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Cover stories as an investment indicator: an investigation of companies listed on the Johannesburg Stock Exchange

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ABSTRACT

Investors rely on secondary information sources, like cover stories, as market indicators due to time, information and resources constraints. However, studies in the US market gave mixed results about the potential use of cover stories while no publish research could be found in South Africa related to investors reaction to cover stories or whether an understanding of investment periods, company-specific characteristics or bounded rational behaviour would yield superior abnormal returns from cover stories.

In total, 1218 cover stories related to publicly listed companies were recorded from *FinWeek* and *Financial Mail* for the period 1985 to 2008 and categorised based on the Likert scale developed by Arnold et al. (2007). Event study methodology was used in the research.

The research found evidence that investors did pay attention to very optimistic cover stories. Positive and neutral cover stories were contrarian indicators, while negative cover stories were momentum indicators of future company investment performances and the abnormal returns for an investment portfolio based on these cover story effects were optimised by short-selling cover story companies from the healthcare, general retail and general mining industries and buying shares in control companies from the same industries and company sizes. The ability to earn long-term abnormal returns proofed weak form market inefficiency for the JSE.

KEYWORDS

Market inefficiency

Behavioural finance

Cover stories

Abnormal returns

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DECLARATION

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

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1.1 INTRODUCTION

Individual investors tended to rely on market indicators as proxies for future company investment performance. Investors used these indicators to make investment decisions instead of doing fundamental calculations to determine the underlying value of the stocks and future earnings potential because of information, time and resource constraints (Barber and Odean, 2008). The research investigated the potential use of cover stories as market indicators in the South African context. Cover stories were more accessible to individual investors, acted as a risk management tool and were broad precursors to changes in market sentiment when used as timing signals for making investments (Ritholtz, 2003).

Barber and Odean (2008) found that individual investors in the United States (US) were net buyers of attention-grabbing shares, a phenomenon that was attributed to time, information and resource constraints. However, studies in the US market gave mixed results about the potential use of cover stories as momentum or contrarian market indicators. On the one hand, research done by Forsyth (1996), Barber, Lehavy, McNichols and Trueman (2001), Stalter (2005) and Arnold, Earl and North (2007) found that cover stories could be used as contrarian indicators of future company investment performance in the US, with companies underperforming after positive cover stories or with improved performance after negative cover stories.

On the other hand, research conducted by Stickel (1995), Womack (1996), Ferreira and Smith (2003) and Desai and Jain (2004) concluded that cover stories or panel interviews, where a group of investment specialists discussed and recommended potential investments in listed companies, were momentum indicators of future company investment performance. No research was found on the potential use of cover stories as market indicators in South Africa.

The use of cover stories as market indicators was based on the assumption that markets were inefficient and that investors could earn higher returns by exploiting these market inefficiencies. Fama and French (1996) stated that it was impossible to obtain returns greater than those obtained by holding a randomly selected portfolio of individual stocks with comparable risk (abnormal returns) in the US market. Fama and French (1996) argued that the US market was an efficient market based on the above findings and no investor in the US could sustainably earn long-run abnormal returns.

In the South African context, Page and Way (1992) and Philpott and Firer (1994) found a weak form of inefficiency in the South African stock market in the long term after investigating share price performance and finding several significantly large share price anomalies that persisted over long periods of time for both high- and low-volume traded stocks. In contrast, High and Honikman (1995), Smith, Jefferis and Ryoo (2002) and Magnusson and Wydick (2002) found evidence to support the weak form of the efficient market hypothesis (EMH) for the JSE.

Bodie, Kane and Marcus (2009) argued that market inefficiency was caused by a combination of irrational investors' behaviour and inefficient action by arbitrageurs to take advantage of the opportunities created by irrational investors. Barber and Odean (2008) highlighted two common mistakes investors made, namely excessive trading and the tendency to hold on disproportionately to losing investments while selling winners. Barber and Odean (2008) suggested that these systematic biases led to market inefficiency.

Investors could take advantage of these opportunities created in the market by understanding how investors' irrational behaviour affected the market and by finding a market indicator that could act as a timing signal for these market inefficiencies. The ability to forecast future company investment performance accurately using these market indicators could lead to significant financial gains for investors.

1.2 THE RELEVANCE OF THIS RESEARCH IN THE SOUTH AFRICAN CONTEXT

Most of the studies conducted in this field of research focused on the US markets with little information about the use of market indicators in South Africa. Historical studies on market efficiency in South Africa were inconclusive with Page and Way (1992) and Philpott and Firer (1994) finding a weak form of market inefficiency, while High and Honikman (1995), Smith et al. (2002) and

Magnusson and Wydick (2002) found evidence to support the weak form of the efficient market hypothesis (EMH) for the JSE.

No information was found relating to cover stories in South Africa and thus the potential use of cover stories as market indicators for future company investment performance for South African organisations was not established. Cover stories were only of financial value to investors when investors could exploit market inefficiencies and earn returns, after trading costs, higher than those obtained by holding a randomly selected portfolio of individual stocks with similar risks (Arnold et al., 2007).

1.3 RESEARCH OBJECTIVES AND RESEARCH PROBLEM

The purpose of this research was to assess whether South African investors could benefit from using cover stories as market indicators and whether an understanding of investment time horizons, company-specific characteristics and bounded rationality behaviour could assist investors to gain superior short-, medium- or long-run returns.

In answering the above questions, the following main objectives were identified for the research:

- To evaluate the past behaviour of investors post the publication of cover stories.
- To assess whether investors responded differently to the different categories of cover stories by reviewing share trade volumes and returns around the cover story publication dates.

- To identify the most appropriate method for calculating abnormal returns that would yield well-specified test statistics and eliminate experimental bias.
- To evaluate the potential use of cover stories as either momentum or contrarian market indicators.
- To maximise abnormal returns by optimising the investment time horizons and selective use of cover stories.

1.4 THE SCOPE OF THE RESEARCH

The scope of the research was limited to companies listed on the JSE that were the subject of cover stories for the specified period and publications. The research was limited to the development of the following academic theory bases to obtain a better understanding of how cover stories affected financial markets, how individual investors behaved after the publication of cover stories and how cover stories could be used as potential market indicators for future company investment performance:

- The cover story event to assess how investors' behaviour post the publication of cover stories affected company share prices and longer term investment potential.
- Price-to-price feedback theory to assess whether cover stories could act as initiators of company share price bubbles and the duration of these bubbles.
- Event studies with the combination of share prices and dividends as a measure of company investment performance pre- and post-event.

- Buy-and-hold abnormal returns calculated using a reference company with similar company-specific characteristics. Evidence was presented as to the appropriateness of using buy-and-hold abnormal returns as a measure of abnormal returns.
- The potential use of cover stories as market indicators in international markets. Previous studies were investigated and theories developed with regard to the effects of cover stories on international financial markets.
- The efficient market hypothesis (EMH) – the potential use of cover stories as market indicators was based on the assumption that markets were inefficient and any measured abnormal returns with well-specified test statistics would support the argument that the South African market was inefficient in allocating resources.
- Active and passive investments – abnormal returns higher than the transaction costs would support the argument for active investing where investors would earn higher returns by exploiting market inefficiency.

These theory bases formed the foundation for the research conducted.

CHAPTER 2: LITERATURE REVIEW

2.1 INTRODUCTION

The use of cover stories as market indicators for future company investment performance was based on the assumption that markets were inefficient and that investors could earn returns in excess of those obtained by holding a randomly selected portfolio of individual stocks with similar risks (Arnold et al., 2007). Womack (1996) concluded that analysts had share-picking and market-timing capabilities and that their recommendations could be used as momentum indicators to predict future company investment performance. Similarly, Ferreira and Smith (2003) found that panel interviews where a group of investment specialists discussed and recommended potential investments in listed companies were momentum indicators of future company investment performance after calculating long-run abnormal returns based on the panel interview recommendations.

In related research, Barber et al. (2001) completed a study on consensus recommendations by analysts. They found that the difference in annual returns between an investment portfolio based on the analysts' consensus recommendations and randomly selected individual stocks was statistically insignificant. In this vein, Desai and Jain (2004) came to the conclusion that investors did not benefit from acting on cover stories, one to three years post-publication dates.

By contrast, Arnold et al. (2007) found cover stories to be a contrarian indicator of future company performance after analysing headlines and feature stories in *Business Week*, *Fortune* and *Forbes* for a 20-year period. Positive cover stories in the US market "generally indicated an end to superior company investment performance while negative cover stories generally indicated an end to poor performance" (Arnold et al., 2007, p. 70).

While the evidence on the usefulness of cover stories was mixed, individual investors in the US relied on these market indicators. The investments were made based on the implicit assumption that the secondary information supplied by analysts reflected their private, unbiased information (Trueman, 1994). However, Trueman (1994) found that analysts displayed herding behaviour by releasing forecasts closer to prior earnings expectations and similar to prior announcements by other analysts, even if these forecasts were not justified by their own information. Similarly, a study by Barber and Odean (2008) found that individual investors invested more in attention-grabbing shares.

There was no conclusive evidence supporting the use of cover stories as market indicators. The value of cover stories in efficient markets was limited to entertainment value due to the nature of information dissemination (Beechey, Gruen and Vickery, 2000), while cover stories could be of significant value in inefficient markets by acting as market indicators for future company performance.

2.2 EFFICIENT MARKET HYPOTHESIS

2.2.1 Introduction

The efficient market hypothesis (EMH), as defined by Fama (1970, p. 383), stated that asset prices in financial markets "always fully reflect all available information" and "a market is efficient when asset prices always fully reflect available information". Fama (1970) linked information-efficient markets to efficient resource allocations by arguing that asset prices that fully reflected all available information provided accurate signals for resource allocations. All relevant information was rationally processed in efficient markets and reflected in the current asset prices (Beechey et al., 2000). This implied that investors could not earn above-average returns without accepting above-average risks (Malkiel, 2003). Another implication was that active trading investment strategies did not yield returns higher than passive investment strategies where the investor placed a constant amount on a periodic basis into the same broadly diversified investment portfolio (Findlay and Williams, 2000).

Fama (1970) drew a distinction between a weak, semi-strong and a strong form of the EMH:

- The *weak form of the EMH* was defined as markets where current asset prices fully incorporated information from the past that affected future asset prices (Fama, 1970). Thus current asset prices reflected all information about future asset price movements caused by historical asset prices (Findlay and Williams, 2000).
- The *semi-strong form of the EMH* was defined as markets where asset prices fully incorporated all publicly available information (including

historical asset prices and data reported in a company's financial statements) (Fama, 1970).

- The *strong form of the EMH* was defined as markets where asset prices fully incorporated all existing public and private information (Fama, 1970). With the strong form of the EMH even insiders with private information would not be able to trade at a profit in efficient markets (Findlay and Williams, 2000). Most investors and economists rejected the strong form of the EMH because it did not reflect reality and was only applicable to perfect markets with many small independent buyers and sellers, with rational costless information available to all investors, homogeneous products and no transaction costs (Findlay and Williams, 2000).

Jensen (1978) later expanded on Fama's definition of the EMH by accounting for the economic costs of information gathering. Jensen (1978) argued that information gathering was costly and that there would be no financial incentive for investors to collect information if the information was already fully reflected in the asset prices. Thus, asset prices in efficient financial markets only reflected information up to a point where the marginal benefits of acting on the information were smaller or equal to the marginal costs of collecting the information (Jensen, 1978).

In the South African context, High and Honikman (1995), Smith et al. (2002) and Magnusson and Wydick (2002) found evidence to support the weak form of the EMH for the JSE. Assuming the weak form of the EMH held and current asset prices reflected the effects of past asset price movements on future asset price movements (Findlay and Williams, 2000), then any technical analysis of the historical performance of the stock market would be a waste of time. Investment portfolios built on historical market performances would not yield any abnormal returns.

In the same vein, Malkiel (2003) and Ozdemir (2008) defined market efficiency where changes in today's asset prices only reflected new information, independent of yesterday's price changes or news. Lawrence, McCabe and Prakash (2007) listed the foundations of an efficient market and stated that market anomalies caused by irrational investors would disappear over time because of the random nature of the anomalies and the behaviour of rational arbitrageurs:

- Investors were assumed to be rational and therefore valued securities rationally.
- Some investors were not rational, but their random trades cancelled each other out with no ultimate effect on asset prices.
- If investors were irrational, they would be met in the market by rational arbitrageurs who would eliminate any influence they had on the market.

The weak and semi-strong forms of the EMH were adopted for the research considering that the strong form of the EMH did not reflect actual, imperfect markets (Findlay and Williams, 2000).

2.2.2 Implications of market efficiency with regard to investment returns

Fama and French (1996) stated that it was impossible to obtain returns greater than those obtained by holding a randomly selected portfolio of individual stocks with comparable risk (abnormal returns) in an efficient market. In line with the findings of Fama and French (1996), Malkiel (2003) argued that relevant information or news was, by definition, unpredictable and therefore the resulting asset price changes in the market were unpredictable and random. Neither technical nor fundamental analysis would enable an investor to earn abnormal returns in efficient markets because of the unpredictability of the relevant information (Malkiel, 2003).

The widely held belief in the EMH started to weaken. By the start of the twenty-first century, the intellectual dominance of the EMH had become far less universal (Malkiel, 2003) and more researchers started to observe anomalies in the market that could not be fully explained using the EMH.

2.2.3 Potential use of the EMH

Findlay and Williams (2000, p. 197) argued that the EMH should be used as a "useful benchmark for measuring relative efficiency" after demonstrating that the EMH was neither well-defined nor empirically refutable. Findlay and Williams (2000) defined relative efficiency as measuring the market efficiency of a particular market relative to the efficiency in another market on a continuous scale, where the EMH represented the highest point and market inefficiency the lowest point of the scale.

Findlay and Williams (2000) postulated that the testing of market efficiency should focus on whether efficiency could be observed in actual, imperfect markets and measurements of relative market efficiency, instead of focusing on proving or rejecting the EMH empirically. Relative market efficiencies could be measured using cover stories and assuming a semi-strong form of the EMH where asset prices fully reflected all publicly available information (Fama, 1970).

2.2.4 Efficient market anomalies

Fama and French (1996) found that most cumulative long-run abnormal returns in the US stock markets could be attributed to a combination of excess returns on a broad market portfolio and company-specific characteristics, such as company size (based on market capitalisation) and book-to-market ratios, that disappeared after changing the method used to calculate the abnormal returns.

Fama (1998, p. 283) continued to support the efficient market theory, even after observing several market anomalies, by stating that market anomalies "with apparent overreaction to information were as common as under reaction and post-event continuation of pre-event abnormal returns were as frequent as post-event reversal". Different results thus cancelled out over time. Furthermore, the model of efficient market theory should hold for suboptimal decision making as long as the "marginal investor" made rational decisions (Thaler, 1999).

Bodie et al. (2009) argued that the apparent market anomalies might be a result of data mining or risk premiums not captured by the simple models used to calculate abnormal returns. In related research, Basiewicz and Auret (2010) showed that most cumulative long-run abnormal returns measured in the South African stock market disappeared after adjusting the reference portfolios for company size (based on market capitalisation) and book-to-market ratios.

2.2.5 Market inefficiency

Findlay and Williams (2000) described an inefficient market as one in which assets were underpriced or overpriced by market participants with the underpriced or overpriced assets creating opportunities for investors to earn abnormal returns. According to the EMH, the difference between an inefficient market and an efficient market depended on whether investment decisions were made based on the best available information to maximise expected utility (Thaler, 1999) and if participants acted rationally when making investment decisions in the market (Shiller, 2003).

In the South African context, Page and Way (1992) found a weak form of inefficiency in the South African stock market in the long term after investigating share price performances for 240 JSE-listed companies over a 15-year period (July 1974 to July 1989). In the same vein, Philpott and Firer (1994) found that the JSE stock market was not efficient (period of investigation: 1987 to 1991) after finding several significantly large share price anomalies that persisted over long periods of time for both high- and low-volume traded stocks.

