Application of pattern recognition to portfolio management

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Dissertation submitted in fulfilment of the requirements for the degree

Master of Engineering in Computer and Electronic Engineering at the

Potchefstroom Campus of the North-West University

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November 2011
ACKNOWLEDGEMENTS

The author would like to acknowledge and thank the following persons:

- First and foremost I thank the Lord God Almighty for the ability and opportunity to be able to complete this task.
- My mother, Kotie Swart, for her continued support and motivation, but most importantly for enabling me in so many ways and showing me by example what really matters.
- My sister, Alda Leversage, for her willingness to always help out and all the other little things that definitely did not go unnoticed.
- Prof A.J. Hoffman for his guidance, support and endless patience.
ABSTRACT

In this research the market’s reaction to earnings announcements is investigated. The investigation can be divided into three parts: testing whether earnings announcements convey any information to the market; finding any patterns in the market’s response to the earnings announcements and testing the exploitability of patterns through the simulation of trading strategies.

The three part investigation essentially focuses on two parts of the market’s reaction to earnings announcements on the Johannesburg Stock Exchange (JSE) for the period 1991 to 2010. The first part focuses on the short-term market reaction around earnings announcements including the dynamics of the response and the information content of earnings announcements, the predictability of the earnings surprise and the exploitability of the predictability.

We found that the magnitude of the cumulative returns for the days [0; 2] is on average positive and decreases with an increase in firm size. The average information content of earnings announcements also decreases with an increase in firm size. This therefore means information uncertainty decreases with size. The earnings surprise is on average found to be predictable for firms in the two smallest size categories and shares with relatively low liquidity. Proxies for the value effect and particularly the autocorrelation structure of unexpected earnings provide some additional information to predict future unexpected earnings. Our findings regarding the autocorrelation structure of the three-day reaction (event returns) to earnings announcements are consistent with that found by Bernard and Thomas [1]. We however found that the autocorrelation is largely restricted to small size firms.

The second part of the investigation involves the longer-term reaction to earnings announcements which includes investigating the statistical significance and exploitability of the post-earnings announcement drift (PEAD). The Post-Earnings Announcement Drift anomaly has been widely researched and confirmed for several markets around the world. It is observed that contrary to previous research conducted on the JSE that confirmed the overreaction phenomenon for the period 1975-1989 [2], evidence suggests that for the
period under investigation the PEAD effect occurred on the JSE for the period from 1991 to 2010 and it is found to be statistically significant and independent of the size, value and/or momentum effect. All these effects are however found to have a significant influence on the magnitude of the PEAD effect. The results indicate that the market reacts very quickly to the announced earnings and it is not until about the 20th to 40th trading day after the earnings announcement that the market starts drifting in the direction of the initial reaction. The market therefore seems not to underreact to the earnings information at first, but that it receives confirmation in the two months following the announcement that is indicative of better future prospects and that the higher than expected earnings might persist. In retrospect, when only considering earnings news, it thus seems that the market under-reacted to the information released at the earnings announcement.

We however found no conclusive evidence in the trading simulation analysis to indicate that the PEAD effect can be exploited on a profitable basis. What the simulation analysis however did reveal was that the liquidity limitations imposed by the simulator lowered the overall returns achieved. It can therefore be argued that the PEAD effect is related to market frictions that prevent arbitrageurs to exploit the apparent profit opportunity. Our results tend to agree with the limited arbitrage hypothesis of Mendenhall [3] who argued that the magnitude of PEAD is related to the risk faced by arbitrageurs and Chordia et al. [4] who found that the PEAD anomaly mainly occurs for the highly illiquid shares.
OPSOMMING

Met hierdie navorsing word die mark se reaksie op aankondigings van maatskappy-verdienste ondersoek. Die ondersoek word in drie dele verdeel: eerstens word gekyk of die aankondiging van verdienste enige nuwe inligting aan die mark oordra, tweedens word daar gesoek na patrone in die mark se reaksie op die aankondiging van verdienste en derdens word die winsgewende ontginbaarheid van dié patrone deur die simuliasie van verhandelings-strategieë getoets.

Die drieledige ondersoek fokus hoofsaaklik op twee dele van die mark se reaksie op aankondigings van maatskappy-verdienste op die Johannesburgse Effektebeurs (JSE) vir die tydperk vanaf 1991 tot 2010. Die eerste deel fokus op die korttermyn markreaksie rondom aankondigings, insluitend die dynamika van die reaksie en die inligting vervat in aankondigings van verdienste, die voorspelbaarheid van die verrassing in verdienste en die winsgewende ontginbaarheid van die voorspelbaarheid.

Die grootte van die kumulatiewe opbrengste vir die dae [0; 2] is gemiddeld positief en daal met 'n toename in firma grootte. Die gemiddelde inligting vervat in verdienste-aankondigings verminder ook met 'n toename in firma grootte. Dit beteken dus dat die onsekerheid rakende verdienste-aankondigings verminder met 'n toename in firma grootte.

Die resultate dui daarop dat die verrassing in verdienste gemiddeld voorspelbaar is vir maatskappe in die twee kleinste grootte-kategorieë en vir aandele met 'n relatief lae likiditeit. Veranderlikes verteenwoordigend van die waarde-effek en veral die outokorrelasie struktuur van onverwagte verdienste verskaf ekstra inligting om toekomstige onverwagte verdienste te voorspel. Ons bevindinge ten opsigte van die outokorrelasie struktuur van die drie-dag reaksie op verdienste-aankondigings stem ooreen met dié van Bernard en Thomas [80]. Ons het egter gevind dat die beduidende outokorrelasie grootliks beperk is tot kleiner firmas.

Die tweede deel van die ondersoek behels die langer termyn reaksie op verdienste-aankondigings. Dit omvat toetse wat die statistiese beduidendheid en winsgewende ontginbaarheid van die neiging in opbrengs na verdienste aankondigings (PEAD) bepaal. Die PEAD-anomalie is wyd nagevors en vir verskeie markte regoor die wêreld bevestig. Vorige navorsing wat op die JSE gedoen is, het bevind dat die oorreaksie-verskynsel vir die
tydperk vanaf 1975 tot 1989 [1] voorgekom het. In teenstelling daarmee dui die resultate van hierdie navorsing daarop dat die PEAD-verskynsel vir die tydperk 1991 tot 2010 op die JSE statisties beduidend was. Verder is dit ook onafhanklik van die grootte, waarde en/of momentum effek. Al hierdie verskynsels het egter 'n beduidende invloed op die grootte van die PEAD-verskynsel. Dit is bevind dat die mark baie vinnig reageer na die aankondiging van onverwagte verdienste, en dit is nie voor die 20ste tot 40ste dag na die aankondiging dat die mark begin neig in die rigting van die aanvanklike reaksie nie. Dit blyk dus dat die mark aanvanklik nie onderreageer op die verdienste-aankondiging nie, maar dat dit oënskynlik bevestiging van beter vooruitsigte in die tweede maand na die aankondiging ontvang en dat die hoër as verwagte verdienste kan voortduur. In retrospek, wanneer slegs verdienste nuus oorweeg word, blyk dit dus dat die mark onderreageer op die inligting vervat in verdienste aankondigings.

Ons het egter geen oortuigende bewyse in die simulasi-analise gevind wat daarop dui dat die PEAD winsgewend ontginbaar is nie. Die simulasi-analise het egter aan die lig gebring dat die likiditeitsbeperkinge wat deur die simulator opgelê word, die algehele opbrengste wat behaal kan word, verlaag. Die argument word aangevoer dat die PEAD-verskynsel verwant is aan markwrywing wat verhoed dat arbitrageurs die skynbare winsgeleentheid ontgin. Ons is geneig om saam met die beperkte arbitrage-hipotese van Mendenhall [3] te stem, wat aanvoer dat die grootte van PEAD verwant is aan die risiko wat arbitrageurs in die gesig staar, asook die bevindinge van Chordia et al. [4] wat aandui dat die PEAD-anomalie hoofsaaklik vir die uitsers illikiede aandele voorkom.
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GLOSSARY AND ABBREVIATIONS

AMEX – American Stock Exchange
APT – Arbitrage Pricing Theory
B/M (and B2M) – Book-to-market
CAL – Capital allocation line
CAPM – Capital Asset Pricing Model
DA – Dynamic allocation
DY – Dividend Yield
EMH – Efficient Markets Hypothesis
EY – Earnings Yield
FF – Fixed fractions
HML – High minus low
IR – Information Ratio
IU – Information Uncertainty
JSE – Johannesburg Stock Exchange
LDT – Last date to trade
NYSE – New York Stock Exchange
P/E – Price-to-earnings
PEAD – Post earnings-announcement drift
RMSE – Root mean square error
SENS – Stock Exchange News Service
SMB – Small minus big
SML – Security Market Line
SUE – Standardised unexpected earnings
UE – Unexpected Earnings
1. **INTRODUCTION**

“While in theory randomness is an intrinsic property, in practice, randomness is incomplete information.”

- **Nassim Nicholas Taleb**

1.1 **BACKGROUND CONTEXT**

The South African Concise Oxford Dictionary defines investment as the putting of money into financial schemes; shares, or property with the expectation of achieving a profit [5]. In other words investment can be defined as the use of money or capital in order to gain profitable returns, as interest, income or appreciation in value. Usually investing comprises the buying of assets in order to sell them in the future for more than they were bought or buying them for the income generated by the assets.

The goal of investment management is firstly to analyse the assets to determine their current value, probable future value as well as the growth in income if applicable or any other indication of price appreciation or depreciation in the future [6]. This is done in order to identify assets with a higher than average probability for growth and to optimise the time to invest in them. Secondly, investment management aims to efficiently and optimally allocate capital to these opportunities while managing the risks involved to achieve the specific investment goals [6].

The Efficient Market Hypothesis (EMH) [7] is a cornerstone of modern finance theory and is based on the premise that all market participants form rational expectations about future security returns. Therefore a security’s price at any point in time is the aggregate expected value of the present value distribution calculated from all future estimated cash flows [7]. In other words, a security’s (asset) price already contains the market’s expectation of future cash flows and growth. The EMH has come under scrutiny and a great deal of research effort has gone into identifying and analysing anomalies to this hypothesis. Although some of the anomalies that have been observed can be explained by some form of risk premium, others claim to contradict the EMH and questions its validity.
A specific anomaly to the efficient market, called the overreaction hypothesis, has been observed by De Bondt and Thaler [8]. Their research indicates that the stock market tends to overreact to unexpected news events such as earnings announcements that exceed expectations. They further show that equities that experience the highest (lowest) return in response to an event tend to underperform (outperform) in the subsequent period, therefore ‘correcting’ its mistake. They hypothesise that the reason for the overreaction is the market’s inefficient response to the earnings information. Research has found the random walk model to be a good description of companies’ earnings behaviour, except where earnings tend to revert to the mean after experiencing extremes [9].

An anomaly opposite to the overreaction hypothesis, the under-reaction anomaly, has also been found to exist. This anomaly is explained by the slow reaction of market participants to new information such as earnings announcements, which constitute an initial under-reaction which is gradually corrected as cumulative share returns tend to drift in the same direction of the earnings response for a substantial period after the announcement has been made [10], [11], [12], [13]. Thus the cumulative share returns of companies which announce higher (lower) than expected earnings tend to drift upwards (downwards) for a period after the information has been made public. The under-reaction phenomenon is more commonly known as the post-earnings announcement drift (PEAD) anomaly.

A fundamental principle of efficient markets is that any new information ought to be reflected in share prices almost instantaneously and the adjustments should be fair according to the new information received. Predictable patterns such as market overreactions and under-reactions and their respective subsequent corrections should not exist in a perfectly efficient market.

Although much of the anomaly research is directed at discrediting the EMH, the anomaly research is of huge practical importance to the active money management industry in their quest to outperform the market [14], [7]. To outperform the market one has to be more accurate in forecasting future returns. The anomalies identified in academic research are a source of predictability used to forecast future returns. According to Grinold and Kahn [14] active management is forecasting.
The second problem of investment management, namely to efficiently allocate capital in order to achieve the investment goals, is addressed by what is commonly known as portfolio management. Portfolios are constructed to each investor’s personal risk preferences. Markowitz [15] developed the mean-variance framework for optimal capital allocation to achieve the best possible return for a specified amount of risk as defined by the variance of a portfolio. The purpose of portfolio management is thus to find an optimal trade-off between risk and return according to the investor's risk preferences.

1.2 PROBLEM STATEMENT

The overall goal of this research is to find patterns and predictability in financial data through analysing the market’s reaction to new information and to test the profitable exploitability of the patterns and predictability.

The problem investigated in this research focuses on a specific information event, namely earnings announcements. The research problem can be divided into three parts: testing whether earnings announcements actually convey any information to the market; finding any patterns in the market’s response to the earnings announcements and testing the exploitability of patterns through the simulation of trading strategies, with each successive part depending on the outcome of the former.

The problem can be stated into three hypotheses:

**Hypothesis 1:**

- \( H_0 \): Earnings announcements do not convey any new information to the market and therefore no significant reaction is expected.

If hypothesis one is proven to be false, the implications are investigated by investigating the following hypotheses:

**Hypothesis 2:**

- \( H_0 \): There is no relationship between unexpected earnings (earnings surprise) and subsequent post-earnings announcement returns for the period 1991 to 2010 on the JSE.
Hypothesis 3:

- \( \text{H}_0 \): The earnings surprise cannot be predicted with significant accuracy.

Each of the three hypotheses is statistically tested and depending on the outcome of hypothesis two and three, the exploitability of the patterns is evaluated by simulating trading strategies aimed at exploiting the abovementioned effects. The simulation study investigates the economic significance of the last two hypotheses and whether or not the results correspond with the statistical analysis.

1.3 OBJECTIVES AND METHODOLOGY

The purpose of this research is firstly to establish whether earnings announcements convey new information to the market by analysing how the market reacts to earnings announcements. Thus the first objective is to test hypothesis 1 and analyse the market dynamics surrounding earnings announcements.

Secondly, the market’s reaction to earnings announcements are investigated to establish whether the PEAD anomaly occurred on the Johannesburg Stock Exchange (JSE) for the period 1991 to 2010 and determine which other variables are predictive of return subsequent to earnings announcements; this will establish whether the PEAD anomaly is a manifestation of other well documented anomalies such as the size effect, the value effect or the momentum effect or if it is an anomaly independent of other factors.

Historical daily equity price data for the period from 1991 to the end of 2010 for companies listed on the JSE is downloaded from McGregor BFA, as well as the earnings and dividend announcement dates. Necessary adjustments for share splits are made and data is cleansed by removing extreme outliers, which mostly constitutes data that is further than 5 to 6 standard deviations from the mean. The data is then analysed to find statistical evidence of the anomaly occurring on the South African market, by performing cross-sectional correlation, cross-sectional sorts and cross-sectional multivariate regression analysis. Variations of the post-earnings announcement returns as function of market capitalisation (size effect), relative value (value effect) and momentum are also investigated.
The third objective is to test the predictability of the earnings surprise itself and its relation to other anomalies mentioned above. The same methodology mentioned above will be used to test hypothesis 3.

After establishing the statistical significance and testing both hypotheses, the fourth and final objective is to test the economic significance and thus the profitable exploitability of any predictable patterns in security returns. This is accomplished by designing trading strategies, developing software in MATLAB® and Microsoft Excel® and running simulations which take real-world constraints such as transaction costs and liquidity constraints into account. Several performance measures are applied to each simulation’s results to establish whether abnormal risk adjusted returns are achieved. Detailed aspects of the analysis methodology used in investigating the three hypotheses and the simulation methodology are discussed in chapter 4.

1.4 LIMITATIONS OF THE RESEARCH

Some limitations to the research have been identified; these include the following:

- The research focuses on a specific event and ignores the impact of other simultaneous events, such as other news releases, may have on the price of a security.

- Performance evaluation is done on historical data and though the simulation will be thoroughly designed to prevent data-snooping, history is not an exact predictor of the future. Financial data is not guaranteed to be stationary and therefore the characteristics of the data may change over time.

- This research is an empirical investigation and focuses on the analysis and simulation of a system. Thus the research is limited in the degree to which it contributes to the theoretical literature, but the empirical investigation will nonetheless contribute to improving the understanding of the underlying market mechanics related to earnings announcements.

- The data is limited to firms that were listed on the JSE in the year of 2010 and is therefore not free from survivorship bias.
1.5 Outline and Applications

Chapter 2 gives a background overview of financial theory with specific reference to the efficient market hypothesis (EMH) and a brief look at the market as a stochastic dynamic information processing system; this includes an overview of relevant matter from dynamical systems theory and reference to selected relevant findings from information theory. The chapter proceeds with an overview of empirical evidence that challenges the EMH and some new thinking regarding market efficiency. The practice of active management is discussed by building on the groundwork of modern portfolio theory, the capital asset pricing model and arbitrage pricing theory. Specific tools and techniques used in active portfolio management are then briefly discussed with an emphasis on the techniques used in this research.

Chapter 3 provides a review of the literature regarding the post-earnings announcement drift (PEAD) anomaly and the market’s reaction surrounding earnings announcements. Possible explanations for the PEAD anomaly are reviewed as well as research done locally that provides evidence contrary to the PEAD effect. Research investigating whether the PEAD anomaly is exploited by institutional investment managers and investigating the implementation of a strategy that exploits the effect are reviewed. Literature regarding the earnings surprise, its predictability and the market’s reaction to such announcements are reviewed in light of market efficiency and the information content of earnings announcements.

Chapter 4 takes a closer look at the data and methodology used to conduct the research. The specific data used as well as the data preparation and cleaning methodology used are discussed. The statistical techniques used in testing the hypotheses are reviewed as well as the simulation methodology and all the constraints that are taken into account. Short descriptions of the algorithms used are also given without going into too much software specific details.

In chapter 5 results of the statistical analysis are presented and discussed. This chapter consists of three sections; each presenting the results obtained from the tests analysing each of the three hypotheses. Clear evidence regarding each hypothesis on the local market
for the period 1991-2010 is presented as well as findings that might explain and illuminate the effects studied.

**Chapter 6** gives the results of the trading simulations that were performed. Several simulations are performed to test the profitable exploitability of the PEAD effect and the predictability of the earnings surprise. The simulation parameters and forecasting method are varied and the sensitivity of the return and risk to each are given. The results give a good indication to whether the anomalies can be exploited in a real-world strategy, but rather than providing the optimal trading strategy, it aims to illuminate the effect each parameter and variable have on the results achieved.

In **chapter 7** the research is concluded and the findings are discussed. Some possible future extensions to this research are also discussed briefly.

The research gives evidence on the significance and information content of earnings announcement as well as the market’s reaction to an earnings surprise and whether it could be profitably exploited. This research therefore provides the necessary results for institutional money managers or private investors to decide whether to use, adapt and apply the information and strategies in an investment/trading program. It should however be kept in mind that this research reflects what happened in the past and the results may not hold in the future.
2. BACKGROUND

“The first duty of intelligent men is the restatement of the obvious.”

- George Orwell

In this chapter an overview of financial theory with specific reference to the efficient market hypothesis (EMH) and a brief look at the market as stochastic dynamic information is provided. Empirical evidence that challenges the EMH and some new thinking regarding market efficiency and behavioural finance and how it may explain some of the anomalies is also reviewed. The practice of active management is discussed by building on the groundwork of modern portfolio theory, the capital asset pricing model and arbitrage pricing theory. Specific tools and techniques used in active portfolio management are then briefly discussed with an emphasis on the techniques used in this research.

2.1. INTRODUCTION

Widely accepted financial theory maintains that active management is a futile endeavour. Evidence however exists that active managers may consistently beat the market [14].

2.2. EFFICIENT MARKETS HYPOTHESIS

According to the efficient markets hypothesis (EMH), a cornerstone of modern finance, all market participants act rationally and immediately and therefore all available information is immediately reflected in the price of the security, thereby eliminating any profit opportunity. Because all new information arrives in a random fashion and the information is itself unpredictable and random, security prices should also be unpredictable and random. This is the reasoning behind the argument that security prices should follow a random walk [7]. If the information was not unpredictable, it would have been part of current information and thus be reflected in current prices.

The EMH comes in three different forms:

- The weak form suggests that the market already reflects all information that can be derived from historical data.
The semi-strong form suggests that all publicly available information regarding the prospects of the security is already reflected in the price of the security.

The strong form suggests that all information is reflected in the security price and there exists absolutely no profit opportunity.

The implications of the efficient markets hypothesis are quite profound. If the weak form hypothesis is correct it suggests that technical analysis\(^1\) is a futile endeavour and not worth the effort. If the semi-strong form is correct it suggest that fundamental analysis will also bear no fruit and the forecasting of future earnings, dividend yield, supply and demand and macro-economic factors will yield no performance above that of the market.

The implications of the strong form of the hypothesis are quite extreme and it states that not even insiders or those with privileged information can beat the market. The fact that insider trading is illegal, suggests that they might have an edge and that the strong form might be a bit outrageous [7].

If one believes that the market is semi-strong efficient then active management is not worth the costs and should be abandoned totally. Therefore advocates of the semi-strong and strong form of the efficient market hypothesis support a passive management strategy that doesn't try to outperform the market, but follow a certain market index and keep transaction costs as low as possible.

2.3. **THE MARKET AS A STOCHASTIC DYNAMIC SYSTEM**

A stock market can be regarded as a dynamical system that takes information as input and produces a change in price as output as shown in *Figure 1*.

Assuming linear system dynamics, the returns are directly proportional to the amount of information. The random walk hypothesis states that the information input is random and therefore the market can be regarded as a stochastic dynamic system with a random return as output.

---

\(^1\) Technical analysis can be defined as the search for repeated and predictable patterns in security prices.
Assuming all market participants behave rationally, a security’s price at any point in time is the present value of all future estimated cash flows, either emanating from dividend payments, capital appreciation or both [7]. The input to the system is the current estimate of future cash flows – the less information we have about future cash flows the less certain the estimate is. The risk involved in an investment can be regarded as the uncertainty about the present value of all future cash flows. Information is therefore the removal of uncertainty.

In the mathematical theory of information [16], [17], information is defined in terms of the concept of entropy. Entropy is defined as the uncertainty in the outcome of an event. The entropy $H(X)$ of a random variable $X$ is a measure of the uncertainty of a random variable; it is a measure of the average amount of information $I(X)$ required to describe a random variable [17].

$$H(X) = - \sum_k p(x_k) \log(p(x_k)) = \sum_k p(x_k) I(X = x_k)$$  
(1)

- $p(x_k)$ – Probability of random variable $X$ being equal to the value $x_k$: $P(X = x_k)$
- $I(X)$ – Amount of information conveyed regarding the outcome of an uncertain event. It is mathematically equal to the negative logarithm of the probability of the outcome. Thus the more likely the outcome of an event, the less information is conveyed by knowing its outcome.

Accounting earnings information is central in price formation and is a widely used measure to evaluate a firm’s ability to generate future profits and cash flows.

Assuming that in the long run the difference between cash based and accrual accounting methods is negligible, security prices should follow earnings in the long run [18]. As new
information is released, the market updates its estimates of earnings and the price adjusts according to the system dynamics of the specific security. Assuming that the availability of information for firms differ, one would expect earnings announcements on average to convey more information in the case of firms with high levels of earnings uncertainty. Firms with high earnings uncertainty can thus be regarded as firms with high entropy. The reaction to individual earnings announcements are however related to the specific information \( I(X = x_k) \) content in an announcement and not the average amount of information required or entropy of that firm or group. In other words, the more unlikely the announced earnings are, the bigger surprise it is to the market and the larger the reaction in prices.

Figure 2 depicts a diagram of a typical input-output system with feedback. This is a much simplified version of a real stock market and the weak form of the EMH argues that the system doesn’t contain any feedback. To accurately predict the output of a system, one has to accurately predict the input and know the system dynamics to get a reasonably accurate estimate of the output. If the input to the system is totally stochastic and unpredictable as the EMH and random walk theory suggests, the output is also unpredictable.

Substantial evidence has been found that contradicts or can't be explained by the random walk model. Whether this evidence refutes the efficient market hypothesis is still debated among academics. Much of the evidence is explained by some risk premium that compensates for the returns achieved, although some evidence suggests above average

2.4. **Empirical Evidence**

Substantial evidence has been found that contradicts or can't be explained by the random walk model. Whether this evidence refutes the efficient market hypothesis is still debated among academics. Much of the evidence is explained by some risk premium that compensates for the returns achieved, although some evidence suggests above average
returns even after adjusting for risk. In most cases the return is adjusted by risk as determined by the capital asset pricing model (CAPM) [7]. Where the returns are still abnormally high after risk adjustment, the CAPM is questioned for accuracy. Amongst certain schools of thought there seem to be an unwillingness to let go of the efficient market hypothesis.

Empirical evidence found in the literature that challenges the EMH is briefly summarised below; no explanation is given for the source of excess returns that were observed or whether it truly defies the EMH.

Evidence that tests the weak form of the EMH [7]:

- The momentum effect – Short term positive serial correlations in returns time series have been found in several markets. This effect is the basis for a trend following investment strategy [7], [19], [20], [21], [22], [23].

- Contrarian effect – Longer term negative serial correlations have been observed. It is found that markets tend to revert to the mean and there are thus periods of correction and overreaction. The mean that the market tends to revert to is referred to as the fundamental value of the market and is determined by fundamental analysis. Thus, mean reversion (contrarian effect) is the basis for a value investment strategy [7], [24], [25], [26].

- Recurring price patterns as used by technical analysts in predicting future trends [27], [28], [29].

Evidence that tests the semi-strong form of the EMH:

- Value effect
  - P/E ratio – Securities with a low price-to-earnings (P/E) ratio tend to outperform stocks with a high P/E ratio. A low P/E ratio is an indicator of an undervalued stock [7], [30].
  - High book-to-market ratio – This is also an indication of value and evidence suggests that firms with high B/M ratios tend to provide superior returns [7], [20], [31].
• Small firm effect – Smaller companies tend to provide superior returns even on a risk adjusted basis [7], [20], [32].

• Post-earnings announcement drift - prices tend to drift in the direction of the earnings surprise after an earnings announcement [2], [7], [10], [13], [21].

In addition to the abovementioned anomalies the returns of securities are not normally distributed as assumed in many financial models such as the random walk model, the CAPM and the Black-Scholes model for option pricing. Some of the irregularities with the normal distribution are:

• Excess kurtosis or what is commonly referred to as fat tails [33], [34].
• Skewness of the distribution [33], [34].
• Time varying volatility, volatility clustering and long memory [33].
• Asymmetry of prices – Bull markets are longer and move slowly while bear markets are sudden and usually don't last as long [33].
• The occurrence of extreme events - Market crashes and bubbles [33], [35], [36].

The evidence clearly indicates some discrepancies with the EMH, however it is argued that some anomalies can be explained by some risk premium, whether as explained by the CAPM or some other model. It should however be noted that tests of market efficiency usually try to find profit opportunities, but it is argued that the converse – the lack of profit opportunities – does not imply market efficiency [7], [37]. While the EMH has not been totally discarded, the quest for a hypothesis that better explains the empirical evidence has delivered quite a few candidates, which will be discussed next.

2.5. NEW PERSPECTIVES

In this section hypotheses that aim to explain the observed phenomena are briefly discussed.

BEHAVIOURAL FINANCE

Behavioural Finance aims to explain empirical anomalies by introducing investor psychology as a determinant of asset pricing [38], [39]. The basis of behavioural finance is that conventional finance theory is not based on how real people make decisions. Conventional financial theory assumes a rational decision maker with infinite computing power and one
that does not form opinions about the world as time goes on. A rational decision maker thus always makes the optimal decision under uncertainty and maximises his utility function. In contrast to the rational decision maker, a real human decision maker does not have infinite computing power and does not have all information at hand. Human decision makers also have emotions that influence the decisions they make. Sub-optimal decisions are thus inevitable. However, the existence of 'irrational' decision makers are not sufficient to make markets inefficient: if arbitrageurs see a miss-pricing caused by some irrational behaviour and try to profit from it, the profit opportunity will quickly disappear and render markets efficient. However, behaviourists argue that the actions of such arbitrageurs are limited [7].

