(9/10), 1-12.

Lee, C. M. (2001). Market efficiency and accounting research:a discussion of ‘capital market research in accounting' by S.P Kothari. *Journal of Accounting and Economics, 31*(1-3), 233-253.

Lev, B., & Thiagarajan, S. R. (1993). Fundamental information analysis. *Journal of Accounting Research, 31*(2), 190-215.

Li, J. (2012). Prediction of Corporate Bankruptcy from 2008 Through 2011. *Journal of Accounting and Finance, 12*(1), 31-42.

Lim, K.-P., & Brooks, R. D. (2010). Why do emerging stock markets experience more persistent price deviations from a random walk over tome? A country-level analysis. *Macroeconomic Dynamics, 14*(S1), 3-41.

Lintner, J. (1965). The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *The review of economics and statistics, 47*, 13-37.

Mackintosh, J. (2007, September 15). Hedge funds cash in after 'shorting'. *Financial Times*, p. 4.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance, 7*(1), 77-91.

Mckinsey & Company. (2010). *Valuation: Measuring and Manageing The Value of Companies.* Hoboken: John Wiley & Sons.

© University of Pretoria

Michaels, R. (2016, January 17). *The Impact of China's Economic Slowdown on Commodities Markets*. Retrieved April 29, 2016, from International Banker: http://internationalbanker.com/brokerage/the-impact-of-chinas-economic-slowdown-on-commodities-markets/

Mohanram, P. S. (2005). Separating winners from losers among lowbook-to-market stocks using financial statement analysis. *Review of Accounting Studies, 10*(2-3), 133-170.

Muller, C., & Ward, M. (2012). Emperical testing of CAPM on the JSE. *Investment Analyst Journal, 76*, 1-12.

Muller, C., & Ward, M. (2013). Style-based effects on the Johannesburg Stock Exchange: a graphical time-series approach. *Investment Analysts Journal, 77*, 67-82.

OECD. (2012). *OECD Science, Technology and Industry Outlook 2012.* Paris: OECD Publishing.

Ohlson, J. A. (1980). Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research, 18*(1), 109-131.

Ou, J. A., & Penman, S. H. (1989). Financial statement analysis and the prediction of stock returns. *Journal of Accounting and Economics, 11*(4), 295-329.

Pastor, L., & Stambaugh, R. F. (2003). Liquidity risk and expected stock returns. *Journal of Political Economy, 111*(4), 642-685.

Piotroski, J. D. (2000). Value investing: The use of historical financial statement information to separate winners from losers. *Journal of Accounting Research, 38*, 1-41.

Piotroski, J. D. (2005). Discussion of "Separating Winners from Losers among Low Book-to-Market Stocks using Financial Statement Analysis. *Review of Accounting Studies, 10*(2-3), 171-184.

Piotroski, J. D., & So, E. C. (2012). Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach. *The Review of Financial Studies, 25*(9), 2841-2875.

© University of Pretoria

Power, G. J., Vedenov, D. V., Anderson, D. P., & Klose, S. (2013). Market Volatility and the dynamic hedging of multi-commodity price risk. *Applied Economics, 45*(27), 3891-3903.

Ross, S. A. (1976). The arbitrage theory of capital asset pricing. *Journal of Economic Theory , 13*(3), 341-360.

Saunders, M., & Philips, L. (2014). *Doing Research in Business & Management.* England: Pearson Education Limited.

Schleifer, A., & Summers, H. L. (1990). The Noise Trader Approach to Finance. *Journal of Economic Perspectives, 4*(2), 19-33.

Schostak, F. (1997). In Defence of Fundamental Analysis:A Critique of Efficient Market Hypothesis. *Review of Austrian Economics, 10*(2), 27-45.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The Journal of Finance, 19*(3), 425-442.

Shiller, R. J. (2003). From Efficient Markets Theory to Behavioral Finance. *Journal of Economic Perspectives, 17*(1), 83-104.