Philpott and Firer (1994) identified three potential reasons for South African market inefficiency, namely the liquidity ratio or liquidity premium for the more actively traded shares, the value ratio code due to the inability of many investors in the market to interpret or remember historical information and low shareholder activity due to passive investors.

In related research, Findlay and Williams (2000) demonstrated that the evidence supporting the EMH was weak, with most of the arguments used in the EMH being supported by assumptions rather than facts. Findlay and Williams (2000, p. 181) described the EMH as a "fraud-on-the-market" in light of the point of view of Grossman and Stiglitz (1980) that the EMH was an economically unrealisable idealisation. The EMH, even in its weak form, was neither well defined nor empirically refutable and could only be tested in combination with an auxiliary hypothesis (Findlay and Williams, 2000). However, any rejection of the joint hypothesis did not specify which aspect of the joint hypothesis was empirically refutable and inconsistent with the data.

Several academics began to argue that Fama's (1970) interpretation of market efficiency and explanations for market anomalies (Fama, 1998) reflected an incorrect understanding of the psychology underlying human behaviour. Beechey et al. (2000, p. 3) did not agree with Fama's (1970) definition of market efficiency and stated that information efficiency should not be linked to efficient resource allocations by arguing that "an informationally efficient asset market need not generate allocative or production efficiency". Furthermore, Beechey et al. (2000) found that market prices were at times subject to substantial resource allocation misalignment or market inefficiency.

Campbell and Shiller (2001, p. 101) argued that Fama's (1998) criticism regarding historically identified market anomalies reflected his incorrect understanding of the "psychological underpinnings of behavioural finance". Campbell and Shiller (2001) argued that the fact that market anomalies reverse or disappear was a basic phenomenon suggested by market inefficiency and was not proof of market efficiency.

Campbell and Shiller (2001) went on to state that it was irrational to expect inefficient markets to display regular and lasting patterns considering that there were no psychological principles based on human behaviour stating that people would always over- or under-react. Campbell and Shiller (2001) argued that Fama's (1998) observations of apparent over- and under-reaction and frequent post-event continuation and reversal of pre-event abnormal returns could not be taken as proof of market efficiency, but reflected market inefficiency caused by human behaviour.

The findings of Page and Way (1992) and Philpott and Firer (1994) with regard to market inefficiency in the South African context contradicted the findings of Basiewicz and Auret (2010) of a weak form of market efficiency. Nevertheless, Grossman and Stiglitz (1980), Page and Way (1992), Philpott and Firer (1994), Findlay and Williams (2000), Beechey et al. (2000) and Campbell and Shiller (2001) presented strong evidence against the EMH.

2.3 BOUNDED RATIONAL BEHAVIOUR

2.3.1 Introduction

Behavioural finance focused on the role of human behaviour in financial markets by incorporating psychology and social sciences into the analysis of investment decision making (Thaler, 1999). It was developed based on the premise that conventional financial theory ignored the influence of human decision-making processes on financial markets. Herbert Simon started the theory of bounded rationality based on the notion that the rationality of individuals' decision-making processes was limited by the information they had, the cognitive limitations of their minds and time constraints (Selten, 1999). Selten stated that individuals made rational decisions within the cognitive bounds of human beings that were non-optimising after simplifying the choices available due to ability, information and resource constraints (Selten, 1999).

In the same vein, Thaler (1999) argued that the efficient market theory did not reflect reality because of cognitive biases. Efficient markets could not have too many suboptimal or "quasi rational" investors in order for the rational investors to be marginal. Efficient markets also required costless short selling to drive down high prices and rational investors to have long-term horizons to invest in shares until true equilibrium prices were reached (Thaler, 1999). Thaler (1999) argued that this type of behaviour was highly unlikely in the real world.

Using the behavioural finance framework, Trueman (1994) found that analysts displayed herding behaviour by releasing forecasts similar to previous announcements by other analysts, while possessing contradictory personal information. This behaviour strengthened Thaler's (1999) argument that real market behaviour was not rational because of the irrational "marginal investor".

Barber and Odean (2008) highlighted two common mistakes investors made, namely excessive trading and the tendency to hold on disproportionately to losing investments while selling winners. Barber and Odean (2008) suggested that these systematic biases led to market inefficiency. The tendency for human beings to be overconfident caused the first bias in investors, while the human desire to avoid regret prompted the second bias (Barber and Odean, 2008).

Campbell and Shiller (2001) defined investor sentiment as individual beliefs about the future performance of a company. Investors might obtain feedback from the overall macroeconomic conditions of the market, as well as from the advice of experts and market analysts, but ultimately their beliefs and actions were their own.

In related research, Kahneman (2003) argued that individual investors reacted more intuitively when making investment decisions because of time, information and resource constraints. Intuition resembled perception, the role of optimism in risk taking, effects of emotions in decision weights, the role of fear and the like or dislike by the individual of predictions (Kahneman, 2003).

Definitions aside, it was found that such intuition led to irrational decision making by Trueman (1994), Selten (1999), Thaler (1999), Campbell and Shiller (2001), Kahneman (2003) and Barber and Odean (2008). Bodie et al. (2009)

argued that the behaviour of irrational investors on its own would not be sufficient to cause market inefficiency if arbitrageurs took full advantage of the opportunities created by the irrational investors. The actions taken by these arbitrageurs would push prices back to market equilibrium or intrinsic values.

Market inefficiency was caused by a combination of irrational investors' behaviour and inefficient action by arbitrageurs to take advantage of the opportunities created by irrational investors (Bodie et al., 2009). Bodie et al. (2009) further argued that a lack of measuring of abnormal returns was not sufficient proof of market efficiency, but reflected arbitrageurs' inability to take advantage of the opportunities created by irrational investors.

2.3.2 Price-to-price feedback theory

Shiller (2003) defined price-to-price feedback as a situation where abnormal returns earned by investors on speculative stocks attracted more public interest in the stocks which, in turn, led to further investment in the stocks. It also resulted in stock price increases, word-of-mouth enthusiasm and heightened expectations of further stock price increases based on the historical performance of the stocks. Psychological experiments conducted by Tversky and Kahnemann (1974) and Marimon, Spear and Sunder (1993) demonstrated the price-to-price feedback theory where speculative bubbles were created due to the representativeness heuristic (where the sample tried to predict future performance based on past price patterns).

Trueman (1994) found that analysts displayed herding behaviour by disregarding their own personal information and releasing forecasts closer to prior earnings expectations and similar to prior announcements by other analysts. Shiller (2003) used feedback models developed by Charles MacKay in the nineteenth century to explain speculative behaviour in markets that led to investment speculative bubbles. According to MacKay, investment speculative bubbles were created when abnormal returns earned by investors on speculative stocks attracted more public interest in the stocks (Shiller, 2003).

Many rounds of the speculative process and misallocation of resources resulted in speculative bubbles where high current stock prices were supported by expectations of higher future stock price increases without an increase in the underlying value of the stocks (Shiller, 2003). The speculative bubble would eventually burst, with stock prices tumbling, because of the lack of underlying value in the stocks and the feedback effects caused by the negative bubble in the market (Shiller, 2003).

Based on the feedback models used by Shiller (2003), cover stories could potentially act as market signalling tools that had the potential to create either positive or negative speculative bubbles in the market. Investments based on these cover stories could yield significant abnormal returns by timing the market around the speculative bubbles.

2.3.3 Potential to earn abnormal returns due to bounded rational behaviour

Barber et al. (2001) were able to produce an abnormal gross return of more than four per cent after doing daily portfolio rebalancing and timely responding to the momentum indicators based on consensus analyst recommendations. Similarly, findings from research done by Desai and Jain (2004) pointed to irrational investor behaviour where investors' overreaction to Briloff's recommendations led to short-run (mostly one day post the publication date) abnormal returns that reversed in subsequent days to zero abnormal returns. (Briloff was a famous economist in the US who made weekly stock recommendations on television.)

Barber and Odean (2008) found that these short-run abnormal returns were short-lived and reversed to zero in subsequent days. In related research, Puckett and Yan (2008) found strong evidence that institutional investors could time the market and earn significant abnormal returns on their intra-quarter round-trip trades. Furthermore, the stocks institutions bought significantly outperformed the stocks institutions sold within a quarter, suggesting that these institutions had superior skills in timing their trades (Puckett and Yan, 2008).

This raised the question of whether sustainable abnormal returns could be obtained from active investment decisions with cover stories as one of the market signalling tools and to what extent investors' reactions to cover stories contributed to market anomalies. Thaler (1999) concluded that real market behaviour often deviated from rational efficient market behaviour, but the anomalies were not large enough to create sustainable abnormal returns for investment groups.

2.4 MARKET INDICATORS

Market indicators acted as a risk management tool for investors when used as timing signals for making investments (Ritholtz, 2003). Ritholtz (2003) grouped the market indicators into internal and external market indicators. Ritholtz (2003) stated that internal indicators (such as abnormal daily trading volumes and a share’s previous one-day returns) were more appealing to investors because of precise time signals, a mathematical basis and accuracy in revealing secondary reversals. Unfortunately, access to these internal indicators limited their usefulness for individual investors (Barber and Odean, 2008). By contrast, external indicators, such as cover stories, acted as broad precursors to changes in market sentiment (Ritholtz, 2003) and were more accessible to individual investors.

Ritholtz (2003, p. 1) described contrarian indicators as “data points, signs and events whose actual significance to the market is the exact opposite of what their initial impression suggested”. Ritholtz (2003) attributed these inflection points to overwhelmingly bullish or bearish sentiments prior to or coincident with the inflection points and described this behaviour as “group-think or group-feel”. Market indicators were only valid as trading tools for forecasting future company investment performance if the time horizon and trading style of the investor matched the specific market indicators used (Ritholtz, 2003).

Contrarian buyers bought attention-grabbing shares with negative reviews and sell recommendations, while momentum buyers bought attention-grabbing shares with positive reviews and buy recommendations (Barber and Odean, 2008). Investors reacted differently to different market indicators due to behavioural biases (Barber and Odean, 2008), how the information was disseminated through the markets and resource constraints. Some market indicators were better predictors of future company investment performance based on the predictability of the behaviour of investors towards these market indicators (Ritholtz, 2003).

The information sources selected as market indicators for the research had to be accessible to most individual investors to maximise the potential impact of investors' behaviour on the markets after the information was disseminated. Cover stories were selected as external market indicators for the research due to the availability of cover stories as an information source, and time and resource constraints for individual investors (Ritholtz, 2003). Ritholtz (2003) found internal market indicators to be more accurate and precise timing signals for the markets, but most individual investors would not have access to these internal market indicators and the reaction of irrational investors to the information, or the effect of irrational investors on the market, would be limited.

2.5 COVER STORIES AS MARKET INDICATORS

2.5.1 Introduction

Arnold et al.'s (2007) study focused on the usefulness of cover stories as market indicators with a bias towards the hypothesis that cover stories did not reveal new pertinent information about a company. Arnold et al. (2007) argued that the contrarian indication potentially coincided with shares being mispriced, thus pointing to market inefficiencies.

Assuming cover stories did not reveal new information (Arnold et al., 2007), then the market would be information efficient (semi-strong form of the EMH) and any observed market inefficiency, measured as abnormal returns, could be attributed to irrational investor behaviour. Thaler (1999) and Beechey et al. (2000) argued that information-efficient markets were not linked to efficient resource allocations. Cover stories that acted as momentum indicators in information-efficient markets pointed to irrational investor behaviour, or herding behaviour, where the reaction of investors to the cover stories had to coincide with the popularity of the shares (Arnold et al., 2007).

2.5.2 Investor reaction to positive and negative cover stories

Investors' responses and the potential of positive and negative cover stories as market indicators might be completely different and non-related in real markets. Womack (1996) found that the ratio of buy-to-sell recommendations in his sample was about seven to one. Womack (1996) attributed the asymmetry in buy-to-sell recommendations to the substantial costs and risk of disseminating sell recommendations to investors. Sell recommendations could harm an analyst's present and potential investment banking relationships, limit or cut the flow of information to the analyst, took longer to receive approval for publication and were more visible because of the lower frequency of sell recommendations in cover stories (Womack, 1996).

In the same vein, research done by Hong, Lim and Stein (2000) found that negative company-specific information diffused more slowly through to the investment public and led to more pronounced momentum effects. Similarly, the work done by Arnold et al. (2007) highlighted the difficulty in obtaining negative cover stories with only 18.2% negative cover stories in the sample.

Based on the literature, it was anticipated that negative cover stories would be more reliable market indicators than positive cover stories and the potential to use positive and/or negative cover stories as market indicators required separate investigations.

2.5.3 Difference in behaviour of individual versus institutional investors

Barber and Odean (2008) found that individual investors invested more in attention-grabbing shares. The investments were made based on the implicit assumption that the secondary information supplied by analysts reflected their private, unbiased information. Attention-driven buying behaviour of individual investors was caused by time, information and resource constraints when searching for shares to buy (Barber and Odean, 2008). Attention-driven behaviour did not affect individual investors' selling behaviour because individual investors only sold shares they owned and they held only a few common shares in their portfolios (Barber and Odean, 2008).

Institutional investors' investment decisions were less affected by attention-grabbing shares. They devoted more time and resources to studying companies before making buying or selling decisions, and were less dependent on secondary information sources (Barber and Odean, 2008).

The effects of cover stories as market indicators might not be as evident in the South African market when compared to the US markets (Arnold et al., 2007), considering that institutional investors dominated the South African stock market (Philpott and Firer, 1994) and institutional investors' investment decisions were less affected by attention-grabbing shares (Barber and Odean, 2008).

2.5.4 Cover story categorisation

Womack (1996) and Arnold et al. (2007) proposed a five-point Likert scale to classify cover stories:

- *Category 1*: Company was doing or had done something innovative that would differentiate the company from its competitors – this was considered a very optimistic cover story.
- *Category 2*: Company was planning something innovative – this was considered an optimistic cover story.
- *Category 3*: The analyst gave no particular opinion – this was considered a neutral cover story.

- *Category 4*: The company was currently performing badly, but performance should improve in future – this was considered a moderately pessimistic view.
- *Category 5*: The company was performing poorly or a scandal had been uncovered – this was considered a pessimistic view.

2.6 ACTIVE VERSUS PASSIVE INVESTMENTS

2.6.1 Introduction

Assuming the markets were efficient (semi-strong and strong form of the EMH), then investors would earn higher returns by placing a constant amount on a periodic basis into the same broadly diversified investment portfolio (Findlay and Williams, 2000) instead of making active investment decisions with higher transaction costs.

In the same vein, Beechey et al. (2000) found that active managers, as a group, could not beat the market consistently to produce abnormal returns. Their conclusion was that these investment professionals did not have stock-picking or market-timing capabilities.

2.6.2 Passive investments

Sharpe (1991) and Findlay and Williams (2000) defined passive investors as investors who placed a constant amount on a periodic basis into the same broadly diversified investment portfolio. This broadly diversified investment portfolio normally contained every security from the market in equal proportions to the value of the securities in the market or to a market index. Passive investment, as an extension of the modern portfolio theory (MPT), was founded on the efficient market hypothesis (Sharpe, 1991). Passive investors would thus earn exactly the average market returns or market index returns, before costs, with a broadly diversified investment portfolio (Sharpe, 1991) and would obtain zero value from cover stories regardless of whether the markets were efficient or inefficient.

2.6.3 Active investments

Active investors normally held securities in unequal proportions to the market and traded more frequently based on perceptions of mispricing in the market (Sharpe, 1991). The costs of active portfolio investing were significantly higher than the costs of passive investing (Sharpe, 1991). Active investing would only yield abnormal returns if the active investor exploited market inefficiencies well enough to overcome trading costs.