The limit of arbitrage can be explained by investors' inability or unwillingness to exploit the apparent opportunity. This can be attributed to several factors such as implementation costs, limited mandates, risk of being wrong about the opportunity and also the risk that the rest of the market may not see the same opportunity and 'correct' the price for some time [7].

EVOlUtIoNARY FINANCE AND ADepATIVE MARKET HYPOTHESIS

New models and hypotheses trying to reconcile traditional financial theories based on the EMH with behavioural finance have been proposed. Investors and traders are modelled as heterogeneous agents who do not always behave rationally, have different goals, different investment horizons and different information sets [40], [41].

One of these models is the adaptive market hypothesis proposed by Lo [37], [42]. This hypothesis is based on evolutionary principles such as competition, adaptation and natural selection. It states that prices reflect as much information as imposed by the combination of environmental conditions and the number and nature of participants in the market. With this approach, traditional models of modern finance can co-exist with behavioural models. According to Lo [42], the adaptive market hypothesis can be viewed as a new version of the efficient market hypothesis, derived from evolutionary principles.

Another hypothesis with similar implications and basis of reasoning is the fractal market hypothesis proposed by Peters [43], [44], [45]. While behavioural finance studies the
anomalies and their respective explanations in terms of individual behaviour, the abovementioned hypotheses take a macro view of the market and therefore try to explain the aggregate behaviour of all market participants. This implies that the market is a complex non-linear dynamic self-organising system. The aggregate behaviour of heterogeneous agents leads to emergent properties of the system and may explain some of the anomalies observed in empirical studies.

2.6. Framework for Active Management

According to many commentators, investment management has transformed from an art to a science in the last few decades, but the process is not yet complete and the practice is continuously evolving. By using quantitative techniques and following structured processes, investment management is now also considered a systematic practice.

Active portfolio management is the process of finding mispriced securities with an above average probability for abnormal growth in the future. As stated earlier, according to Grinold and Kahn active management is forecasting [14]. Therefore the process of finding mispriced securities can be regarded as a forecasting problem.

To assess the pricing of securities and detect mispricing from the forecasts, a benchmark or reference value is needed against which security forecasts and portfolio performance can be measured. In order to be successful in active management one has to ‘beat’ this benchmark in terms of risk-adjusted return.

Calculating abnormal risk-adjusted return therefore requires a model for measuring normal performance [46]. A very basic model would be the constant mean-return model.

\[ R_{t,t} = \mu_t + \zeta_{t,t} \]  

(2)

The normal return of a security is equal to a constant plus a normally distributed innovation with zero mean. This model has its shortcomings; it does not take relative risk into account and assumes all assets behave the same. This model should not be used in all but the simplest of cases. The capital asset pricing model is a more advanced model of theoretical normal return that is used in investment management practice.
The capital asset pricing model (CAPM) is a theoretical model to determine the rate of return required from an asset to be fairly compensated for the non-diversifiable risk taken.

The CAPM is used for pricing individual assets or portfolios. The model determines the fair expected return in relation to the market return, the risk-free rate and the asset or portfolio’s sensitivity to systemic risk or market risk.

\[
E(R_i) = R_f + \beta_i (E(R_m) - R_f)
\]

\(E(R_i)\) – Expected return of asset \(i\).
\(R_f\) – Risk-free rate of return.
\(E(R_m)\) – Expected market return.
\(\beta_i\) – (Beta) The sensitivity of the expected asset returns to the expected excess market returns.

The CAPM gives us the tool to estimate an asset or portfolio’s abnormal risk-adjusted return. The regression model parameters of any security can be estimated using ordinary least-squares estimation. The market model that will be estimated is:

\[
E(R_i) - R_f = \alpha_i + \beta_i (E(R_m) - R_f) + \epsilon_{i,t}
\]

where \(\alpha_i\) is the abnormal risk-adjusted return as estimated by the CAPM. This can be used to determine securities that are undervalued or overvalued. It should however be noted that this is only useful for making investment decisions when one has reasonably accurate estimates (forecasts) of future expected returns and systematic risk. The CAPM is thus useful for determining consensus expected returns, which serves as a standard of comparison for forecasts made. Investment decisions are driven by the difference in forecasts and the consensus.

The security market line (SML) in Figure 3 gives a graphical representation of the CAPM. The SML is a plot of a security’s expected return against the systematic risk (\(\beta\)). The slope of the line is equal to the market risk premium \(E(R_m) - R_f\) at any given time.
The CAPM is considered a one factor model, because the only factor it takes into account to price an asset is the market return. Several multi-factor models have been proposed that provide a better description of security returns.

The Fama-French three factor model is probably the most famous multi-factor model.

**Fama-French Three Factor Model**

Fama and French introduced two additional systematic factors to the CAPM’s single market factor, namely firm size and the book-to-market ratio [47], [7]. These additional factors are motivated by the empirical evidence which show that small firms and firms with high book-to-market ratios provide higher returns than predicted by the security market line of the CAPM. They argue that these two factors are proxies for risk not captured by the CAPM beta and thus result in the return premium associated with these factors.

The size premium is calculated by sorting firms by market capitalisation and grouping those with smaller than median market capitalisation and those with larger than median market capitalisation into the small and large groups respectively. The size premium SMB (small minus big) is then calculated as the difference between the equally weighted return of the small and large groups. Similarly the firms are sorted according to book-to-market ratio and grouped into three equal groups each representing 33.3% of the firms. The value premium HML (high minus low) as measured by the book-to-market ratio is then calculated as the

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return of the group with the highest book-to-market ratio minus the return of the lowest book-to-market group.

This gives the three factor model equation

\[ E(R_i) - R_f = \alpha_i + \beta_{M,i}(E(R_m) - R_f) + \beta_{SMB,i}(SMB) + \beta_{V,i}(HML) \]  

(5)

The three factor model serves as an example of the more general class of multi-factor models which are widely used in active portfolio management. The financial theory provides a framework to investigate not only the efficiency of the market but factors that are predictive of abnormal returns. These factors are the source of alpha (profits) for active managers.

**ARBITRAGE PRICING THEORY**

Factor models are tools that allow us to describe and quantify the different factors that affect the rate of return on a security during any time period. The arbitrage pricing theory (APT) developed by Stephen Ross in 1976 [48] provides the theory behind factor models. Similar to the CAPM, the APT predicts a SML which links expected returns to risk. The APT makes three assumptions: security returns can be described by a factor model; there are enough securities to diversify away firm specific risk; and well-functioning markets do not allow for the persistence of arbitrage opportunities³.

The APT equation to calculate expected excess returns is:

\[ E(R_i) = \sum_{k=1}^{K} \beta_{i,k} \cdot R_k \]  

(6)

According to the APT the expected excess return on any security is determined by the security’s factor exposures and the factor return forecasts associated with those factors assuming stationarity in the relationship between the factors and excess returns.

The APT points the active manager toward the relationship between factors and expected returns and is useful as a model to forecast expected excess returns [14]. Using the APT in forecasting is a two-step process. Firstly the factors should be identified and each firm’s

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³ Arbitrage opportunities arise whenever the Law of One Price is violated. The Law of One Price states that if two securities are equivalent in all relevant aspects, then they should have the same market price.
exposure to those factors calculated ($\beta_{i,k}$). Secondly the factor forecasts ($R_k$) should be estimated.

The difficulty however lies in identifying the factors to use in forecasting expected returns, because the APT does not guide the modeller in selecting factors. Forecasting the factor returns is also no easy task. Both these tasks make active portfolio management a challenging endeavour.

**PORTFOLIO SELECTION**

The theoretical base for forecasting and measuring excess security returns has been laid, but there is one facet of active portfolio management that has not been addressed. After possible investment opportunities have been identified the active manager needs to optimally allocate capital to each opportunity/security in order to achieve maximum return for a given risk level or minimise the risk for a specific return.

Assuming that an active manager has recognised two investment opportunities or securities to invest in from his forecasts, what is the optimal allocation of capital to maximise return or minimise risk?

The expected return $E(R_p)$ of a portfolio consisting of two securities (asset1 and asset2), are calculated as:

$$E(R_p) = w_1 E(R_1) + w_2 E(R_2)$$  \hspace{1cm} (7)

$w_1$ and $w_2$ are the weights allocated to each security. The variance of the portfolio is calculated as:

$$\sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2Cov(R_1, R_2)$$ \hspace{1cm} (8)

The covariance of the two securities can be written in terms of their correlation coefficient $r_{1,2}$ such that the portfolio variance is:

$$\sigma_p^2 = w_1^2 \sigma_1^2 + w_2^2 \sigma_2^2 + 2w_1w_2\sigma_1\sigma_2 r_{1,2}$$ \hspace{1cm} (9)
Figure 4 gives an example of the expected portfolio return when the weighting in the securities changes. If the active manager’s only goal is to optimise return, no matter the risk, he would choose to only invest in asset 2 (100% weight). The portfolio standard deviation for different correlations ($r$) between the 2 assets is given in Figure 5. It is clear that the lower the correlation between the assets, the more opportunity for lowering the risk by combining assets; this generalises to more than 2 assets.

In Figure 6 the above two figures are combined. From this figure it is clear that the lower the correlation between the assets the lower the risk for a given return.

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4 For illustration purposes the expected return for asset 1 is 10% and for asset 2, 25%.
5 The standard deviations for asset 1 and 2 are 15% and 25% respectively.
This simple example gives the basic argument behind Markowitz’s [15] portfolio selection and mean-variance optimisation for optimal capital allocation. When this is applied to multiple assets one gets the chart as shown in Figure 7 [7]. The efficient frontier is the minimum variance portfolios obtainable for every possible expected portfolio return.

Portfolios consisting of risky assets all lay on the efficient frontier; this is the opportunity set of risky assets. But if the risk-free asset (with return $R_f$) is added to the portfolio we get the risk-return relationship as depicted by the capital allocation line (CAL) in Figure 8 [7]. Although the CAL can go through any point on the efficient frontier, the optimal CAL is the
line that is tangent to the efficient frontier because this is the line which maximises the slope. The slope $S$ is calculated as

$$S = \frac{E(R_p) - R_f}{\sigma_p}$$

The slope is the reward-to-variability ratio, which is also known as the Sharpe ratio, so by maximising the slope one maximises the reward for each unit of variability. This enables the investor to make an optimal investment according to his risk preference by increasing/decreasing his capital allocated to the risk-free asset.

For a constant risk-free rate the portfolio with the highest Sharpe ratio is also the portfolio with the highest geometric growth rate. In the long run the logarithmic wealth of the investor will be maximised when following the Kelly criterion for optimal capital allocation. The Kelly criterion calculates the optimal allocation to the risky portfolio and the risk-free asset to maximise long term logarithmic wealth and to minimise the risk of ruin [49].

The derivation of the Kelly formula is outside the scope of this research, but the interested reader may refer to Thorpe [49]. The Kelly formula is:
\[ f^* = \frac{E(R_p) - R_f}{\sigma_p^2} \] (11)

\( f^* \) is the fraction of capital that should be allocated to the risky portfolio \( P \) which is at the unique point on the efficient frontier where the capital allocation lines is tangent to the efficient frontier at \( P \) (see Figure 8). The expected return and variance of portfolio \( P \) is given by \( E(R_p) \) and \( \sigma_p^2 \) respectively.

The fraction \( f^* \) is not constraint to be between zero and one, which allows for shorting and leveraging the risky portfolio.

Fully invested in the risky portfolio \( P \):

\[ f^* = 1 \text{ when } \mu = R_f + \sigma^2 \] (12)

Leverage position:

\[ f^* > 1 \text{ when } \mu > R_f + \sigma^2 \] (13)

Partly invested in portfolio \( P \) and the risk-free asset:

\[ f^* < 1 \text{ when } \mu > R_f + \sigma^2 \] (14)

The optimal growth rate over the long term when adhering to the Kelly optimal allocation formula is:

\[ g_\infty = \frac{(E(R_p) - R_f)^2}{2\sigma_p^2 + R_f} \] (15)

Which can be written in terms of the Sharpe ratio \( S \):

\[ S = \frac{E(R_p) - R_f}{\sigma_p} \] (16)

\[ g_\infty = \frac{S^2}{2 + \frac{R_f}{\sigma_p^2}} \] (17)
2.7. **Active Management Strategies**

As stated earlier, portfolio management theory unfortunately does not provide a hint where to look for factors that are predictive of excess returns. Therefore investment analysts have to look to anomaly research literature as mentioned in the section on *Empirical Evidence* or be creative and find novel opportunities. Methods of identifying opportunities that are used in active management strategies broadly fall into one of three categories: technical analysis, fundamental analysis and quantitative analysis.

Technical analysis is the study of price and volume charts in order to identify recurring patterns. Most technical analysis strategies rely on a momentum based indicator that are indicative of trends that are forming and therefore trend-following is a core technical strategy. Trend-following usually tends to be a short to medium term endeavour, but is also used in high frequency trading where price trends that last from a few seconds to a couple of hours are exploited. The approach used by technical analysts are frowned upon by many academics and finance professionals, but if one takes a behavioural approach to finance, the fact that many participants base their decisions mainly on technical analysis can’t be ignored. Their influence on price dynamics is substantial and provides the source of a value investing approach. Technical traders, also known as momentum traders or feedback traders are responsible for driving prices above fair value or, stated otherwise, the overreaction of the market [12].

Fundamental analysis determines the fundamental value of a security based on many factors such as earnings, cash flow, and book-value etc. in the case of shares. Fundamental analysis based investment strategies usually come in two styles, namely growth and value strategies. Value and growth investing are usually a longer term investment strategy and several studies have shown that a value approach is generally more profitable than a growth approach, but a growth strategy outperforms a value strategy for certain periods [50]. Value investing is also sometimes called contrarian investing and they rely on temporary mispriced securities for profits. The premise of value investing is that the irrational behaviour of some participants leads to overreactions in the markets. The market temporarily overreacts to information and provides profit opportunities because it will again revert to its mean [24]. Shares with higher (lower) earnings relative to their long term
mean would revert back to the mean in the following years and therefore provide excess negative (positive) returns if the market has not already discounted this in the price. Growth investing relies on earnings of firms with high valuations to persist and even to exceed expectations. Both these methods however rely heavily on forecasting a firm’s fundamental prospects.

Quantitative portfolio management is regarded as more of a structured process than an investment style or analysis category itself. Quantitative analysis is the process of automating traditional technical and fundamental analysis and removing the subjective decision making process by replacing it with a systematic automated process [14], [51], [52], [53], [54], [55]. Some analysis techniques are however unique to the quantitative domain and are not encountered in the manual and subjective application of fundamental and technical analysis. These include automated pattern recognition techniques such as data mining, principal component analysis, machine learning and signal processing for identifying possible factors. Regression modelling, differential equations and other modelling tools such as neural networks are also used in forecasting and learning relationships in data [56], [33]. The proliferation of quantitative techniques in financial theory has transformed investment management more and more into a fully-fledged quantitative discipline using a systematic methodology for decision making. One factor that makes it so useful is the fact that one can test investment ideas on historic data through simulation before committing any money to it. This is in contrast to the subjective methodologies used where it is only possible to estimate a manager’s investment skill after a performance history has been established.

2.8. PERFORMANCE EVALUATION

Investment performance is measured in terms of risk-adjusted returns; however there are some measures that focus only on risk or return alone. Financial theories such as the CAPM, APT and Markowitz’ Portfolio Theory provide us with the tools to accurately calculate performance measures where risk is defined as the variance or standard deviation of returns. The basic descriptive statistics for portfolio performance measurement are:

- Mean annualised return
- Standard deviation (volatility)
From the CAPM the following measures can also be calculated by regressing the portfolio under consideration on the market portfolio:

\[ R_p - R_f = \alpha + \beta (R_M - R_f) + \epsilon_{i,t} \]  

(18)

- **Alpha** \( \alpha \) - a risk-adjusted estimate of the active return on an investment.
  - \( \alpha_i < 0 \): Negative risk-adjusted return relative to the market portfolio.
  - \( \alpha_i = 0 \): No excess return relative to the market portfolio.
  - \( \alpha_i > 0 \): Excess risk-adjusted return earned relative to the market portfolio.
- **Beta** \( \beta \) – systematic risk exposure relative to the market portfolio.
- **Sharpe ratio** – Return to variability ratio.

In an efficient market, the expected value of the alpha coefficient is zero.

The **information ratio** (IR) calculates the value added by active management over and above the benchmark strategies considered. It is a ratio of active excess return to active risk or tracking error as it is sometimes called. An essential part of this technique is the choice of benchmark \( R_b \) to which active excess return and risk are measured [14].

\[ IR = \frac{E(R_p - R_b)}{\sigma_{R_p - R_b}} \]  

(19)

Grinold and Kahn proposed the fundamental law of active management which breaks down the sources of active return into two components [14]. The fundamental law tells us that the information ratio (IR) grows in proportion to the skill (IC) of the investor and in proportion to the square root of the breadth [14].

\[ IR \propto IC \times \sqrt{\text{Breadth}} \]  

(20)
The information coefficient (IC) is a measure of ability to forecast each asset’s excess return, also called the depth of the analysis performed. The breadth is the number of times per year that the skill can be applied. Figure 9 [53] shows the relation between the skill and breadth needed for a given return/risk ratio. This clearly illustrates the advantage that can be gained through quantitative management that follows a structured automated investment process on several securities versus the traditional approach of stock picking where one has to be very skilled because the analysis can only be applied to a limited number of securities.

The fundamental law of active management is valuable for the insight it provides into the drivers of return, as well as the guidance it can give in designing a research strategy [14].

A standalone measure of risk often used is the **maximum drawdown**. It is a measure of the maximum loss an investment can undergo from a historical peak to the following trough. This measure is favoured by those who critique the standard deviation as the sole risk measure. The critics say that the only risk to an investment is the risk of losing money, which is why the maximum drawdown as a risk measure is considered more in line with the risk preferences of real-world investors than other more academic risk measures such as volatility as measured by standard deviation.

The maximum drawdown can be calculated in two ways, on historical return data or an estimated maximum drawdown can be calculated from a linear Brownian motion stochastic
process; for an exposition on calculating the expected maximum drawdown of a Brownian motion and its relation to the Sharpe ratio see [57].

It should however be noted that the maximum drawdown only measures the maximum loss possible on paper, it is not necessarily the realised losses if the investor do not liquidate his positions.

2.9. CHAPTER SUMMARY

In this chapter the efficient markets hypothesis was presented. According to the hypothesis, risk-free profit opportunities do not exist, but the empirical evidence suggests that markets are not always efficient and profit opportunities may present themselves from time to time. A quick review of newly proposed hypotheses that consider the empirical evidence and which may explain (and remedy) some of the shortcomings of the EMH were also presented.

A framework for active management based on modern financial theory was then outlined; this framework provides the foundation for an active management strategy while leaving enough flexibility to how exactly it should be done. A high-level look at the strategies commonly employed in active management gave possibilities for finding opportunities and an overview of established techniques used in the investment industry for analysis and implementation.

Probably the best tool coming from modern financial theory is the performance evaluation measures emanating from comparing the theoretical benchmark to the actively managed returns. This enables the active manager to compare different strategies on a risk-adjusted return basis.

The central tenet of this chapter is summarised best by two of active portfolio management’s most influential proponents, Grinold and Kahn [14]:

“Return, risk, benchmarks, preferences, and information ratios are the foundations of active portfolio management. But the practice of active management requires something more: expected return forecasts different from the consensus.”
3. **Literature Review**

“Markets are constantly in a state of uncertainty and flux and money is made by discounting the obvious and betting on the unexpected.”

– George Soros

The previous chapter looked at the foundations of active portfolio management. As mentioned in the previous chapter one needs to make forecasts that are different from the consensus to earn excess returns. This chapter reviews previous research regarding earnings announcements and the market’s reaction to the new information. This investigation focuses on a particular source of predictability, under- and/or over-reaction to new information. The post-earnings announcement drift (PEAD) anomaly is one widely known occurrence of under-reaction which receives special attention. Possible explanations for the PEAD anomaly are reviewed as well as research done locally that provides evidence to the contrary of the PEAD effect. Research reviewing whether the PEAD anomaly is exploited by institutional investment managers and the implementation of a strategy that exploits the effect, are reviewed. Literature regarding the earnings surprise, its predictability and the market’s reaction to such announcements are reviewed in light of market efficiency.

3.1. **Introduction**

Several researchers have considered the effect of uncertainty on firm value, with particular interest in the uncertainty of a firm’s future cash flows that underlie firm value. Since accrual accounting earnings represent a theoretical proxy for future cash flows, the effect of earnings uncertainty on firm value is of considerable interest. The uncertainty in accounting earnings may however be attributable to two main factors: fundamental or real uncertainty of expected future cash flows and/or noise in the accounting earnings due to accounting practices, etc. Theory suggests that the different factors contributing to uncertainty may have varying effects on firm value [58]. In this chapter research investigating the relationship between earnings announcements and the price response is reviewed. This research focuses on patterns, irregularities or anomalous behaviour which may be
exploitable in some way and therefore research regarding market inefficiency surrounding earnings announcements is especially important.

3.2. REACTION TO EARNINGS ANNOUNCEMENTS

Previous research investigating the relative importance of the information content of earnings announcements and the returns around earnings announcements offer dissimilar results and conclusions. Although international research covering earnings announcements is vast and all the findings cannot be discussed here, a brief overview of some of the main findings and views is given below.

Ball and Shivakumar [59] investigate how important earnings announcements are in providing new information to the share market. They calculate the r-squared from a regression of shares’ calendar year returns on their four quarterly earnings announcement “window” returns. Their calculated r-squared value measures the proportion of total information incorporated in share prices over a year that is associated with earnings announcements. They conclude that the average quarterly announcement is associated with approximately one to two percent of total annual information and one quarter of one percent of annual trading volume, thus providing only a small amount of incremental information to the market. Their results are consistent with the view that the primary economic role of accounting earnings is not to provide timely new information to the share market, but may be of more use in, for example, the settling of contracts and in correcting prior expectations. They also report that the relation between the information released surrounding earnings announcements and size is mathematically convex, which they stated could be due to increased simultaneous release of forecasts from management, particularly for larger firms. They also find that substantial information is released in analyst forecast revisions prior to earnings announcements, but not after.

Ball and Kothari [60] examine risk, return, and abnormal return behaviour in the days around quarterly earnings announcements. They employ a research design that allows risk to vary daily in event time. They investigate the effect of earnings announcements on security prices, ignoring both the sign and the magnitude of announced earnings. They argue that earnings announcements convey information about firms’ activities and resolve some uncertainty about future cash flows, but the simultaneous price reactions increase the
variance and covariance of securities’ returns during announcements. They hypothesise that return variances and betas, and therefore expected returns increase during earnings announcement periods. While previous research provided evidence of anomalous positive abnormal returns during earnings announcements, risk was not allowed to vary in event time. They therefore argue that it does not adequately distinguish between increased expected returns and true abnormal returns. They however report abnormal results even after controlling for increasing risk around earnings announcements and also that the abnormal returns are not related to any over- or under-reaction by the market to earnings news, because they do not differentiate between the sign or magnitude of earnings. They further investigate whether cross-sectional variation in announcement-period risks and returns is related to firm size, which they argue is in turn a proxy for the increase in information arrival during earnings announcement periods. The results indicate that, after controlling for risk increases, abnormal returns are on average positive and decreasing with an increase in firm size. They find that abnormal returns for the smallest decile of firms in the ten days up to and including the earnings announcement are approximately 1.75 percent in the average quarter, or about 7 percent over a period of only 40 trading days per year.

Zhang [61] investigates the role of information uncertainty in price continuation anomalies and cross-sectional variations in stock returns. Zhang defines information uncertainty as the uncertainty with respect to the implications of new information for a firm's value, which may come from two sources: the volatility of a firm's underlying fundamentals and poor information. Zhang uses six proxies for information uncertainty: firm size, firm age, analyst coverage, dispersion in analyst forecasts, return volatility and cash flow volatility. Zhang provides substantial evidence of short-term share price drift, which previous literature regularly attributes to behavioural biases such as under-reaction to new information. Zhang argues that if short-term price drift is due to investor behavioural biases, greater information uncertainty should be accompanied by greater price drift. The results supports the argument and it is found that greater information uncertainty produce relatively higher expected returns following good news and relatively lower expected returns following bad news.
Imhoff and Lobo [58] examine the effect of the uncertainty in analysts’ earnings forecasts on the relation between unexpected returns and unexpected earnings. They investigate the effect of uncertainty in earnings before the earnings announcements by using the known linear relation between unexpected returns and unexpected earnings, with 3167 firm-year observations for the six-year period 1979-84. They use the variance in analysts’ earnings forecasts before a firm’s annual earnings announcement as proxy for earnings uncertainty. Their results indicate a systematic relation between pre-earnings-announcement uncertainty and the information content of earnings announcements, specifically a unit of earnings news has a greater effect on unexpected returns as the amount of uncertainty decreases. Firms with relatively high earnings uncertainty display little or no price change at the time earnings are announced. Sensitivity tests also suggest that the results are not driven by either firm size or the amount of available information for a firm. They also find that after controlling for the effects of uncertainty, the disagreement in analysts’ earnings forecasts is more likely to be a proxy for noise in the financial reporting system than a proxy for fundamental uncertainty in a firm’s future cash flows.

3.3. **EXPLANATION OF THE PEAD EFFECT**

Ball and Brown [10] were the first to discover that even a while after earnings announcements, cumulative returns continue to drift upwards for positive unexpected earnings announcements or “good news” and downwards for negative unexpected earnings announcements or “bad news”. This phenomenon known as the post-earnings announcement drift anomaly has been widely researched since.

Two kinds of anomalies, namely under-reaction and overreaction, have been established by an impressive record of empirical work and although this research focuses mainly on under-reaction and specifically the PEAD anomaly, under-reaction and overreaction are inextricably linked as shown by Kaestner [39]. While under-reaction defines a delayed reaction of security prices to new information, overreaction is the extreme reactions of security prices to previous information or past performance. Theoretical Behavioural Finance models have shown that both anomalies can potentially be explained by investor irrationality. Kaestner investigates current and past earnings surprises and the market’s subsequent reaction over the period 1983-1999 for listed US equities. The results suggest
that investors simultaneously exhibit short-term under-reaction to earnings surprises and long-term overreaction to past highly unexpected earnings (momentum behaviour).

Lundstrum [62] reviews many of the conflicting views regarding the explanation of post-earnings announcement drift over the years. Among the numerous explanations for post-earnings announcement drift are investor under-reaction or delayed price response [63], [64], [65], inflation[66], information uncertainty [67], arbitrage risk [3], [68], firm size [13] and liquidity risk [4], [69], an earnings surprise risk factor [70], transaction costs [71], trading volume [11] and trader behaviour [72], [73]. According to Lundstrum the leading explanations for the post-earnings announcement drift anomaly include the limited arbitrage hypothesis and the illiquidity hypothesis. The limited arbitrage hypothesis claims that arbitrageurs are deterred from exploiting excess returns associated with PEAD because they are concerned about the associated idiosyncratic risk involved. Lundstrum presents new evidence that illiquidity, rather than limited arbitrage as proposed by Mendenhall [3] and Shleifer and Vishny [68] explains the post-earnings announcement drift.

Bernard and Thomas [63] seek an explanation for the post-earnings announcement drift phenomenon. They put forth two competing classes of explanations: Firstly, the price response to the new information is delayed, because traders either fail to process the available information, or because certain costs exceed the potential gains from immediate exploitation of information. Secondly, the capital-asset-pricing model (CAPM) used to calculate abnormal returns is either incomplete or its parameters is wrongly estimated, thus researchers fail to adjust raw returns fully for risk. As a result, the so-called abnormal returns are nothing more than fair compensation for bearing risk that is priced but not captured by the CAPM estimated by researchers. They conclude that the results that they found are difficult to reconcile with reasonable explanations based on incomplete risk adjustment, however, it agrees with a delayed response to new information. Hou and Moskowitz [64] ask the question the other way round by examining the extent to which market frictions affect a security. They define market frictions to include incomplete information, asymmetric information, short sale constraints, taxes, liquidity, noise trading and sentiment risk and they use the delay with which a security’s price responds to new information as a measure of friction. The most delayed firms command a large return premium not explained by size, liquidity, or micro-structure effects. They further find that
delay captures part of the size effect, post-earnings announcement drift increases with an increase in the delay and that for non-delayed firms the post-earnings announcement drift is non-existent. Frictions associated with investor recognition appear most responsible for the delay effect. Delayed firms represent only 0.02% of the market, but generate substantial variation in average returns, highlighting the importance of frictions.