Shkilko, A., Van Ness, B., & Van Ness, R. (2012). Short selling and intraday price pressures. *Financial Management, 41*(2), 345-370.

Stambaugh, R. F., Yu, J., & Yuan, Y. (2012). The short of it:Investor sentiment and anomalies. *Journal of Financial Economics, 104*(2), 288-302.

Strachman, D. A. (2002). Hedge funds: Do they make sense? behind the mystique - and fees - lies an investment approach that may suit some clients. *On Wall Street,1*.

Turan, G. B., Nusret, C., & Fousseni, C.-Y. (2015). A new approach to measuring riskiness in the equity market. *Journal of Banking and Finance, 57*, 101-117.

Wagley, J. (2000, November 13). Volatility forces hedge funds to get hip to shorting. *The Investment Dealers' Digest : IDD*, pp. 1-15.

© University of Pretoria

Westerlund, J., & Narayan, P. (2013). Testing the efficient market hypothesis in conditionally heteroskedastic futures markets. *Journal of Futures Markets, 33*(11), 1024-1045.

World Economic Forum. (2014). *Towards the Circular Economy: Accelerating the scale-up across global supply chains.* Geneva: World Economic Forum.

Yalcin, K. C. (2016). Market rationality: Efficient market hypothesis versus market anomalies. *European Journal of Economic and Political Studies, 3*(2), 23-38.

Yao, T., Yu, T., Zhang, T., & Cheng, S. (2011). Asset growth and stock returns: Evidence from Asian financial markets. *Pacific-Basin Finance Journal , 19*(1), 115-139.

Zeytinoglu, E., & Akarim, Y. D. (2013). Financial failure prediction using financial ratios: An empirical application on Istanbul Stock Exchange. *Journal of Applied Finance and Banking, 3*(3), 107.

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APPENDIXES

Appendix 1: List of Companies in the Sample

A E C I LTD	EASTERN PLATINUM LIMITED
ACUCAP PROPERTIES LTD	EDGARS CONS STORES LTD
ADCOCK INGRAM HLGS LD	ELLERINE HOLDINGS LTD
ADVTECH LTD	EMIRA PROPERTY FUND
AECI LIMITED	EOH HOLDINGS LTD
AFGRI LTD	EXXARO RESOURCES LTD
AFRICAN OXYGEN LIMITED	FAMOUS BRANDS LTD
AFRICAN RAINBOW MINERALS	FIRST URANIUM CORPORATION
ALLIED ELECTRONICS CORP	FORTRESS INC FUND LTD B
ALLIED TECHNOLOGIES	FOSCHINI LTD ORD
ANGLO AMERICAN PLC	FOUNTAINHEAD PROP TRST
ANGLO PLATINUM LTD	GOLD FIELDS LTD
ANGLOGOLD ASHANTI LTD	GRINDROD LTD
APEXHI PROPERTIES -A-	GROWTHPOINT PROP LTD
AQUARIUS PLATINUM LTD	HARMONY G M CO LTD
ARCELORMITTAL SA LIMITED	HIVELD STEEL AND VANADUM
ASPEN PHARMACARE HLDGS LTD	HOSKEN CONS INV LTD
ASSMANG LTD	HULAMIN LIMITED
ASSORE LTD	HYPROP INVESTMENTS LTD