The use of cover stories as market indicators to earn abnormal returns was based on the assumption that the markets were inefficient or relatively weakly efficient (Findlay and Williams, 2000). Investors could earn abnormal returns, after trading costs, by creating and actively managing investment portfolios based on these market indicators in an inefficient market environment.

2.7 EXPLANATORY VARIABLES

Barber et al. (2001) used a modified Fama and French (1993) traditional event study framework to calculate holding period abnormal returns. The modified framework compensated for the potential contributions of company-specific characteristics such as company size (based on market capitalisation), growth attributes and historical company investment performance (Barber et al., 2001). Fama and French (1993) questioned the influence of company-specific characteristics on analysts' share-picking capabilities. They argued that contributions from these known characteristics should be excluded when assessing whether analysts did, in fact, have special share-picking capabilities.

2.7.1 Attention-grabbing stocks

Barber and Odean (2008) used three proxies to assess whether investors were paying attention to a company, namely abnormal daily trading volumes, shares' previous one-day returns and whether the company had appeared in the news that day. Barber and Odean (2008) warned that high abnormal trading volumes could be attributed to liquidity or information-based trades of a few large investors. They argued that rational investors would realise that information associated with attention-grabbing shares was already impounded into the share prices or that attention-grabbing events might not reflect the future performance of the company (Barber and Odean, 2008).

2.7.2 Investment time horizon

The opportunity of benefiting from cover stories as market indicators was a function of investors' investment time horizons. Womack (1996) measured a 2.4% short-run abnormal return after analyst buy recommendations and a significant medium-run (six month) abnormal return of 9.1% post sell recommendations. After analysing the performance of active managers in the US for the period 1985 to 1997, Sorensen, Miller and Samak (1998) found that active managers could outperform the market during bearish markets, but underperformed when compared to passive investments during bullish markets.

Similar to Barber et al. (2001), Seaholes and Wu (2004) measured short-run abnormal returns for attention-grabbing shares that reversed back to zero within ten trading days of the event. They found that only a small group of professional investors profited from attention-grabbing shares by anticipating the temporary surge in prices and demand. By comparison, Ferreira and Smith (2003) found that cover stories were momentum indicators of long-run future company investment performance.

Based on the findings of Sorensen et al., (1998), Barber et al. (2001) and Seaholes and Wu (2004), the duration of the investment (investors' time horizon) and the nature of the market at the time of the investment (bullish or bearish market) were important factors in measuring abnormal returns.

2.7.3 Industry

Shiller (2003) commented that speculative stock market bubbles often appeared for specific classes of assets such as the late 1990s technology stock bubble or the late 2000 UK and US housing stock bubble. Shiller (2003) further argued that these specific asset classes go through periods of boom and bust cycles amplified by the feedback model. Abnormal returns calculated for cover story event studies had to account for industry-specific factors to eliminate the probability that the excess returns were due to speculative industry bubble effects (Shiller, 2003) or the popularity of shares within that industry at that point in time (Arnold et al., 2007).

2.7.4 Company size

Hong et al. (2000) and Van Rensburg and Robertson (2003) found that the profitability of momentum strategies sharply declined with an increase in company size (based on market capitalisation). Similarly, Basiewicz and Auret (2009) measured positive abnormal returns for investment portfolios developed based on company size (based on market capitalisation) for JSE-listed companies for the period December 1989 to July 2005. Basiewicz and Auret (2009) concluded that the abnormal returns remained positive even after accounting for restricted liquidity and prices caused by trading in small market capitalisation stocks and transaction costs.

Based on the findings of Hong et al. (2000), Van Rensburg and Robertson (2003) and Basiewicz and Auret (2009), the reference portfolios or companies used in calculating abnormal returns should account for excess returns due to company size.

2.7.5 Value stocks

Campbell and Shiller (2001) found that stocks with low price-to-earnings and/or book-to-market multiples produced above-average returns over time. Van Rensburg and Robertson (2003) came to a similar conclusion as Cambell and Shiller (2001) after investigating companies listed on the JSE for the period July 1990 to June 2000. Basiewicz and Auret (2009) found that a value portfolio based on high book-to-market ratios gave the highest abnormal returns, while a value portfolio based on low price-to-earnings ratios gave the lowest abnormal returns.

Basiewicz and Auret (2009) also found that the size and book-to-market variables independently affected abnormal returns. Thus company size and book-to-market variables had to be accounted for independently in the reference portfolios or companies used when investigating cover story effects.

2.7.6 Historical share performance

There was no conclusive evidence in literature that historical share performance affected future abnormal returns. DeBont and Thaler (1985) and Page and Way (1992) found that stocks with low long-term past returns tended to have higher future returns. Similarly, Malkiel (2003) believed that future stock prices were somewhat predictable on the basis of past stock price patterns and fundamental valuation techniques.

In contrast, Jegadeesh and Titman (1993) found that stocks with higher long-term past returns, over a twelve-month period, tended to have higher future returns. Based on the weak form of the EMH, the effects of historical share price performance should be fully incorporated in current asset prices (Findlay and Williams, 2000).

2.7.7 Market context

Harvey (1995) claimed that stock returns in emerging countries were highly predictable and had a low correlation with stock returns in developed countries. Harvey (1995) further stated that emerging markets were less efficient than developed markets, leading to higher returns for lower risk investments.

High and Honikman (1995), Smith et al., (2002) and Magnusson and Wydick (2002) found evidence to support the weak form of the EMH for the JSE. By contrast, Page and Way (1992) and Philpott and Firer (1994) found evidence of market inefficiency in the JSE.

These company-specific characteristics must be taken into account when calculating abnormal returns to ensure that the measured abnormal returns were due to market inefficiency and not merely the result of data mining or risk premiums associated with investing in the specific companies (Bodie et al., 2009).

2.8 INVESTMENT PERFORMANCE EVALUATION

2.8.1 Introduction

Fama (1998) found that most long-run abnormal returns calculated in literature were statistically insignificant or disappeared after changing the method used to calculate the long-run abnormal returns. Three approaches were identified in literature for calculating abnormal returns (Barber and Lyon, 1997). The first approach used a reference portfolio, such as an equally weighted market index or size deciles portfolio (Forsyth, 1996; Stalter, 2005), where the control portfolio was constructed with the population mean abnormal return equal to zero. The second approach used a control company of similar characteristics (Ferreira and Smith, 2003; Arnold et al., 2007). The third approach used the three-factor model developed by Fama and French (1996) to explain abnormal returns by allowing for average market portfolio returns, company size (based on market capitalisation) and book-to-market ratio corrections.

The abnormal returns could either be calculated as cumulative abnormal returns (CAR) or buy-and-hold abnormal returns (BHAR) (Barber and Lyon, 1997). The CAR, calculated as the sum of the daily, weekly or monthly abnormal returns, gave positively biased test statistics, while the BHAR, calculated as the compounded return on a single company minus the compounded return on a reference portfolio, yielded negatively biased test statistics (Barber and Lyon, 1997).

Only BHAR calculated as the compounded return on a single company minus the compounded return on a reference company of similar characteristics yielded no biased test statistics and was recommended by Barber and Lyon (1997) as the preferred method for calculating abnormal returns.

2.8.2 Reference portfolio approach

For the traditional event study framework (Barber et al., 2001), CAR or BHAR was calculated based on a reference portfolio. Traditional event study frameworks yielded abnormal returns that accurately reflected investors' experiences. However, they increased the risks of cross-sectional dependency between sample companies and bias due to poorly specified asset pricing models where the empirical rejection rates exceeded the theoretical rejection rates (Lyon, Barber and Tsai, 1999). Barber and Lyon (1997) identified the following three biases using the traditional event study framework:

- *New-listing bias* where the reference portfolio consisted of new companies that began trading subsequent to the event, while the sample companies generally had a long post-event history of returns with no new companies in the sample (Barber and Lyon, 1997)
- *Rebalancing bias* where the compounded returns on the reference portfolio were rebalanced on a monthly basis, while there was no rebalancing of the sample companies (Barber and Lyon, 1997)
- *Skewness bias* with the abnormal returns positively skewed with some sample companies with excess returns above 100%, especially if the high returns were associated with industry-specific effects, while it was uncommon to have more than 100% returns on the market index or reference portfolio (Barber and Lyon, 1997).

These biases had different impacts on the CAR and BHAR calculations using the traditional event study framework (Barber et al., 2001), with positively biased test statistics when calculating CAR and negatively biased test statistics when calculating BHAR. CAR calculations were subject to measurement, new-listing and skewness biases, while BHAR calculations were subject to new-listing, skewness and rebalancing biases (Barber and Lyon, 1997).

2.8.3 Control company with similar characteristics

The second approach used a control company with similar characteristics as the sample companies (Ferreira and Smith, 2003; Arnold et al., 2007). Barber and Lyon (1997) found that the second approach yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases in virtually all sampling situations that they considered. In the second approach, both the sample and the control companies were listed in the identified event month, eliminating new-listing biases.

The returns on the sample and the control companies were calculated without rebalancing, thus eliminating rebalancing biases. The sample and control companies were equally likely to experience high positive returns, thus eliminating skewness biases (Barber and Lyon, 1997).

The acceptable convention in research was to use CAR, calculated on a daily or monthly basis. However, Barber and Lyon (1997) recommended that abnormal returns should be calculated based on the buy-and-hold return on the sample company less the buy-and-hold return on the control company to eliminate biased test statistics. The difference between CAR and BHAR resulted from the effects of monthly compounding where CAR excluded monthly compounding, while it was included in BHAR (Barber and Lyon, 1997). CAR calculations were a biased predictor of long-run abnormal returns where the calculated abnormal returns were higher than the BHAR for volatile company shares (Barber and Lyon, 1997).

2.8.4 The three-factor Fama and French (1996) model

The third approach used the three-factor model developed by Fama and French (1996) to explain abnormal returns by allowing for average market portfolio returns, company size (based on market capitalisation) and book-to-market ratio corrections. The three-factor model was applied by regressing the post-event monthly returns for the sample companies on market, size and book-to-market factors (Barber and Lyon, 1997).

Some of the disadvantages of the third method were the complexity of the calculations, the number of data points required to calculate abnormal returns, the creation of survivor biases among the remaining sample companies and the assumption that the sample companies' market, size and book-to-market characteristics were stable over the period of investigation (Barber and Lyon, 1997). Barber and Lyon (1997) recommended the second method of using control companies with similar characteristics to the sample companies when calculating BHAR to eliminate the survivor bias and disadvantages of using the three-factor Fama and French (1996) model.

The second method, with a control company of similar characteristics, was used to calculate BHARs in this study. Using a control company of similar characteristics yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases when calculating abnormal returns (Barber and Lyon, 1997).

2.8.5 Event study method

The research was conducted using an event study method where the effects of an event on the share prices of companies were investigated for a period of time. The event study method was developed in 1969 and became the standard method for investigating the effects of announcements or events on shareholder wealth (Binder, 1998). Event studies allowed for the statistical analysis of abnormal returns obtained from making investment decisions based on the events and were used for two major purposes (Binder, 1998):

- To test the null hypothesis of market efficiency
- To test the impact of an announcement or event on shareholder wealth.

The event study method was used in the research to test the impact of a cover story event on shareholder wealth.

2.9 CONCLUSIONS

There was no conclusive evidence supporting the use of cover stories as market indicators. Research done by Forsyth (1996), Barber et al. (2001), Stalter (2005) and Arnold et al. (2007) found that cover stories could be used as contrarian indicators, while research by Stickel (1995), Womack (1996), Ferreira and Smith (2003) and Desai and Jain (2004) came to the conclusion that cover stories or panel interviews could be used as momentum indicators of future company investment performance. In contrast, Barber et al. (2001) and Desai and Jain (2004) came to the conclusion that investors did not benefit from acting on cover stories.

Cover stories were selected as external market indicators for the study based on Barber and Odean's (2008) finding that individual investors in the US were net buyers of attention-grabbing shares and they made irrational investment decisions due to information, time and resource constraints (Ritholtz, 2003).

The study focused on the South African environment where no prior research was found relating to the use of cover stories as market indicators for JSE-listed companies. Page and Way (1992) and Philpott and Firer (1994) found evidence supporting market inefficiency in South Africa, but in contrast, Basiewicz and Auret (2010) found evidence supporting the weak form of market efficiency for JSE-listed companies.

Cover stories were only of financial value to investors when investors could exploit market inefficiencies and earned returns, after trading costs, higher than those obtained by holding a randomly selected portfolio of individual stocks with similar risks (Arnold et al., 2007).

The inefficient allocation of resources and the inability of arbitrageur investors to take full advantage of the opportunities created by irrational investors created opportunities for investors to earn abnormal returns (Bodie et al., 2009). The study attempted to provide evidence supporting the use of cover stories as either momentum or contrarian indicators of future company investment performance for JSE-listed companies.

CHAPTER 3: RESEARCH HYPOTHESES AND QUESTIONS

3.1 INTRODUCTION

As evident in the literature review, a significant amount of research was conducted in the US relating to market efficiency and the effects of bounded rational behaviour by individual investors on financial markets. Previous research yielded varying results and these inconsistencies made it difficult to predict the usefulness of cover stories as market indicators for future company investment performance. The research focused on the South African environment where no prior research was found relating to the use of cover stories as market indicators. It attempted to provide evidence supporting the use of cover stories as either momentum or contrarian indicators of future company performance for JSE-listed companies.

To explore the potential use of cover stories as momentum or contrarian indicators of future company investment performance in South Africa, the research hypotheses were broken down into eight components. The past behaviour of investors in reaction to cover stories, the appropriate method for calculating BHARs, the potential usefulness of cover stories and how to maximise abnormal returns by selectively using cover stories as market indicators and/or by optimising the investment time horizons were investigated. The hypotheses tested in this research are detailed below.

3.2 RESEARCH HYPOTHESES

3.2.1 Research Hypothesis 1

The purpose of the first research hypothesis was to test whether investors were net buyers of attention-grabbing shares in South Africa by reviewing share trade volumes and returns around the cover story event dates. The criteria used in the first hypothesis test were based on Barber and Odean's (2008) three proxies for attention-grabbing stocks, namely abnormal daily trading volumes, the share's previous one-day returns and whether the company appeared in the news on the event day.

The null hypothesis stated that investors were not net buyers of attention-grabbing shares based on Barber and Odean's (2008) argument that rational investors would not buy attention-grabbing shares because they realised that the information associated with these shares was already impounded into the share prices and that attention-grabbing events might not reflect future performance of the companies.

For the null hypothesis, the difference in abnormal trading volumes and buy-and-hold investment returns (BHRs) calculated before and after the cover story event was equal to or smaller than zero. Arnold et al. (2007) identified ten investment time horizons (*t*) for calculating abnormal trading volumes and BHRs, namely one week (five trading days), one month (21 trading days), six months (125 trading days), one year (250 trading days) and two years (500 trading days) before and after the cover story event. Longer periods were evaluated to allow for information leakage before the events.

The alternative hypothesis stated that investors were net buyers of attention-grabbing shares. The difference in calculated abnormal trading volumes and BHRs before and after the cover story events was larger than zero for the different investment time horizons and cover story categories:

H_{1a0}: (Abnormal trading volumes $_{after}$ – Abnormal trading volumes $_{before}$) $_t \leq 0$

H_{1aA}: (Abnormal trading volumes $_{after}$ – Abnormal trading volumes $_{before}$) $_t > 0$

H_{1b0}: (BHR $_{after}$ – BHR $_{before}$) $_t \leq 0$

H_{1bA}: (BHR $_{after}$ – BHR $_{before}$) $_t > 0$

3.2.2 Research Hypothesis 2

The purpose of the second research hypothesis was to assess whether investors responded differently to the different categories of cover stories or sources of cover stories by reviewing abnormal share trading volumes and BHRs around the cover story events for the five cover story categories. Research done by Hong et al. (2000) found that negative company-specific information diffused more slowly through the investment public and led to more pronounced momentum effects, while positive company-specific information diffused quickly through the investment public.