Chordia and Shivakumar [66] examine the implications of the so-called inflation illusion hypothesis for the post-earnings announcement drift. The inflation illusion hypothesis suggests that stock market investors fail to incorporate inflation in forecasting future earnings growth rates, and this causes firms whose earnings growths are positively (negatively) related to inflation to be undervalued (overvalued). They argue and show that the sensitivity of earnings growth to inflation varies monotonically across stocks sorted on standardised unexpected earnings (SUE) and, consistent with the inflation illusion hypothesis, showed that lagged inflation predicts future earnings growth, abnormal returns, and earnings announcement returns of SUE-sorted stocks. When they controlled for the return predictive ability of inflation, the ability of lagged SUE to predict future returns also weakened.

Kim and Kim [70] construct a risk factor related to the unexpected earnings surprise, and propose a four-factor model by adding this new risk factor to Fama and French’s three-factor model. The risk factor they developed is related to the view that investors know that there will be a possible surprise compared to the expected earnings when earnings are announced. The uncertainty about the direction of an earnings surprise and the fact that the share price will respond positively (negatively) to unexpected higher (lower) earnings, causes investors to face the risk of an unexpected earnings surprise. This earnings surprise risk factor provides a remarkable improvement in explaining post-earnings announcement drift when included in addition to the three factors of Fama and French. After they adjust the raw returns for the four risk factors, the cumulative abnormal returns over the 60 trading days subsequent to quarterly earnings announcements are economically and statistically insignificant. They thus argue that most of the post-earnings announcement drift observed in prior studies may be a result of using miss-specified models and failing to appropriately adjust raw returns for risk.
Francis et al. [67] examine whether rational investors’ response to information uncertainty (IU) explains properties of and returns to the post-earnings-announcement-drift (PEAD) anomaly. They measure information uncertainty as the mapping of the current accruals portion of earnings into cash flows. The less current accruals translate into cash flows, the lower the information quality of earnings is and therefore the greater the uncertainty of earnings. They find that: (1) unexpected earnings (UE) signals that are characterised as having greater IU have more subdued initial market reactions; (2) extreme UE portfolios are characterised by securities with higher IU than non-extreme UE portfolios; and (3) within the extreme UE portfolios, high IU securities are more prevalent and earn larger abnormal returns than low IU securities. Further tests show that previous evidence of greater PEAD profitability for higher volatility securities is explained by the greater information uncertainty associated with these securities.

Mendenhall [3] examines whether the magnitude of post-earnings-announcement drift is related to the risk faced by arbitrageurs who may view the anomaly as a trading opportunity. Mendenhall finds that the magnitude of the drift is strongly related to the arbitrage risk and that the effect of arbitrage risk is statistically and economically significant under a wide range of specifications. Mendenhall defines arbitrage risk as the idiosyncratic risk of a stock that cannot be hedged away by holding offsetting positions. The results suggest that post-earnings-announcement drift represents an under-reaction to earnings information and that arbitrage risk impedes arbitrageurs from eliminating it.

Foster et al. [13] find that variables coding the sign and magnitude of the earnings forecast error and firm size independently explain 81 percent and 61 percent respectively of the variation in post-announcement drifts with a joint explanatory power of 85 percent. They also find that systematic post-announcement drifts in security returns are found only for a subset of the earnings expectations models examined. Of the four expectations models they use in their research, they find post-announcement drifts for the two expectations models based on the past quarterly earnings series. However, for the two expectations models based on the security return series, post announcement drifts are not found.
Figure 10 [13] graphically presents the cumulative abnormal return for each decile (numbered 1 to 10) of unexpected earnings for the 60 day period prior to and after the earnings announcement day.

Sadka [69] investigates the components of liquidity risk that are important for asset-pricing anomalies. Sadka decomposes firm-level liquidity into variable and fixed price effects. Unexpected systematic (market-wide) variations of the variable component rather than the fixed component of liquidity are shown to be priced within the context of momentum and post-earnings-announcement drift (PEAD) portfolio returns. According to Sadka the variable component is typically associated with private information, thus the results suggest that a substantial part of momentum and PEAD returns can be viewed as compensation for the unexpected variations in the aggregate ratio of informed traders to noise traders.

Chordia et al. [4] investigate the post-earnings-announcement drift anomaly. They find that the post-earnings-announcement drift occurs mainly in the highly illiquid stocks. A trading strategy that goes long the high earnings surprise stocks and short the low earnings surprise stocks earns a return of 0.24% in the most liquid stocks and 1.79% per month in the most
illiquid stocks. The illiquid stocks have high trading and market impact costs. They further estimate that transaction costs account for anywhere from 66% to 100% of the paper profits from the long-short strategy they designed to exploit the PEAD anomaly.

Choi et al [11] develop a simple model in which trading volume contains information about future stock returns. Their model explains why high trading volume is observed when a firm announces earnings news and how trading volume can be related to the initial under-reaction of the stock price. Their model has a clear testable implication that high abnormal trading volume predicts a stronger drift. Their test results provide strong evidence for the model in the case of positive news, but weaker evidence is found in the case of negative news.

Shanthikumar [72] analyses trade-initiation by small and large traders for one year following earnings announcements and examines the predictive ability of trading activity around events for future returns. With earnings surprises based on a seasonal random walk expectations model, small traders react slightly more weakly than large traders, during the event window, to the first surprise in a series of similar surprises, but more strongly than large traders to the later surprises. With earnings surprises based on analyst forecasts, small traders react more weakly than large traders regardless of the past series. Large traders trade in the direction of the earnings surprise for one month after the earnings announcement, while small traders do not. Starting in month two this switches and small traders trade in the direction of the surprise, while large traders do not. The strength of the small trade event-time reaction is a weak positive predictor of returns in the first month after the announcement and a weak negative predictor of drift after the first month. Large trade reaction is generally a negative predictor of future drift. The collection of evidence points to both small and large trader under-reaction to earnings announcements, with small trader under-reaction more severe in the first month. In month one, large traders capitalise on drift, but after that small traders seem to correct and possibly overreact.

Kaniel et al. [73] also investigate the behaviour of individual investors around earnings announcements. They use a dataset consisting of all executed orders of all individual investors trading on the NYSE over a four year period (200-2003). Their findings differ from that of Shanthikumar [72] mentioned above, and they argue that it may be due to the data
used that indicate that small traders is not necessarily individual traders, especially in recent years. They find that strong individual buying (selling) prior to the announcement is associated with significant positive (negative) abnormal returns in the three months following the announcement. They find that compensation for liquidity risk seems to account for approximately half of the abnormal return, but a significant remaining component could be due to private information or skill. They also examine the trading behaviour of individuals after the earnings announcement and find that they trade in the opposite direction to both pre-announcement returns and the earnings surprise. They argue that the latter behaviour could possibly delay the price response to earnings news and contribute to the post-earnings announcement drift.

Livnat [74] studies the persistence of earnings surprises and post-earnings announcement drift for each quarter in the fiscal year. The results indicate that extremely negative and extremely positive earnings surprises in the fourth quarter have lower levels of persistence than those in the first to third quarters. Livnat further shows that the effect is not symmetrical, that is, extremely negative earnings surprises in the fourth quarter have lower levels of persistence than extremely positive earnings surprises in that quarter. Similar to the patterns of persistence in the earnings surprise, the post-earnings-announcement drift decreases through the successive four quarters of the financial year, with the smallest drift occurring after the announcement of the fourth quarter earnings. The drift after the fourth quarter is nearly non-existent for extremely negative earnings surprises and smaller for extremely positive surprises, in line with the differential persistence of the earnings surprises. Livnat provides the explanation that investors, who under-react to extreme earnings surprises, seek further information and when newly released information confirms the initial surprise, prices tend to drift in the same direction.

3.4. LOCAL RESEARCH

Published local research regarding the reaction to earnings announcements and the PEAD anomaly on the JSE is limited. Previous local studies that investigated the market’s reaction to announcements include, amongst others, the investigation of the reaction of the market
to the announcement of special dividends [75], share dividends\(^6\) [76], share repurchases [77] and the announcement of management buyouts [78].

Notable local research on the market’s reaction to earnings announcements was however done by Bhana [2] in his investigation of the overreaction hypothesis on the Johannesburg Stock Exchange (JSE). Bhana’s research provides evidence that for the period under investigation (1975 to 1989) the market overreacted to unexpected earnings announcements. This behaviour was found not to be symmetrical resulting in firms with lower than previous earnings (negative change) performing better than the market in the subsequent period, thus constituting an initial overreaction to the lower expected earnings, but firms with a positive change in earnings not perform significantly worse than the market.

Bhana’s analysis of the abnormal share returns accumulated over twelve-month periods following annual earnings announcements reveals that a strategy of buying shares of companies that announced a negative change in earnings, and holding these shares for the next twelve months, would generate positive risk-adjusted abnormal returns of about 12.5% before transactions costs. The observed negative earnings effect exists independently of any small-firm effect. It was also found that companies reporting negative earnings in any test year experienced, on average, strong earnings recovery over the next two years.

3.5. EXPLOITING THE ANOMALY

Research has also been done to find to which extent the anomaly is exploited and by whom. If the market is inefficient and anomalies exist, one would expect the efficiency to disappear once it is widely known and exploited.

Ali et al. [79] investigate to which degree investors can profitably trade on the post earnings announcement drift (PEAD) using portfolio holdings and returns of mutual funds. They find that actively-managed US equity mutual funds on average trade on PEAD, even after controlling for different investment styles and momentum trading. They further find that trading on PEAD is profitable: net of both transaction costs and fund expenses, the annual four-factor alpha of the top 10% of funds actively following the PEAD strategy is 2.10%.

\(^6\) Dividends in the form of newly issued shares or shares held in treasury and not ordinary cash dividends.
higher than that of a group of benchmark funds not actively using the strategy. However, across funds, more active trading on PEAD is associated with less portfolio diversification, higher volatility in fund returns and higher volatility in fund flows, representing adverse consequences of arbitrage risk. Finally, they document the temporal dynamics between fund trading and the profitability of the PEAD strategy: higher profitability attracts more intense trading by funds, which in turn, leads to lower future profitability.

Ke and Ramalingegowda [80] also ask whether institutional investors exploit the PEAD anomaly. Their findings indicate that those institutions which actively trade to maximise short term profits, do exploit it and they generate an estimated annualised abnormal profit of about 22% through their arbitrage activities. These institutions’ arbitrage activities also tend to accelerate the speed at which the prices reflect the implications of current earnings for future earnings. They also find that the arbitrage activities of these transient institutional investors are much more limited for firms with higher transaction costs, thus one would expect a more pronounced effect for these firms as it remains unexploited.

McDonald and Mendenhall [81] examine the profitability of implementing a strategy based on the earnings surprise anomaly. Their approach is twofold. First, they attempt to identify variables, in addition to earnings surprise, that will improve their ability to predict post-earnings-announcement drift. Second, they test a trading strategy that attempts to profit from the PEAD effect using a stock-market simulation that considers real-world issues such as transactions costs, short-sales constraints and cash management issues. Their results were however inconclusive. For the five-year period they investigated (1988 through 1992), the strategy achieved significantly higher returns than a buy-and-hold strategy by outperforming the NYSE-AMEX value weighted portfolio by nearly 7.4%, but the outperformance was limited to a two-year sub-period.

While reasons for the differing performance among the different studies are not apparent, they all provide evidence that the PEAD anomaly is profitably exploited to some extent and despite this fact it continues to persist.
3.6. **EARNINGS SURPRISE**

Liu [82] compares the efficiency with which the market and financial analysts react to earnings announcements. Liu’s results show that the market reacts more quickly to earnings announcements than financial analysts. In the quarters before the announcement the market reacts more than analysts, and the analysts gradually catch up in the quarters after announcement. Liu’s results led him to reach the opposite conclusion to prior research on this subject.

Bernard and Thomas [1] show that share prices fail to fully reflect the implications of current earnings for future earnings. The three-day price reactions to announcements of earnings for quarters $t+1$ through $t+4$ are predictable, based on earnings of quarter $t$. Even more surprisingly, the signs and magnitudes of the three-day reactions are related to the autocorrelation structure of earnings, as if share prices fail to reflect the extent to which each firm’s earnings series differ from a seasonal random walk. Agipova and Malibayeva [83] however made the argument that investors’ fixation on patterns of earnings and a sudden break in these patterns are the drivers of short-term market reaction to earnings announcements. Their results show that in the presence of clear earnings patterns, individual investors fail to incorporate information signals regarding company performance into their valuation of shares, which result in differential market reaction to newly released earnings news between firms for which the earnings pattern persists and for firms which break the earnings pattern.
4. DATA AND METHODOLOGY

“Engineering is too important to wait for science.”

– Benoit Mandelbrot

4.1. INTRODUCTION

In the previous chapter we looked at some of the possible explanations and sources of the anomalies or market inefficiencies related to earnings announcements. In this chapter we proceed to investigate the techniques and tools that will be used to establish the statistical significance of these anomalies for JSE listed shares. For this purpose we developed a set of simulation and performance evaluation techniques to allow us to experiment with an active management process as displayed in Figure 11 in order to test the economic significance and exploitability of the anomalies under study.

The above workflow however excludes the data collecting and pre-processing process. Before any analysis may commence the necessary data are collected and checked for accuracy and cleaned of outliers and errors.

4.2. DATA

JSE share data was sourced from McGregor BFA and other public websites for the period from the start of 1991 to the end of 2010. All interim and final announcement data of which the announcement date is known over the 20 years are used. This represents a sample of 4838 observations including 284 different companies, which consists mainly of dividend paying stocks, because the announcement dates are not available for the stocks that declare no dividends. Although as much as possible non-dividend paying data was manually

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included by extracting it from SENS\textsuperscript{8} announcements, the sample is somewhat biased towards dividend paying stocks, which in turn is biased toward larger market capitalisation shares. This limitation is clearly stated to ensure the correct interpretation of our results. We can however pose the argument that this will not detract from the validity and usefulness of our findings, as an investor always has the option to limit his investments to shares that comply with specific criteria. It is furthermore a reality that those shares that are paying dividends represent the major portion of market capitalisation; the shares that are excluded from our study will therefore provide limited investment opportunities to all but the small investor.

The data is also not free from survivorship bias, because only the shares that were still listed by 2010 are included in the sample. This is a possible shortcoming of the research, but it is also the case that the majority of shares that delist is forced to do so due to non-compliance with exchange rules regarding the timely announcement of earnings and reporting standards. The argument is made that the information content of the earnings announcements are questionable and therefore it is deemed acceptable to exclude them from this research. The majority of companies that delist also do not pay dividends (which would have excluded them on the basis of non-availability of data) and represent a minor portion of the market capitalisation. Their exclusion is therefore expected to have an immaterial effect on the analysis and its outcomes.

Pre-processing of the data included removal of outliers. The threshold above which data is excluded from the dataset was subjectively chosen for each variable depending on the variability of the data and the frequency of occurrence of extreme outliers. The thresholds were mostly chosen to exclude the data which fell outside 4 to 5 standard-deviations from the mean. Whenever an aggregated measure fell outside these 4 or 5 standard deviations from the mean, the specific observation was dropped from the dataset. This was done in order to reduce possible effects which come forth from mergers/acquisitions, unbundling and disposal of assets for which no data is available to make the necessary adjustments. The data samples removed in this way constitutes less than 0.1% of the total dataset. The data was however adjusted for all share splits and corporate actions for which sufficient data exists. Although as much care as possible has been taken to ensure the accuracy of the

\textsuperscript{8} The JSE’s news service
data used during calculations, some erroneous data samples will no doubt be included, but for the most part their impact on results and conclusions can be expected to be minimal.

All ratios used in the research are calculated using the last available month-end data before each announcement date. Unless otherwise stated, all aggregate return data is equally weighted, due to the difficulty of weighting data according to market capitalisation that is dispersed through time. Dividends have been included in return series at the time of the dividend pay-out date to form total return equally weighted portfolios wherever return data is aggregated.

Although the data is not representative of all companies that were listed on the JSE for the period 1991-2010, the sample period includes all possible market regimes or phases of the market business cycle to allow us to effectively test the stationarity and persistence of the post-earnings announcement drift effect over a representative data set.

4.3. Methodology

As stated in the first chapter, this research aims to investigate the response of security returns to earnings announcements in order to establish whether significant predictable patterns exist which may be profitably exploited. This research firstly analyses the price dynamics of securities around earnings announcements and how it varies for certain groups. Secondly, the aim is to establish whether the PEAD effect occurred on the JSE for the period 1991-2010 and to test whether it is merely a manifestation of other well-known anomalies. Thirdly, the predictability of the unexpected earnings (or earnings surprise) is investigated after which the exploitability of the patterns is established through simulation.

In order to accomplish the research goals, the event study methodology as discussed in [46] and the simulation methodology developed in [81] is partly followed and used as a guideline in the design of this research study, of which the details will now be discussed in detail.

In order to establish when the announced earnings deviate from the expectations and ‘surprise’ the market, it is necessary to define a way of calculating or estimating the expected earnings. The models used to define or estimate the expected earnings are called expectation models and previous research used several ways to estimate these expectation models. A favourite method used by researchers is the consensus estimates provided by
data providers and sourced from analysts. Due to the lack of a historical database of consensus estimates before each earnings announcement, other expectation models are used in this research.

Another method used is to fit a linear model to previous earnings numbers and to use that to forecast the earnings to be announced. Yet another method is to ignore estimating the expected earnings and to use the market’s reaction on the day of announcement as an indication of how surprised the market is to the announced earnings \[13\], \[2\].

The following expectations models are used in this research. Instead of fitting a linear model to historical earnings-per-share (EPS), the first model uses the last previously announced EPS as the expected earnings. The change in EPS is thus used as a proxy for unexpected earnings. The change in EPS is defined as:\(^9\)

\[
\Delta EPS_{t,t} = \frac{EPS_{t,t} - EPS_{t,t-1}}{|EPS_{t,t-1}|}
\]  \hspace{1cm} (21)

It should however be noted that the above definition of unexpected earnings is not necessarily measuring a surprise to the market, because the market’s consensus earnings estimate may be correct no matter what the change in EPS is.

The second model uses cumulative security returns on the day of announcement as a proxy for unexpected earnings. Because some uncertainty about the time of the announcement exists and which day the market reacts thereto\(^10\), the reaction on the days \([0; +2]\) is used as an indication of the market’s surprise to the announced earnings. The unexpected returns are calculated as:\(^11\)

\[
ER_i = \sum_{t=0}^{2} R_{i,t}
\]  \hspace{1cm} (22)

All returns are calculated as the natural logarithm of the price to the previous period’s price also known as the continuous compounding return.

\(^{9}\Delta EPS – \text{Change in earnings per share}\)

\(^{10}\text{If the announcement is made after the market is closed, the market reacts the following day.}\)

\(^{11}\text{ER – Event Return}\)
Excess post-earnings announcement returns using the market model can be defined as:

\[ R_{PEAD,i} - R_f = \alpha_{PEAD,i} + \beta_i (R_{PEADM,i} - R_f) + \epsilon_{i,t} \]  

(24)

Due to the lack of data covering the whole period and to simplify matters the risk-free rate is taken to be a constant throughout this research:

\[ R_f = 0.04 \text{ per annum} \]  

(25)

\( \alpha_{PEAD,i} \) - Excess risk-adjusted post-earnings announcement returns.

The Post-Earnings Announcement Drift for observation \( i \) during period \( t \) for the period subsequent to the announcement \((t = 0)\) is calculated as:

\[ R_{PEAD,i,t} = R_{i,t} \forall t \in [3; 120] \]  

(26)

The market return for the period subsequent to the announcement is calculated as:

\[ R_{PEADM,i,t} = R_{M,t} \forall t \in [3; 120] \]  

(27)

\( R_{M,t} \) is the value weighted total (dividends included) market return.

4.3.1. RESPONSE TO EARNINGS ANNOUNCEMENT

The price response to earnings announcements is analysed to establish the dynamics of the simplified system shown in Figure 2 in chapter 2. Identification of a system’s dynamics is usually done through a controlled experiment where the inputs to the system can be accurately controlled and the output measured. This system identification procedure can however not be implemented in finance due to the impossibility of controlling the inputs to the system. To simplify matters, the investigation is focused only on the event window surrounding earnings announcements. The window includes the ten days prior to and after the earnings announcement. The input to the system is taken to be the information content of the announced unexpected earnings and in order to filter out the influence of other inputs or sources of information; the response is calculated as the market-adjusted returns \( \alpha_{i,t} \) using the following equation:
In order to simplify the estimation of market-adjusted returns the beta $\beta_i$ is assumed to be 1 for all observations. Although this may at first seem as a crude assumption, the beta estimated using longer estimation periods is not representative of the higher volatility and relative risk surrounding earnings announcements. It is however also difficult to estimate the beta accurately for such a short period. Therefore, it is argued that because the data in aggregate has an average beta equal to 1, any analysis on a representative group assuming a beta of 1 for individual observations would in aggregate be accurate. It is also notable that the risk-free rate has been left out of the equation. This is because of the relative small period of time over which the response to earnings announcements are analysed and the risk-free rate is deemed negligibly small.

The data is further de-trended by removing the mean of all shares from the market-adjusted returns for each day.

In general the system’s (market) response $\alpha_{i,t}$ to new information $x(t)$ can be described as the convolution integral of a system’s impulse response $h(t)$ and the new information.

$$\alpha_{i,t} = \int_{-\infty}^{\infty} x(\tau) h(t-\tau) d\tau + \varepsilon_{i,t} = x(t) * h(t) + \varepsilon_{i,t}$$  \hspace{1cm} (29)

$\varepsilon_t$ – Random variable with mean $\mu = 0$ and variance $\sigma = \sigma_i$ equal to the variance of firm $i$’s daily return.

The impulse response $h(t)$ is the system’s response to an impulse input. The impulse function (also known as the Dirac-delta) is defined as:

$$\delta(t-t_0) = 0, t \neq t_0$$  \hspace{1cm} (30)

$$\int_{-\infty}^{\infty} \delta(t-t_0) dt = 1$$  \hspace{1cm} (31)

If the information input $x(t)$ is modelled as an impulse function with amplitude $A$ related to the information content in earnings announcements, the system response to the new information reduces to:
Ideally one would be able to estimate the system response $h(t)$ from the data, but due to the low signal-to-noise ratio in financial data, an accurate estimate of the dynamics of the system for individual observations is believed to be impractical. We however pose the argument that at each point in time, announced information relevant to the fundamental value of a firm would impact the price of the firm forever. The average aggregate response to new information for all individual observations is therefore assumed to be a step function. If we consider earnings announcements and especially the unexpected earnings to convey information relevant to the fundamental value of a firm and thus relevant to the price formation process, the dynamics of the system on average can be considered to be that of an integrator and the information as the impulse input.

$$h(t) = \int_{-\infty}^{t} \delta(\tau) \, d\tau = u(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases}$$  \hspace{1cm} (33)

This reduces the system response equation to:

$$\alpha_{i,t} = Au(t) + \varepsilon_{i,t}$$  \hspace{1cm} (34)

The response $\alpha_{i,t}$ is therefore considered to be related to the information content of the earnings announcement which is mathematically equivalent to a unit step function $u(t)$. It should however be kept in mind that this description of the dynamics of the system is assumed to only hold for aggregate data consisting of a sufficient sample size. The stochastic nature of financial data also suggests that the theoretical unit step function $u(t)$ used in the above equations may be a too simplified view. Therefore we propose an adjusted stochastic unit step function:

$$u_s(t) = \begin{cases} \pi, & t \geq 0 \\ \psi, & t < 0 \end{cases}$$  \hspace{1cm} (35)

Where $\pi$ is a random variable with mean $\mu_{\pi} = 1$ and variance equal to the variance of the average market-adjusted return $(E(\alpha_{i,t})))$, $\sigma_\pi = \sigma_{E(\alpha_{i,t})}$ and $\psi$ a random variable with mean $\mu_\psi = 0$ and variance $\sigma_\psi = \sigma_{E(\alpha_{i,t})}$. 
The information content (amplitude of input) is not directly apparent from the earnings announcement and is estimated using a function of several relevant variables:

\[ A = f(X_i) \]  \hspace{1cm} (36)

Where \( X_i \) is a variable representative of several variables that will be further discussed below. The premise that underlies the first null hypothesis is that earnings do not convey any new information to the market and therefore \( f(X_i) = 0 \);

The null hypothesis:

\[ H_0: \text{The earnings announcement does not convey any new information to the market and therefore no significant response is expected.} \]

The hypothesis is tested by establishing the statistical significance of the relation between earnings announcements and the price response.

However, if the hypothesis is proved false, two questions arise: What is the theoretically expected efficient response to the unexpected earnings and is the earnings announcement truly new information or does the market inefficiently process the available information. The market reaction to announced earnings that exceeds expectations and the magnitude of the unexpected earnings is known to be linearly related \[58\] and therefore the output is also expected to be a step function with amplitude proportional to the information content of unexpected earnings. This corresponds with the notion of the EMH that new information should be incorporated into the price immediately. Therefore it is expected that the amplitude function \( f \) is a linear function of the information content of unexpected earnings.

\[ f(X_i) = g(UE_i) \]  \hspace{1cm} (37)

The response to earnings announcements is further investigated to establish whether the response, in addition to unexpected earnings, is a function of firm size, price momentum (delayed feedback) and the value effect. \( \Delta \text{EPS} \) is used as a proxy for unexpected earnings, earnings yield (EY) as a proxy for the value effect, the relative momentum for the previous six months (RS6) and the market capitalisation (MC) as a measure of firm size. The variable \( X_i \) therefore consists of the components:
\[ X_i = [\Delta EPS_i, Value_i, Momentum_i, Size_i] \]  

(38)

And the amplitude function is now written as:

\[ f(\Delta EPS_i, Value_i, Momentum_i, Size_i) \]  

(39)

This is investigated through a multivariate regression analysis and tested on out-of-sample data to establish the accuracy of the model in describing the response to announced \( \Delta EPS \).

Although the response is only evaluated for the short time period before and after the announcements to reduce the influence other events may have on the response, it is important to investigate whether a delayed reaction to the earnings announcement exist. This is discussed in the next section: Investigating the PEAD Anomaly. The efficiency of the market to processes new information is established by analysing the predictability of the unexpected earnings. If it is predictable and the market still reacts as expected, then it may present a profit opportunity. This analysis is outlined in the section: Investigating the Earnings Surprise following the discussion on the investigation of the PEAD anomaly.

4.3.2. Investigating the PEAD Anomaly

The hypothesis that the PEAD anomaly does not exist on the JSE is repeated here for reference purposes.

\[ H_0: \] There is no relationship between unexpected earnings (earnings surprise) and subsequent post-earnings announcement returns for the period 1991 to 2010 on the JSE.

Three sets of empirical tests are implemented to evaluate the null hypothesis. In order to thoroughly test the null hypothesis, it is not satisfactory to solely test the significance of the relationship between unexpected earnings and post-earnings announcement returns, but to evaluate the relationship between post-earnings announcement returns and other known anomalies. Therefore three sets of tests are carried out on all of the variables which fall into the following four categories\(^\text{12}\):

1. Unexpected earnings with its two variables defined by the two expectation models.
   - Event Return (ER)

---

\(^{12}\) See appendix A for the definition and formula of all explanatory variables used.
2. Anomaly variables related to the measurement of the value effect.
   - Change in earnings per share (ΔEPS)
   - Earnings yield (EY)
   - Dividend yield (DY)
   - Book-to-market (B2M) ratio

3. The momentum of the share price.
   - The six month share price momentum (Mom6).
   - The six month momentum of the value weighted market return (MS6).
   - The six month share price momentum relative to the market (RS6).
   - Drift in returns for the ten days prior to the earnings announcement (PreEAD).