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ASTRAL FOODS LTD	ILLOVO SUGAR LTD
AVENG LTD	IMPALA PLATINUM HLGS LD
AVI LTD	IMPERIAL HOLDINGS LTD
BARLOWORLD LTD	INTU PROPERTIES PLC
BHP BILLITON PLC	INVICTA HOLDINGS LTD
BIDVEST LTD	ITALTILE LTD
BLUE LABEL TELECOMS LTD	KAP INDUSTRIAL HLDGS LTD
BRAIT S.A.	KUMBA IRON ORE LTD
BRITISH AM. TOBACCO PLC	LEWIS GROUP LTD
CAPITAL & COUNTIES PROP PLC	LONMIN P L C
CAPITAL PROPERTY FUND	MARTPROP PROPERTY FUND
CAPITAL SHOP CENTRES GRP PLC	MASSMART HOLDINGS LTD
CAPITAL SHOP CENTRES GRP PLC	MEDICLINIC INTERNAT LTD
CAXTON CTP PUBLISH PRINT	MEDICLINIC INTERNATIONAL
CITY LODGE HTLS LTD ORD	METOREX LTD
CLICKS GROUP LTD	METOREX LTD
CURRO HOLDINGS LIMITED	MITTAL STEEL SA LTD
DATATEC LTD	MONDI LIMITED
DIMENSION DATA HLDGS PLC	MR PRICE GROUP LTD
DISTELL GROUP LTD	MTN GROUP LTD
DRDGOLD LTD	MURRAY & ROBERTS HLDGS
MVELAPHANDA GROUP LTD	SASOL LIMITED

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MVELAPHANDA RESOURCES LD

NAMPAK LTD

NASPERS LTD -N-

NET 1 UEPS TECH INC

NETCARE LIMITED

NETWORK HEALTHCARE HLDGS

NEW CLICKS HLDGS LTD

NEW EUROPE PROP INV PLC

NORTHAM PLATINUM LTD

OANDO PLC

OCEANA GROUP LTD

OCTODEC INVEST LTD

OMNIA HOLDINGS LTD

OPTIMUM COAL HLDGS LTD

PALABORA MINING CO ORD

PAN AFRICAN RESOURCE PLC

PANGBOURNE PROP LTD

PEERMONT GLOBAL LTD

PEREGRINE HOLDINGS LIMITED

PICK N PAY STORES LTD

PIK N PAY HOLDINGS LTD

PIONEER FOODS GROUP LTD

PPC LIMITED

SENTULA MINING LTD

SHOPRITE HLDGS LTD ORD

SIBANYE GOLD LIMITED

SIMMER AND JACK MINES

STEINHOFF INT HLDGS LTD

SUN INTERNATIONAL LTD

SUPER GROUP LTD

SYCOM PROPERTY FUND

TELKOM SA LTD

TELKOM SA SOC LTD

THE FOSCHINI GROUP LIMITED

THE SPAR GROUP LTD

TIGER BRANDS LTD ORD

TONGAAT HULETT LTD

TRENCOR LTD

TRUWORTHS INT LTD

TSOGO SUN HOLDINGS LTD

UNITRANS LTD

URANIUM ONE INC

VENFIN LTD

VODACOM GROUP LTD

VUKILE PROPERTY FUND LTD

WESCO INVESTMENTS LTD

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PRIMEDIA LTD

RAINBOW CHICKEN LTD

RAUBEX GROUP LTD

RCL FOODS LIMITED

REDEFINE INCOME FUND LTD

REDEFINE INTERNATIONAL P.L.C

REDEFINE PROPERTIES LTD

REINET INV SOC ANON

REMGRO LTD

RESILIENT PROP INC FUND

REUNERT ORD

ROYAL BAFOKENG PLATINUM LTD

SA CORP REAL ESTATE FUND

SA CORP REAL ESTATE LTD

SABMILLER PLC

SAPPI LTD

WEZIZWE PLATINUM LTD

WESTERN AREAS LTD

WILSON BAYLY HLM-OVC ORD

WOOLWORTHS HOLDINGS LTD

ZEDER INV LTD

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Appendix 2: Ethics Approval Letter

Dear Mr Akinboye Oyebode

Protocol Number: Temp2016-01627

Title: Application of the Altman Z (EMS) and Piotroski F-score to the Johannesburg Securities Exchange as short selling instrument.

Please be advised that your application for Ethical Clearance has been APPROVED.

You are therefore allowed to continue collecting your data.

We wish you everything of the best for the rest of the project.

Kind Regards,

Adele Bekker

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Appendix 3: Turnitin Originality Report

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