The null hypothesis stated that investors' responses to the different categories of cover stories were the same regardless of the category. The absolute difference in calculated abnormal trading volumes and BHRs for different cover story categories was equal to zero.

The alternative hypothesis stated that the absolute difference in calculated abnormal trading volumes and BHRs for the different cover story categories was larger than zero:

H_{2a0}: |Difference in abnormal volumes $_{cx}$ – Abnormal volumes $_{cy}$ $|_t$ = 0

H_{2aA}: |Difference in abnormal volumes $_{cx}$ – Abnormal volumes $_{cy}$ $|_t$ > 0

H_{2b0}: |Difference in BHR $_{cx}$ – BHR $_{cy}|_t$ = 0

H_{2bA}: |Difference in BHR $_{cx}$ – BHR $_{cy}|_t$ > 0

3.2.3 Research Objective 3

The purpose of the third research objective was to assess whether company-specific characteristics (such as industry, company size (based on market capitalisation) and price-to-earnings ratio) and cover story-specific information (source and category) affected BHRs.

One-way analysis of variance (ANOVA) and Pearson's correlation coefficients were used to assess whether there were relationships between company-specific characteristics, cover story-specific information and BHRs. Pearson's correlation coefficient larger than zero indicated a positive correlation and values smaller than zero indicated a negative correlation (Statistics Solutions, 2010).

3.2.4 Research Hypothesis 4

The purpose of the fourth research hypothesis was to assess whether the control-company approach, proposed for calculating BHAR, was required to eliminate skewness biases in the population. This was based on Fama and French's (1996) and Basiewicz and Auret's (2010) findings that most cumulative long-run abnormal returns disappeared after adjusting the reference portfolios for company-specific characteristics such as company size. Abnormal returns calculated using a reference portfolio led to positively skewed results (Barber and Lyon, 1997) when there were strong correlations between BHRs and the company-specific characteristics.

The null hypothesis stated that the BHR was not correlated to company-specific characteristics. The alternative hypothesis stated that BHRs were correlated to company-specific characteristics:

H_{40}: $|BHR_{\text{Company type X}} - BHR_{\text{Company type Y}}|_{t\,c} = 0$

H_{4A}: $|BHR_{\text{Company type X}} - BHR_{\text{Company type Y}}|_{t\,c} > 0$

3.2.5 Research Hypothesis 5

The purpose of the fifth research hypothesis was to evaluate whether investors could use cover stories as momentum or contrarian indicators for future company investment performance, independently of cover story categories or source. BHARs defined as the BHRs for the experimental company minus the BHRs for the control company (Research Objective 3), were calculated for the investment periods as per the Arnold et al. (2007) study.

The hypothesis test was done for both momentum and contrarian indicators. With regard to contrarian indicators, the first null hypothesis stated that cover stories were momentum indicators of future company investment performance. The first alternative hypothesis stated that cover stories were contrarian indicators of future company investment performance:

H_{5a0}: BHAR $_t \geq 0$

H_{5aA}: BHAR $_t < 0$

With regard to momentum indicators, the second null hypothesis stated that cover stories were contrarian indicators of future company investment performance. The second alternative hypothesis stated that cover stories were momentum indicators of future company investment performance based on the investment time horizons:

H_{5b0}: BHAR $_t \leq 0$

H_{5bA}: BHAR $_t > 0$

3.2.6 Research Hypothesis 6

The purpose of the sixth research hypothesis was to assess whether an investment portfolio based on a particular category of cover stories would yield higher BHARs. Hong et al. (2000) found that negative external company-specific information led to more pronounced momentum effects in the market.

The first step was to assess whether the difference in BHARs for the different cover story categories was statistically significant followed by an evaluation of the different cover story categories as potential momentum or contrarian indicators for future company investment performance.

The null hypothesis stated that the absolute difference in BHARs for different cover story categories was equal to zero. The alternative hypothesis stated that the absolute difference in BHARs for different cover story categories was larger than zero:

H_{60}: $|BHAR_{\text{Category } cx} - BHAR_{\text{Category } cy}|_t = 0$

H_{6A}: $|BHAR_{\text{Category } cx} - BHAR_{\text{Category } cy}|_t > 0$

Considering contrarian indicators, the first null hypothesis stated that cover stories were momentum indicators of future company investment performance for cover story category *c*. The first alternative hypothesis stated that cover stories were contrarian indicators of future company investment performance for cover story category *c*:

For positive cover and feature stories:

H_{6b0}: $BHAR_{ct} \geq 0$

H_{6bA}: $BHAR_{ct} < 0$

and for negative cover and feature stories:

H_{6b0}: BHAR $_{ct} \leq 0$

H_{6bA}: BHAR $_{ct} > 0$

Considering momentum indicators, the second null hypothesis stated that cover stories were contrarian indicators of future company investment performance for cover story category *c*. The second alternative hypothesis stated that cover stories were momentum indicators of future company investment performance for cover story category *c*, based on the investment time horizons:

For positive cover and feature stories:

H_{6c0}: BHAR $_{ct} \leq 0$

H_{6cA}: BHAR $_{ct} > 0$

and for negative cover and feature stories:

H_{6c0}: BHAR $_{ct} \geq 0$

H_{6cA}: BHAR $_{ct} < 0$

3.2.7 Research Objective 7

The purpose of the seventh research objective was to maximise BHARs for an investment portfolio based on attention-grabbing shares by optimising company selection criteria and investment time horizons. Womack (1996), Barber et al. (2001) and Seaholes and Wu (2004) measured short-run abnormal returns for attention-grabbing shares that reversed back to zero within a few days of the events.

The next step was to assess the impact of transaction costs on the optimal investment period. The costs of active portfolio investing were significantly higher than the costs of passive portfolio investing (Sharpe, 1991) and active investors had to earn returns higher than the returns on a passive investment plus the transaction costs.

3.2.8 Research Hypothesis 8

The purpose of the eighth research hypothesis was to validate whether investment portfolios with the company-specific characteristics and investment time horizons identified in Research Objective 7 yielded higher BHARs when compared to the investment time horizons used by Arnold et al. (2007).

The null hypothesis, based on the optimal company-specific characteristics, stated that the absolute difference between the average daily BHARs calculated for companies with company-specific characteristics *x* and company-specific characteristics *y* was equal to zero for cover story category *c*. The alternative hypothesis stated that the absolute difference between the average daily BHARs calculated for companies with company-specific characteristics *x* and company-specific characteristics *y* was larger than zero for cover story category *c*:

H_{8a0}: $|BHAR_{\text{Company } x} - BHAR_{\text{Company } y\ c}| = 0$

H_{8aA}: $|BHAR_{\text{Company } x} - BHAR_{\text{Company } y\ c}| > 0$

The null hypothesis, based on the optimal investment period, stated that the absolute difference between the average daily BHARs calculated for the optimal investment time horizon and investment time horizon *t* was equal to zero for cover story category *c*. The alternative hypothesis stated that the absolute difference between the average daily BHARs calculated for the optimal investment time horizon and investment time horizon *t* was larger than zero for cover story category *c*:

H_{8b0}: $|BHAR_{\text{Optimal investment time horizon}} - BHAR_{\text{Investment time horizon } t \text{ c}}| = 0$

H_{8bA}: $|BHAR_{\text{Optimal investment time horizon}} - BHAR_{\text{Investment time horizon } t \text{ c}}| > 0$

The research provided evidence to support or reject the use of cover stories as momentum or contrarian indicators of future company investment performance and the notion that individual investors were dependent on the secondary information sources, such as cover stories, for making investment decisions. The research identified the critical parameters for selecting reference companies to calculate BHARs and the most appropriate method for calculating BHARs. It also assisted in obtaining a better understanding of the effects of cover stories on investor behaviour and how to maximise abnormal returns for investment portfolios based on these cover story effects.

CHAPTER 4: RESEARCH METHOD

4.1 CHOICE OF METHOD

4.1.1 Introduction

Cover stories from *FinWeek* and the *Financial Mail* were collected for a twenty-four year period from 1985 to 2008. The cover stories were captured as feature or headline stories and categorised based on the Likert scale developed by Arnold et al. (2007). The first step in the analysis was to assess whether South African investors were net buyers of attention-grabbing shares by evaluating share trading volumes and BHRs around the cover story event dates. This was followed by an analysis to identify the correlation between investment returns and company-specific characteristics. The company-specific characteristics with the strongest correlation to investment returns were used as sorting criteria for selecting control companies used in the calculation of BHARs based on the Barber et al. (2001) study.

The third step was to assess whether cover stories were momentum or contrarian indicators. This was followed by an optimisation step to maximise BHARs for investment portfolios based on either the momentum or contrarian cover story effects. The benefits of investments based on the cover story effects were maximised by identifying the optimal investment duration and strategy.

The research was conducted using an event study methodology where the effects of the cover stories on the share prices of companies were investigated. Womack (1996), Michaly and Womack (1999), Barber et al. (2001), Ferreira and Smith (2003), Desai and Jain (2004) and Arnold et al. (2007) used event studies to investigate the potential use of secondary information sources as market indicators in the US.

4.1.2 Unit of analysis

The unit of analysis was publicly listed companies on the JSE who were the subject of cover stories in the selected financial magazines during the period 1985 to 2008. A long sample period was selected for sufficient data collection per cover story category for parametric test statistics and to minimise the potential experimental biases caused by incorrect cover story categorisation.

4.1.3 Population

The population for the research was all South African companies listed on the JSE for the period 1985 to 2008, with the experimental group consisting of listed companies who had been the subject of cover stories during the period of investigation. The control group for the research included all companies in the population that were excluded from the experimental group. South African private companies were excluded from the population because they were difficult to trade and due to limited access to historical financial information. The research aimed to evaluate the benefits of cover stories as external market indicators and as such, the use of cover stories for investment in private companies was limited.

A number of steps had to be followed to obtain the relevant information from the leading financial magazines, as well as the I-Net Bridge and McGregorBFA financial databases:

- Identifying and recording of all company-related headlines on the covers of the financial magazines for the period 1985 to 2008. All the headlines on the covers of the magazines were recorded and the main headlines were categorised as feature cover stories if identifiable. Lead stories were extracted from the earlier editions of the financial magazines (1985-1988) where the cover format did not include company headlines.
- Categorising of the cover stories based on the content of the articles. The Likert scale developed by Arnold et al. (2007) was used to categorise the cover stories. Some of the cover stories were more difficult to categorise with some level of subjectivity in deciding whether the article was generally positive or negative. The same criteria were used to assess all cover stories. A large sample was obtained to minimise potential experimental error caused by misinterpretation of individual cover stories.
- Eliminating of all cover stories relating to private companies. Cover stories relating to private companies were eliminated from the population due to the lack of financial information and illiquidity in trading of these companies.
- Eliminating subsequent cover stories for a specific company from the experimental group for a window period of 60 days after the appearance of the first headline or lead story.
- Extracting of the company-specific information for all the JSE-listed companies from the I-Net Bridge and McGregorBFA databases for the

period 1985 to 2008. The daily closing share prices, dividend yields, market capitalisation, price-to-earnings ratios and volumes of shares traded were extracted from the I-Net Bridge database. The industry categorisation was extracted from the McGregorBFA database. The historical dividend data obtained from the financial databases was incomplete and led to the use of dividend yield data for calculating company dividends.

- Eliminating of target companies in the population for which company-specific information was not available.

4.1.4 Sampling method and size

The population of relevance was extracted from the cover stories obtained from *FinWeek* and *Financial Mail* magazines over a twenty-four year period. In total, 2 222 headline stories relating to companies were recorded from the 2 503 financial magazines assessed. Of the 2 222 headline stories, only 1 218 were classified as unique cover stories based on the 60-day window period and included in the experimental group.

A total of 336 feature cover stories were recorded from the 2 222 headline stories, of which 235 were classified as unique feature cover stories. The study by Arnold et al. (2007) recorded double the amount of feature cover stories for a similar volume of publications in the US. Arnold et al. (2007) found that only 593 out of 2 080 feature stories in the US in *Business Week, Fortune* and *Forbes* related to specific publicly listed companies and were classified as unique.

4.2 DATA COLLECTION

FinWeek was the largest weekly financial magazine in South Africa with just over 30 000 copies in circulation (FinWeek, 2010), followed by the *Financial Mail* with 27 560 copies in circulation (Avusa, 2010). The two selected magazines were the leading financial magazines in South Africa (SA Press, 2010). The cover stories from these media sources were categorised based on Arnold et al.'s (2007) five-point Likert scale. The financial data (daily closing share prices, dividend yields, volumes traded, market capitalisations and price-to-earnings ratios) relating to these companies was obtained from I-Net Bridge and McGregorBFA. The investment time horizons of one week, one month, six months, one year and two years were based on the Arnold et al. (2007) study.

The data was tabulated to reflect the following information: share code, company name, date of cover story, source of cover story, cover story category, industry, daily closing share price, market capitalisation, dividend (calculated), volume traded and price-to-earnings ratio.

4.3 DATA ANALYSIS

Most international research used the event study methodology to relate the effects of secondary information sources on the financial performance of companies. This was in line with the studies by Forsyth (1996), Barber et al. (2001), Stalter (2005) and Arnold et al. (2007). The events of interest for the purpose of this study were the publication of the company headlines. The impact on the share prices of the cover story companies was measured daily over a period of two years, starting from the fixed event day, t_o, and working backwards for two years from t_o to $t_{-500\ trading\ days}$ and forwards to $t_{+500\ trading\ days}$.

The calculation of the abnormal trading volumes was the first step in analysing the data, followed by calculating the dividends, BHR and BHAR calculations. The control-company approach was used to determine BHARs for the reasons set out in Paragraph 2.8.3. Barber and Lyon (1997) found that this approach yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases in virtually all sampling situations that they considered.

The research objectives were tested for both cover and feature stories, with feature stories as a subset of cover stories, to:

- assess whether the momentum or contrarian effects were the same for cover and feature stories
- determine whether cover stories were more reliable market indicators
- assess whether cover stories could be used as a proxy for feature stories.

This would reduce the research period required for future research and give investors more flexibility when managing an investment portfolio based on these cover story effects.

4.3.1 Research Hypothesis 1

The abnormal trading volumes (AV_{it}) were calculated based on the volume of shares *i* traded on day *t* (V_{it}) divided by the average volume of shares *i* traded over the period *t*–126 trading days to *t*+126 trading days (V_{itavg}) (Barber and Odean, 2008). The abnormal trading volumes for investment period *t* were calculated as the difference in average abnormal trading volumes before and after the cover story event date for time period *t.*

$AV_{it} = V_{it} / V_{itavg}$ with $$\mathrm{Vitavg} = \sum_{d=1}^{252} \frac{Vid}{252} \tag{1.1}$$

and the average abnormal trading volumes for investment period *t:*

$$\mathrm{AVitavg} = \sum_{d=1}^{t} \frac{AVid}{\mathrm{t}} \tag{1.2}$$

The first step in calculating the dividends using the daily closing share price and dividend yield data was to calculate a daily rolling dividend (Equation 1.3), followed by identifying the ex-dividend dates (Equation 1.4) and then calculating the dividends (Equation 1.5).