4. The fourth category relates to size and/or liquidity. The anomaly variables in this category are proxies for several related effects that have been widely studied in the literature; they are the size-effect or small firm effect, the neglected firm effect, liquidity effect and the low price effect. The variables used are
   - The natural logarithm of the market capitalisation of a firm (MC).
     - Four size groups are used throughout this research. The groups correspond with the 0-50, 51-75, 76-90 and 91-100th percentile, the lowest 50% is classified as micro firms; the following 25% is classified as small firms, the next 15% as medium and the last 10% as large.
   - The share turnover as measured by the average monthly traded volume as a fraction of the number of issued shares for the past three months (ST3).
   - The natural logarithm of the absolute closing price (PC).

Analysts usually do not spend time analysing smaller firms and therefore they are somewhat neglected [7]. Institutional investment managers also tend to ignore shares with a very low absolute share price, the so-called penny shares; therefore they are also largely neglected. It is argued that this neglect leads to lower trading volume and thus lower liquidity. This forms the basis of the argument that low price, small size and low trading volume are related effects [7].

All variables are calculated at the last month end before the announcement date.
The three tests that are implemented to test the hypothesis are cross-sectional correlation analysis, cross-sectional analysis by sorting and grouping and cross-sectional regression analysis. Firstly the sample correlation coefficients are calculated between each of the abovementioned variables and the excess PEAD returns.

Secondly, the data is sorted according to each of these variables and grouped into quartiles; the corresponding mean excess PEAD return of each group is then calculated and tested for statistical significance.

The sorting and grouping technique is better at establishing the degree to which explanatory variables can be used to differentiate between or predict future extreme returns. As most investment strategies are only concerned with extreme behaviour, a variable that is successful at differentiating between the extremes in future returns is very valuable in designing an investment or trading strategy. Although the sample correlation coefficient is a good measure of the overall relationship between two variables, it is an average linear measure and thus not the preferred technique for establishing the strength of extreme and non-linear relationships. The sorting technique also does not assume normally distributed data.

The third technique involves regression analysis. Two regression analysis methods are normally used in anomaly research [84]. The first method involves grouping shares into portfolios based on a particular characteristic and then undertaking time-series regressions of each group’s returns on the market return. The dependant variable is thus the market return and the independent variables are each group’s return. It is then followed by an analysis of the portfolios’ regression intercepts, to test for statistical significance. This method often implicitly assumes a stationary return generating process [84].

The second methodology involves cross-sectional regression of returns on predetermined attributes (explanatory variables). This method need not assume stationarity. Here the dependent variable is each security’s excess PEAD return and the independent variables are its normalised exposures to the attributes [85], [84].
The second method will be utilised in this research because stationarity cannot be assumed and the way PEAD portfolios are formed\textsuperscript{13} does not lend itself naturally to a time-series regression.

All the variables in the four anomaly categories mentioned are used in the cross-sectional regression analysis. Each variable is normalised by subtracting its equally weighted mean $\mu_{\text{anomaly}}$ and dividing by its standard deviation $\sigma_{\text{anomaly}}$.

$$anomaly_{\text{Normalised}} = \frac{anomaly - \mu_{\text{anomaly}}}{\sigma_{\text{anomaly}}} \quad (40)$$

In addition to the 12 anomaly variables the following binary dummy variables will also be used.

- Nine industry categories – Shares on the AltX, venture capital, development capital and the JSE Africa boards are grouped together in one industry category. The other industry categories are: Basic Materials, Consumer Goods, Consumer Services, Financials, Health Care, Industrials, Oil & Gas, Technology, and Telecommunications.
- The four seasons of the year to test the seasonality of the PEAD effect – Summer, Autumn, Winter and Spring.

In total there are 25 independent variables and one dependent variable $\alpha_{\text{PEAD},i}$ the excess risk-adjusted post-earnings announcement returns for each security. The simplified regression model equation in vector form is thus:

$$\alpha_{\text{PEAD},i} = \alpha + \beta X + \varepsilon_i \quad (41)$$

Where $\beta$ is a vector consisting of all the coefficients to each of the independent variables (column vectors) in the matrix $X$.

A multivariate linear regression model where all variables are simultaneously regressed on the excess PEAD return to establish each factor’s pure contribution is calculated using ordinary least squares estimation [84], [85]. Each regression coefficient represents the

\textsuperscript{13} Different earnings announcements dates leads to different dates of inclusion of each security in the portfolio, thus at each point in time a portfolio consists of securities that are in different parts of the PEAD cycle, which does not lend itself to statistical analysis, but which would be more representative of a real portfolio implementation which utilizes the PEAD effect.
marginal return to a stock with an exposure to that factor of one cross-sectional standard deviation.

The model is tested for linearity by sorting the residuals according to the excess return and then graphically inspecting the results.

4.3.3. Investigating the Earnings Surprise

By definition the earnings surprise should be unpredictable otherwise it won’t be a surprise, but the question is whether it really is unpredictable. In this section we outline the analysis to establish whether the earnings surprise is merely due to inherent uncertainty about earnings (information uncertainty) or the market’s inefficient processing of information.

When investigating the earnings surprise the following questions need to be answered:

- Firstly we ask whether there exists evidence to suggest that unexpected earnings can be predicted. Thus, the null hypothesis:

  \[ H_0: \text{The earnings surprise can’t be predicted with significant accuracy.} \]

  In other words, can the function \( f(X_t) \) be predicted before the earnings information is available? The relation between the input and output \( f \) is analysed to establish whether it is a function of variables known before the earnings is announced.

- Secondly, if it can be proven that unexpected earnings is predictable, the question to why it is predictable arises. It may be a market inefficiency, which will question the EMH.

  - If that is true it may also be an exploitable profit opportunity.
  - It may be due to market frictions which have no implications for market efficiency nor present a profit opportunity.

As stated earlier, non-zero \( \Delta \text{EPS} \) is not necessarily indicative of a surprise to the market, and therefore predicting it, no matter how accurate, would not provide conclusive evidence regarding the predictability of unexpected earnings. The accurate prediction of \( \Delta \text{EPS} \) is also not directly exploitable, because earnings appreciation does not directly translate into price appreciation especially when it is already discounted by the market. It would be very difficult to determine whether the market expected the change in earnings without having
the consensus estimate data, thus when analysing the predictability of the earnings surprise. The analysis regarding the predictability of unexpected earnings therefore focuses on predicting only one proxy for unexpected earnings, namely the event return ($ER$).

To answer the questions regarding the predictability of unexpected earnings and what it means for market efficiency and profit opportunities, the same procedures as with investigating the PEAD anomaly are used. The multivariate regression analysis is however adapted to a combination of a time-series and cross-sectional regression analysis, because lagged values of the unexpected earnings measure ($ER$) is also included as explanatory variables.

In addition to all the explanatory variables, lagged values of unexpected earnings are used to calculate correlation and autocorrelation.

4.3.4. **Exploiting the Anomalies**

The previous section looked at the techniques to establish the statistical significance of the PEAD effect and the predictability of earnings surprise. In this section we look at techniques with which the economic significance and exploitability of the anomalies can be analysed. There is only one realization of the return generating process and therefore the only method to test the exploitability is to ‘back-test’ trading strategies using simulations on historical data.

**Simulation Methodology**

First of all it should be stated that the goal of the simulation study is not to find the optimal investment strategy that can be directly implemented in a real-world investment environment, but rather to test the exploitability of the effects studied in this research, the influence of the simulation parameters on the performance of the strategy and the stationarity of the return generating process. These findings will not only prove whether or not the effects studied are economically significant, but also determine the consequence of real-world constraints on the performance and exploitability of academically studied market anomalies. Most academic studies usually make a lot of simplifying assumptions about real-world trading conditions and therefore do not consider some of the aspects that influence investment performance. This study aims to incorporate as much realism without complicating matters too much.
The simulation methodology used in research is somewhat based on the research by McDonald and Mendenhall [81].

A high-level overview of the simulation process is illustrated in Figure 12. The simulations are run on a year by year basis. All the simulation parameters relevant to decision making is estimated at the start of each year and in order to give a large enough initial estimation window of roughly 1000 trading days, no simulation starts before the year 1995 given the data sample. At the end of each year new data is loaded and at the end of the last year in the simulation (2010), all the relevant performance and portfolio statistics are calculated. Each simulation is started with a cash amount of which the balance is carried over to the next year.

The ‘Run Simulation’ block in the flowchart in Figure 12 is explained by the flowchart in Figure 13. This process is run for each trading day of each year. Each day all relevant
information for each share is updated. This includes the share price, trading volume and all the anomaly indicators used in the statistical analysis. According to this information, the simulation parameters and the specific decision criteria, a decision is made to include the share on the sell list or the buy list or ignore it altogether. After the update procedure has been completed for all shares, the firms already owned and on the sell list, (depending on the simulation specific constraints) are sold. All the transactions for all the firms not yet owned and on the buy list, are completed depending on the constraints and the cash remaining before each transaction.

The logic governing the decision to include a firm on the buy list for a generic PEAD exploitation strategy is shown in Figure 14. If a firm is not already owned, meets the decision criteria and it is within ten days after its earnings announcement, it is added to the buy list. The decision criteria depend on the specific trading strategy used, but usually comprise of a specific factor of a share compared to a historic threshold. The historic

FIGURE 13: HIGH LEVEL OVERVIEW OF THE SIMULATION PROCESS FOR A SPECIFIC DAY
threshold is calculated at the beginning of each year using a look-back window with a length of 1000 trading days. This is better illustrated with an example. After the earnings announcement (within 10 days), a certain firm has an EY of 20 and the 75th percentile of EY for all firms in the look-back window is calculated to be 17.5. The decision criteria states that firms with an EY above that of the 75th percentile should be bought. This specific firm conforms to the criteria and is thus added to the buy list.

The logic governing a sell decision is shown in Figure 15. If shares of a firm are already owned and it meets the decision criteria, it is added to the sell list. The decision criteria, as with buying, is dependent on the specific strategy employed, but usually involve the shares of a firm being held for longer than a maximum threshold period, or performed worse than expected etc.
EXECUTION OF TRANSACTION

After all the firms in the sample have been reviewed for inclusion on a list on a particular day, the sell transactions commences first, after which all the buy transactions will be executed.

The selling process involves going through each of the entries on the sell list until all shares have been sold and the portfolio cash account credited with the proceeds. Buying differs from selling with regard to the limit of cash available in the cash account. Each day when the buying process commences, all the entries in the buy list are randomly shuffled and starting from the top, the shares are bought one by one until there is no cash left or the list is completed.

The size of the transaction, of which the calculation is explained below, and the related transaction costs is calculated before each transaction is executed. This is done for all entries on the list. The transaction execution process for a buy transaction is illustrated in the flowchart in Figure 16, but the process for a sell transaction is similar. The maximum transaction cost mentioned in the flowchart in Figure 16 is a simulation parameter set manually before simulation commences and is used to limit positions in which the transaction cost is too high compared to the average expected return. The simulation procedure tries to emulate the reality as close as possible, but due to unavailable transaction data and the fact that historical transactions are not necessarily representative of the future, some simplifying assumptions are made. It is assumed that the transaction
can be executed without delay at the previous day’s closing price before the bid-ask spread and other transaction costs are added, thus slippage cost and intraday price movements are ignored.

![Diagram of Transaction Execution Process]

**FIGURE 16: TRANSACTION EXECUTION PROCESS**

The theory underlying optimal capital allocation was discussed in chapter 2. The difficulty with implementing the optimal mean-variance portfolios calculated using Markowitz’ portfolio theory and the criterion for optimal long-term wealth developed by Kelly lies in the estimates of the expected mean and covariance of each asset potentially included in the portfolio. The optimal portfolio is highly dependent on the accuracy of these estimates and therefore can’t be used in an inaccurate estimation environment. As the results will later demonstrate the returns attributable to each prediction variable is non-stationary and varies substantially from year to year. Another potential caveat to implementing the theoretical optimal capital allocation strategies is the constant rebalancing required, especially for the strategies considered in this study which enter positions throughout the year and non-periodically. To keep things simple, the strategies will use one of two simpler capital allocation strategies, namely fixed fractions of the total portfolio value and a dynamic allocation strategy based on a control systems approach.
The size of a position is calculated with several constraints taken into account to minimise the impact of the transaction on the price of the share. These constraints also enable us to determine what effect the size of a portfolio has on the return generated for a particular strategy. This is probably most significant for investment strategies that focus on or are highly correlated with smaller sized firms. The size of the portfolio is surely limited by the number of opportunities and the market capitalisation of each opportunity.

**Fixed Fractions**

Due to the difficulty of calculating market impact and incorporating it into transaction costs, all trading strategies are designed to minimise the market impact by putting constraints on the transaction size in place. The following constraints are assumed for all trades and all simulations:

- The maximum number of shares that may be owned are limited to 5% of a firm’s issued shares.
- No more than three times the average daily volume of shares traded in the past ten days may be traded in any transaction.

The transaction size is then calculated using the following formula:

\[
I_{\text{max}} = \min(0.05 \times \text{SharesIssued}, 3 \times \text{Volume}_{\text{Avg}}, \frac{\text{MaxInvest}}{\text{Price}})
\]  

\(I_{\text{max}}\) is a simulation parameter that limits the maximum amount of capital allocated to any individual firm, it is a fraction of the total portfolio value to ensure sufficient diversification or limit overexposure. The minimum of the three constraints is taken to be the maximum allowed transaction size (in number of shares) per transaction.

The actual transaction size are however calculated as the minimum of \(I_{\text{max}}\) and \(I_0\).

\[
I_0 = \frac{\text{StartInvest}}{\text{Price}}
\]

\[
I = \min(I_{\text{max}}, I_0)
\]

\(StartInvest\) is another simulation parameter that sets the initial investment amount of any transaction. It is a fixed fraction of the total portfolio value.
If the cash in the cash account is enough to complete the transaction, the transaction costs are then calculated.

**Dynamic Allocation**

A brief description of the dynamic capital allocation strategy developed by Barmish [86], [87] follows:

The objective of the controller is to calculate the amount to invest in a security at any point in time. The controlled input shown in *Figure 17* relies on the feedback (gain) and the current price of the security.

![Figure 17: Dynamic Control System Approach to Capital Allocation](image)

Variables used:

- \( I(t) \) – Amount invested at time \( t \)
- \( dl \) – Incremental investment
- \( I_{max} \) – Maximum investment limit per share
- \( I_0 \) – Initial investment amount
- \( g(t) \) – Gain at time \( t \)
- \( dg \) – Incremental gain.

The incremental amount invested is related to the investment gain through the controller gain constant \( K \). The constant \( K \) is a parameter that has to be set beforehand and determines how fast the controller reacts to changes in the price of a share.
\[ dl = Kdg \] (45)

The gain is defined as the incremental change in the share’s price multiplied by the investment amount.

\[ dg = \frac{dp}{p} l \] (46)

When the controller’s recommended investment amount \( I(t) \) is larger than the maximum allowed investment per security the controller is said to be in saturation. Any additional gains are added to the cash account by limiting the amount invested to \( I_{max} \). The gain/loss dynamics before saturation are:

\[ dg = \frac{dp}{p} (I_0 + Kg) \] (47)

This can be rewritten as:

\[ \frac{dg}{I_0 + Kg} = \frac{dp}{p} \] (48)

Integrating the above equation and solving for \( g(t) \) gives:

\[ g(t) = \frac{I_0}{K} \left[ \left( \frac{p(t)}{p_0} \right)^K - 1 \right] \] (49)

Solving for \( I(t) \) gives:

\[ I(t) = I_0 \left( \frac{p(t)}{p_0} \right)^K \] (50)

The above equations are for the continuous case. Discretising the equations yields:

\[ g(k + 1) = g(k) + r(k)I(k) \] (51)

\[ I(k + 1) = (1 + Kr(k))I(k) \] (52)

This is the equations implemented in software to calculate the recommended investment amount \( I(k + 1) \). Implementing the above capital allocation strategy directly leads to many transactions, which translates to high transaction costs and lower overall returns. To limit
the amount of transactions, limits are imposed on the minimum incremental change in $I(k + 1)$. The limit is calculated as the amount which leads to the minimum overall transaction cost as a percentage of the transaction value.

**Transaction Cost**

When making the simulation as realistic as possible it is necessary to include the cost involved with executing each transaction. Thus far we have made two simplifying assumptions that allow us to ignore certain aspects when calculating the total transaction costs. Slippage costs and market impact, which is minimised by the abovementioned measures, are left out of the equation of total transaction costs.

\[
Total\ Transaction\ Cost = Brokerage + BidAsk\ Spread + Tax \tag{53}
\]

![Diagram showing total transaction costs](image)

**Figure 18: Contributors to Total Transaction Cost**

The different constituents of total transaction costs are shown in Figure 18. In calculating total transaction costs it is assumed that trading occurs through a broker and trades are done directly in shares and not in derivative instruments.

**Brokerage Commissions and Taxes**

The total brokerage cost is calculated as:

- Brokerage\(^{14}\) - the maximum of R120 or 0.4% of the transaction value.

\(^{14}\)The specific brokerage is dependent on the broker used and the total value of the account. The values used are applicable to a private trading account at a local broker.
- STRATE – maximum of R10,92 and 0.00005459 times the value of the transaction.
  \[ \text{STRATE} = \text{minimum of R54,59 and STRATE} \]
- Investor protection levy - IPL = 0.000002*Value
- VAT on STRATE, IPL and the broker’s commissions

  \[ \text{VAT} = 0.14 \times (\text{STRATE} + \text{IPL} + \text{Brokerage}) \]  \hspace{1cm} (54)

Security transfer tax, which is only paid when a share is bought.

  \[ \text{STT} = 0.0025 \times \text{Value} \]  \hspace{1cm} (55)

For a buy-transaction the cost would be:

  \[ \text{Total} = \text{Brokerage} + \text{STRATE} + \text{IPL} + \text{VAT} + \text{STT} \]  \hspace{1cm} (56)

And for a sell-transaction it is:

  \[ \text{Total} = \text{Brokerage} + \text{STRATE} + \text{IPL} + \text{VAT} \]  \hspace{1cm} (57)

While the above formula for transaction cost includes taxes, it is only in the form of sales and securities tax. The major contributors to an investor/trader’s tax bill are income and capital gains tax. This depends on multiple factors such as the legal entity which manages the money, personal income tax rates in case of a natural person, other investments, debt etc. This therefore makes it very difficult to incorporate taxes into a simulation. Although it will be ignored in all simulations, it should however be stressed that taxes can reduce returns substantially and particularly for shorter term trading strategies whose returns are taxed at the income tax rate and not at the lower effective capital gains tax rate.

**Bid-Ask Spread**

The bid-ask spread is the difference between the offering price to sell a share and the bid price offered to buy shares. The bid-ask spread varies by firm and time and can’t be established exactly. The bid-ask spread used in this research is estimated with a model using a firm’s market capitalisation, trading volume and price as inputs.

  \[ \text{BidAsk Spread} = \alpha + \beta_M \text{MarketCap} + \beta_V \text{Volume} + \beta_P \left(\frac{1}{\ln(Price)}\right) \]  \hspace{1cm} (58)
The above model is fitted on historical daily average bid-ask spread data for the period from May 2004 to March 2011 and contains a total of 572526 observations. The data was obtained from www.sharenet.co.za. The model was found to be a reasonably accurate estimate of the bid-ask spread. To control for the effects of outliers in the data, upper and lower limits in the bid-ask spread are set.

If the estimate of the transaction cost is lower than the maximum allowed transaction costs the share bought are added to the owned list in the case of a buy transaction and removed from the owned list when a share is sold. This completes the simulation process for a specific day. This whole process is repeated for each day in every year for the period over which the simulation is run.

**Simulation Strategies**

As mentioned earlier, all strategies are simulated for the sixteen year period from 1995 to 2010 to leave an initial parameter estimation period of ±1000 days (1991 – 1994).

The simulated strategies can be classified into several categories using the following different criteria.

The anomaly which the strategy is trying to exploit:

- The PEAD anomaly (PEAD)
- The Predictability of Unexpected Earnings (UE)
- A strategy which tries to combine the exploitability of both the PEAD and unexpected earnings predictability (UE-PEAD)

The positions allowed:

- Long positions only.
- Long and short positions allowed.

The investment holding period:

- A pre-specified fixed holding period (120 days)
- A method to dynamically decide when to exit, increase or decrease a current position.
The PEAD strategies are simulated for use in the analysis of the PEAD effect. The value of the variable (factor score) is compared with the historical values to determine in which quartile it lies.

**LONG-ONLY**

The long-only strategy only takes long positions in shares. The decision criteria involve investing only in those with a factor above that of the historical $75^{th}$ percentile.

$$Long: ER_t > P_{75}(ER_{t-1000:t-1})$$  \hspace{1cm} (59)

The strategy is simulated for various fixed holding periods and the dynamic allocation strategy.

**LONG/SHORT**

A long/short strategy is simulated by taking long positions in the shares with a factor score above the $75^{th}$ percentile and short those with a score lower than the $25^{th}$ percentile.

$$Short: ER_t < P_{25}(ER_{t-1000:t-1})$$  \hspace{1cm} (60)

The simulations strategies are presented as the simulation matrix in Table 1.

<table>
<thead>
<tr>
<th></th>
<th>Long Fractions</th>
<th>Dynamic Allocation</th>
<th>Long/Short Fractions</th>
<th>Dynamic Allocation</th>
</tr>
</thead>
<tbody>
<tr>
<td>PEAD</td>
<td>PEAD-Long-FF</td>
<td>PEAD-Long-DA</td>
<td>PEAD-LongShort-FF</td>
<td>PEAD-LongShort-DA</td>
</tr>
<tr>
<td>UE</td>
<td>UE-Long-FF</td>
<td></td>
<td>UE-LongShort-FF</td>
<td></td>
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<tr>
<td>UE-PEAD</td>
<td>UE-PEAD-Long-FF</td>
<td></td>
<td>UE-PEAD-LongShort-FF</td>
<td></td>
</tr>
</tbody>
</table>

**TABLE 1: MATRIX OF SIMULATION STRATEGIES**

The influence of transaction costs is analysed by simulating the abovementioned strategies ignoring transaction costs and comparing the results to those that incorporate transaction costs.

**RANDOM**

In addition to the abovementioned strategies, a random strategy is also implemented to analyse the sensitivity of the excess returns to each simulation parameter without other effects influencing the returns.

The random strategy is in all aspects the same as the general strategy described above, except in the decision criteria employed. Instead of only taking positions in shares with a forecast score in the upper quartile, all shares fulfilling the basic criteria of being within the
specified period from the earnings announcement date are included on the *buy list*. Because the *buy list* is randomly shuffled before execution commences, the strategy is considered random, because no other criteria is imposed to exclude a share from the *buy list*. The execution of the transaction proceeds exactly as described above with the same constraints taken into account.

Due to time and resource limitations, a full-scale Monte-Carlo simulation of the parameters is not performed to fully test the effects, but a limited sample of parameter values that is deemed representative of practical possible values were used in the simulations.

In each simulation, one of the parameters takes on a specified value, while all others are kept constant at their average value. For each successive simulation the value is changed to the next of the set of possible values. This continues until all values of each controllable parameter have been used in a simulation.

The following directly controllable parameters are changed in successive simulations:

- Initial investment amount as a percentage of the total portfolio value - $I_0$
- Maximum percentage of portfolio allocated to individual share - $I_{max}$
- Maximum allowed transaction cost – MaxTransCost

Implicit parameters to which the sensitivity of excess PEAD return is also calculated:

- Average number of days a share is held in the portfolio before it is sold - AveDaysHeld
- Average cash in portfolio - AveCash
- Median market capitalisation of share portfolio – MarketCap

The method of calculating the sensitivity of output variable to the changes in the input variable is the simple derivative of the output $Y$ with respect to an input factor $X$, while keeping all other variables constant. Because an analytical function that relates the output with the input does not exist, the results from multiple simulations are used to fit a function of which the derivative is calculated and in the case of a linear function, the derivative is equal to the regression coefficient.
The sensitivity formula is defined as the change in excess return ($\alpha$) for each unit of change in an input parameter $x$:
\[
\frac{\partial y}{\partial x}\bigg|_{x=x_k}
\] (61)

For non-linear functions, the sensitivity is a function of the input parameter and therefore has to be evaluated at a specific point $x_k$, but to simplify matters only linear functions are fit to the random simulation results. This however proves to be adequate.

**Performance**

Several performance measures are calculated to gauge the risk and return of each simulated strategy. They include the following measures\(^{15}\):

- Mean Return
- Standard Deviation
- Sharpe ratio
- Alpha
- Beta
- Information Ratio
- Maximum Drawdown
- Percentage Winners
- Average Gain (Edge per trade)

To calculate the performance measures the strategy’s simulated returns are converted to monthly returns. A risk-free rate of 4% p.a. and the value weighted market return is used as benchmark throughout the research unless otherwise specified.

**4.4. Chapter Summary**

In this chapter the detailed aspects of the analysis and methodology used in this research were outlined. This presents a comprehensive strategy to establish the statistical significance of the effect of earnings announcements on returns as well as an analysis to determine whether the market efficiently process information and if there exist any profit

\(^{15}\) For definitions of each measure refer to chapter 2.
opportunities. A strategy studying the economic significance of the profit opportunities (if any) through simulation was also outlined. In the next chapter the results of the statistical analysis are presented and the simulation results are presented in chapter 6.
5. **Statistical Analysis Results**

“Not everything that can be counted counts, and not everything that counts can be counted.”

- Albert Einstein

5.1. **Introduction**

This chapter consists of three sections; each presenting the results obtained from the tests analysing each of the three hypotheses. Clear evidence regarding each hypothesis on the local market for the period 1991-2010 is presented as well as findings that might explain and illuminate the effects studied.

5.2. **Analysis of the Response to Earnings Announcements**

The first hypothesis investigated in this research is that earnings announcements do not convey any new information to the market. The average daily and cumulative daily market-adjusted response of all observations to earnings announcements for the period 60 days prior to the announcement up to 120 days after the announcement is shown in Figure 19. It is clear that on average the market reacts positively to earnings announcements (day 0) regardless of the sign or magnitude of the change in announced earnings from the last previous announcement.

![Figure 19: Average Response](image-url)
The average return is 0.005 above the market return on the day of announcement and it is statistically significant with a t-statistic of 7.7081 as shown in Table 2.

<table>
<thead>
<tr>
<th>Mean</th>
<th>StdDev</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0050</td>
<td>0.0447</td>
<td>7.7081*</td>
</tr>
</tbody>
</table>

* Significant at 1%, ** Significant at 5%, *** Significant at 10% confidence level

Table 2: Average Response to Earnings Announcements

The null hypothesis that earnings do not convey any new information to the market is therefore proven to be false and consequently \( f(X_i) \neq 0 \) in the simplified model that relates the market response to a unit step input.

\[
\alpha_i(t) = u_s(t) f(X_i) + \varepsilon_t
\]  (62)

Since the market on average responds positively to earnings announcements, the data is adjusted by removing the mean of all observations for each day in the [-10; 10] day period which is used in further investigation of the response to earnings announcements. A new model for the mean- and market-adjusted response to earnings announcements is suggested where \( f(X_i) \) is equal to a random variable \( w_t \) with mean \( \mu_w = 0 \) and variance equal to the variance of the average daily market-adjusted return \( E(\alpha_{i,t}) \), \( \sigma_w = \sigma_{E(\alpha_{i,t})} \).

\[
\alpha_i(t) = u_s(t)w_t + \varepsilon_i
\]  (63)

We will now investigate whether the relationship is truly random, or whether it is a function of \( \Delta EPS \), firm size (MC), earnings yield (EY - proxy for the value effect) and the relative price momentum for the six months leading up to the announcement (RS6).