The rolling dividend for company *c* and date *t:*

$$Rolling\ dividend\ ct = \frac{(Share\ Price\ (day\ t-1) * Dividend\ yield\ (day\ t))}{100} \tag{1.3}$$

The ex-dividend date *d* for company *c*:

$$If\ (Rolling\ dividend\ (day\ t) <> Rolling\ dividend\ day(t-1)$$

$$Ex - dividend\ date\ cd = \ ct \tag{1.4}$$

The dividends for company *c* and date *t*:

$$If\ (year\ (Ex - dividend\ date\ (d)) > year\ (Ex - dividend\ date\ (d-1))$$

$$Dividend\ ct = Rolling\ dividend\ d$$

$$If\ (year\ (Ex - dividend\ date\ (d)) = year\ (Ex - dividend\ date\ (d-1)$$

$$Dividend\ ct = Rolling\ dividend\ (d) - Rolling\ dividend\ (d-1) \qquad (1.5)$$

BHRs for investment period *t* were calculated as the return on share *c* based on the difference in share price at date *t* and the share price one day before or after the event date plus the dividends for the same period, with one day before the event date used for *–t* and one day after the event date used for *+t.* The method used for calculating BHRs was based on the research by Barber and Lyon (1997) and Arnold et al. (2007):

$$BHRct = \frac{\left(Share\ Price\ (day\ t) - Share\ Price\ (day\ 1) + \sum_{k=1}^{t} (Dividends_k)\right)}{Share\ Price\ (day\ 1)} \qquad (1.6)$$

Research hypothesis 1 was evaluated by calculating the difference in AV_{it} and BHR_i for shares *i* and investment period *t* and using ANOVA test statistics (Albright, Winston and Zappe, 2007).

4.3.2 Research Hypothesis 2

The calculated difference in AV_{it} and BHR_i values were grouped based on the cover story categories. The absolute difference AV_{it} and BHR_i hypotheses (H_{2a} and H_{2b}) for all five cover story categories were evaluated using ANOVA test statistics (Albright, Winston and Zappe, 2007).

4.3.3 Research Objective 3

ANOVA test statistics were used to assess which company-specific characteristics directly affected BHRs. This was followed by calculating Pearson's correlation coefficients and the degree of correlation between BHR_{it} and the identified company-specific characteristics.

Descriptive test statistics were used to assess whether the sample met the requirements set by the Pearson's correlation coefficients method (Statistics Solutions, 2010):

- The sample consisted of independent cases.
- The variables were normally distributed.
- There were cause-and-effect relationships between the company-specific characteristics and company returns.
- The variables were linearly correlated.

The explanatory variables were grouped into five categories based on Pearson's correlation coefficient with Pearson's correlation coefficient larger than zero indicating positive correlation and values smaller than zero indicating negative correlation (Statistics Solutions, 2010). The five degrees of correlation were as follows (Statistics Solutions, 2010):

- *Category 1*: Perfect correlation with the absolute Pearson's correlation coefficient above 0.95
- *Category 2*: High degree of correlation with the absolute Pearson's correlation coefficient between 0.75 and 0.95

- *Category 3*: Moderate degree of correlation with the absolute Pearson's correlation coefficient between 0.25 and 0.75
- *Category 4*: Low degree of correlation with the absolute Pearson's correlation coefficient between 0.05 and 0.25
- *Category 5*: No correlation with the absolute Pearson's correlation coefficient below 0.05.

Stepwise regressions were used to eliminate correlated explanatory variables (Albright et al., 2007). The highest correlated explanatory variables were used as sorting criteria for selecting control companies for the BHAR calculations.

The explanatory variables were defined as follows:

$$\text{Market capitalisation} = Share\ Price\ (t) * No\ of\ ordanry\ shares\ in\ issue\ (t) \quad (3.1)$$

$$\frac{\text{Price}}{\text{Earnings}}\text{ratio} = \frac{\text{Share price (t)}}{\text{Most recent headline earnings (t}-1)} \quad (3.2)$$

$$\text{Dividend Yield (t)} = \frac{Most\ recent\ dividend}{\text{Share price (t)}} \quad (3.3)$$

4.3.4 Research Hypothesis 4

BHR_{it} for share *i* traded on day *t* was calculated using Equation 1.6 and subdivided based on company-specific category variables identified in Research Objective 3. The hypothesis for absolute difference in BHR_{it} (H_4) was evaluated using t-test statistics (Albright et al., 2007).

4.3.5 Research Hypothesis 5

The control-company method was used to calculate BHARs based on Barber and Lyon's (1997) findings that the control-company method yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases. Each company in the experimental group (X) was matched to a company from the control group (Y) with similar company-specific characteristics identified in Research Objective 3. $BHAR_{it}$ was calculated as the difference in BHR_{it} for company *c* in the experimental group and BHR_{it} for the matching company in the control group (Equation 5.1).

$$\mathrm{BHARit} = \mathrm{BHRit}\ (\mathrm{company}\ c) - \mathrm{BHRit}\ (\mathrm{control\ company}) \tag{5.1}$$

4.3.6 Research Hypothesis 6

$BHAR_{it}$ values calculated using Equation 5.1 were grouped based on the cover story categories. The difference in the $BHAR_{it}$ hypothesis (H_{6a}) for the cover story categories was evaluated using ANOVA test statistics (Albright et al., 2007). The hypotheses for momentum and contrarian indicators per cover and feature story category H_{6b} and H_{6c} were tested using parametric t-test statistics for the cover story categories and non-parametric t-test statistics for the feature story categories.

4.3.7 Research Objective 7

The optimal investment time horizons ($t_{optimal-i}$) were calculated for each company based on the minimum (contrarian indicators) or maximum (momentum indicators) daily average $BHAR_{ti}$ for company *i* and assuming zero per cent transaction costs (Equation 7.1).

$$\text{Daily average BHARit} = \sum_{k=1}^{t} \text{BHARch/t} \tag{7.1}$$

The number of days between the event date and the date of minimum or maximum daily average $BHAR_{tc}$ gave the optimal time periods $t_{optimal-i}$. The optimal investment time periods ($t_{optimal-ic}$) per cover and feature story category were obtained from a frequency distribution of $t_{optimal-i}$ per cover story category.

The optimal investment time horizons ($t_{optimal-i}$) including transaction costs were calculated for each company by adjusting the minimum (contrarian indicators) or maximum (momentum indicators) average daily $BHAR_{ti}$ for company *i* with the percentage transaction costs (Equation 7.2). The percentage transaction costs *x* were based on the original investment amount.

$$\text{Daily average BHARit (x\% transaction costs)} = \sum_{k=1}^{t} (\text{BHARik} \pm \frac{\text{x}}{\text{BHRik}})/\text{t} \tag{7.2}$$

The company-specific characteristics that yielded the highest BHRs were obtained from Research Objective 3. The maximum BHARs were evaluated by assessing whether the differences in BHARs between company-specific category *x* and *y* were statistically significant (Equation 7.3).

$$\text{Difference } \mathrm{BHARit} = \mathrm{BHAR\ x} - \mathrm{BHAR\ y} \tag{7.3}$$

4.3.8 Research Hypothesis 8

The average daily $BHAR_{ct}$ for the optimal investment periods per cover and feature story category was compared to the average daily $BHAR_{ct}$ for the investment periods used in the Arnold et al. (2007) study. The difference in the $BHAR_{it}$ for the six investment periods was evaluated using ANOVA test statistics (Albright et al., 2007).

4.4 RESEARCH LIMITATIONS

The research was limited to South African publicly listed companies for the period 1985 to 2008, with cover stories from selected media sources:

- Private companies were excluded from the research because private companies have limited share liquidity and limited information was available on the historical financial performance of these companies.
- Cover stories from other publications, such as private investment houses and online sources, were excluded in the research because of limited access for individual investors and restricted access to historical publications.
- Abnormal trading volumes were more reliable as a proxy for attention-grabbing shares for large market-capitalisation companies when compared to small market-capitalisation companies where large transactions by single investors contributed to abnormal trading volumes.
- A sample collection period of 24 years was selected to ensure sufficient data was collected for parametric t-test statistics and to minimise the influence of incorrectly categorised individual cover stories. Small sample sizes for subcategories led to non-parametric test statistics and increased the potential for Type II experimental errors.
- BHAR calculations excluded transaction costs. The returns on an active investment portfolio built on the cover story effects had to be higher than the sum of the returns earned by holding a randomly selected portfolio of individual stocks with similar risks and the transaction costs of active trading.

Notwithstanding these limitations, the research was important in the South African context where no prior information relating to the use of cover stories as market indicators was found. The research gave valuable insight into the behaviour of investors after the publication of cover stories and the information sources for cover stories. It evaluated the potential use of cover stories as market indicators for JSE-listed companies and identified opportunities to maximise abnormal returns for investment portfolios based on these market indicators. Addressing the identified limitations of this research could be the subject of future research.

CHAPTER 5: RESULTS

5.1 INTRODUCTION

The research assessed the past reaction of investors to cover stories, the appropriate method for calculating BHARs and the potential use of cover stories as market indicators. The first part of the results focused on descriptive statistics and identifying dependencies between company-specific characteristics, cover story sources and cover story categories. The second part of the results focused on hypotheses testing and assessing the potential use of cover stories as market indicators.

5.2 DESCRIPTION OF SAMPLE

5.2.1 Introduction

In total, 2 503 magazine covers were reviewed and 2 222 headline stories recorded. Of the 2 222 headlines, 1 840 headlines related to public companies, 304 to private companies, 53 to international companies not listed on the JSE and 90 to state-owned enterprises. Only 1 218 headlines were classified as unique cover stories based on the 60-day window period used in the Arnold et al. (2007) study. The unique cover stories were categorised based on the Likert scale developed by Arnold et al. (2007). The distribution of cover stories for the two magazines is shown in Table 5.1.

A total of 336 feature stories was identified from the 2 503 magazine covers (Table 5.1), of which only 235 were classified as unique feature stories and categorised using the Likert scale developed by Arnold et al. (2007).

5.2.2 Cover story categorisation

Almost equal proportions of cover stories came from *FinWeek* and the *Financial Mail* (49% versus 51% for cover stories and 47% versus 53% for feature stories) (Table 5.1). Of the 1 218 unique cover stories, 16% were classified as very optimistic, 29% as optimistic, 19% as neutral, 20% as moderately pessimistic and 17% as pessimistic cover stories. The split between positive, neutral and negative cover stories for *FinWeek* and the *Financial Mail* was similar. The distribution of feature stories was marginally more pessimistic (40% versus 37%) when compared to the cover story category distribution. The distribution of feature stories was similar for both financial magazines.

Table 5.1 Cover and feature story categorisation

Cover stories

Categories	Positive		Neutral	Negative		Total
Periodical	1	2	3	4	5	
FinWeek	14%	28%	19%	18%	20%	49%
FM	17%	29%	18%	22%	14%	51%
Total	16%	29%	19%	20%	17%	

Feature stories

Categories	Positive		Neutral	Negative		Total
Periodical	1	2	3	4	5	
FinWeek	10%	31%	17%	21%	21%	47%
FM	15%	27%	20%	19%	18%	53%
Total	13%	29%	19%	20%	20%	

The number and categories of cover stories recorded for five-year intervals throughout the period of investigation are shown in Table 5.2. Only a small percentage (20%) of the cover stories in the experimental group came from the first ten years (1985 to 1994). The number of unique cover stories significantly improved from 1995 onwards with the highest percentage of unique cover stories recorded per year (7%) for the period 2000 to 2004.

Table 5.2 Percentage unique cover stories for five-year intervals

	Positive		Neutral	Negative		Total	Percentage cover
Periodical	1	2	3	4	5		stories per year
1985-1989	27%	31%	8%	18%	16%	7%	1%
1990-1994	10%	33%	20%	22%	15%	13%	3%
1995-1999	17%	28%	19%	20%	16%	25%	5%
2000-2004	16%	26%	20%	20%	19%	33%	7%
2004-2008	13%	29%	19%	21%	17%	22%	6%
Total	16%	29%	19%	20%	17%		

5.2.3 Company size

Market capitalisation was used as an indicator of company size. There was a complete set of market capitalisation data available for 917 of the 1 218 companies that were the subject of unique cover stories (Table 5.3) and for 69 of the 235 companies that were the subject of unique feature stories (Appendix A1, Table A5.1.2). The distribution of market capitalisation based on cover story category and source is shown in Table 5.3.

Cover stories relating to the smaller companies (as measured based on market capitalisation) tended to be more negative with 37% of the cover stories rated as pessimistic (65% rated as negative) for companies with market capitalisations of less than R0.4 billion. Cover stories relating to the larger companies (as measured based on market capitalisation) were more positive with 38% of the cover stories rated as optimistic (51% rated as positive) for companies with market capitalisations larger than R72.7 billion. The percentage of neutral cover stories increased (14% to 27%) as the company size increased.

The relationships between market capitalisation and cover story categories were similar for cover and feature stories (Appendix A1, Table A5.1.2), even with the reduction in number of data points for the feature stories. The mean market capitalisation distribution based on the cover story categories was similar for both *FinWeek* and the *Financial Mail* (Table 5.3).

Table 5.3 Size of companies (as measured based on market capitalisation)

Percentiles	Value billion R	Positive 1	2	Neutral 3	Negative 4	5
0-10	≤0.40	4%	16%	14%	28%	37%
10-20	0.40<x≤1.06	11%	27%	15%	17%	29%
20-30	1.06<x≤2.17	20%	30%	13%	21%	16%
30-40	2.16<x≤4.46	18%	26%	18%	16%	21%
40-50	4.46<x≤7.75	13%	36%	18%	22%	11%
50-60	7.75<x≤13.61	22%	32%	19%	14%	13%
60-70	13.61<x≤22.86	15%	24%	26%	22%	13%
70-80	22.86<x≤41.02	21%	32%	22%	15%	10%
80-90	41.02<x≤72.71	17%	30%	26%	18%	8%
90-100	>72.71	13%	38%	27%	12%	10%

Market capitalisation (billion R)	Positive 1	2	Neutral 3	Negative 4	5	Total
<u>Mean</u>						
FinWeek	26	28.3	31.3	15.4	11	29.9
FM	20.7	27.1	44	13.4	10.6	31.8
Total	23	27.7	37.5	14.3	10.8	30.9
<u>Median</u>						
FinWeek	15.7	10.2	10.6	6.5	1.7	8.1
FM	7.5	8	16.6	4.5	2.7	7.2
Total	11.4	9	14.6	5.7	2.3	7.8

5.2.4 Industry

The distribution of cover stories based on industry and cover story categories is shown in Table 5.4. The cover and feature stories in the experimental group related mainly to the financial, mining and industrial industries with 24% of the cover stories from the financial, 22% from mining and 17% from the industrial industry (Table 5.4). The gambling and hotel industries were the worst represented in the experimental group with only 11 cover stories relating to the gambling industry and six to the hotel industry (Table 5.4).

There was some correlation between the industries and the cover story categories. The services, IT, property and industrial industries had the largest percentage of negative cover stories while the building, construction and engineering, chemical and food industries had the largest percentage of positive cover stories (Appendix A1, Table A5.1.3). Services, IT and healthcare had the largest percentage of negative feature stories while the building, construction and engineering, and electronic equipment and electric industries had the largest percentage of positive feature stories (Appendix A1, Table A5.1.3). The test statistics for feature stories were less reliable due to the smaller sample size.

The distribution of cover stories based on industry for the two magazines was similar for most industries (Table 5.4), except for the financial and mining industries where cover stories in *FinWeek* were more focused on the financial sector and cover stories in the *Financial Mail* on the mining industry. The distribution of feature stories based on industry for the two magazines was very similar for all industries (Appendix A1, Table A5.1.3).