The top figure in Figure 20 shows the market-adjusted response to earnings announcements for the different \( \Delta EPS \) quartiles. It is evident that the market reacts to earnings announcements and the reaction is related to \( \Delta EPS \). The bottom (top) quartile of \( \Delta EPS \) corresponds with a negative (positive) reaction to the announcement. The reaction related to \( \Delta EPS \) in the middle two quartiles is subdued and with a less clear discerning pattern. The graphical evidence suggests that \( f(X_i) \) is not totally random, but is a function of \( \Delta EPS \). The bottom figure in Figure 20 shows the market-adjusted reaction to earnings announcements divided into four quartiles when sorted in terms of the event return (ER). One can say that \( \Delta EPS \) in the top (bottom) quartile explains roughly about 50% of the market response (ER) in

---

\( ^{16} \) * Significant at 1%, ** Significant at 5%, *** Significant at 10% confidence level

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the top (bottom) quartile, because the [-10; 10] day market-adjusted return for the top (bottom) ΔEPS quartile is about 0.03 (-0.02) and the top (bottom) quartile of returns regardless of ΔEPS is about 0.06 (-0.05).

The price adjusts quickly to the new levels after an announcement and then levels off with no significant movement from that level in the short term. This shows that on average the response fits a (somewhat smoothed) step function, which confirms the assumption that on average the system dynamics can be modelled as an integrator responding to an impulse information input. The response of the system is said to be critically damped for the short period under investigation, as one would expect in an efficient market where the price adjusts almost instantaneously to the new level with no significant delay or subsequent
overshoot. One interesting aspect from the graphs is that the market seems to anticipate the higher (lower) ΔEPS in the days prior to an announcement by adjusting the price slowly upwards. The inverse seems to be happening for the top and bottom quartiles of market response to earnings announcements as sorted by the event returns (ER). Figure 21 shows the cumulative market-adjusted returns surrounding earnings announcements for the 4 quartiles when sorting by the drift for the 10 days prior to the announcement. It is clear that it is not significantly indicative of the response to the earnings announcements and therefore the drift prior to the announcement can’t be used to accurately predict the response as one would’ve expect from the results in Figure 20.

The predictability of the response in general is investigated in the section: Analysis of the Earnings Surprise.

<table>
<thead>
<tr>
<th>Input</th>
<th>Output</th>
<th>Mean</th>
<th>Mean</th>
<th>StdDev</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔEPS 1st Q</td>
<td></td>
<td>-0.3788</td>
<td>-0.0128</td>
<td>0.0968</td>
<td>-3.9608*</td>
</tr>
<tr>
<td>ΔEPS 2nd Q</td>
<td></td>
<td>0.0120</td>
<td>-0.0087</td>
<td>0.0779</td>
<td>-3.4070</td>
</tr>
<tr>
<td>ΔEPS 3rd Q</td>
<td></td>
<td>0.1005</td>
<td>0.0045</td>
<td>0.0723</td>
<td>1.6826</td>
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<tr>
<td>ΔEPS 4th Q</td>
<td></td>
<td>0.8159</td>
<td>0.0197</td>
<td>0.0882</td>
<td>6.4087*</td>
</tr>
</tbody>
</table>

TABLE 3: RESPONSE TO EARNINGS ANNOUNCEMENTS FOR ΔEPS QUARTILES

The significance of the response (day [0; 10]) to earnings announcements related to ΔEPS quartiles is shown in Table 3 and the relation between the cumulative amplitude of the steady state response and ΔEPS is shown in Figure 22. The data is based on groups of
observations filtered on successive ΔEPS thresholds of the successive decile values for which the corresponding mean ΔEPS and response are calculated. The average ΔEPS values on the x axes are calculated as:

\[
\bar{\Delta EPS}_i = \frac{1}{N} \sum_{k=1}^{N} [\Delta EPS_i > P(\Delta EPS, i \times 10)], \forall i \in [0; 9]
\]  

(64)

\(P(\Delta EPS, i \times 10)\) represents the \(i \times 10^{th}\) percentile of ΔEPS and \(N\) is the number of observations left after the filter is applied. The corresponding y axes values are calculated as the average of the cumulative amplitude of the steady state response for the same group after the ΔEPS filter is applied.

This method of calculation derives from the notion that many investment strategies involve investing only in those companies with a specific attribute higher than a certain threshold. It can be seen that the relationship resembles a logarithmic relationship, which may be partially caused by the way in which returns are calculated. The most important observation is however that the function \(f(X_i)\) which relates the amplitude of the step function response to the input information impulse is clearly also a function of ΔEPS.

\[y = 0.0108\ln(x) + 0.0296\]
\[R^2 = 0.9503\]

**FIGURE 22: LOGARITHMIC RELATION BETWEEN ΔEPS AND THE MARKET RESPONSE**

The variation in the response to earnings announcement for the different size groups is presented in Figure 23. The size groups are defined as described in chapter 4. From the bottom four figures in Figure 23 it is evident that, when sorting in terms of the event response, the market reaction varies from significantly negative to significantly positive.
(compared to average response) across all size groups. The top four figures however shows that, when sorting in terms of ΔEPS, only the micro capitalisation group seems to follow a distinctive pattern, while no apparent discernible reaction on or subsequent to the day of announcement is visible for the other size groups. The magnitude of the response is inversely related to firm size. Thus it can be argued that the announcement of high or low ΔEPS (top and bottom quartile) on average presents little new information to the market for small, medium and large capitalisation firms. Deviation from the EMH in this respect therefore seems to be restricted to micro capitalisation firms only.

![Graphs showing response to ΔEPS for different size groups](image)

FIGURE 23: RESPONSE TO ΔEPS (TOP) AND ACTUAL MARKET REACTION (BOTTOM) FOR THE DIFFERENT SIZE GROUPS
The bottom set of figures show that large firms on average tend to react more severely to negative news and less severely to positive news relative to firms in the micro capitalisation size group. This asymmetry in response is possibly due to an asymmetry in expectations: the market is on average over optimistic of the future prospects of larger firms relative to smaller firms. This may be a result of the asymmetry in terms of availability of information.

The results thus suggest that $f(X_i)$ is not only a function of $\Delta$EPS, but also a function of the size of the firm. The relation between $\Delta$EPS and the return response is dependent on size and the relation for the smallest and largest size groups is shown in Figure 24. For large firms, the relation between $\Delta$EPS and the magnitude of the response is insignificant.

The event return relative to firm size is further investigated by ranking the shares by market capitalisation, sorting the data into bins of 100 observations each and then calculating the statistics of the event return for each bin. The average, standard deviation, absolute maximum return as well as the frequency of above average returns for each bin is calculated. The results are presented in Figure 25 where the specific measure for a bin is plotted versus the average logarithm of that bin’s market capitalisation.
The results establish the following:

- For the smallest size firms, the average magnitude of response, the standard deviation and the frequency of above average responses is small, indicating that on average the market don’t react much. This is consistent with the notion that the illiquidity of the shares in this size category prevents the price to react substantially to new price information.

- As size increases from the smallest micro-cap shares the size of the response increases and reaches a maximum value at about $\ln(MC)=18$.

- Beyond this size the average magnitude of the response declines as size increases. This is partly because the number of negative responses increases with size and therefore lowering the average.

- The standard deviation of the response also declines as size increases beyond this value.

- Similarly, the absolute value of the maximum response declines with size, but less so than the average magnitude of the response.

- The frequency of above average responses decreases with size.

Average information uncertainty, also known as entropy $H(X)$ is maximised when every outcome is equally probable $p(x_k)$, therefore the higher the standard deviation the higher
the probability of extreme occurrences and therefore also the average uncertainty (entropy). Refer to chapter 2 for the definitions of all the variables.

\[ H(X) = - \sum_k p(x_k) \log(p(x_k)) = \sum_k p(x_k) I(X = x_k) \]  

It can reasonably be assumed that the magnitude of the response to an announcement is proportional to the information content of the announcement.

It can furthermore be seen that the probability of extreme occurrences decreases with size as the trend in standard deviation suggests, therefore on average, the uncertainty regarding earnings also decreases with increase in size. Given the abovementioned assumption, information uncertainty thus decreases with size. Since information is by definition the removal of uncertainty, the average information content of earnings announcements therefore decreases with size.

The response to earnings announcements for the different ΔEPS quartiles and value quartiles as measured by EY is shown in Figure 26 and for the respective momentum (RS6) quartiles in Figure 27. The response to announcements for the different value and momentum groups does not seem to follow a clear pattern and varies for the respective ΔEPS quartiles. It is nonetheless notable that for high EY firms, the reaction to high ΔEPS leads to a significant positive response and the high EY firms on average realise relatively higher returns for the [-10; 10] day period irrespective of ΔEPS. This agrees with the view that the ratio of expected EPS to price (future EY) is relatively stable over time and that firms with a high historic EY have discounted bad future earnings prospects into the share price with the expectation of lower future EPS. The newly announced EPS surprises the market and therefore the market reacts accordingly. Announced ΔEPS in the top quartile of ΔEPS and the top quartile of EY can on average be regarded as unexpected earnings and new information. Average response of 0.08 is more than double the top quartile of the average response of nearly 0.03 which is shown in Figure 20 (top). It should also however be noted that EY is strongly correlated with size, having a sample correlation coefficient of -0.2837. The response related to EY is therefore also to an extent attributable to size.
It also seems that the firms in the highest and lowest quartiles of momentum are more sensitive to announced ΔEPS and react more severely, but momentum doesn’t seem to have a clear relation with the response following earnings announcements.

**FIGURE 26: RESPONSE TO ΔEPS FOR DIFFERENT VALUE (EY) QUARTILES**

**FIGURE 27: RESPONSE TO ΔEPS FOR DIFFERENT MOMENTUM (RS6) QUARTILES**

The above qualitative and graphical analysis gave indication pertaining to how ΔEPS, size, value and momentum affect the relation between the earnings announcement and the price response.
The same insight is gained by calculating the sample covariance matrix of the variables used in the analysis. Table 4 shows the normalised covariance matrix of all five variables namely ΔEPS, the value effect (EY), size (MC), relative momentum (RS6) and the three-day announcement return (ER). The results show that EY and momentum (RS6) is significantly correlated with ΔEPS, but ΔEPS, EY and MC is correlated with ER. This means that on average only ΔEPS, EY and MC provides information regarding the relation between the announcement and the response. Momentum is not significantly related to the short term response and it is argued that it is representative of the market’s expectations, while the actual response is representative of the surprise. The correlation between the response and MC and EY questions the market’s efficacy in processing information. Both MC and EY are known before the earnings announcement is made and the relatively high correlation with the response following the announcement suggests that the response can be predicted beforehand to some degree. This is however further investigated later in this chapter in section 5.4.

<table>
<thead>
<tr>
<th></th>
<th>ΔEPS</th>
<th>ER</th>
<th>EY</th>
<th>MC</th>
<th>RS6</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔEPS</td>
<td>1.0000</td>
<td>0.0706*</td>
<td>-0.0956*</td>
<td>-0.0122</td>
<td>0.0696*</td>
</tr>
<tr>
<td>ER</td>
<td></td>
<td>1.0000</td>
<td>0.0769*</td>
<td>-0.1265*</td>
<td>0.0057</td>
</tr>
<tr>
<td>EY</td>
<td></td>
<td></td>
<td>1.0000</td>
<td>-0.2997*</td>
<td>-0.2089*</td>
</tr>
<tr>
<td>MC</td>
<td></td>
<td></td>
<td></td>
<td>1.0000</td>
<td>0.0431*</td>
</tr>
<tr>
<td>RS6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.0000</td>
</tr>
</tbody>
</table>

*TABLE 4: NORMALISED COVARIANCE MATRIX*

It is however still unclear how accurately one can model the amplitude of the cumulative return response as the response to a given announced ΔEPS, given a firm’s size, value, and momentum attributes, i.e. the value of \( f(X_i) \), in equation 61.

To quantify \( f(X_i) \), univariate regression analysis was performed for the return response using each explanatory variable separately, as well as a multivariate regression analysis where all variables are used simultaneously. All variables are normalised by removing their mean and scaling by their standard deviation. The results are presented in Table 5 below.
The last two columns in Table 5 also report the accuracy achieved in predicting the response using each model. The prediction accuracy is determined by calculating the root mean square error (RMSE) between the cumulative return response \( r_i(t) \) of an individual observation and the predicted return response \( \alpha_i(t) \) for the 10 day period from the day of the earnings announcement.

\[
RMSE = \sqrt{\frac{1}{11} \sum_{t=0}^{10} (\alpha_i(t) - r_i(t))^2}
\]  

(66)

If the RMSE is smaller than the standard deviation of the daily return \( \varepsilon_t \), the prediction is considered accurate and the percentage of accurate predictions out of the total sample of predictions is used as the prediction accuracy. For the random case the model defined in equation 63 is used where \( f(X_i) \) (as used in equation 62) is now equal to a random variable \( w_t \).

The prediction accuracy for all cases is determined on data not included in the model estimation sample.

The multivariate regression coefficients for the normalised variables are shown in Table 6, all of which are significant at the 1% level.

<table>
<thead>
<tr>
<th>Model</th>
<th>( R^2 )</th>
<th>F-Stat</th>
<th>Prediction Accuracy</th>
<th>Sign</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random</td>
<td>0.0415</td>
<td>68.9607*</td>
<td>0.0739</td>
<td>0.4783</td>
</tr>
<tr>
<td>( \Delta EPS )</td>
<td>0.0110</td>
<td>9.0347</td>
<td>0.1175</td>
<td>0.5655</td>
</tr>
<tr>
<td>Negative ( \Delta EPS )</td>
<td>0.0198</td>
<td>16.4271*</td>
<td>0.0993</td>
<td>0.5248</td>
</tr>
<tr>
<td>EY</td>
<td>0.0023</td>
<td>4.1723**</td>
<td>0.1103</td>
<td>0.5279</td>
</tr>
<tr>
<td>RS6</td>
<td>0.0041</td>
<td>8.5313*</td>
<td>0.1120</td>
<td>0.4991</td>
</tr>
<tr>
<td>MC</td>
<td>0.0092</td>
<td>19.5273*</td>
<td>0.1049</td>
<td>0.5276</td>
</tr>
<tr>
<td>Multivariate</td>
<td>0.0525</td>
<td>22.3231*</td>
<td>0.0851</td>
<td>0.4123</td>
</tr>
</tbody>
</table>

**TABLE 5: REGRESSION ANALYSIS RESULTS**

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \Delta EPS )</td>
<td>0.0198</td>
</tr>
<tr>
<td>MC</td>
<td>-0.0067</td>
</tr>
<tr>
<td>EY</td>
<td>0.0087</td>
</tr>
<tr>
<td>RS6</td>
<td>-0.0049</td>
</tr>
</tbody>
</table>

**TABLE 6: SIGNIFICANCE OF MULTIVARIATE REGRESSION COEFFICIENTS**
A coefficient attribution of 0.0198 to the natural logarithm of ∆EPS means that for every standard deviation in announced ln(∆EPS), the price responds with a return of roughly 2% above the market return over the period of 10 days.

Thus the relationship between the step input and output can be modelled as:

\[
\begin{align*}
    f(X_i) &= -0.0052 + 0.0198 \ln(\Delta EPS_i) - 0.0065 \ln(MC_i) + 0.0097 \text{ER}_i \\
    &\quad - 0.0049 \text{RS}_i
\end{align*}
\] (67)

And the response model of equation 61 is found to be about 8.5% accurate in predicting the response and 40% accurate in predicting the sign alone. This is about 1% more accurate than a random model and less accurate than any of the univariate models. The linear regression model is therefore unable to model the relationship of individual observations accurately. This substantiates the initial assumption which said that the average aggregate response to new information for all individual observations is a step function. The high variance among individual observations defies a clear description of the dynamics of the response to earnings announcements on the individual observation level, but on the aggregate level it has been shown that it is a clear function of the three variables included in the regression.

**SUMMARY**

A brief summary of the key findings of the above analysis is in order:

- The market on average reacts to earnings announcements and the null hypothesis is rejected.
- The response to earnings announcements is on average related to ∆EPS.
- The relationship between the reaction and ∆EPS is close to logarithmic.
- The response to earnings announcements (and its relation to ∆EPS) is related to firm size. The market reaction to earnings announcements for firms in the micro capitalisation group is higher than for small, medium and large firms.
- ∆EPS on average explains roughly 50% of the magnitude of the response for the top and bottom quartiles when sorting firms based on actual response.
• The asymmetry in the actual top and bottom quartiles of response reveal that the market may on average be overly optimistic about the future prospects of larger firms relative to smaller firms.

• The average information content of earnings announcements decreases with an increase in firm size.

• The response to earnings announcements for firms with high EY is on average higher compared to other firms and firms with a high announced ΔEPS and high EY experience a relatively big jump in price subsequent to announcements.

• Linear multivariate regression model provides 8% out-of-sample predictability of response and explains only about 5% of variance.

• While these findings accurately describe the average behaviour of firms falling into specific categories, the large variations among the individual observations averts accurate prediction at the level of individual firms.

5.3. ANALYSIS OF THE PEAD ANOMALY

In the previous section the market reaction to earnings announcements and the information content of the announcements were analysed. We found that earnings announcements do convey new information to the market. The question however remains whether the earnings surprise is related to the return for the period subsequent to the earnings announcement. This relationship has been documented and is well-known to occur as the post-earnings announcement drift (PEAD) [7], [10], [13]. In this section the results obtained from analysing the returns for the 120 trading day period after earnings releases (the [3; 120] period) are presented and discussed. The analysis provides evidence to whether or not the PEAD anomaly occurred on the JSE for the period 1991-2010.

We will firstly look at the statistical properties of the post-earnings announcement returns after which the relationships with each explanatory variable are presented as measured by cross-sectional correlation and cross-sectional sorts and regression analysis. Although the influence of unexpected earnings is at the core of testing the null hypothesis, the results obtained from analysing the relationships between other anomaly variables and post-earnings announcement returns are essential to establishing whether the PEAD effect is
truly an independent effect or if it is merely a manifestation of other well-known anomalies such as the momentum effect, the value effect or the size effect.

**Statistical properties of post-earnings announcement returns**

Due to the fact that earnings announcements are dispersed through time there are several methods of aggregating data to make accurate comparison with alternative investments such as the market return. The method used here stems from the view that after any particular earnings announcement (on day 3) an investor has the choice to invest in the particular firm which has just announced earnings or the overall market, which is generally implemented by investing in an instrument such as a market tracking exchange traded fund or a futures contract on a market index. The average daily return for the six month period (roughly 120 trading days) subsequent to the earnings announcement for all earnings announcements and for each of the two choices is then calculated. The calculated cumulative daily average returns for the twenty years 1991 to 2010 is shown in *Figure 28* and the average return for the full six month period is presented in *Table 7*. It should however be noted that *Figure 28* does not give an accurate representation of the variability in returns faced by an investor due to the fact that it is an average of many observations.

The average nominal logarithmic returns for the six month period subsequent to earnings announcements for all the observations are 0.0628; if the three-day announcement returns (previously also called the event returns) are included, it increases to 0.074. It is just short of the 0.0766 average total return achieved by the value weighted market. The average excess risk-adjusted return for the same period is calculated to be 0.0207 due to the lower beta of the equally weighted PEAD returns with the value-weighted market returns. The higher than zero excess PEAD returns could possibly be due to other risk related effects not captured by a single factor CAPM market model. The average excess PEAD return should be kept in mind when evaluating the results obtained.

<table>
<thead>
<tr>
<th></th>
<th>Average Return</th>
</tr>
</thead>
<tbody>
<tr>
<td>PEAD</td>
<td>0.0628</td>
</tr>
<tr>
<td>Event + PEAD</td>
<td>0.0740</td>
</tr>
<tr>
<td>VW Total Return</td>
<td>0.0766</td>
</tr>
<tr>
<td>EW Total Return</td>
<td>0.0268</td>
</tr>
<tr>
<td>Excess PEAD</td>
<td>0.0207</td>
</tr>
</tbody>
</table>

*Table 7: Average returns for the post-announcement period*
The respective average cumulative returns for the six months after earnings announcements are shown in Figure 28; this does not include the returns for the three-day period on and immediately after the announcement.

Figure 29 shows the dispersion of annualised returns for the six month period after earnings announcements overlaid on the normal distribution. From the chart it is evident that extreme occurrences are more frequent than one would expect from a pure normal distribution. Calculating the 3<sup>rd</sup> and 4<sup>th</sup> central moment quantifies the graphical evidence. The skewness (3<sup>rd</sup> moment) is negative which means that values lower than the mean occurs with a higher frequency than what would be expected from the normal distribution. The kurtosis measures the tendency of a distribution to have fat tails and to peak at the mean (peakedness); a value of 5.3623 indicates a more frequent occurrence of outliers than expected from a normal distribution.
FIGURE 29: HISTOGRAM OF THE ANNUALISED POST-EARNINGS ANNOUNCEMENT RETURNS

Two tests measuring the normality of a distribution, the Kolmogorov-Smirnov test and the Lilliefors test both reject the null hypothesis that the post-earnings announcement returns are normally distributed. This is important in several aspects. Firstly, most statistical techniques and tests assume normally distributed data; therefore the results of each measure and test should be critically analysed. Secondly, the higher frequency of outliers also increases the risk above what is measured by the standard deviation alone.

<table>
<thead>
<tr>
<th></th>
<th>PEAD</th>
<th>Normal</th>
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</thead>
<tbody>
<tr>
<td>Skewness</td>
<td>-0.6114</td>
<td>0.000</td>
</tr>
<tr>
<td>Kurtosis</td>
<td>5.3623</td>
<td>3.000</td>
</tr>
</tbody>
</table>

TABLE 8: THIRD AND FOURTH CENTRAL MOMENTS OF THE PEAD SAMPLE AND THE NORMAL DISTRIBUTION

PREDICTORS OF EXCESS POST-EARNINGS ANNOUNCEMENT RETURNS

In this section the results from the analysis testing the relationship between post-earnings announcement returns and the anomaly variables will be presented. The main relationship central to this research is that between unexpected earnings and the excess PEAD. The degree to which they are related are presented first, and evidence whether or not the PEAD effect is a manifestation of another known anomalies follows.

UNEXPECTED EARNINGS

As mentioned in chapter 4, two proxies for unexpected earnings are used in this research, namely the three-day announcement returns, also called the event returns (ER), and the normalised change in EPS, ∆EPS. In the previous section we found that, over the period 0 to 10 days after the announcement, ∆EPS on average accounts for roughly about 50% of the actual extreme return responses.
Figure 30 shows the cumulative market-adjusted return for the [-60; 120] day period prior and subsequent to the earnings announcements. An interesting aspect of the response relevant to the current analysis is that for the bottom (top) ΔEPS quartile, the prices continue to drift in the same direction as the response from the 20th day after the announcement up to the next announcement (±120 days from the previous). This phenomenon is known as the post-earnings announcement drift (PEAD) anomaly.

We start the statistical analysis by calculating the Pearson sample correlation coefficient between unexpected earnings proxies and the excess risk-adjusted post-announcement returns over the [3; 120] day period, which is estimated by the market model described in
chapter 4. The sample correlation coefficient between the post-earnings announcement returns and the unexpected earnings determines the strength of the relationship between the two variables. Table 9 presents the sample correlation coefficients for each of the two proxies for unexpected earnings with excess PEAD. The correlations are both significant at the 1% level.

<table>
<thead>
<tr>
<th></th>
<th>Correlation Coeff.</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ER</td>
<td>0.0961</td>
<td>6.6041*</td>
</tr>
<tr>
<td>ΔEPS</td>
<td>0.0609</td>
<td>3.5738*</td>
</tr>
</tbody>
</table>

*TABLE 9: SAMPLE CORRELATION COEFFICIENTS OF UNEXPECTED EARNINGS AND PEAD RETURN*

Testing the null hypothesis involves testing the strength of the relationship between the unexpected earnings and the subsequent excess returns (PEAD). The sample correlation coefficients clearly indicate that there is a strong relationship, but to reject the null hypothesis with confidence we need some further evidence.

Testing the predictive ability of the same variables by sorting each variable, grouping it into quartiles and calculating each group’s corresponding excess PEAD returns reveals that the unexpected earnings as measured by ER and ΔEPS are able to separate the winners from the losers. The bottom quartile of unexpected earnings as measured by ER corresponds with average excess PEAD return of -0.0245 which is statistically significant at the 1% level and the top quartile corresponds with a mean return of 0.0566 which is also significant at the 1% level. This gives an average excess hedged (taking a long position in the winning quartile and shorting the losing quartile) return of 0.0811 before transaction costs for the six month period post-announcement. Although ΔEPS is also able to separate winners from losers, this is true to a lesser extent (lower t-statistic).

<table>
<thead>
<tr>
<th>Quartile</th>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ER</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0245</td>
<td>-5.4645*</td>
</tr>
<tr>
<td>2</td>
<td>0.0264</td>
<td>0.7439</td>
</tr>
<tr>
<td>3</td>
<td>0.0163</td>
<td>-0.6178</td>
</tr>
<tr>
<td>4</td>
<td>0.0566</td>
<td>4.7533*</td>
</tr>
<tr>
<td>ΔEPS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0056</td>
<td>-1.7631**</td>
</tr>
<tr>
<td>2</td>
<td>0.0268</td>
<td>0.7057</td>
</tr>
<tr>
<td>3</td>
<td>0.0248</td>
<td>0.5827</td>
</tr>
<tr>
<td>4</td>
<td>0.0446</td>
<td>2.7235*</td>
</tr>
</tbody>
</table>

*TABLE 10: PEAD RETURNS CORRESPONDING TO UNEXPECTED EARNINGS QUARTILES*
The separation ability of unexpected earnings, as represented by ER, is shown in *Figure 31* where the average absolute cumulative return corresponding to each ER quartile is displayed together with the average cumulative return for all observations after earnings announcements.

While the above may be sufficient evidence to prove the significance of the relationship between unexpected earnings and PEAD, the question arises to how stable (stationary) the relationship has been over the twenty years under study. The average values for each year and each quartile of ER is shown in *Table 11* with the number of observations per year in the last column.
The difference in the average value of Table 11 and the values in Table 10 is due to the different weighting each year carries in the total sample. The total number of observations per year is relatively small in the first decade compared to the second decade which thus carries a larger weighting. Hedged returns, although quite volatile, experienced only two negative years, in 1998 during the Asian and emerging market crisis and again in 2009 during the global financial crisis, with an average excess return of 0.0877 for the six month post-announcement period.

**SIZE AND LIQUIDITY**

The relation between size and the response to earnings announcements have been established. In this section we further investigate this relationship for the period subsequent to the initial reaction, in other words, the relationship between PEAD and size. The cumulative return for the four size groups and the four ΔEPS quartiles is displayed in Figure 32.