Table 5.4 Industry distribution

Sector	Positive 1	Positive 2	Neutral 3	Negative 4	Negative 5	Fin-Week	Financial Mail	Total
Broadcasting, entertainment and telecommunications	24%	29%	17%	20%	10%	4%	3%	3%
Gambling	9%	36%	18%	18%	18%	1%	1%	1%
Hotels	0%	50%	33%	0%	17%	1%	1%	1%
Property	0%	22%	33%	17%	28%	1%	2%	2%
Services, IT	18%	25%	8%	24%	25%	4%	5%	4%
Financial	17%	24%	23%	19%	16%	27%	21%	24%
Retail	20%	24%	13%	21%	17%	8%	7%	8%
Building, construction and engineering	24%	32%	9%	18%	18%	2%	4%	3%
Chemicals	20%	38%	11%	21%	11%	5%	4%	5%
Healthcare	35%	18%	24%	6%	18%	1%	2%	1%
Electronic equipment and electrics	6%	31%	38%	0%	25%	1%	2%	1%
Food	20%	37%	20%	16%	9%	8%	6%	7%
Industrial	10%	29%	17%	25%	18%	17%	18%	17%
Mining - Combined	13%	31%	21%	18%	18%	21%	25%	23%

5.2.5 Price-to-earnings ratio

The distribution of cover story categories based on price-to-earnings ratios is shown in Table 5.5. Cover stories relating to companies with smaller price-to-earnings ratios were more negative with 40% of the cover stories rated as pessimistic and 64% as negative for the lowest price-to-earnings category (Table 5.5).

Table 5.5 Price-to-earnings distribution

		Positive		Neutral	Negative	
Percentiles	Ratio	1	2	3	4	5
0-10	≤6.1	11%	18%	6%	24%	40%
10-20	6.1<x≤8.3	9%	33%	21%	17%	20%
20-30	8.3<x≤10.0	16%	32%	26%	17%	9%
30-40	10.0<x≤11.3	16%	37%	12%	23%	12%
40-50	11.3<x≤12.8	17%	27%	26%	17%	13%
50-60	12.8<x≤14.4	20%	34%	21%	15%	10%
60-70	14.2<x≤16.7	18%	31%	27%	17%	6%
70-80	16.7<x≤20.4	17%	33%	24%	17%	9%
80-90	20.4<x≤29.4	19%	32%	16%	15%	17%
90-100	>29.4	17%	28%	18%	22%	15%

	Positive		Neutral	Negative		Total
Price-to-earnings (ratio)	1	2	3	4	5	
Mean						
FinWeek	14.8	12.3	15.8	12.8	48.6	27.4
FM	46.9	22.6	18.6	89	34	53.9
Total	33	17.5	17.1	54.5	42.5	41
Median						
FinWeek	13.7	12.8	13.3	12.5	10.8	12.8
FM	13.3	13.1	12.7	11.6	10.6	12.8
Total	13.5	12.9	13.2	12	10.8	12.8

Cover stories relating to the higher price-to-earnings ratio companies were more positive with 28% of the cover stories rated as optimistic and 55% as positive for the highest price-to-earnings category. The trends were similar for feature stories (Appendix A1, Table A5.1.4) with 100% of the lowest price-to-earnings category ranked as negative and 100% of the highest price-to-earnings category ranked as neutral or positive.

The median price-to-earnings ratios were used to compare the distribution of cover story categories based on source. The median price-to-earnings ratios for *FinWeek* and *Financial Mail* cover stories were the same at 12.8 (Table A5.5) and marginally different for feature stories (Appendix A1, Table A5.1.4).

5.3 HYPOTHESIS TEST RESULTS

5.3.1 Research Hypothesis 1

The difference in abnormal share trading volumes and BHRs was used as a proxy for attention-grabbing shares to assess whether South African investors were using the cover stories published in the two financial magazines to make investment decisions while ignoring the content of the cover stories. The descriptive statistics for the differences in abnormal share trading volumes are shown in Table 5.6.

The differences in abnormal trading volumes were close to zero and statistically insignificant for the different investment time periods and cover story sources (Appendix A2, Table A5.2.1).

Table 5.6 Abnormal share trading volumes test statistics – Cover stories

	p-value	Hypothesis	Reject Ho
2 days	0.23	Ha>0	No
3 days	0.71	Ha>0	No
4 days	0.86	Ha>0	No
5 days	0.93	Ha>0	No
1 week	0.97	Ha>0	No
1 month	0.97	Ha>0	No
6 months	0.90	Ha>0	No

The difference in BHRs was used as a second proxy for attention-grabbing shares based on the assumption that the demand for company shares that were the subject of cover stories would increase and thus lead to an increase in the share prices. The descriptive statistics for the difference in BHRs are shown in Appendix A2, Table A5.2.2.

The difference in BHRs decreased as the investment period increased from two to 125 days (Appendix A2, Table A5.2.2). The difference in BHRs for all cover and feature story categories was statistically insignificant for investment periods of two days to six months and an alpha of 0.05 (Table 5.7). There was no conclusive evidence, based on the abnormal share trading volumes and BHRs, that investors were net buyers of attention-grabbing shares based on the face value of the cover stories and ignoring the cover story contents.

Table 5.7 BHR test statistics – Cover stories

	p-value	Hypothesis	Reject Ho
2 days	1.00	Ha>0	No
3 days	1.00	Ha>0	No
4 days	1.00	Ha>0	No
5 days	1.00	Ha>0	No
1 week	1.00	Ha>0	No
1 month	0.99	Ha>0	No
6 months	0.99	Ha>0	No

5.3.2 Research Hypothesis 2

The second research hypothesis was an extension of the first research hypothesis and assessed whether investors responded differently to the different categories of cover stories by reviewing abnormal share trading volumes and BHRs around the cover story event dates for the different cover story categories.

There was a statistically significant difference between the abnormal trading volumes for cover story categories one and five based on an alpha of 0.08 two days after the events. The trading volume for very optimistic cover stories initially increased after the events (statistically significant at an alpha of 0.12

and investment period of two days), but subsequently decreased as the investment period increased (Appendix A2, Table 5.2.1). The lowest difference in abnormal trading volumes was measured for an investment period of one week for very optimistic cover stories. The abnormal trading volumes for optimistic, neutral and negative cover stories were close to zero or negative (Appendix A2, Table A5.2.1). The negative abnormal trading volumes for neutral and pessimistic cover stories were statistically significant at an alpha of 0.092, five days and six months after the events respectively (Table 5.8).

Table 5.8 Abnormal share trading volumes test statistics per category – Cover stories

Tukey-Kramer's Simultaneous Confidence Intervals

	p-value	Reject Ho	
2 days	0.04	Yes	Category 1 different from 5
3 days	0.91	No	
4 days	0.38	No	
5 days	0.39	No	
1 week	0.17	No	
1 month	0.17	No	
6 months	0.13	No	

Category 1 and 5 (p-values)

	Alternative hypothesis: Ha>0					Alternative hypothesis: Ha<0				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
	1	2	3	4	5	1	2	3	4	5
2 days	0.06	0.93	0.87	0.16	0.90	0.94	0.07	0.13	0.84	0.10
3 days	0.60	0.38	0.88	0.82	0.60	0.40	0.62	0.12	0.19	0.40
4 days	0.77	0.22	0.94	0.70	0.66	0.23	0.78	0.06	0.31	0.34
5 days	0.81	0.51	0.96	0.66	0.51	0.19	0.49	0.04	0.35	0.49
1 week	0.91	0.32	0.88	0.93	0.55	0.09	0.68	0.12	0.07	0.45
1 month	0.93	0.40	0.90	0.31	0.93	0.07	0.60	0.10	0.69	0.07
6 months	0.94	0.89	0.86	0.18	0.95	0.06	0.11	0.14	0.82	0.05

The highest abnormal trading volumes were measured one week before the events for very optimistic cover stories, one week after the events for optimistic cover stories, six months before the events for neutral cover stories, six months after the events for moderately pessimistic cover stories and one month before the event for pessimistic cover stories. The trend for feature stories was similar with higher trading volumes for very optimistic feature stories two days after the event that decreased to negative abnormal trading volumes for longer investment periods.

The difference in BHRs was less than zero for positive and neutral cover stories and more than zero for negative cover stories with large standard deviations (Appendix A2, Table A5.2.2). The difference in BHRs between the different cover story categories was statistically significant at an alpha of 0.05 (Table 5.9). The lower BHRs after the event for very optimistic cover stories were statistically significant up to a week after the events and at an alpha of 0.08 (Table 5.9). The lower BHRs after the event for optimistic and neutral cover stories were statistically significant one to six months after the events and at an alpha of 0.065 (Table 5.9). The increase in BHRs after the events for negative cover stories was only statistically significant at an alpha of 0.05 two days after the events for moderately pessimistic cover stories.

The difference in BHRs for feature stories was statistically insignificant, except for neutral cover stories where the lower BHRs after the events were statistically significant at an alpha of 0.08 (Appendix A2, Table A5.2.2).

Table 5.9 BHR test statistics per category – Cover stories

Anova-Tukey-Kramer's Simultaneous Confidence Intervals

	p-value	Reject Ho	
2 days	0.12	No	
3 days	0.00	Yes	Category 1 different from 4
4 days	0.01	Yes	Category 1 different from 4, 5
5 days	0.60	No	
1 week	0.20	No	
1 month	0.00	Yes	Category 1, 2, 3, 4 different from 5
6 months	0.00	No	Category 1, 2 different from 4, 5

Category 1 and 5 (p-values)

	Alternative hypothesis: Ha>0					Alternative hypothesis: Ha<0				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
	1	2	3	4	5	1	2	3	4	5
2 days	0.00	0.75	0.49	1.00	0.74	1.00	0.25	0.13	0.00	0.26
3 days	0.00	0.64	0.68	0.27	0.95	1.00	0.36	0.12	0.73	0.06
4 days	0.01	0.18	0.54	0.86	0.50	1.00	0.83	0.06	0.14	0.50
5 days	0.04	0.31	0.25	0.59	0.61	0.96	0.70	0.04	0.41	0.39
1 week	0.01	0.01	0.32	0.49	0.85	0.99	0.99	0.12	0.51	0.15
1 month	0.16	0.00	0.01	0.16	0.95	0.84	1.00	0.10	0.84	0.05
6 months	0.08	0.00	0.03	0.10	0.41	0.92	1.00	0.14	0.90	0.59

Investors responded positively to the very optimistic cover stories from the two financial magazines based on the increase in abnormal trading volumes two days after the event. The investors used these very optimistic cover stories as a market indicator to invest in the companies. There was no statistically significant increase in abnormal share trading volumes for companies that were the subject of optimistic, neutral and negative cover stories. The measured differences in BHRs for the different categories of cover stories were counterintuitive with negative differences in BHRs for positive cover stories and positive differences in BHRs for negative cover stories for two-day to six-month investment periods.

5.3.3 Research Objective 3

The first steps in assessing whether company-specific characteristics (such as industry, company size (based on market capitalisation) and price-to-earinings ratio) and cover story-specific information (source and category) affected BHRs were to assess the co-linearity between independent variables and whether the data points were normally distributed. These steps were required before the Pearson's correlation coefficients could be calculated.

There was no correlation between the explanatory variables, namely market capitalisation, cover story categories and company industry, based on a Pearson's correlation coefficient of less than 0.05 (Appendix A3, Table A5.3.1). The price-to-earnings ratios were weakly correlated to cover story categories and industry based on a Pearson's correlation coefficient of 0.07 and 0.09 respectively (Appendix A3, Table A5.3.1).

The Pearson's correlation coefficients and Pearson's correlation categories for the company-specific characteristics are shown in Table 5.10. There was only a weak form of correlation between the independent variables and BHRs based on Pearson's correlation coefficients of less than 0.25, with the BHRs most strongly correlated to the industry category and most weakly correlated to the price-to-earnings ratios. The industry category was used as the primary and market capitalisation as the secondary sorting criterium for selecting control companies to calculate BHARs for the subsequent test statistics. BHRs after the events were negatively correlated to market capitalisation and positively correlated to price-to-earnings ratio.

Table 5.10 Variable correlation – Pearson's correlation coefficients

	Industry category	Market capitalisation	Price-to-earnings ratio
2 years prior	0.06	-0.01	0.00
1 year prior	0.01	0.01	0.01
6 months prior	0.00	0.01	0.01
1 month prior	-0.01	0.03	-0.01
1 week prior	-0.01	-0.01	0.01
1 week after	0.02	0.05	0.01
1 month after	-0.06	-0.03	0.01
6 months after	-0.02	-0.01	0.02
1 year after	-0.07	-0.06	0.05
2 years after	-0.05	-0.07	-0.02

Pearson's correlation category

	Industry category	Market capitalisation	Price-to-earnings ratio
2 years prior	4	5	5
1 year prior	5	5	5
6 months prior	5	5	5
1 month prior	5	5	5
1 week prior	5	5	5
1 week after	5	5	5
1 month after	4	5	5
6 months after	5	5	5
1 year after	4	4	5
2 years after	5	4	5

Investments in smaller companies (measured based on market capitalisation) on average performed better than investments in larger companies after the events based on the negative Pearson's correlation coefficients, while investments in companies with larger price-to-earnings ratios on average performed better after the event than investments in companies with smaller price-to-earnings ratios. The improved performance of smaller companies was measured relative to the other companies in the sample and did not account for risk, macroeconomic changes in the environment or the performance of other companies with the same company-specific characteristics.

5.3.4 Research Hypothesis 4

T-test statistics were used to assess whether the control-company approach was required to calculate BHARs based on the Fama and French (1996) and Basiewicz and Auret (2010) findings that BHARs calculated using a reference portfolio led to experimental biases due to the correlation between BHARs and company-specific characteristics. The test results are shown in Appendix A3, Table A5.3.1.

The correlation between BHRs and the industry category was statistically significant at an alpha of 0.05 for the investment periods one month and one week before the events and one week, one month, and one and two years after the events. The correlation between BHRs and company size (based on market capitalisation) was only statistically significant at an alpha of 0.05 for the investment period two years after the events, while the correlation between BHRs and price-to-earnings ratios was statistically significant at an alpha of 0.05 for the investment periods six months before the events and one and two years after the events.

The correlations of BHRs with industry, market capitalisation and price-to-earnings ratio were statistically significant and led to the rejection of the null hypothesis. Using a reference portfolio to calculate BHARs would lead to skewness, new-listing and rebalancing biases that were eliminated by using the control-company approach.

5.3.5 Research Hypothesis 5

The BHARs, calculated as the difference in BHRs for the experimental and control companies, were used to assess whether cover stories could be used as momentum or contrarian indicators of future company investment performance. The test statistics for cover and feature stories are shown in Table 5.11 and Appendix A4, Table A5.4.1 respectively.

Companies in the experimental group on average performed better than companies in the control group (ignoring the cover story categories) before the events with positive BHARs. The positive BHARs were statistically significant at an alpha of 0.05 one week, and one and two years before the events. The positive BHARs before the events were not statistically significant for feature stories. The positive trend reversed one week after the events with companies in the experimental group on average performing worse than companies in the control group.

The negative BHARs were statistically significant six months, and one and two years after the events with an alpha of 0.05 for cover stories. The negative BHARs after the events were statistically significant at an alpha of 0.05 one and two years after the events for feature stories.