<table>
<thead>
<tr>
<th>YEAR</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>#</th>
</tr>
</thead>
<tbody>
<tr>
<td>1991</td>
<td>0.0341</td>
<td>0.0336</td>
<td>0.0214</td>
<td>0.2100</td>
<td>13</td>
</tr>
<tr>
<td>1992</td>
<td>0.0149</td>
<td>0.0013</td>
<td>0.1043</td>
<td>0.0794</td>
<td>108</td>
</tr>
<tr>
<td>1993</td>
<td>0.0139</td>
<td>0.1251</td>
<td>0.1028</td>
<td>0.1808</td>
<td>112</td>
</tr>
<tr>
<td>1994</td>
<td>0.0735</td>
<td>0.1166</td>
<td>-0.0423</td>
<td>0.0765</td>
<td>121</td>
</tr>
<tr>
<td>1995</td>
<td>0.1168</td>
<td>0.0980</td>
<td>0.1559</td>
<td>0.3036</td>
<td>144</td>
</tr>
<tr>
<td>1996</td>
<td>-0.0473</td>
<td>-0.0350</td>
<td>-0.0636</td>
<td>-0.0092</td>
<td>150</td>
</tr>
<tr>
<td>1997</td>
<td>-0.0937</td>
<td>-0.0016</td>
<td>0.0051</td>
<td>0.0875</td>
<td>155</td>
</tr>
<tr>
<td>1998</td>
<td>-0.1646</td>
<td>-0.1700</td>
<td>-0.1811</td>
<td>-0.1975</td>
<td>172</td>
</tr>
<tr>
<td>1999</td>
<td>-0.0422</td>
<td>-0.0365</td>
<td>0.0384</td>
<td>0.0470</td>
<td>187</td>
</tr>
<tr>
<td>2000</td>
<td>-0.0765</td>
<td>-0.0528</td>
<td>-0.0148</td>
<td>0.0338</td>
<td>211</td>
</tr>
<tr>
<td>2001</td>
<td>0.0393</td>
<td>-0.0236</td>
<td>-0.0484</td>
<td>0.0480</td>
<td>233</td>
</tr>
<tr>
<td>2002</td>
<td>-0.0285</td>
<td>0.0441</td>
<td>0.0131</td>
<td>0.0950</td>
<td>249</td>
</tr>
<tr>
<td>2003</td>
<td>0.0348</td>
<td>0.1132</td>
<td>0.1223</td>
<td>0.1548</td>
<td>260</td>
</tr>
<tr>
<td>2004</td>
<td>0.0377</td>
<td>0.1566</td>
<td>0.1117</td>
<td>0.2117</td>
<td>270</td>
</tr>
<tr>
<td>2005</td>
<td>0.0635</td>
<td>0.1216</td>
<td>0.0854</td>
<td>0.1480</td>
<td>293</td>
</tr>
<tr>
<td>2006</td>
<td>0.0175</td>
<td>0.0559</td>
<td>0.0630</td>
<td>0.0507</td>
<td>304</td>
</tr>
<tr>
<td>2007</td>
<td>-0.1271</td>
<td>-0.0997</td>
<td>-0.0967</td>
<td>-0.0246</td>
<td>328</td>
</tr>
<tr>
<td>2008</td>
<td>-0.1230</td>
<td>-0.1667</td>
<td>-0.0808</td>
<td>-0.0627</td>
<td>351</td>
</tr>
<tr>
<td>2009</td>
<td>0.0924</td>
<td>0.0370</td>
<td>0.0435</td>
<td>0.0902</td>
<td>339</td>
</tr>
<tr>
<td>2010</td>
<td>-0.0186</td>
<td>0.0380</td>
<td>0.0183</td>
<td>0.0479</td>
<td>338</td>
</tr>
</tbody>
</table>

**Table 11: Excess PEAD Returns for Each Year from 1991-2010 Sorted by Unexpected Earnings Quartile**

The difference in the average value of Table 11 and the values in Table 10 is due to the different weighting each year carries in the total sample. The total number of observations per year is relatively small in the first decade compared to the second decade which thus carries a larger weighting. Hedged returns, although quite volatile, experienced only two negative years, in 1998 during the Asian and emerging market crisis and again in 2009 during the global financial crisis, with an average excess return of 0.0877 for the six month post-announcement period.

**SIZE AND LIQUIDITY**

The relation between size and the response to earnings announcements have been established. In this section we further investigate this relationship for the period subsequent to the initial reaction, in other words, the relationship between PEAD and size. The cumulative return for the four size groups and the four ΔEPS quartiles is displayed in Figure 32.
The relationship between the three size and liquidity proxy variables and the excess PEAD returns are analysed by calculating the sample correlation coefficients. The results are presented in Table 12.

From Table 12 it is evident that excess PEAD returns are highly correlated with the market capitalisation, the absolute price and the average share turnover of a firm. The calculated correlation is significant at the 1% level for all three variables. This result now poses the question whether the relationship between PEAD and unexpected earnings is not merely a manifestation of the size effect.

<table>
<thead>
<tr>
<th>Correlation Coeff.</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>MC</td>
<td>-0.1089</td>
</tr>
<tr>
<td>PC</td>
<td>-0.1111</td>
</tr>
<tr>
<td>ST3</td>
<td>-0.0534</td>
</tr>
</tbody>
</table>

TABLE 12: SAMPLE CORRELATION COEFFICIENTS OF LIQUIDITY AND/OR SIZE AND EXCESS PEAD RETURNS

Before the question is answered we first take a further look at the ability of these three size and liquidity measures to separate the winners from the losers. The sample was sorted by size into four groups as described in chapter 4. Share turnover (ST3), and the log of the absolute closing share price (PC) are sorted and grouped into quartiles giving the results as shown in Table 13.
It is clear that all of these variables are statistically significant predictors of excess PEAD returns and thus size and liquidity as measured by these three variables are good at separating winners from losers. The margin by which large capitalisation shares underperform the average after earnings announcements is noteworthy.

To investigate the effect of size on the relationship between unexpected earnings and post-announcement returns, the sample was sorted by size and grouped into the four size groups. Each group was then further sorted by unexpected earnings as measured by ER and divided into quartiles. The results obtained are presented in Table 14.
<table>
<thead>
<tr>
<th>Quartile</th>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MicroCap</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0294</td>
<td>-4.0448*</td>
</tr>
<tr>
<td>2</td>
<td>0.0413</td>
<td>0.5066</td>
</tr>
<tr>
<td>3</td>
<td>0.0343</td>
<td>-0.1175</td>
</tr>
<tr>
<td>4</td>
<td>0.0748</td>
<td>3.3647*</td>
</tr>
<tr>
<td><strong>SmallCap</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.006</td>
<td>-1.7212**</td>
</tr>
<tr>
<td>2</td>
<td>0.015</td>
<td>-0.1412</td>
</tr>
<tr>
<td>3</td>
<td>0.0161</td>
<td>-0.0701</td>
</tr>
<tr>
<td>4</td>
<td>0.0516</td>
<td>2.6547*</td>
</tr>
<tr>
<td><strong>MidCap</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0133</td>
<td>-1.2389</td>
</tr>
<tr>
<td>2</td>
<td>-0.0105</td>
<td>-1.0556</td>
</tr>
<tr>
<td>3</td>
<td>0.0206</td>
<td>1.1134</td>
</tr>
<tr>
<td>4</td>
<td>0.0383</td>
<td>1.878**</td>
</tr>
<tr>
<td><strong>LargeCap</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0598</td>
<td>-0.9784</td>
</tr>
<tr>
<td>2</td>
<td>-0.053</td>
<td>-0.3471</td>
</tr>
<tr>
<td>3</td>
<td>-0.0429</td>
<td>0.0685</td>
</tr>
<tr>
<td>4</td>
<td>-0.0145</td>
<td>1.5594***</td>
</tr>
</tbody>
</table>

*TABLE 14: PEAD RETURNS GROUPED BY SIZE AND DIVIDED INTO UNEXPECTED EARNINGS QUARTILES.*

The results indicate that unexpected earnings as measured by ER are still able to separate winners from losers at the 10% level of significance. The hedged returns for all four size groups are significant at the 5% level at least. When one looks at the hedged returns in the different size groups it is clear that the PEAD effect is more pronounced for the micro capitalisation shares, but the ability of unexpected earnings to separate winners from losers irrespective of size group is evidence that the PEAD effect is not predominantly a size effect.

**VALUE**

The cumulative market-adjusted return for the different value effect (EY) quartiles and the four ΔEPS quartiles is displayed in *Figure 33.*
The relationship of the value effect as measured by earnings yield (EY), dividend yield (DY) and the book-to-market (B2M) ratio with excess PEAD returns is presented by the correlation coefficients in Table 15. Earnings yield (EY) and dividend yield (DY) are both correlated with PEAD return at the 1% level of significance. The correlation of the book-to-market ratio with excess PEAD is significant at the 5% level.

![Diagram](image)

**Figure 33: Cumulative Return Relative to Earnings Announcements for Different \( \Delta EPS \) and EY Quartiles**

From the cross-sectional analysis results in Table 16 it is evident that all value measures are statistically significant predictors of excess PEAD return at the 1% level of significance for the upper quartile, however only B2M and EY are statistically significant predictors for the lower quartile.

<table>
<thead>
<tr>
<th>Correlation Coeff.</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>EY</td>
<td>0.0866</td>
</tr>
<tr>
<td>DY</td>
<td>0.0909</td>
</tr>
<tr>
<td>B2M</td>
<td>0.0357</td>
</tr>
</tbody>
</table>

**Table 15: Sample Correlation Coefficients of Value Measures with PEAD Returns**
<table>
<thead>
<tr>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2M</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0006</td>
</tr>
<tr>
<td>2</td>
<td>0.0184</td>
</tr>
<tr>
<td>3</td>
<td>0.0171</td>
</tr>
<tr>
<td>4</td>
<td>0.0583</td>
</tr>
</tbody>
</table>

| DY          |             |
| 1           | 0.0104      | -1.1212      |
| 2           | -0.0015     | -2.8405      |
| 3           | 0.0293      | 1.167        |
| 4           | 0.0621      | 5.3486*      |

| EY          |             |
| 1           | -0.0043     | -2.8441*     |
| 2           | 0.0163      | -0.6151      |
| 3           | 0.0249      | 0.5504       |
| 4           | 0.0598      | 4.4733*      |

TABLE 16: EXCESS PEAD RETURNS CORRESPONDING TO VALUE QUARTILES

The best discriminator between winners and losers from the value effect group of measures are taken to investigate its effect on the relationship between unexpected earnings and post-announcement returns. The sample was sorted by EY and grouped into quartiles and each group is further sorted by unexpected earnings as measured by ER and divided into quartiles.

<table>
<thead>
<tr>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 25% EY</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0502</td>
</tr>
<tr>
<td>2</td>
<td>-0.0035</td>
</tr>
<tr>
<td>3</td>
<td>0.0235</td>
</tr>
<tr>
<td>4</td>
<td>0.0130</td>
</tr>
</tbody>
</table>

| 26-50% EY   |             |
| 1           | 0.0025      | -0.8995      |
| 2           | 0.0044      | -0.7724      |
| 3           | 0.0042      | -0.883       |
| 4           | 0.0601      | 2.8644*      |

| 51-75% EY   |             |
| 1           | -0.0168     | -2.8381*     |
| 2           | 0.0470      | 1.3848       |
| 3           | 0.0085      | -0.9565      |
| 4           | 0.0580      | 2.2976**     |

| 76-100% EY  |             |
| 1           | 0.0152      | -2.4315*     |
| 2           | 0.0692      | 0.4692       |
| 3           | 0.0615      | 0.0640       |
| 4           | 0.0886      | 2.010**      |

TABLE 17: PEAD RETURNS GROUPED BY EY QUARTILES WHICH IS FURTHER DIVIDED INTO UNEXPECTED EARNINGS QUARTILES
After sorting by EY, the unexpected earnings measure (ER) is still able to separate winners from losers in each value quartile. The top ER quartile in the 1st EY quartile and the bottom ER quartile in the 2nd EY quartile is however not significantly different from the mean of each respective EY quartile. For all other EY quartiles and ER extremes (1st and 4th quartile), the values is significant at not less than the 5% level. The evidence suggests that the relationship between unexpected earnings and PEAD is not predominantly a value effect, but that value is significantly related to excess PEAD returns.

MOMENTUM

Several measures of momentum are used to test the correlation of momentum with excess PEAD returns. The results in Table 18 show that all variables except the 6 month market momentum is correlated with excess PEAD return at a 1% level of significance.

<table>
<thead>
<tr>
<th></th>
<th>Correlation Coeff.</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>PreEAD</td>
<td>0.0672</td>
<td>4.6125*</td>
</tr>
<tr>
<td>RS6</td>
<td>0.1117</td>
<td>7.4831*</td>
</tr>
<tr>
<td>Mom6</td>
<td>0.0906</td>
<td>6.0619*</td>
</tr>
<tr>
<td>MS6</td>
<td>-0.0135</td>
<td>-0.8996</td>
</tr>
</tbody>
</table>

TABLE 18: SAMPLE CORRELATION COEFFICIENTS OF MOMENTUM EXCESS WITH PEAD RETURNS

Sorting by momentum and grouping into quartiles reveals that RS6 best separates winners from losers with a hedged return of 0.0717. The 10 day momentum prior to earnings announcements (PreEAD), although significantly correlated with excess PEAD, is a relatively meagre source of predictability in hedged returns.
<table>
<thead>
<tr>
<th>PreEAD</th>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.0133</td>
<td>-3.8050*</td>
</tr>
<tr>
<td>2</td>
<td>0.0273</td>
<td>0.9277</td>
</tr>
<tr>
<td>3</td>
<td>0.0388</td>
<td>2.5293*</td>
</tr>
<tr>
<td>4</td>
<td>0.0222</td>
<td>0.1996</td>
</tr>
<tr>
<td>RS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0191</td>
<td>-4.4874*</td>
</tr>
<tr>
<td>2</td>
<td>0.0047</td>
<td>-2.2494</td>
</tr>
<tr>
<td>3</td>
<td>0.0396</td>
<td>2.8103*</td>
</tr>
<tr>
<td>4</td>
<td>0.0526</td>
<td>3.9168*</td>
</tr>
<tr>
<td>Mom6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0160</td>
<td>-4.3279*</td>
</tr>
<tr>
<td>2</td>
<td>0.0081</td>
<td>-1.5873***</td>
</tr>
<tr>
<td>3</td>
<td>0.0445</td>
<td>3.5395*</td>
</tr>
<tr>
<td>4</td>
<td>0.0412</td>
<td>2.6611*</td>
</tr>
<tr>
<td>MS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0253</td>
<td>0.5701</td>
</tr>
<tr>
<td>2</td>
<td>0.0144</td>
<td>-0.7860</td>
</tr>
<tr>
<td>3</td>
<td>0.0163</td>
<td>-0.5650</td>
</tr>
<tr>
<td>4</td>
<td>0.0197</td>
<td>-0.1311</td>
</tr>
</tbody>
</table>

Each sorted quartile of the best predictor of excess returns selected from the momentum group was further grouped into ER quartiles. The results in Table 20 indicate that for each momentum quartile the unexpected earnings separate winners from losers. The hedged returns for each momentum quartile is on average higher after further sorting and grouping by unexpected earnings, than using any of the measures alone.
This establishes that the PEAD anomaly is not a manifestation of the momentum effect, but that momentum exacerbates the separation of excess PEAD returns.

The results obtained thus far indicate that unexpected earnings is a predictor of excess post-earnings announcement drift and that it is not a manifestation of any of the anomalies, namely the size effect, the value effect or momentum effect. The anomalies are however all correlated with unexpected earnings to some degree, but the fact that they all pronounce the excess returns indicate that they each provide additional information. It would have been ideal if we could control all variables while varying one and testing its return attribution, however such controlled experiments are impossible in finance. The best method at our disposal to disentangle the excess return uniquely attributable to each anomaly variable is by undertaking a multivariate linear regression on the excess PEAD returns as the dependent variable and the entire group of anomaly variables (and others mentioned in chapter 4) as independent variables.

**CROSS-SECTIONAL REGRESSION ANALYSIS**

The use of so many interrelated variables in a multivariate regression raises the problem of multicollinearity between the variables. When the explanatory variables in a multivariate regression are highly correlated with each other the estimated regression coefficients are

<table>
<thead>
<tr>
<th></th>
<th>Mean Return</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt; 25% RS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0668</td>
<td>-2.4528*</td>
</tr>
<tr>
<td>2</td>
<td>-0.0049</td>
<td>0.8971</td>
</tr>
<tr>
<td>3</td>
<td>-0.0144</td>
<td>0.3132</td>
</tr>
<tr>
<td>4</td>
<td>0.0081</td>
<td>1.6457***</td>
</tr>
<tr>
<td>26-50% RS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>-0.0471</td>
<td>-3.4641*</td>
</tr>
<tr>
<td>2</td>
<td>0.0075</td>
<td>0.1782</td>
</tr>
<tr>
<td>3</td>
<td>0.0213</td>
<td>1.5016***</td>
</tr>
<tr>
<td>4</td>
<td>0.0455</td>
<td>2.8248*</td>
</tr>
<tr>
<td>51-75% RS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0091</td>
<td>-2.0572**</td>
</tr>
<tr>
<td>2</td>
<td>0.0493</td>
<td>0.7203</td>
</tr>
<tr>
<td>3</td>
<td>0.0320</td>
<td>-0.6172</td>
</tr>
<tr>
<td>4</td>
<td>0.0597</td>
<td>1.5778***</td>
</tr>
<tr>
<td>76-100% RS6</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0157</td>
<td>-2.3658*</td>
</tr>
<tr>
<td>2</td>
<td>0.0499</td>
<td>-0.1927</td>
</tr>
<tr>
<td>3</td>
<td>0.0233</td>
<td>-1.7214</td>
</tr>
<tr>
<td>4</td>
<td>0.1167</td>
<td>4.2106*</td>
</tr>
</tbody>
</table>

**TABLE 20: PEAD RETURNS GROUPED BY MOMENTUM QUARTILES EACH DIVIDED INTO UNEXPECTED EARNINGS QUARTILES**
not very stable and are highly dependent on model structure and the data on which it is estimated. Thus, before the results are presented the measures taken to address multicollinearity are discussed.

It involves calculating cross-correlations, fitting the model on subsets of the data and removing variables to test the variance of coefficients.

The obvious sources of perfect multicollinearity are the binary dummy variables which together are linearly dependent on the constant term in the regression model. One variable from the seasons and one from the industry sectors were removed. They are selected to minimise the loss of information:

- The summer season, because it represents the time of year with the fewest announcements.
- The industry category that contained all the companies on the development boards of the JSE (AltX, Venture Capital, Development Capital and the JSE Africa board), which is highly correlated with market capitalisation and therefore it is argued that the information is already captured.

A third variable, the 6 month momentum (Mom6), is also removed. By definition it is the sum of the relative momentum (RS6) and the market momentum (MS6) and therefore linearly dependent on these two variables.

Another source of multicollinearity identified is the correlation between the market capitalisation and the price of shares with a sample correlation coefficient of 79%. The scatter plot is shown in Figure 35. It should be noted however that a model containing both variables is not incorrect and the coefficients represent the marginal contribution of each variable separately as long as the correlation between the two variables remain stable over time, but the risk of estimation error increases substantially because of the sensitivity to the underlying data.
The model was fitted first with both the price and market capitalisation variables included and then without including price. The calculated coefficients from the cross-sectional regression analysis excluding the price variable are shown in Table 21. When both market cap and price are included in the model it is interesting that market capitalisation has an almost negligible attribution of -0.0038 and price a negative attribution of -0.0233. Thus it seems that market capitalisation do not affect excess return when controlling for price. This results should however be seen in the light of the highly sensitive nature of the two coefficients to the underlying data and not be taken too seriously. When the price variable is removed the coefficients are more stable and the attribution to market capitalisation is -0.0184 which is significant at the 1% level. The results from the regression analysis indicate that smaller firms on average earn higher excess returns which are in agreement with the results from the correlation and cross-sectional sorts analysis.
<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Average</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔEPS</td>
<td>0.0128</td>
<td>3.2255*</td>
</tr>
<tr>
<td>ER</td>
<td>0.0197</td>
<td>6.7452*</td>
</tr>
<tr>
<td>EY</td>
<td>0.0177</td>
<td>4.6418*</td>
</tr>
<tr>
<td>DY</td>
<td>0.0196</td>
<td>5.1571*</td>
</tr>
<tr>
<td>B2M</td>
<td>0.0002</td>
<td>0.0410</td>
</tr>
<tr>
<td>MarketCap</td>
<td>-0.0196</td>
<td>-6.3594*</td>
</tr>
<tr>
<td>ST3</td>
<td>0.0013</td>
<td>0.4201</td>
</tr>
<tr>
<td>PreEAD</td>
<td>0.0129</td>
<td>4.4512*</td>
</tr>
<tr>
<td>RS6</td>
<td>0.0306</td>
<td>9.9471*</td>
</tr>
<tr>
<td>MS6</td>
<td>0.0063</td>
<td>2.0564**</td>
</tr>
<tr>
<td>Autumn</td>
<td>0.0094</td>
<td>0.7874</td>
</tr>
<tr>
<td>Winter</td>
<td>0.0329</td>
<td>2.3502*</td>
</tr>
<tr>
<td>Spring</td>
<td>0.0061</td>
<td>0.5163</td>
</tr>
<tr>
<td>Basic Materials</td>
<td>0.0154</td>
<td>0.8092</td>
</tr>
<tr>
<td>Consumer Goods</td>
<td>0.0310</td>
<td>1.1685</td>
</tr>
<tr>
<td>Consumer Services</td>
<td>0.0461</td>
<td>2.4832*</td>
</tr>
<tr>
<td>Financials</td>
<td>0.0287</td>
<td>2.0249**</td>
</tr>
<tr>
<td>Health Care</td>
<td>0.0802</td>
<td>0.5989</td>
</tr>
<tr>
<td>Industrials</td>
<td>-0.0138</td>
<td>-0.9285</td>
</tr>
<tr>
<td>Oil &amp; Gas</td>
<td>0.0892</td>
<td>0.2798</td>
</tr>
<tr>
<td>Technology</td>
<td>-0.0053</td>
<td>-0.0571</td>
</tr>
<tr>
<td>Telecommunications</td>
<td>0.0219</td>
<td>0.1097</td>
</tr>
</tbody>
</table>

*TABLE 21: CROSS-SECTIONAL REGRESSION COEFFICIENTS*

The coefficients can be interpreted as the marginal excess return to a share with an exposure to that factor of one cross-sectional standard deviation while the exposure to all other variables is neutral. It is best explained by an example: say the EY distribution among all shares have an average of 10 and a standard deviation of 1 at any particular time, then a factor coefficient of 0.02 means that a share with an EY of 11 would outperform the market by 0.02 (2%) on a risk-adjusted basis.

The coefficients of all the anomaly variables in Table 21 were found to be stable. The coefficient values of the dummy variables are however found to be more sensitive to changes in model structure and underlying data, but most are also not found to be statistically significant. Firms in the consumer services and financial industry categories are expected to earn excess PEAD returns of 0.0461 and 0.0287 respectively which is statistically significant at the 1% and 5% level. The exact coefficient values shouldn’t be relied upon, but rather compared relatively.

Unexpected earnings as measured by ΔEPS and ER are both attributable to excess PEAD with t-statistics of 3.2255 and 6.7452 respectively, thus the null hypothesis (H₀) that there is no relationship between unexpected earnings (earnings surprise) and subsequent post-
earnings announcement returns for the period 1991 to 2010 on the JSE can be rejected with confidence. The results indicate that the PEAD anomaly exists independently of the value, size and momentum effects and that it is statistically significant. It is also interesting to note that both $\Delta$EPS and ER are uniquely attributable to excess return; they thus each contain independent information that is relevant to price formation for the six month period subsequent to earnings announcements.

The value effect represented by EY and DY is also both independently attributable to excess post-earnings announcement drift with t-statistics of 4.6418 and 5.1571 respectively. The payoff due to the two momentum variables, PreEAD and RS6, is 0.0129 (t-statistic of 4.4512) and 0.0306 (t-statistic of 9.9471) respectively. It is evident that the relative momentum for the six months prior to the announcement on average persists for the six months subsequent to the announcement to some degree.

The regression statistics is presented in Table 22. According to the $R^2$-statistic the regression model only explain about 5.7% of the variance in excess returns.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.0566</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>9.1125</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

*Table 22: Regression Model Statistics*

While the high level of significance of the F-statistic tells us that the model is good at explaining the variance in excess returns, one questions whether the model captures the fat tails in the distribution of PEAD returns and other non-linear phenomena. *Figure 36* shows the regression residuals (bottom) after sorting by the dependent variable, excess returns (top).
This indicates that the model fails to capture the non-linearity in the data at the extremes, thus a non-linear modelling technique should give better results, but this is beyond the scope of this research.

SUMMARY

A brief summary of the results thus far seems in order. The correlations are shown in Figure 37. All the anomalies considered in this research, namely unexpected earnings, proxies for the value effect, size and momentum, correlates with excess returns for the period after earnings announcements.

\[ \Delta \text{EPS} = \text{DEPS} \]
Considering the evidence in Figure 37, no judgement can yet be made regarding the null hypothesis. Disentanglement of the effects by multivariate cross-sectional regression analysis provided the anomaly attributions as presented in Figure 38, all of which presented are statistically significant at the 1% level. It is found that the size and liquidity proxies are collinear and the unique attribution to share turnover is negligible. Thus the size and liquidity effects are effectively captured by market capitalisation alone. Excess PEAD returns are related to the relative momentum (RS6) for the six months before the earnings announcements. This momentum behaviour therefore on average persists for the six months after the earnings announcements. It is also evident that excess PEAD returns are related to unexpected earnings and it is not merely a manifestation of other known anomalous effects.

We now return to the results from the sorts analysis for each year from 1991-2010 to investigate the stability of each variable’s ability to separate winners from losers. The boxplot in Figure 39 shows the median and variability of hedged returns for the 20 years which indicates the stationarity in each variable’s ability to separate winners from losers. In terms of average hedged returns for the 6 month period subsequent to earnings announcements, ER and market cap are the leading contenders, but when one also takes variability into account, ER is the runaway leader in hedged returns which is highlighted by its corresponding t-statistic of 5.82.
The same data as in Figure 39 is presented in Figure 40 where the average hedged risk-adjusted return over the 20 years is plotted versus the standard deviation. The size of the circles is the return to risk ratio\textsuperscript{18}. ER clearly stands out above the somewhat linear relation of return versus risk for each anomaly variable.

\textbf{FIGURE 39: BOXPLOT OF HEDGED RETURNS FOR THE PERIOD FROM 1991-2010}

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|c|c|c|}
\hline
& 1 & 2 & 3 & 4 & 5 & 6 & 7 & 8 & 9 & 10 & 11 & 12 \\
\hline
AVERAGE & 0.048 & 0.049 & 0.052 & 0.088 & 0.069 & 0.082 & 0.030 & -0.007 & 0.068 & 0.025 & 0.065 & 0.024 \\
STDDEV & 0.079 & 0.089 & 0.081 & 0.067 & 0.107 & 0.120 & 0.122 & 0.093 & 0.124 & 0.078 & 0.103 & 0.092 \\
t-Statistic & 2.75* & 2.45 & 2.06 & 5.82* & 2.89* & 3.06* & 1.11 & -0.33 & 2.45 & 1.44 & 2.81* & 1.17 \\
\hline
\end{tabular}
\end{table}

\textbf{FIGURE 40: AVERAGE RETURN VS. STANDARD DEVIATION OF HEDGED RETURNS FOR THE PERIOD 1991-2010}

\textsuperscript{18} Modified Sharpe ratio with a risk-free rate of 0.
It is arguable that all the anomaly variables represent a risk-factor not captured by the single factor CAPM. If one makes this assumption and would further adjust the returns by subtracting the average linear relation between annual variation and average hedged excess PEAD returns, the excess return related to ER still stands out. While the abovementioned methodology is not scientifically justifiable, it is argued that the relation between ER and excess PEAD return is not due to an uncaptured risk effect, but represents a clear violation of market efficiency and may present an exploitable profit opportunity.

While the evidence suggests that it may be profitably exploitable, the effect of transaction cost should however be incorporated to test whether superior risk-adjusted returns are indeed achievable. The results of the simulation study investigating the exploitability is presented in chapter 6.

5.4. Analysis of the Earnings Surprise

In this section the results obtained from analysing the predictability of unexpected earnings are presented and discussed. The analysis results aims to answer the questions posed in chapter 4 to whether the earnings surprise is predictable and, if yes, whether the predictability in earnings surprise is due to market inefficiency and that it can be profitably exploited or whether it is only an effect of market frictions that has no implication for the EMH.

As mentioned in chapter 4, the change in earnings (ΔEPS) is not necessarily a surprise to the market and establishing the predictability of ΔEPS would not mean that the market did not already anticipate this ΔEPS. The null hypothesis that unexpected earnings are not predictable is therefore tested using unexpected earnings as measured by ER only.

We will firstly look at the statistical properties of unexpected earnings where after the relationships with each explanatory variable, obtained through cross-sectional correlation, sorts and a combination of time-series and cross-sectional regression analysis will be presented.

Statistical properties of the Earnings Surprise

In the first part of this chapter it has already been established that the market is on average positively surprise by the announced earnings. The descriptive statistics in Table 23 shows
the mean, standard deviation, skewness and kurtosis for the event returns (ER) as well as the value weighted market return for the same three day period.

<table>
<thead>
<tr>
<th></th>
<th>ER</th>
<th>VWMarket</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.0106</td>
<td>0.0016</td>
</tr>
<tr>
<td>StdDev</td>
<td>0.0557</td>
<td>0.0244</td>
</tr>
<tr>
<td>Skewness</td>
<td>0.6861</td>
<td></td>
</tr>
<tr>
<td>Kurtosis</td>
<td>7.6556</td>
<td></td>
</tr>
</tbody>
</table>

**Table 23: Descriptive Statistics of Unexpected Earnings Measures**

*Figure 41* shows the distribution of ER fitted to the normal distribution. From the results in *Table 23* and *Figure 41* it is clear that the data is positively skewed and has fat tails. Both the Kolmogorv-Smirnov and Lilliefors tests reject the null hypothesis that the data is normally distributed; therefore all statistical calculations assuming a perfect normal distribution will not be absolutely accurate, but still suitable for the analysis at hand.

![Figure 41: Histogram and QQ-plot of Unexpected Earnings](image)

The average and cumulative market-adjusted return for the period [-20; 20] days prior and post announcement is shown in *Figure 42*. The dip in returns starting from around the 11th day up to about the 16th day is due to the timing of the inclusion of dividends. The dividends are only added at the date at which they are paid out to investors, although the investors have the right to the dividends if the share has been held on the LDT19 date (on average any day between the 11th and 16th after announcement). The price reflects that the

---

19 LDT – Last date to trade
share is trading ex-dividend after the right to the dividend has been foregone (after LDT date) and the dividend is on average received only after the 16th day.

This decision may at first glance seem strange, but is made to more accurately reflect the actual situation in a simulation environment to prevent the buying of assets with the cash proceeds from dividends before they are received.

The dip in price is therefore not a real (and potentially exploitable) movement in price, but only a feature emanating from the specific methodology used.

With an average market-adjusted return of 0.008 for the three-days starting with the announcement day, one would expect an arbitrageur to make a profit if the round trip transaction costs can be kept sufficiently low, but if it were so easy, the profit opportunity would have possibly diminished by now. It can be argued that the average predictability of the returns on the day of announcement may be due to market frictions that prevent the arbitrageur from exploiting the opportunity.

**Predictors of the Earnings Surprise**

In this section the results from the analysis testing the predictability of unexpected earnings will be presented.
The autocorrelation of ER are presented in Figure 43 for lags up to 10 previous announcements excluding the current announcement. The 1% and 5% significance level lines are overlaid on the autocorrelation coefficients. The 1% and 5% significance levels are determined by calculating the correlation values at which the t-statistics are 1% and 5% likely. The coefficients are significant at the 1% level up to the 4th lag (the last 4 previous announcements).

![Figure 43: Autocorrelation of ER](image)

The correlation coefficients in Table 24 indicate that unexpected earnings is strongly correlated with size and liquidity (MC, Price and ST3), but also correlated with value (B2M and EY).

<table>
<thead>
<tr>
<th>Correlation Coeff.</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>B2M</td>
<td>0.0431</td>
</tr>
<tr>
<td>DY</td>
<td>0.0014</td>
</tr>
<tr>
<td>EY</td>
<td>0.0707</td>
</tr>
<tr>
<td>MC</td>
<td>-0.1232</td>
</tr>
<tr>
<td>Price</td>
<td>-0.1286</td>
</tr>
<tr>
<td>ST3</td>
<td>-0.0484</td>
</tr>
<tr>
<td>PreEAD</td>
<td>-0.0192</td>
</tr>
<tr>
<td>Mom6</td>
<td>0.0167</td>
</tr>
<tr>
<td>RS6</td>
<td>0.0152</td>
</tr>
<tr>
<td>MS6</td>
<td>0.0083</td>
</tr>
</tbody>
</table>

**Table 24: Correlation of Unexpected Earnings with Other Variables**

The correlation coefficients are also shown in Figure 44. The strong correlation with size and liquidity may explain why the seemingly profitable opportunity remains. Transaction costs represented by the bid-ask spread is directly related to size and liquidity and therefore it is possible that the higher transaction costs prohibit arbitrageurs from exploiting the opportunity.
The results from cross-sectional analysis by sorting and dividing into quartiles are presented in Table 25.

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>ER_{lag1}</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0088</td>
<td>-1.1158</td>
</tr>
<tr>
<td>2</td>
<td>0.0100</td>
<td>-0.5476</td>
</tr>
<tr>
<td>3</td>
<td>0.0079</td>
<td>-1.5724</td>
</tr>
<tr>
<td>4</td>
<td>0.0166</td>
<td>3.1787*</td>
</tr>
<tr>
<td><strong>B2M</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0076</td>
<td>-1.8365**</td>
</tr>
<tr>
<td>2</td>
<td>0.0091</td>
<td>-0.9256</td>
</tr>
<tr>
<td>3</td>
<td>0.0130</td>
<td>1.2908</td>
</tr>
<tr>
<td>4</td>
<td>0.0171</td>
<td>3.0174*</td>
</tr>
<tr>
<td><strong>EY</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0087</td>
<td>-1.2456</td>
</tr>
<tr>
<td>2</td>
<td>0.009</td>
<td>-1.193</td>
</tr>
<tr>
<td>3</td>
<td>0.0107</td>
<td>-0.0699</td>
</tr>
<tr>
<td>4</td>
<td>0.0187</td>
<td>3.3669*</td>
</tr>
<tr>
<td><strong>DY</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0129</td>
<td>1.0856</td>
</tr>
<tr>
<td>2</td>
<td>0.0091</td>
<td>-1.0263</td>
</tr>
<tr>
<td>3</td>
<td>0.0112</td>
<td>0.2162</td>
</tr>
<tr>
<td>4</td>
<td>0.0141</td>
<td>1.6464***</td>
</tr>
<tr>
<td><strong>MC</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0178</td>
<td>5.2209*</td>
</tr>
<tr>
<td>2</td>
<td>0.0064</td>
<td>-3.0922</td>
</tr>
<tr>
<td>3</td>
<td>0.0037</td>
<td>-4.1181</td>
</tr>
<tr>
<td>4</td>
<td>0.0001</td>
<td>-4.8672*</td>
</tr>
<tr>
<td><strong>Price</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0223</td>
<td>5.2544*</td>
</tr>
<tr>
<td>2</td>
<td>0.0104</td>
<td>-0.2792</td>
</tr>
<tr>
<td>3</td>
<td>0.0084</td>
<td>-1.7399</td>
</tr>
<tr>
<td>4</td>
<td>0.0034</td>
<td>-5.4147*</td>
</tr>
<tr>
<td><strong>ST3</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0139</td>
<td>2.1382**</td>
</tr>
</tbody>
</table>
The ability of size (MC and Price) to separate the winners from losers again stands out, but EY and the ER at the previous announcement also seems to be a good predictor of unexpected earnings.

The ability of lagged ER and value to separate winners form losers while controlling for size is shown in *Table 26*. Lagged ER is able to separate high current event returns from low event returns for the small, medium and large firm size categories. The magnitude of the hedged returns is small compared to the average event returns for the micro firm size and is on average statistically insignificant.

EY also seems able to separate winners from losers, but the magnitude of hedged event returns is small compared to event returns in the micro firm size category and is statistically insignificant.

The results for B2M indicate that B2M is somewhat able to separate winners from losers for all firm size categories. For the two smallest firm size categories (micro and small), firms with a high B2M ratio have a higher event return than firms with a lower B2M. For the 2 largest firm size categories the relationship is the opposite with low B2M firms having a
higher event return than high B2M firms. The relationship with B2M is thus non-linear across the size groups. The magnitude of hedged event returns as determined by separating according to B2M is statistically insignificant.

It is also evident that high average ER mainly occurs for the micro capitalisation firms and size is found to be the only variable that is significantly able to separate winners from losers. The correlation between the value effect measures (EY and B2M) and MC seems to be responsible for the apparent relation of the value effect to event returns found in the previous analysis.

<table>
<thead>
<tr>
<th></th>
<th>Micro</th>
<th>Small</th>
<th>Medium</th>
<th>Large</th>
</tr>
</thead>
<tbody>
<tr>
<td>ERlag1</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0197*</td>
<td>0.0043**</td>
<td>0.0027*</td>
<td>0.0001*</td>
</tr>
<tr>
<td>2</td>
<td>0.0139**</td>
<td>0.0059</td>
<td>-0.0002*</td>
<td>-0.009*</td>
</tr>
<tr>
<td>3</td>
<td>0.0167</td>
<td>0.0069</td>
<td>0.0012*</td>
<td>-0.0023*</td>
</tr>
<tr>
<td>4</td>
<td>0.0247*</td>
<td>0.0086</td>
<td>0.0117</td>
<td>0.005</td>
</tr>
</tbody>
</table>

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
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<th></th>
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</thead>
<tbody>
<tr>
<td>EY</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0151</td>
<td>0.0046**</td>
<td>0.0072</td>
<td>-0.0001**</td>
</tr>
<tr>
<td>2</td>
<td>0.0147</td>
<td>0.0078</td>
<td>0.0038**</td>
<td>0.0041**</td>
</tr>
<tr>
<td>3</td>
<td>0.0174**</td>
<td>0.0113</td>
<td>-0.0036*</td>
<td>-0.0049*</td>
</tr>
<tr>
<td>4</td>
<td>0.0237*</td>
<td>0.0010**</td>
<td>0.0114</td>
<td>0.0053</td>
</tr>
</tbody>
</table>

<p>| | | | | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>B2M</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.0101</td>
<td>0.0042**</td>
<td>0.011</td>
<td>0.0019**</td>
</tr>
<tr>
<td>2</td>
<td>0.0165</td>
<td>0.0082</td>
<td>-0.0001</td>
<td>0.0033**</td>
</tr>
<tr>
<td>3</td>
<td>0.0254*</td>
<td>0.0069**</td>
<td>0.0031**</td>
<td>-0.0011*</td>
</tr>
<tr>
<td>4</td>
<td>0.0209*</td>
<td>0.0103</td>
<td>-0.0069**</td>
<td>-0.0155**</td>
</tr>
</tbody>
</table>

The multivariate regression analysis essentially gave the same results as the cross-sectional correlation and sorts analysis. The existence of multicollinearity in the model was investigated, but the coefficients presented in Table 27 were all found to be stable to changes in model structure and data. Size is again found to be a significant predictor of unexpected earnings. The event returns at previous announcements is also found to be significantly related with current event returns, in contrast with the findings from the cross-sectional sorts analysis which found past values to be insignificant predictors of current event returns when also sorting by size.

The positive attribution to EY and the negative attribution to DY raise some questions. Further research into this seeming peculiarity is required to provide an answer, but it is beyond the scope of this research. The two variables are correlated (0.4392) and in practice
it is somewhat difficult to separate the two in an investment strategy, but the attributions are found to be both statistically significant and stable.

<table>
<thead>
<tr>
<th>Anomaly</th>
<th>Average</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>EY</td>
<td>0.0028</td>
<td>3.2122*</td>
</tr>
<tr>
<td>DY</td>
<td>-0.0026</td>
<td>-2.9217*</td>
</tr>
<tr>
<td>B2M</td>
<td>-0.0003</td>
<td>-0.3697</td>
</tr>
<tr>
<td>MC</td>
<td>-0.0076</td>
<td>-10.6715*</td>
</tr>
<tr>
<td>ST3</td>
<td>0.0018</td>
<td>2.5022*</td>
</tr>
<tr>
<td>PreEAD</td>
<td>-0.0010</td>
<td>-1.4402</td>
</tr>
<tr>
<td>RS6</td>
<td>0.0001</td>
<td>0.1036</td>
</tr>
<tr>
<td>MS6</td>
<td>0.0006</td>
<td>0.8899</td>
</tr>
<tr>
<td>ER\text{lag1}</td>
<td>0.0041</td>
<td>5.7460*</td>
</tr>
<tr>
<td>ER\text{lag2}</td>
<td>0.0026</td>
<td>3.6439*</td>
</tr>
<tr>
<td>ER\text{lag3}</td>
<td>0.0019</td>
<td>2.7401*</td>
</tr>
<tr>
<td>ER\text{lag4}</td>
<td>0.0006</td>
<td>0.8164</td>
</tr>
</tbody>
</table>

**TABLE 27: CROSS-SECTIONAL REGRESSION COEFFICIENTS**

Although the regression analysis found that proxies for the value effect (EY, B2M and DY) and particularly the autocorrelation structure of unexpected earnings provide some additional information to predict future unexpected earnings, it can be stated at this stage that ER is mainly predictable for firms in the two smallest size categories and low liquidity shares. It can also be assumed that it is not profitably exploitable due to the high transaction costs associated with smaller capitalisation and illiquid shares, but this will be thoroughly investigated in the next chapter.

The frequent occurrence of outliers (fat tails) in the distribution of unexpected earnings prompts the question whether the linear model is adequate to explain the data. The model
statistics is presented in Table 28 and the $R^2$-statistic is statistically significant at less than the 1% level. The linear model therefore is capable of explaining about 3% of the variance in the three-day announcement returns. Although the $R^2$-statistic is statistically significant, there exists non-linearity in the data that a linear regression model cannot capture.

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$R^2$</td>
<td>0.0324</td>
</tr>
<tr>
<td>F-Statistic</td>
<td>9.6928</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

**Table 28: Regression Model Statistics**

It is also arguable that the difference in results achieved by the cross-sectional sorts analysis and the regression analysis may be due to non-linearity in the data. A cross-sectional sorts analysis is not dependant on the normality and linearity of the data and is therefore more suited to the analysis of non-linear data.

It is therefore argued that a non-linear regression model should explain the data better and improve on the predictive ability of the earnings surprise. Implementation of a non-linear model is however beyond the scope of this research.

**Summary**

The key findings of the analysis are summarised below:

- The earnings surprise is on average found to be predictable for small sized firms and the magnitude of the predicted event returns is significant. The predictability of the earnings surprise for larger firms is much less significant.
- This predictability may be explained by the market’s inability either to effectively process the available information correctly or to eliminate the apparent profit opportunity due to market frictions such as transaction costs or the risk faced due to the higher uncertainty in earnings for these firms.
6. **SIMULATION ANALYSIS RESULTS**

“Markets can remain irrational a lot longer than you and I can remain solvent.”

– John Maynard Keynes

6.1. **INTRODUCTION**

This chapter answers the question regarding whether any of the identified inefficiencies or anomalies are exploitable and if it can earn excess risk-adjusted return above that of the value weighted market return. Several simulations are performed to test the profitable exploitability of the PEAD effect and the predictability in the earnings surprise. In order to establish the influence of each parameter on the results simulations are performed where the values of the parameters are varied and the sensitivity of excess risk-adjusted return with respect to each parameter is calculated (see chapter 4 section 4.3.4 for a more complete explanation). The simulation results give a good overall indication of whether the anomalies can be profitably exploited in a real-world strategy by illuminating the influence of each strategy, parameter and variable on the results achieved, without necessarily trying to find the optimal strategy.

6.2. **PRELIMINARY REMARKS**

One of the difficulties in designing a trading strategy that is linked to the uncertain outcome of events dispersed through time is to optimally allocate capital to each potential opportunity, while having enough cash on hand to invest in future opportunities that arrive randomly. This need to be accomplished while adhering to risk constraints that limit the fraction of capital that is to be invested in a single opportunity, but also minimising the cash in the portfolio that earns potentially suboptimal returns. One possible solution would be to constantly rebalance a portfolio when new opportunities arrive, thus keeping the cash on hand to a minimum and allocating the capital in a Markowitz mean-variance or Kelly optimal way. This solution is however prone to higher transaction costs due to the relatively frequent trading by the simulated strategies.

*Figure 46* shows the frequency of earnings announcements for each month of the year. February, May, August and November are the busiest months in the corporate calendar as
This corresponds to firms with a financial year end in December/June and March/September.

![Figure 46: Dispersion of Announcements Throughout the Year](image)

The rather simple capital allocation strategies outlined in chapter 4 that are used in this research may not be the optimal capital allocation strategies, but are still useful to effectively test the exploitability of the PEAD effect and the predictability in the earnings surprise. We pose the argument that the outcomes of the simulation present a very conservative estimate of the exploitability of each anomalous effect and that it should be possible to improve on the results achieved.

The performance statistics for the value weighted market return for the simulation period from 1995 – 2010 is shown in Table 29. This is used as a benchmark in evaluating the performance of the simulated strategies. The risk-adjusted return computed by the Sharpe ratio is especially important for evaluating the performance of the simulated strategies, but two additional measures, the CAPM alpha and the information ratio (IR) also provide an indication of superior risk-adjusted returns compared to the benchmark.
Due to the capital allocation strategy that is employed, the average cash holding in the portfolios is much higher than the average actively managed equity portfolio. It is however assumed that a higher/lower cash component would only move the risk-return characteristics of a portfolio along the capital allocation line (CAL) as shown in Figure 8 in chapter 2. The slope of the line, which is the Sharpe ratio, will not change. This assumption may not always hold true, but it provides a rough estimate.

6.3. EXPLOITING THE PEAD ANOMALY

In this section the simulation results for the strategies designed to exploit the predictability in PEAD returns are presented.

A detailed explanation of the decision criteria and investment methodology as well as the fixed fractions (FF) and dynamic allocation (DA) capital allocation strategies are given in chapter 4 section 4.3.4.

From the statistical analysis results in chapter 5 it is apparent that ER is the most significant predictor of PEAD returns. The average results of simulations using other variables as predictors are presented in Table 30, but only for the strategies employing long positions and the fixed fractions (FF) capital allocation strategy. For brevity only the results using event returns (ER) as decision variable are presented for all other simulation categories.

The results presented in Table 30 were attained with the following simulation parameter values:

- A maximum holding period of 120 trading days, the strategy is thus forced to close a position just before the next earnings announcement.
- An initial investment amount of 7.5% of the portfolio value at any particular moment. \( I_0 = 0.075 \)
- A maximum exposure to any single share of 15% of the portfolio value. \( I_{\text{max}} = 0.15 \)
• A maximum allowed transaction cost of 2% of the amount to be invested in a security. Any potential transaction with a higher calculated transaction cost will not be executed.

The performance measures presented in Table 30 are calculated as defined in chapter 2. The Mean reported in column 2 is the average annualised absolute returns for the 16 year period from 1995 to 2010. The average gain in the last column is the average return for each transaction before subtracting transaction costs. The difference between the average gain reported for a strategy that includes transaction costs and those that excludes it, is due to the variability introduced by the random component of the simulation strategies, the limitation on the maximum transaction cost that is effectively lifted (for simulations excluding transaction costs) as well as more cash that are available (due to no transaction costs) which allows more transactions to be completed (about 20 more on average for the 16 year period).

The percentage winners are calculated as the percent of all transactions having a gain (before transaction costs) higher than zero.

It should however be kept in mind that all the strategies are designed to behave randomly to some extent as explained in chapter 4 section 4.3.4. The absolute results attained are consequently subject to small fluctuations and the performance measures are averaged values and should be evaluated on a relative basis.
<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean</th>
<th>StdDev</th>
<th>Sharpe</th>
<th>IR</th>
<th>Alpha</th>
<th>Beta</th>
<th>MaxDD</th>
<th>% Winners</th>
<th>Ave Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Only – FF 20</td>
<td>0.0828</td>
<td>0.1315</td>
<td>0.3256</td>
<td>-0.3932</td>
<td>0.0041</td>
<td>0.4136</td>
<td>0.5183</td>
<td>60.8</td>
<td>0.0370</td>
</tr>
<tr>
<td>ΔEPS</td>
<td>0.1475</td>
<td>0.1455</td>
<td>0.7386</td>
<td>-0.0404</td>
<td>0.0677</td>
<td>0.4326</td>
<td>0.4442</td>
<td>60.5</td>
<td>0.0507</td>
</tr>
<tr>
<td>ER</td>
<td>0.078</td>
<td>0.149</td>
<td>0.255</td>
<td>-0.365</td>
<td>0.006</td>
<td>0.398</td>
<td>0.708</td>
<td>59.8</td>
<td>0.047</td>
</tr>
<tr>
<td>B2M</td>
<td>0.031</td>
<td>0.109</td>
<td>-0.083</td>
<td>-0.621</td>
<td>-0.028</td>
<td>0.291</td>
<td>0.617</td>
<td>49.8</td>
<td>-0.010</td>
</tr>
<tr>
<td>DY</td>
<td>0.080</td>
<td>0.115</td>
<td>0.348</td>
<td>-0.409</td>
<td>0.004</td>
<td>0.387</td>
<td>0.595</td>
<td>55.4</td>
<td>0.018</td>
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<tr>
<td>EY</td>
<td>0.079</td>
<td>0.159</td>
<td>0.245</td>
<td>-0.437</td>
<td>-0.008</td>
<td>0.447</td>
<td>0.655</td>
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<td>0.011</td>
</tr>
<tr>
<td>PreEAD</td>
<td>0.060</td>
<td>0.172</td>
<td>0.116</td>
<td>-0.615</td>
<td>-0.045</td>
<td>0.550</td>
<td>0.674</td>
<td>58.8</td>
<td>0.016</td>
</tr>
<tr>
<td>RS6</td>
<td>0.060</td>
<td>0.172</td>
<td>0.116</td>
<td>-0.615</td>
<td>-0.045</td>
<td>0.550</td>
<td>0.674</td>
<td>58.8</td>
<td>0.016</td>
</tr>
<tr>
<td><strong>Long Only – FF – No Transaction Cost</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER</td>
<td>0.1639</td>
<td>0.1462</td>
<td>0.8473</td>
<td>0.0326</td>
<td>0.0800</td>
<td>0.4391</td>
<td>0.5479</td>
<td>61.5</td>
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</tr>
<tr>
<td><strong>Long Only – DA 21</strong></td>
<td></td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>ER</td>
<td>0.0350</td>
<td>0.0967</td>
<td>-0.0516</td>
<td>-0.6524</td>
<td>-0.0349</td>
<td>0.3203</td>
<td>0.7634</td>
<td>50.5</td>
<td>0.0244</td>
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<tr>
<td><strong>Long Only –DA – No Transaction Cost</strong></td>
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<td></td>
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<td></td>
<td></td>
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</tr>
<tr>
<td>ER</td>
<td>0.1382</td>
<td>0.0931</td>
<td>1.0547</td>
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<td>0.0749</td>
<td>0.2853</td>
<td>0.3200</td>
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<td>0.0261</td>
</tr>
<tr>
<td><strong>Long/Short - FF</strong></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>0.0793</td>
<td>0.1195</td>
<td>0.3286</td>
<td>-0.3673</td>
<td>0.0347</td>
<td>0.0519</td>
<td>0.3217</td>
<td>54.4</td>
<td>0.0374</td>
</tr>
<tr>
<td><strong>Long/Short – FF – No Transaction Cost</strong></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER</td>
<td>0.0946</td>
<td>0.1298</td>
<td>0.4203</td>
<td>-0.2857</td>
<td>0.0530</td>
<td>0.0408</td>
<td>0.3278</td>
<td>55.0</td>
<td>0.0385</td>
</tr>
<tr>
<td><strong>Long/Short - DA</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER</td>
<td>0.0284</td>
<td>0.0533</td>
<td>-0.2175</td>
<td>-0.6186</td>
<td>-0.0122</td>
<td>-0.0260</td>
<td>0.1655</td>
<td>44.1</td>
<td>0.0193</td>
</tr>
<tr>
<td><strong>Long/Short –DA – No Transaction Cost</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER</td>
<td>0.075</td>
<td>0.1039</td>
<td>0.3369</td>
<td>-0.3750</td>
<td>0.0421</td>
<td>-0.0537</td>
<td>0.2729</td>
<td>47.6</td>
<td>0.0237</td>
</tr>
</tbody>
</table>

* TABLE 30: PERFORMANCE RESULTS OF THE SIMULATED TRADING STRATEGIES EXPLOITING THE PEAD ANOMALY

The probability of the decision variables ER and ΔEPS to pick a winning trade is about the same, with a roughly 60% chance. The average return per trade for ER is however higher than for ΔEPS.

The average return per trade of 0.0507 (calculated assuming an equal weighting per transaction) is lower than one would expect given the average excess PEAD return of 0.0566 for the top quartile of event returns (ER). Referring to Figure 31, the absolute PEAD returns corresponding to the top quartile of ER is almost 0.1 for the six months post announcement. If one views the 0.1 return as the theoretical maximum attainable average PEAD return, then the actual average PEAD return of about half the maximum (0.0507), attained with the simulation, should be due to the limitations imposed by the simulator. It is at this stage deemed in order to review the limitations put on executing orders:

- Liquidity constraints are imposed
- Maximum transaction cost per transaction
- Limited cash available at any moment

---

20 FF – Fixed fractions  
21 DA – Dynamic allocation
If we assume that the liquidity constraints are not stricter than what would be experienced in an actual trading environment, the reduced return due to the imposed liquidity constraints is a fair reflection of reality. The maximum limit set on transaction costs may also reduce the average return per trade, but the higher transaction costs incurred when the limitation on transaction costs is lifted will certainly counter the higher average returns achieved. It should however be noted that due to the calculation of the position size (explained in chapter 4 section 4.3.4) and the abovementioned limitations imposed by the simulator, not all positions are equal in size and does not carry the same weighting.

It is therefore argued that the only cause of reduced returns which could potentially be improved is the effective allocation of capital. Improved cash management may allow as much as possible of the potential candidate transactions to be executed and allocating more capital to the opportunities that are more likely to be profitable. The precise magnitude of the potential improvements is however unknown, but limited to less than an extra 0.05 per transaction.

The average return of 0.1475 per year for the long-only strategy is more than one would expect from an average gain of 0.0507 per transaction before transaction costs. The distribution of the gains per transaction achieved with the long-only fixed fraction strategy is shown in Figure 47. Although each share bought is held for only about six months and two transactions can therefore be executed with the same money each year, doubling the total average return per annum to 0.1 before transaction costs, it is still short of the 0.1475
average returns per year. From the difference in the simulation incorporating transaction cost and the simulation ignoring transaction cost it is seen that the average transaction costs amount to about 1-2% per year and from Table 31 it is seen that the average fraction of capital allocated to the trading strategy amounts to about 65%, the other 35% is held in cash which earns 0.04 per year. This adds to:

\[
\text{Average Return} = (0.65 \times 0.1) + (0.35 \times 0.04) - 0.015 = 0.064 \quad (68)
\]

which is less than half of the average annual return of 0.1457.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Average Cash %</th>
</tr>
</thead>
<tbody>
<tr>
<td>ΔEPS</td>
<td>51.26</td>
</tr>
<tr>
<td>Long Only – FF</td>
<td>34.73</td>
</tr>
<tr>
<td>Long Only - DA</td>
<td>43.78</td>
</tr>
<tr>
<td>Long/Short - FF</td>
<td>17.34</td>
</tr>
<tr>
<td>Long/Short - DA</td>
<td>8.80</td>
</tr>
</tbody>
</table>

**TABLE 31: AVERAGE CASH HELD IN PORTFOLIO AS PERCENTAGE OF PORTFOLIO VALUE**

To further illuminate the apparent discrepancy between the actual mean simulated returns and the expected returns, each is calculated on an annual basis for the period from 1995 to 2010. The results in Table 32 shows that the average expected return is still somewhat lower than the actual simulated return, but higher than the 0.064 calculated above. The relatively high variability in the average cash held in the portfolio (shown in Figure 48) and the non-equal allocation of capital (due to simulator constraints explained above) is deemed responsible for the lower average returns.
We therefore argue that the higher than expected return can only be attributed to the timely allocation of capital to potential opportunities and a potential improvement on a true fixed fractions capital allocation strategy emanating from the limitations imposed on the size of positions. Efficient capital allocation is therefore not only a potential source of improvement in the strategies, but also a major source of higher than expected returns.

The above exposition of where the returns come from clearly shows the difference in results achieved from a pure statistical analysis and a simulation analysis. This also clearly demonstrates the value of a simulation study.
Returning to the results presented in Table 30 it is clear that the long-only strategy using ER as prediction variable and employing the fixed fractions capital allocation method achieved the best results on a risk adjusted basis. It is also the only strategy beating the value weighted market return with a Sharpe ratio of 0.7386 as opposed to the market Sharpe ratio of 0.5363. The average annual return of 0.1475 is also remarkably high when one considers that the strategy is on average only 65% invested in shares. It is also interesting to note that the maximum drawdown of the strategy was relatively low compared to the others. The absolute return of the highest performing strategy is however still lower than the value weighted market returns and therefore it has a negative information ratio (IR). According to active portfolio management theory an active manager destroys value when the information ratio (IR) is negative. The risk-adjusted return as measured by the CAPM alpha suggests that the long-only fixed fractions simulation strategy using ER as prediction variable outperforms the market and it is statistically significant.