Table 5.11 BHARs test statistics

Cover stories	Mean	Median	Standard deviation	Momentum p-value	Momentum Reject Ho	Contrarian p-value	Contrarian Reject Ho
2 years prior	12.34	7.17	111.08	0.00	Yes	1.00	No
1 year prior	5.50	4.83	62.56	0.00	Yes	1.00	No
6 months prior	1.86	1.65	42.68	0.09	No	0.99	No
1 month prior	0.01	0.00	18.03	0.50	No	0.50	No
1 week prior	0.37	0.00	7.41	0.04	Yes	0.96	No
1 week after	0.01	0.00	7.87	0.49	No	0.50	No
1 month after	-0.47	0.00	15.14	0.82	No	0.18	No
6 months after	-6.50	-0.07	61.03	1.00	No	0.00	Yes
1 year after	-10.93	-1.68	83.38	1.00	No	0.00	Yes
2 years after	-12.46	0.00	109.79	1.00	No	0.00	Yes

Feature stories	Mean	Median	Standard deviation	Momentum p-value	Momentum Reject Ho	Contrarian p-value	Contrarian Reject Ho
2 years prior	7.47	11.16	88.17	0.04	No	0.96	No
1 year prior	1.42	1.89	49.57	0.29	No	0.71	No
6 months prior	1.46	0.00	38.95	0.28	No	0.72	No
1 month prior	0.94	0.17	15.70	0.18	No	0.82	No
1 week prior	0.00	0.00	8.12	0.50	No	0.50	No
1 week after	0.70	0.00	6.61	0.05	No	0.95	No
1 month after	-0.07	0.92	14.31	0.53	No	0.47	No
6 months after	-4.65	0.00	49.60	0.92	No	0.08	No
1 year after	-12.63	-2.99	80.26	0.99	No	0.01	Yes
2 years after	-18.66	0.00	111.96	0.99	No	0.01	Yes

The use of cover stories as contrarian indicators, independently of cover story category, was statistically significant at an alpha of 0.05 and for investment periods of six months, and one and two years after the events. There was no statistical evidence to support the use of cover or feature stories as momentum indicators independently of cover story category. The null hypothesis could not be rejected with p-values close to one.

5.3.6 Research Hypothesis 6

The research hypotheses were an extension of the previous research hypotheses to assess whether cover story categories affected the potential use of cover or feature stories as momentum or contrarian indicators for future company investment performance. The test statistics for cover and feature stories per cover story category are shown in Table 5.12 and Appendix A4, Table A5.4.1.

Investments in companies with positive or neutral cover and feature stories on average gave higher returns or positive BHARs before the events. The positive BHARs were statistically significant at an alpha of 0.05 and investment periods of one week, six months, and one and two years before the events for positive cover stories and one year before the events for neutral cover stories. Feature stories had statistically significant positive BHARs one week, six months, and one and two years before the events for very optimistic feature stories, and two years before the events for optimistic feature stories.

The trend of positive BHARs reversed one week after the events with negative BHARs for both positive and neutral cover and feature story categories. The negative BHARs were statistically significant for optimistic cover and feature stories and investment periods of one and two years after the events with an alpha of 0.05 (Table 5.12).

Investments in companies with negative cover and feature stories on average gave worse returns, or negative BHARs, when compared to investments in companies in the control group before events. The negative BHARs were statistically significant at an alpha of 0.05 and investment periods one and six months, and one year before the events for cover and feature stories. The negative BHARs before the events continued after the events. The negative BHARs were statistically significant six months, and one and two years after the events for negative cover stories and one month, and one and two years after the events for negative feature stories at an alpha of 0.05 (Table 5.12).

There was no statistical evidence to support the use of positive and neutral cover stories as momentum indicators of future company investment performance. Investments in companies that were the subject of positive and neutral cover stories on average gave positive BHARs before the events and negative BHARs after the events. The null hypothesis relating to momentum indicators for positive and neutral cover story categories could not be rejected based on the BHARs and p-values above 0.05 for all investment periods (Table 5.12).

The second null hypothesis relating to contrarian indicators was rejected for positive and neutral cover stories based on the statistically significant positive BHARs before the events for the three categories and statistically significant negative BHARs after the event for optimistic cover stories. The publication of positive and neutral cover stories generally indicated the end of superior investment returns, implying that investments in companies from the control group would yield higher returns when compared to investments in companies from the experimental group that were the subject of positive and neutral cover stories after the events.

Investments in companies that were the subject of negative cover and feature stories on average gave negative BHARs before and after the events. The null hypothesis relating to momentum indicators was rejected for negative cover stories based on negative BHARs before and after the events and p-values below 0.05 for some investment periods. Negative cover and feature stories could be used as momentum indicators of future company investment performance. The second null hypothesis relating to contrarian indicators could not be rejected based on negative BHARs before and after the events and p-values above 0.05 for most investment time intervals.

Investments in companies that were the subject of negative cover stories gave lower returns when compared to investments in control companies from similar industries and company sizes. The largest differences in BHARs were measured for pessimistic cover and feature stories with the biggest negative values two years after the events (Appendix A4, Table A5.4.1). The smallest differences in BHARs were measured for neutral cover and feature stories.

Table 5.12 BHARs test statistics (p-values) per category

Cover stories	Alternative hypothesis: Ha>0					Alternative hypothesis: Ha<0				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
	1	2	3	4	5	1	2	3	4	5
2 years prior	0.00	0.00	0.23	0.90	0.86	1.00	1.00	0.77	0.10	0.14
1 year prior	0.00	0.00	0.03	0.90	0.99	1.00	1.00	0.97	0.11	0.01
6 months prior	0.00	0.00	0.06	0.93	0.99	1.00	1.00	0.94	0.07	0.01
1 month prior	0.23	0.34	0.08	0.61	0.97	0.77	0.66	0.92	0.40	0.03
1 week prior	0.00	0.00	0.39	0.42	0.95	1.00	1.00	0.61	0.58	0.05
1 week after	0.50	0.51	0.39	0.07	0.95	0.50	0.49	0.61	0.93	0.05
1 month after	0.58	0.67	0.72	0.59	0.74	0.42	0.33	0.28	0.41	0.26
6 months after	0.80	0.94	0.60	0.99	0.99	0.20	0.06	0.40	0.01	0.01
1 year after	0.77	0.97	0.40	1.00	1.00	0.23	0.03	0.60	0.00	0.00
2 years after	0.18	0.99	0.67	0.97	0.99	0.83	0.01	0.33	0.03	0.01

	Alternative hypothesis: Ha>0					Alternative hypothesis: Ha<0				
Feature stories	Positive		Neutral	Negative		Positive		Neutral	Negative	
	1	2	3	4	5	1	2	3	4	5
2 years prior	0.08	0.00	0.81	0.30	0.89	0.92	1.00	0.19	0.70	0.11
1 year prior	0.01	0.07	0.78	0.61	0.92	0.99	0.93	0.22	0.39	0.08
6 months prior	0.01	0.14	0.50	0.78	0.97	0.99	0.86	0.50	0.23	0.03
1 month prior	0.06	0.06	0.41	0.07	0.93	0.94	0.94	0.59	0.93	0.07
1 week prior	0.06	0.18	0.45	0.50	0.82	0.94	0.82	0.55	0.50	0.18
1 week after	0.51	0.52	0.04	0.09	0.62	0.49	0.48	0.96	0.91	0.38
1 month after	0.58	0.54	0.09	0.09	0.62	0.42	0.47	0.91	0.91	0.38
6 months after	0.83	0.48	0.09	0.87	0.88	0.18	0.53	0.91	0.13	0.12
1 year after	0.97	0.36	0.25	0.98	0.97	0.03	0.64	0.75	0.02	0.03
2 years after	0.79	0.47	0.29	0.97	1.00	0.21	0.53	0.71	0.03	0.01

5.3.7 Research Objective 7

Positive and neutral cover and feature stories acted as contrarian indicators, while negative cover and feature stories acted as momentum indicators for future company investment performance based on results from Research Hypothesis 6. The next step was to obtain the optimal investment period, assess the effects of company-specific characteristics on BHARs and how transaction costs affected the optimal investment period.

The optimal investment period for all categories of cover stories was two days based on the frequency distribution for the calculated $t_{\text{optimal-c}}$ and zero transaction costs (Table 5.13). The optimal investment periods increased as the percentage transaction costs increased. For example, the optimal investment period for cover story category one increased from two to 28 days with a three per cent increase in the transaction costs. The trend for the optimal investment period for the feature stories was similar to cover stories with longer optimal investment periods at zero per cent transaction costs (Table 5.13).

Table 5.13 Optimal investment periods (days)

	Cover stories					Feature stories				
Transaction	Positive		Neutral	Negative		Positive		Neutral	Negative	
costs	1	2	3	4	5	1	2	3	4	5
0%	2	2	2	2	2	3	2	2	8	2
1%	28	36	7	12	6	6	16	716	15	33
2%	28	414	7	19	30	14	16	716	19	33
3%	28	414	147	19	117	14	16	716	19	33
4%	56	666	147	8	727	14	19	716	19	37
5%	714	679	147	19	728	14	679	716	19	728

Tukey-Kramer's Simultaneous Confidence Intervals were used to assess the effects of the industry category (Table 5.14) and company size (Table 5.15) on BHARs.

Companies in the healthcare and hotel industries gave the highest BHRs (Table 5.14) and outperformed other industries, while companies in the healthcare, general retail and general mining industries gave the largest negative BHARs after the events (Appendix A5, Table 5.5.4) or the largest change in BHARs when compared to the average BHARs for companies from other industries.

Table 5.14 Effect of industry on BHARs

	p-value	Reject H0	Difference
2 years prior	0.277	No	
1 year prior	0.976	No	
6 months prior	0.924	No	
1 month prior	0.980	No	
1 week prior	0.930	No	
1 week after	0.803	No	
1 month after	0.007	Yes	Hotel industry outperformed the other industries
6 months after	0.123	No	
1 year after	0.229	No	
2 years after	0.000	Yes	Healthcare outperformed the other industries

Smaller companies with a market capitalisation of less than R1.6 billion gave the largest positive BHARs before the events (Table 5.15) and largest negative BHARs after the events when compared to BHARs for larger companies (Appendix A5, Table 5.5.2). Short selling of smaller companies from the healthcare, general retail and general mining industries that were the subject of positive or negative cover stories and the buying of control companies in the same proportions from the same industries and similar company sizes would maximise investor returns.

Table 5.15 Effect of company size on BHARs

	p-value	Reject H0	Difference
2 years prior	0.344	No	
1 year prior	0.352	No	
6 months prior	0.24	No	
1 month prior	0.841	No	
1 week prior	0.686	No	
1 week after	0.88	No	
1 month after	0.718	No	
6 months after	0.886	No	
1 year after	0.001	Yes	Category 1 different from 4
2 years after	0.005	Yes	Category 2 different from 4

5.3.8 Research Hypothesis 8

A short investment time period of two days with zero per cent transaction cost gave the highest negative BHARs compared to investment periods of one week, one month, six months, and one and two years (Appendix A6, Table A5.6.1), but the higher BHARs at the optimal investment period (Table 5.16) were not statistically significant at an alpha of 0.05.

Table 5.16 BHARs for optimal investment time periods

	p-value	Hypothesis	Reject Ho
1 week after	0.180	Ha<0	No
1 month after	0.797	Ha<0	No
6 months after	0.761	Ha<0	No
1 year after	0.559	Ha<0	No
2 years after	0.762	Ha<0	No
+2 days	0.670	Ha<0	No
+28 days	0.690	Ha<0	No

The differences in BHARs based on industry and company size were statistically significant (Tables 5.14 and 5.15) with companies in the healthcare, general retail and general mining industries giving the largest negative BHARs (Appendix A5, Table 5.5.4) and smaller companies with a market capitalisation of less than R1.6 billion giving the largest negative BHARs after the events.

Some evidence was found to support the use of cover stories as market indicators for making active investment decisions. Positive and neutral cover stories were contrarian indicators of future company investment performance, while negative cover stories acted as momentum indicators of future company investment performance.

An active investment portfolio based on short selling of shares of companies with a small market capitalisation that were the subject of positive, neutral or negative cover stories from the healthcare, general retail and general mining industries, and the buying of shares of companies from the control group in the same proportions, from the same industries, with similar market capitalisation and optimal investment period (including the transaction costs of active investing) would yield abnormal returns.

CHAPTER 6: DISCUSSION OF RESULTS

6.1 INTRODUCTION

The research explored the potential use of cover stories as momentum or contrarian indicators for making investment decisions in South Africa. Barber and Odean (2008), Barber et al. (2001), Ferreira and Smith (2003) and Desai and Jain (2004) found that US investors did not benefit from making investment decisions based on secondary information sources, while Arnold et al. (2007) found cover stories to be contrarian indicators of future company performance in the US after analysing headlines and feature stories in *Business Week*, *Fortune* and *Forbes* for a 20-year period.

6.2 COVER STORY CATEGORISATION

6.2.1 Cover story source comparison

The distribution of cover stories for the two financial magazines was similar. Almost equal proportions of cover and feature stories came from *FinWeek* and the *Financial Mail* (49% versus 51% for cover stories and 47% versus 53% for feature stories) (Table 5.1) with similar splits between positive, neutral and negative cover stories.

The mean market capitalisation and price-to-earnings ratio distributions per cover story category were similar for both *FinWeek* and the *Financial Mail* (Table 5.3). The distribution of cover and feature story categories based on industry for the two magazines was similar except *FinWeek* had more stories relating to the financial sector and the *Financial Mail* had more stories relating to the mining industry (Table 5.4).

The similarity in cover story categories and company-specific characteristics for the two sources of cover stories pointed to herding behaviour as the two magazines published cover stories with similar recommendations based on prior announcements and were simply reporting historical information that was already in the public domain. Trueman (1994) found that analysts displayed herding behaviour by releasing forecasts closer to prior earnings expectations and similar to prior announcements by other analysts, even if these forecasts were not justified by their own information.

Investments in companies that were the subject of positive and neutral cover stories outperformed investments in companies from the same industry and of similar company size up to two years prior to the publication of the cover stories, while companies that were the subject of negative cover stories underperformed when compared to companies from the same industry and similar company size for an investment period of up to two years before the events. Both publications reported historical information where positive and neutral cover stories followed after two years of outstanding investment returns and negative cover stories followed after two years of poor investment returns. The next step was to perform a detailed assessment of the distribution of cover story categories.

6.2.2 Distribution of cover story categories

The distribution between positive and negative cover stories was similar with marginally more pessimistic feature stories (40% versus 37%). The distribution of cover story categories for the JSE-listed companies was different from what was observed in the US. Womack (1996) found that the ratio of buy-to-sell recommendations in his sample was about seven to one while Arnold et al. (2007) measured only 18.2% negative cover stories for similar research done in the US using *Business Week, Fortune* and *Forbes* magazine covers. Womack (1996) attributed the asymmetry in buy-to-sell recommendations to the substantial costs and risk of disseminating sell recommendations to investors.

The equal distribution of positive and negative cover stories supported the argument that the two financial magazines simply reported historical information and that the potential risks of publishing negative cover stories, as identified by Womack (1996), were not applicable due to the sources of information used in the publications. Investors themselves could measure positive BHARs before the publication of positive and neutral cover stories by doing basic financial analysis. A similar analysis of companies that were the subject of negative cover stories would have revealed poor investment returns up to two years prior to the events.

Investors responded differently to the different categories of cover stories based on the outcomes from the first research hypothesis. A statistically significant increase in abnormal share trading volumes was measured for very optimistic cover stories up to two days after the events, while no or negative abnormal share trading volumes were measured for optimistic, neutral and negative cover and feature stories after the events. Investors only responded to very optimistic cover stories (increase in share trading volumes after the events) and ignored optimistic, neutral and negative cover and feature stories (with no change or negative abnormal trading volumes after the events).

The number of unique cover stories recorded varied over the data collection period. This increased the importance of using the control-company approach when calculating BHARs to eliminate new-listing and skewness biases.

6.2.3 Distribution of cover stories over time

Only a small percentage (20%) of the cover stories in the experimental group came from the first decade of the study (1985 to 1994). The small number of unique cover stories for the first five years was mainly due to the layout of the magazine covers for that period. The magazine covers did not have headlines (1985 to 1988) or only allowed for minimal writing on the cover of the magazines. Lead stories were recorded as cover stories for this period.

The period of 1990 to 1994 also yielded a relatively small number of unique cover stories (13%). The cover stories for this period mainly focused on political events and changes in state-owned enterprises in South Africa. The number of unique cover stories improved significantly from 1995 onwards with the highest percentage of unique cover stories per year for the period 2000 to 2004. South Africa experienced stable political and economic growth throughout 2000 to 2004.