Two of the three performance measures suggest that the PEAD anomaly is profitably exploitable on a risk-adjusted basis.

Other notable findings include:

- Transaction costs don’t seem to play such a big role in the return of the strategies employing the fixed fractions capital allocation method and are less than 2% on average.

- The results also indicate that the dynamic capital allocation strategy is able to significantly reduce the risk associated with the strategy, but at a much higher average transaction cost. This effectively more than cancels the benefits of the risk reduction on a risk-adjusted return basis. The dynamic allocation strategy can be viewed as a dynamic stop-loss strategy, which is often used in some form in many trading strategies. In the case of the strategies investigated it is however seen to reduce the overall risk-adjusted return because of the higher number of transactions and the corresponding higher transaction costs. The dynamic allocation strategy also leads to a lower percentage winning trades and a lower average return per trade.
• None of the long/short strategies provide sufficient returns to compensate for the risk carried. The short positions are on average not profitable. This is clear from Figure 31 in chapter 5, which shows that the post-earnings announcement returns for the lowest quartile (Q1) of ER is still positive and on average about 3% for the six month period subsequent to the earnings announcement.

Figure 49 shows the returns of the various long strategies (top) versus the market return, while the bottom figure shows the return of the long/short strategies for the period 1995-2010.

Figure 50 shows the return of the long-only PEAD strategy using ER as decision variable and employing the fixed fractions capital allocation strategy versus the value weighted return of a segment of the market with roughly the same median market capitalisation.
The performance statistics of the market segment with the same median market capitalisation as the PEAD strategy is shown in Table 33.

<table>
<thead>
<tr>
<th>Market Segment</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.1271</td>
</tr>
<tr>
<td>StdDev</td>
<td>0.1714</td>
</tr>
<tr>
<td>Sharpe</td>
<td>0.5085</td>
</tr>
<tr>
<td>Alpha</td>
<td>-0.0024</td>
</tr>
<tr>
<td>Beta</td>
<td>0.8322</td>
</tr>
<tr>
<td>MaxDD</td>
<td>0.6350</td>
</tr>
</tbody>
</table>

TABLE 33: PERFORMANCE MEASURES FOR MARKET SEGMENT WITH SAME MARKET CAP

SENSITIVITY ANALYSIS

The sensitivity of the excess risk-adjusted return (alpha - $\alpha$) is determined by random simulations and all other non-random simulations. The results from the non-random simulations are however influenced by the strategy employed while the sensitivity calculated from the random simulation data is purely attributable to variation in the parameters. The sensitivity analysis results are shown in Table 34.

<table>
<thead>
<tr>
<th></th>
<th>Random</th>
<th>Non-random</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_0$</td>
<td>-0.6860</td>
<td>0.0140</td>
</tr>
<tr>
<td>$I_{max}$</td>
<td>-0.0980</td>
<td>0.0152</td>
</tr>
<tr>
<td>MaxTransCost</td>
<td>0.4090</td>
<td>-0.0158</td>
</tr>
<tr>
<td>AveDaysHeld</td>
<td>0.0012</td>
<td>0.0002</td>
</tr>
<tr>
<td>AveCash</td>
<td>-0.0003</td>
<td>-0.0004</td>
</tr>
<tr>
<td>MarketCap</td>
<td>0.0547</td>
<td>-0.0106</td>
</tr>
</tbody>
</table>

TABLE 34: SENSITIVITY OF EXCESS RETURN TO CHANGES IN SIMULATION PARAMETERS

The findings of the sensitivity analysis are briefly summarised below:
• Alpha reduces by 0.00686 for every percentage increase in the initial investment amount as a percentage of the portfolio. An increase in the initial investment amount from 5% to 6% of the portfolio value would reduce alpha from 0.1 to 0.09314.

This is however estimated from data with only negative alphas, because none of the random simulations could produce positive alpha. Thus it agrees with the notion that for a strategy producing negative excess returns the returns would further decline when the strategy is more aggressive.

• Alpha reduces by 0.00098 for every percentage increase in the maximum allowed investment as percentage of the total portfolio value.

• Alpha increases by 0.00409 for every percentage increase in the maximum transaction cost, indicating that on average the firms associated with higher transaction costs provide superior returns even after subtracting transaction costs. The results from the non-random simulations disagree with this notion and it is found that it is on average negatively associated with the maximum transaction costs, the relationship is however much weaker.

• Alpha on average increases by 0.0012 for every day the shares are held longer in the portfolio.

• Alpha reduces by 0.0003 for every percent increase in the average cash held in the portfolio. Almost the same (0.0004) is found for the non-random simulations. This weak relationship between alpha and the average cash held in the portfolio reinforces the assumption of linearity in the risk-return relationship, that the cash held in the portfolio only moves the portfolio along the CAL and do not adjust the gradient (Sharpe ratio).

• It is found that alpha on average increases with 0.0547 for every billion rand increase in the median market capitalisation of the portfolio for the random simulations. For the non-random simulations, alpha decreases with 0.0106 for every billion (1 × 10^9) rand increase in the median market capitalisation of the portfolio. This indicates that the strategies employed are negatively correlated with market capitalisation. The variation in the median market capitalisation of the various portfolios is however small and the variation do not exceed a billion rand.
The difference between the sensitivity of excess returns to changes in parameter values for
the non-random strategies and for the random strategies also indicates that the simulation
parameter values are not a major determinant of performance. The performance measures
reported is therefore not dependant on the bias that may have been introduced in the
choice of parameter values and is mostly dependant on the strategy and specifically the
decision variable used.

6.4. Exploiting the Earnings Surprise

In this section the simulation results for the strategies designed to exploit the predictability
of the earnings surprise are presented. To effectively exploit the earnings surprise the event
returns (ER) are predicted.

The performance of the simulated strategies is shown in Table 35.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean</th>
<th>StdDev</th>
<th>Sharpe</th>
<th>IR</th>
<th>Alpha</th>
<th>Beta</th>
<th>MaxDD</th>
<th>% Winners</th>
<th>Ave Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Only – FF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER_{lag1}</td>
<td>0.0321</td>
<td>0.0722</td>
<td>-0.1096</td>
<td>-0.7029</td>
<td>-0.0325</td>
<td>0.1511</td>
<td>0.3132</td>
<td>57.8</td>
<td>0.0219</td>
</tr>
<tr>
<td>Long/Short - FF</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER_{lag1}</td>
<td>0.0118</td>
<td>0.0738</td>
<td>-0.3826</td>
<td>-0.8052</td>
<td>-0.0532</td>
<td>0.1777</td>
<td>0.4651</td>
<td>52.3</td>
<td>0.0039</td>
</tr>
<tr>
<td>Long Only – FF – No Transaction Cost</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ER_{lag1}</td>
<td>0.1098</td>
<td>0.0630</td>
<td>1.1075</td>
<td>-0.3133</td>
<td>0.0501</td>
<td>0.1279</td>
<td>0.1511</td>
<td>57.8</td>
<td>0.0245</td>
</tr>
</tbody>
</table>

**TABLE 35: PERFORMANCE RESULTS FOR SIMULATED TRADING STRATEGIES EXPLOITING THE EARNINGS SURPRISE**

It is clear that transaction costs play an important role in the exploitability of the earnings
surprise. When transaction costs are included negative Sharpe ratios are achieved. All
three risk-adjusted performance measures suggest that the earnings surprise is not
profitably exploitable on a risk-adjusted basis. The long/short strategy has a lower average
percentage winning trades than the long-only strategy. It can therefore be argued that
short positions are on average less profitable. This corresponds with the finding that the
earnings surprise for the most predictable size category (micro caps) is on average positive.

The performance of the various strategies is presented in Figure 51.
6.5. **BEST OF BOTH**

In this section we try to exploit both the predictability of the earnings surprise and post-earnings announcement returns. The strategy is in essence both the earnings surprise strategy and the PEAD strategy running concurrently while saving on transaction costs by holding on to the securities that were bought (or sold short) to exploit the event returns and also qualified for the PEAD strategy.

The results obtained from the simulation are presented in *Table 36*.

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Mean</th>
<th>StdDev</th>
<th>Sharpe</th>
<th>IR</th>
<th>Alpha</th>
<th>Beta</th>
<th>MaxDD</th>
<th>% Winners</th>
<th>Ave Gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>Long Only - FF</td>
<td>0.1005</td>
<td>0.1120</td>
<td>0.4955</td>
<td>-0.3072</td>
<td>0.0178</td>
<td>0.4649</td>
<td>0.6725</td>
<td>57.3</td>
<td>0.0386</td>
</tr>
<tr>
<td>Long Only - DA</td>
<td>0.0535</td>
<td>0.0925</td>
<td>0.1461</td>
<td>-0.5961</td>
<td>-0.0209</td>
<td>0.3127</td>
<td>0.5894</td>
<td>45.0</td>
<td>0.0412</td>
</tr>
<tr>
<td>Long/Short - FF</td>
<td>0.0539</td>
<td>0.1665</td>
<td>0.0836</td>
<td>-0.5775</td>
<td>-0.0430</td>
<td>0.6060</td>
<td>0.6623</td>
<td>50.1</td>
<td>0.0144</td>
</tr>
<tr>
<td>Long/Short - DA</td>
<td>0.0052</td>
<td>0.1663</td>
<td>-0.2092</td>
<td>-0.8384</td>
<td>-0.0897</td>
<td>0.5364</td>
<td>1.2335</td>
<td>40.8</td>
<td>0.0128</td>
</tr>
</tbody>
</table>

*TABLE 36: PERFORMANCE RESULTS FOR SIMULATED TRADING STRATEGIES EXPLOITING BOTH EFFECTS*

The results indicate that the performance of the strategies is on average lower than the strategies that aim to exploit the PEAD effect only. This may be due to the increased number of trades and the matching higher transaction costs incurred when trying to also exploit the predictability in the earnings surprise. This may also leave less cash available to invest in the more profitable PEAD strategy. The exploitation of the predictability in the
earnings surprise is therefore argued to lower the return of the combined strategy when compared to a strategy exploiting the PEAD effect alone.

The comparative return of the various combined strategies is shown in Figure 52.

![Figure 52: Combined Strategies' Returns vs. The Market Return](image)

6.6. Chapter Summary

A summary of the results of all the simulations discussed in this chapter is briefly presented below.

*Figure 53 shows the boxplot representing the median and variation in annual returns from 1995 - 2010 for the various simulations using ER as prediction variable as well as the value weighted market returns (1st plot). Figure 53 shows that the maximum return in any year is*
achieved by the value weighted market return and it also has the highest average and median annual returns.

The corresponding descriptive statistics are shown in Table 37. It should however be noted that the average return, standard deviation and Sharpe ratio reported in Table 37 are the average annual returns, the standard deviation of the annual returns and the Sharpe ratio calculated from the two for the 16 year period from 1995 – 2010, while the previous reported statistics are the annualised monthly standard deviation and average return and their corresponding Sharpe ratio. The first t-statistic column in Table 37 presents the t-statistic of the annual return for the 16 year period compared to the average return of the benchmark for the total 16 year period (0.1521), the last column presents the statistical significance of the annual Sharpe ratios compared to the Sharpe ratio of the benchmark for the total 16 year period (0.5363). The difference between the previously calculated standard deviation and that presented in Table 37 shows how easily a minor calculation difference can lead to different results.
<table>
<thead>
<tr>
<th>Strategy</th>
<th>Average</th>
<th>StdDev</th>
<th>t-Statistic</th>
<th>Sharpe</th>
<th>t-Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 VW Market</td>
<td>0.1519</td>
<td>0.2002</td>
<td>-0.1231</td>
<td>0.5592</td>
<td></td>
</tr>
<tr>
<td>2 PEAD (ER) - Long Only (FF)</td>
<td>0.1466</td>
<td>0.1776</td>
<td>-2.6121**</td>
<td>0.6003</td>
<td>1.3026</td>
</tr>
<tr>
<td>3 PEAD (ER) - Long Only (DA)</td>
<td>0.0343</td>
<td>0.1804</td>
<td>-0.0317</td>
<td>-1.3398</td>
<td></td>
</tr>
<tr>
<td>4 PEAD (ER) - Long/Short (FF)</td>
<td>0.0786</td>
<td>0.1281</td>
<td>-2.2953**</td>
<td>0.3014</td>
<td>-0.4199</td>
</tr>
<tr>
<td>5 PEAD (ER) - Long/Short (DA)</td>
<td>0.0276</td>
<td>0.0541</td>
<td>0.5204*</td>
<td>0.2299</td>
<td>-2.5265**</td>
</tr>
<tr>
<td>6 UE (ER) - Long Only (FF)</td>
<td>0.0321</td>
<td>0.0839</td>
<td>-5.7229**</td>
<td>0.0942</td>
<td>-2.2181**</td>
</tr>
<tr>
<td>7 UE (ER) - Long/Short (FF)</td>
<td>0.0116</td>
<td>0.1005</td>
<td>-5.5935**</td>
<td>0.2825</td>
<td>-2.6975**</td>
</tr>
<tr>
<td>8 UE-PEAD (ER) - Long Only (FF)</td>
<td>0.0994</td>
<td>0.2460</td>
<td>-0.8570</td>
<td>0.2414</td>
<td>0.6320</td>
</tr>
<tr>
<td>9 UE-PEAD (ER) - Long Only (DA)</td>
<td>0.0539</td>
<td>0.1577</td>
<td>-2.4922**</td>
<td>0.0879</td>
<td>-1.0819</td>
</tr>
<tr>
<td>10 UE-PEAD (ER) - Long/Short (FF)</td>
<td>0.0529</td>
<td>0.2273</td>
<td>-1.7448</td>
<td>0.0570</td>
<td>-1.3213</td>
</tr>
<tr>
<td>11 UE-PEAD (ER) - Long/Short (DA)</td>
<td>0.0053</td>
<td>0.2268</td>
<td>-2.5888**</td>
<td>-0.1529</td>
<td>-1.6089</td>
</tr>
</tbody>
</table>

**TABLE 37: SUMMARY STATISTICS FOR THE VARIOUS SIMULATED STRATEGIES**

Figure 54 shows essentially the same data but the average return and standard deviation are again calculated as the annualised standard deviation of monthly returns as previously reported in Table 30, Table 35 and Table 36. The size of the circles representing each strategy’s risk-return characteristics is proportional to the Sharpe ratio of each strategy. The optimal capital allocation line from the risk-free rate (any positive value less than the average market return) goes through the PEAD (ER) – Long Only (FF) strategy.

![Risk vs Return](image)

**FIGURE 54: RISK-RETURN CHARACTERISTICS OF THE VARIOUS STRATEGIES INVESTIGATED**

While Figure 54 indicates that the long-only PEAD strategy using fixed fractions capital allocation is the optimal mean variance portfolio from the set, the results from Table 37 and Figure 54 show that the average Sharpe ratio of the best performing strategy is not much higher than the Sharpe ratio of the value weighted market return and the annual Sharpe ratios of none of the strategies are found to be statistically significant. This result therefore questions the extent to which the PEAD anomaly is exploitable. The liquidity and
other limitations imposed by the simulator (which is an approximation to real-world market frictions and limitations) are arguably responsible for excluding smaller companies from the portfolio, which have been shown in chapter 5 to be responsible for a large portion of excess PEAD returns.

It can however also be argued that the performance of a long/short strategy is a true measure of how well a strategy is able to accurately predict winning trades. The appropriate benchmark to use in this case would be the risk-free rate and not the value weighted market, because the strategy has roughly zero exposure to the market and is said to be market-neutral. In this case the average return from the \textit{PEAD (ER) - Long/Short (FF)} strategy is also found to be statistically insignificant with a t-statistic of 1.2057.

We therefore come to the conclusion that not enough evidence exist to make any judgement on the exploitability of the PEAD anomaly.

The evidence however shows that the predictability in earnings surprise is not exploitable and therefore the predictability is found to be due to market frictions and not the inefficient processing of information by the market.
7. CONCLUDING REMARKS

“Facts are stubborn things, but statistics are more pliable.”

- Mark Twain

In this research the market’s reaction to earnings announcements is investigated. The investigation is divided into three parts: testing whether earnings announcements convey any information to the market; finding any patterns in the market’s response to the earnings announcements and testing the exploitability of behavioural patterns in response to earnings announcements through the simulation of trading strategies.

The three part investigation essentially focuses on two parts of the market’s reaction to earnings announcements. The first part focuses on the short-term market reaction around earnings announcements including the dynamics of the response and the information content of earnings announcements, the predictability of the earnings surprise and the exploitability of the predictability. The second part involves the longer-term reaction to earnings announcements which includes investigating the statistical significance and exploitability of the post-earnings announcement drift.

7.1. SHORT-TERM REACTION TO EARNINGS ANNOUNCEMENTS

The results in chapter 5 show that the market on average reacts to earnings announcements and the first null hypothesis, which stated that earnings do not convey any new information to the market, is rejected.

We modelled the new information (unexpected earnings announcements) as an impulse input and made the assumption that the market acts as an integrator to an impulse input, therefore producing a step-function output (where the output represents the value of the share or its price), with the amplitude of the step function related to the information content of the earnings announcements. An implicit assumption stemming from the EMH and the random walk hypothesis is that the market reacts to new information and the reaction is related to the information content (in the mathematical sense) of the new information.
The results proved the assumption to be acceptable and that on average the market’s reaction to new information can be modelled as an integrator to an impulse input. The reaction to earnings announcements was found to be a smoothed damped step-function (i.e. no measurable overshoot in price was observed).

If viewed more accurately, the response to the earnings announcement is not an immediate step in price, but tends to be a gradual drift before the announcement in the direction of announced EPS compared to the last previous announced EPS (the change in EPS or ΔEPS). In that sense the price impulse response can be viewed as a non-causal system, which effectively means that some information about the pending earnings announcement already starts to leak into the market before the formal announcement. ΔEPS is therefore not totally new information on the day of the earnings announcement and ΔEPS is not an absolute accurate measure of the earnings surprise (unexpected earnings).

The above impulse response model was found to accurately describe the average behaviour of firms falling into specific categories; the large variations amongst the individual observations however avert accurate prediction at the level of individual firms.

Ball and Shivakumar [59] found that earnings announcements are relatively unimportant in providing new information to the market. The methodology used by Ball and Shivakumar differs from what we used in this research; they calculated the strength of the relationship of the announced earnings and a share’s calendar year returns with the r-squared value of a regression of the aforementioned variables. They found that about 1-2% of the total return is associated with earnings announcements.

We calculated the relationship of earnings announcements and the short-term return and the longer-term return after earnings announcements, which is the six months following an earnings announcement up to the next announcement. The response to earnings announcements is on average related to the change in EPS from the last previous announced EPS. We found that ΔEPS on average explains roughly 50% of the magnitude of the response for the top and bottom quartiles when sorting firms based on actual response. We also found a much stronger relationship than Ball and Shivakumar [59]; the change in EPS (ΔEPS) is 7% correlated with returns in the short-term (days [0; 10] relative to the announcement) and 6% to the longer-term returns.
We further found the relationship between the reaction and ΔEPS to be close to logarithmic and that the response to earnings announcements (and its relation to ΔEPS) is related to firm size. The market’s reaction to earnings announcements for firms in the micro capitalisation group is higher than for small, medium and large firms. The results further indicate that the response to earnings announcements for firms with high EY is on average higher compared to other firms, and firms with a high announced ΔEPS and high EY experience a relatively big jump in price subsequent to announcements. This was however found to be mainly contributable to the large negative correlation between market capitalisation (MC) and EY.

The magnitude of event returns (cumulative returns for the days [0; 3]) is on average positive and decreases with an increase in firm size. The average information content of earnings announcements also decreases with an increase in firm size. This therefore means that information uncertainty decreases with size. If the risk of an investment is regarded as the uncertainty about the present value of all future cash flows, smaller firms are higher risk investments. This leads to the argument that smaller firms command a higher premium for the higher average risk carried, but the single factor CAPM does not capture the added risk.

This corresponds with the findings of Ball and Kothari [60] who found that abnormal returns are on average positive and decreasing with an increase in firm size. They also found abnormal returns to persist even after controlling for time-varying risk around earnings announcements.

Our results also agrees with those of Zhang [61] who found that greater information uncertainty is related to higher expected returns following good news and relatively lower returns following bad news. Zhang used size as a proxy for information uncertainty among others.

The earnings surprise is on average found to be predictable for firms in the two smallest size categories and shares with relatively low liquidity. Proxies for the value effect (EY, B2M and DY) and particularly the autocorrelation structure of unexpected earnings provide some additional information to predict future unexpected earnings. Our findings regarding the autocorrelation structure of the three-day reaction (event returns) to earnings announcements are consistent with that found by Bernard and Thomas [1]. They worked
with quarterly announcement whereas this research is only concerned with six monthly announcements which are customary to the local market. We found that the autocorrelation is however largely restricted to small size firms.

This predictability may be explained by the market’s inability either to effectively process the available information correctly or to eliminate the apparent profit opportunity due to market frictions such as transaction costs or the risk faced due to the higher uncertainty in earnings for these firms.

The evidence in chapter 6 shows that the predictability of the earnings surprise is not practically exploitable after taking into account liquidity factors and transaction costs. The predictability is therefore found to be due to market frictions and not the inefficient processing of information by the market.

7.2. POST-EARNINGS ANNOUNCEMENT DRIFT

The empirical evidence in chapter 5 shows that unexpected earnings are a statistically significant predictor of returns subsequent to earnings announcements. The null hypothesis, that there is no relationship between the unexpected earnings and the returns in the period following the announcement, is rejected. The post-earnings announcement drift anomaly, which can be regarded as an initial under-reaction to earnings news, occurred on the JSE for the period from 1991 to 2010 and it is found to be statistically significant and independent of the size, value and/or momentum effect.

This is in contrast to the findings of Bhana [2] who found that on the JSE for the period 1975 to 1989 the market overreacted to earnings announcements. Bhana found that firms announcing a negative change in EPS fared better than the market in the period subsequent to earnings announcements, but that those firms announcing a positive change in EPS did not perform significantly worse than the market.

The linear relation between risk and return found in chapter 5 section 5.3 for the anomaly variables may be a further indication of a risk factor that’s not accounted for by the single factor CAPM. This inability of the single factor CAPM to incorporate all relevant risks may lead to excess returns being overestimated for smaller firms. It is however argued that the ability of ER to separate PEAD returns is significant despite this uncaptured risk factor and
that it seems to represent a clear violation of market efficiency and may present an exploitable profit opportunity.

The two proxies of unexpected earnings used in this research are both found to be related to post-earnings announcement returns at statistically significant levels. The variable $\Delta E_{\text{EPS}}$ is however a less significant predictor of PEAD returns than $ER$, which is in contrast to the findings of Foster et al. [13] who found that unexpected earnings as calculated by the market’s reaction (a measure very similar to $ER$) are not related to post-earnings announcement returns, but that only the change in earnings ($\Delta E_{\text{EPS}}$) is related to the post-announcement returns.

The results in this research provide evidence that makes it very difficult to reconcile the observed PEAD effect with the delayed response explanation of Bernard and Thomas [63] and Hou and Moskowitz [64]. It is found that the market reacts very quickly to the announced earnings and it is not until about the 20th to 40th trading day after the announcement that the market starts drifting in the direction of the initial reaction. The market therefore seems not to underreact to the earnings information at first, but that it receives confirmation in the two months following the announcement that is indicative of better future prospects and that the higher than expected earnings might persist. In retrospect, when only considering earnings news, it thus seems that the market under-reacted to the information released at the earnings announcement. The nature of the confirmation is however unclear, but it may be further information in the form of a management forecast or operational update that is released to the market.

We however found no conclusive evidence in the trading simulation analysis to indicate that the PEAD effect can be exploited on a profitable basis. What the simulation analysis however did reveal was that the liquidity limitations imposed by the simulator lowered the overall returns achieved. It can therefore be argued that the PEAD effect is related to market frictions that prevent arbitrageurs to exploit the apparent profit opportunity.

Our results tend to agree with that of Mendenhall [3] and Chordia et al. [4]. Mendenhall argued that the magnitude of PEAD is related to the risk faced by arbitrageurs. He defined arbitrage risk as the risk that cannot be hedged away by holding offsetting positions. This
occurs most commonly for small sized firms and illiquid shares. Chordia et al. [4] also found that the PEAD anomaly mainly occurs for the highly illiquid shares.

There might however be several possible improvements to the trading strategies used in this thesis that may prove the PEAD anomaly to be exploitable, but the profit opportunity is unquestionably less than what the statistical evidence in chapter 5 would appear to suggest.

7.3. DIRECTIONS FOR FUTURE RESEARCH
Several improvements and directions for future research regarding earnings announcements are possible.

A more complete dataset that also includes analyst consensus estimates might enable the researcher to more accurately determine unexpected earnings based on which to investigate the relationship with the response to earnings announcements. This will also enable a more exact measure of the information content of earnings announcements.

Non-linear models and more sophisticated classification/clustering methods could potentially determine more exact boundaries between groups of shares and also the common characteristics of these groups that react differently to earnings announcements.

As mentioned previously there may exist several improvements that can be made to increase the performance of the simulation strategies, but performance improvements may not necessarily provide a better understanding.

Some of the potential performance improvements include:

- While taking positions using a portion of the available funds according to what the PEAD strategy advises, invest the remainder of the portfolio in a market index instead of in cash. A long/short strategy may then be much more profitable.
- Improve on the decision making logic to simultaneously take several aspects and firm characteristics into account to enhance performance (the current strategy uses only one characteristic at a time).
- Although the earnings announcement dates are known beforehand with reasonable accuracy, it is generally not known which of them would result in a potential profit opportunity. It may therefore be possible to find a better solution to the optimal
capital allocation problem by modelling the potential investment opportunities as a random arrival process.
BIBLIOGRAPHY


APPENDIX A:

Definitions of Explanatory variables:

All values are calculated at the last month-end before the earnings announcement.

- Earnings Yield (EY)
  \[ EY = \frac{\text{Earnings per share}}{\text{Closing Price of share}} \times 100 \]

- Dividend Yield (DY)
  \[ DY = \frac{\text{Dividend per share}}{\text{Closing Price of share}} \times 100 \]

- Book-to-Market (B2M)
  \[ B2M = \frac{\text{Net Asset Value per share}}{\text{Closing Price of share}} \]

The Net Asset Value (NAV) is calculated from the balance sheet according to the following formula:

\[ \text{NAV} = \text{Total Assets} - \text{Total Liabilities} \]

- PreEAD – Cumulative returns for the ten day period just prior to the earnings announcement day \((t=0)\).
  \[ \text{PreEAD}_i = \sum_{t=0}^{0} R_{i,t} \]

- Absolute Momentum (Mom6) - The cumulative returns for the 6 month period before the last month-end prior to the announcement day.
  \[ \text{Mom6}_i = \sum_{t=\text{MonthEnd},i}^{\text{MonthEnd},i-120} R_{i,t} \]

- Market momentum (MS6) - The cumulative value weighted market returns for the 6 month period before the last month-end prior to the announcement day.
  \[ \text{MS6}_i = \sum_{t=\text{MonthEnd},i}^{\text{MonthEnd},i-120} R_{M,t} \]

- Relative Momentum (RS6) – The cumulative returns for the 6 month period before the last month-end prior to the announcement day relative to the cumulative market return for the same period.
\[ RS6_i = \sum_{t=\text{MonthEnd},i-120}^{\text{MonthEnd},i} (R_{i,t} - R_{M,t}) \]

The above equation can also be written as:

\[ RS6_i = \text{Mom}6_i - MS6_i \]

- **Share turnover (ST3)** – Average daily volume of shares traded for the three months prior to the earnings announcement as a fraction of the total number of issued shares.

\[ ST3 = \frac{1}{60} \sum_{t=\text{MonthEnd},i-60}^{\text{MonthEnd},i} \frac{\text{Volume}_{t,i}}{\text{Number of shares issued}} \]

- **Market Capitalisation (MC)**

\[ \text{Market Capitalisation} = \text{Closing Price} \times \text{Number of shares issued} \]