The large sample size and control-company approach used to calculate BHARs eliminated potential new-listing and skewness biases caused by changes in the macroeconomic environment. Barber and Lyon (1997) found that the control-company approach for calculating BHARs yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases. Both the sample and the control companies were listed in the identified event month (eliminating new-listing biases) and the sample and control companies were equally likely to experience high positive returns around the event dates (eliminating skewness biases) (Barber and Lyon, 1997).

6.2.4 Cover versus feature stories

Feature stories formed a subcategory of cover stories and were categorised as features when the main stories on the cover of the magazines were clearly identifiable. Arnold et al. (2007) only collected feature stories and required long data collection periods to obtain a sufficiently large sample for parametric test statistics. The data collection period could be significantly reduced by using cover stories as a proxy for feature stories. The distribution of cover and feature story categories and subcategories, based on market capitalisation, industry, price-to-earnings ratios, abnormal share trading volumes, BHRs and BHARs, was similar based on the research results.

Cover stories were an accurate proxy for feature stories in the South African context and gave more reliable test statistics due to the large number of data points. A total of 1 218 unique cover stories was recorded compared to 235 unique feature stories for the research period 1985 to 2008.

The next step was to assess how the criteria (industry and market capitalisation) used for selecting the control companies correlated to cover story categories and how these variables affected BHARs.

6.2.5 Industry and cover story categories

There was a low degree of correlation between the industry category and cover story categories based on the average BHRs for the different industries and cover story categories (Appendix A3, Table A5.3.1). The services, IT, property and industrial industries had the highest percentage of negative cover stories, while the building, construction and engineering, chemical and food industries had the highest percentage of positive cover stories.

The correlation between BHRs and the industry was statistically significant at an alpha of 0.05 for the investment periods one month and one week before the events, and one week, one month, and one and two years after the events. Barber and Lyon (1997), Ferreira and Smith (2003) and Arnold et al. (2007) used the control-company approach to calculate BHARs, with industry as one of the sorting criteria for selecting the control companies.

Companies in the healthcare and hotel industries gave the highest BHRs (Table 5.14), while companies in the healthcare, general retail and general mining gave the largest negative BHARs after the events (Appendix A5, Table 5.5.4). BHARs could be optimised by developing an investment portfolio with companies from the healthcare, general retail and general mining industries.

6.2.6 Company size and cover story categories

Cover stories relating to smaller companies (as measured based on market capitalisation) were on average more negative with 65% of the cover stories rated as negative cover stories for companies with market capitalisations of less than R0.4 billion, while cover stories relating to the larger companies (as measured based on market capitalisation) were on average more positive with 51% of the cover stories rated as positive cover stories for the companies with market capitalisations larger than R72.7 billion.

Hong et al. (2000), Van Rensburg and Robertson (2003) and Basiewicz and Auret (2009) found that the profitability of momentum strategies sharply declined with an increase in company size (based on market capitalisation). The correlation between BHRs and company size (based on market capitalisations) was statistically significant at an alpha of 0.05 for an investment period of two years after the event dates (Table 5.10).

Smaller companies with a market capitalisation of less than R0.4 billion gave the largest positive BHARs before the events (Table 5.1.5) and the largest negative BHARs after the events when compared to BHARs for larger companies (Appendix A5, Table 5.5.2) in line with the findings of Hong et al. (2000), Van Rensburg and Robertson (2003) and Basiewicz and Auret (2009).

The larger BHARs for smaller companies indicated that the market was less efficient in allocating resources for smaller companies when compared to the larger companies. The increased market inefficiencies for smaller companies were caused by inefficient resource allocations and not by financial information asymmetry or risk premiums.

The large differences in BHARs measured up to two years before and after the events and the fact that the cover stories were based on historical information already in the public domain eliminated financial information asymmetry as a potential cause of the market inefficiency. The control-company approach eliminated risk premiums as a potential cause for the large differences in BHARs between small and large companies.

Thaler (1999) and Beechey et al. (2000) argument supported the above findings. Thaler (1999) and Beechey et al. (2000) argued that information-efficient markets were not linked to efficient resource allocations and it was thus possible to obtain abnormal returns even in information-efficient markets due to inefficient resource allocations.

The industry category was used as the primary and market capitalisation as the secondary sorting criterium for selecting control companies for calculating BHARs based on the outcomes from Research Objective 3. The use of industry and market capitalisation as sorting criteria for control companies was in line with previous research in the US (Arnold et al., 2007).

Fama and French (1996) developed a three-factor model to explain abnormal returns by allowing for average market portfolio returns, company size (based on market capitalisation) and book-to-market ratio corrections. Arnold et al. (2007) calculated average BHARs as the difference in BHR for a given company and another company that was a match in size and industry.

6.2.7 Price-to-earnings and cover story categories

Cover stories relating to companies with smaller price-to-earnings ratios (or lower market premiums on share prices and typically more mature companies) were more negative with 40% of the cover stories rated as pessimistic and 64% as negative for the lowest price-to-earnings category. Cover stories relating to the higher price-to-earnings companies (typically growth companies) were more positive with 28% of the cover stories rated as optimistic and 55% as positive for the highest price-to-earnings category (Appendix A1, Table A5.1.4).

The correlation between BHRs and price-to-earnings ratios was statistically significant at an alpha of 0.05 for investment periods six months before, and one and two years after the events and in line with Basiewicz and Auret's (2009) findings that size and book-to-market variables independently affected abnormal returns. Companies with small price-to-earnings ratios were on average the subject of negative cover stories and needed to provide above-average returns after the event to meet the findings of Campbell and Shiller (2001) and Van Rensburg and Robertson (2003).

6.3 INVESTOR BEHAVIOUR

The research found evidence to support the hypothesis that investors paid attention to very optimistic cover stories when abnormal share trading volumes were used as a proxy for attention-grabbing shares. Investors used the cover stories as market indicators to invest in companies that were the subject of very optimistic cover stories and created a speculative bubble between one week before and two days after the events that reversed within a week after the events. The highest difference in abnormal share trading volumes for very optimistic cover stories were measured two days after the events and the lowest difference in abnormal share trading volumes was measured one week after the events.

Tversky and Kahnemann (1974) and Marimon, Spear and Sunder (1993) demonstrated the price-to-price feedback theory where speculative bubbles were created due to the representativeness heuristic (where the sample tried to predict future performance based on past price patterns). A speculative bubble was created with the expectation of higher future stock price increases without any proof of an increase in the underlying value of the stocks (Shiller, 2003) based on the past performance of the stocks. The speculative bubble eventually burst three days after the events with a significant reduction in the abnormal share trading volumes for the very optimistic cover story effects.

The differences in abnormal trading volumes were statistically significant at an alpha of 0.08 for cover story categories one and five, two days after the events. The trends for very optimistic feature stories were similar. There was no statistically significant evidence to prove that investors were paying attention to optimistic, neutral or negative cover stories based on the difference in abnormal trading volumes as a proxy for attention-grabbing shares.

The difference in BHRs was used as a second proxy for attention-grabbing shares based on the assumption that the demand for company shares with positive cover stories would increase and thus lead to an increase in the share prices, compared to negative cover stories where the demand and share prices would decrease (Barber and Odean, 2008).

Companies with positive cover and feature stories had lower BHRs after the events compared with their BHRs before the event, while companies with negative cover and feature stories had higher BHRs after the events compared with their BHRs before the events. The differences in BHRs were statistically significant and contrary to what was expected based on the use of BHRs as a proxy for attention-grabbing shares.

The increase in abnormal trading volumes for companies that were the subject of very optimistic cover stories was statistically significant, but the difference in BHRs before and after the events for the very optimistic cover stories did not support the finding. Using BHRs as a proxy for attention-grabbing shares led to a higher risk of skewness biases due to changes in the macroeconomic environment during the period of investigation. The BHRs did not take the performance of similar sized companies from the same industry and at the same point in time into account and were potentially biased due to macroeconomic changes.

BHARs did account for macroeconomic environmental effects and showed positive BHARs up to a week after the events for positive and neutral cover and feature stories. The positive BHARs up to one week after the events were not statistically significant at an alpha of 0.05, but indicated an increase in abnormal returns around the events in line with what was expected during a speculative bubble. Abnormal share trading volumes were a more reliable proxy for evaluating attention-grabbing shares and eliminated potential skewness biases.

A speculative bubble was caused by a human desire to avoid regret (Barber and Odean, 2008) where investors did not want to miss out on potential opportunities to earn abnormal returns by investing in companies that were the subject of very optimistic cover stories.

Negative cover and feature stories led to more pronounced momentum effects with the largest change in BHARs measured for pessimistic cover and feature stories and an investment period of up to two years. This confirmed Hong et al.'s (2000) findings that negative information diffused more slowly through to the investment public and led to more pronounced momentum effects.

The increased negative difference in BHARs after the publication of negative cover stories indicated that the market was less efficient when dissiminating negative information. Investors reacted differently to loss-making versus profitable investments where investors retained loss-making investments for longer periods when compared to profitable investments.

Barber and Odean (2008) highlighted two common mistakes investors made, namely excessive trading and the tendency to hold on disproportionately to loss-making investments while selling winners. The tendency of investors to hold on disproportionately to losing investments increased market inefficiency and created opportunities for rational investors to earn higher abnormal returns by exploiting these market inefficiencies.

6.4 COVER STORIES AS MOMENTUM OR CONTRARIAN INDICATORS

The use of all cover or feature stories as contrarian indicators, independently of cover story category, was statistically significant at an alpha of 0.05 and for investment periods one and two years after the events. An investor could exploit these market inefficiencies and yield abnormal returns by selling all companies that were the subject of cover stories and buying shares in the control companies from similar industries and company sizes. The ability to earn short- to long-term abnormal returns, after compensating for industry, company size and transaction costs, proved market inefficiency for the JSE. The cover stories acted as market signalling tools to mispriced stocks (contrarian indicators).

Abnormal returns for an investment portfolio based on the cover story effects could be increased through more selective use of the cover stories. Positive and neutral cover stories were contrarian indicators, while negative cover stories were momentum indicators of future company investment performance (Table 5.12).

Arnold et al. (2007) attributed the negative BHARs after the event dates for positive and neutral cover stories to mispriced stocks (contrarian indicators) or a continuation of historically poor performance for negative cover stories (momentum indicators) when the cover stories revealed no new pertinent information.

6.5 MAXIMISATION OF BHAR

Short selling of shares in companies that were the subject of either positive (contrarian indicators), neutral or negative (momentum indicators) cover stories for the two financial magazines and buying of shares in companies that were not the subject of cover stories (for a period of 60 days after the events) from the same industries and similar company sizes would yield positive abnormal returns. The BHARs could be further improved by selecting shares only from smaller companies from the healthcare, general retail and general mining industries.

The optimal investment period was a function of the transaction costs of active investing and increased as the transaction costs increased. A tipping point was reached where a passive investment portfolio was more profitable than an active investment portfolio due to high transaction costs.

The measured BHARs before and after the events, after compensating for industry, company size and transaction costs, indicated a weak form of market inefficiency in the JSE. This was in line with the findings of Page and Way (1992) and Philpott and Firer (1994) of a weak form of inefficiency in the JSE in the long term and contradicted the findings of High and Honikman (1995), Smith et al. (2002) and Magnusson and Wydick (2002) that supported the weak form of the efficient market hypothesis (EMH) for the JSE.

Active investors could exploit these market inefficiencies by using cover stories as momentum (for negative cover stories) and contrarian indicators (for positive and neutral cover stories) of future company investment performance to gain superior returns.

CHAPTER 7: CONCLUSIONS AND RECOMMENDATIONS

7.1 CONCLUSIONS

The purpose of the research was to assess whether South African investors could benefit from using cover stories as market indicators, to obtain a better understanding of how investors reacted to cover stories and whether an understanding of investment time horizons, company-specific characteristics and bounded rational behaviour could assist investors to gain superior short-, medium- or long-term returns.

Barber and Odean (2008) found that individual investors in the US tended to rely on market indicators as proxies for future company investment performance due to time, information and resource constraints. However, studies in the US market gave mixed results about the potential usefulness of cover stories as market indicators, while no published research could be found relating to the use of cover stories as market indicators in the South African context.

The use of cover stories as market indicators was based on the assumption that markets were inefficient and that the inefficiency was caused by irrational investor behaviour. Behavioural finance focused on the role of human behaviour in financial markets by incorporating psychology and social sciences into the analysis of investment decision making (Thaler, 1999).

Cover stories from the two leading financial magazines in South Africa, *FinWeek* and the *Financial Mail*, were collected for the period 1985 to 2008 and used as secondary information sources for the research. In total, 2 503 covers were reviewed and 2 222 headline stories recorded. Of the 2 222 headlines, only 1 218 headlines were classified as unique cover stories and categorised using Arnold et al.'s (2007) Likert scale. A total of 336 feature stories was identified from the 2 503 magazine covers (Table 5.1), of which only 235 were classified as unique feature stories.

Positive cover stories were defined as stories about companies that were doing or had done something innovative that would differentiate them from their competitors, the companies were performing well and would continue to perform well or the companies were planning something innovative (Arnold et al., 2007). Positive cover stories were contrarian indicators of future company investment performance with positive BHARs before and negative BHARs after the events. Positive cover stories generally indicated the end of superior financial performance by these companies, while an investment portfolio consisting of control companies from the same industries and similar size (based on market capitalisation) yielded higher returns after the events.

Neutral cover stories (where the analyst gave no particular opinion about the future performance of the companies (Arnold et al., 2007)) were also contrarian indicators of future company investment performance with positive BHARs before and negative BHARs after the events.

Negative cover stories (where the companies were currently performing badly, but performance should improve in future or a scandal had been uncovered

(Arnold et al., 2007)) were momentum indicators of future company investment performance with negative BHARs before and after the events. The poor performance of these companies continued after the events, while an investment portfolio consisting of control companies from the same industries and similar company sizes (based on market capitalisation) yielded higher returns after the events.

The returns on an investment portfolio based on these cover story effects could be optimised by accounting for transaction costs when selecting the optimal investment periods and by short selling companies that were the subject of positive (contrarian indicators), neutral or negative (momentum indicators) cover stories and buying shares in control companies from the same industries and company sizes.

The research found evidence that investors did pay attention to very optimistic cover stories from the selected financial magazines, with increased abnormal share trading volumes for up to two days after the events. The increase in share trading volumes for optimistic, neutral and negative cover stories was statistically insignificant. The differences in BHRs were used as a second proxy for attention-grabbing shares based on the research by Barber and Odean (2008). The results for the differences in BHRs were inconclusive and it was argued that abnormal share trading volumes were a more reliable proxy for evaluating attention-grabbing shares.

The positive BHARs for positive cover stories and negative BHARs for negative cover stories before the events in combination with the distribution of cover stories based on category, industry, market capitalisation and price-to-earnings ratios for both *FinWeek* and the *Financial Mail* pointed to some level of herding behaviour. The two magazines published cover stories with similar recommendations based on prior announcements and the magazines were simply reporting historical information that was already in the public domain.

The ability to generate abnormal returns for an investment portfolio based on cover story effects proved that the South African stock market is inefficient and superior returns can be obtained by exploiting these market inefficiencies. This finding was in line with the research of Page and Way (1992) and Philpott and Firer (1994) that concluded that the JSE is inefficient after observing several significantly large share price anomalies that persisted over long periods of time for both high- and low-volume traded stocks.

The BHARs were calculated as the difference in BHRs for the company of interest minus the BHRs for the control company from the same industry and company size (based on market capitalisation). The BHAR calculation method used in the research yielded well-specified test statistics by eliminating new-listing, rebalancing and skewness biases. Both the sample and the control companies were listed in the identified event month (eliminating new-listing biases), rebalancing of a reference portfolio was not required (eliminating rebalancing biases) and the sample and control companies were equally likely to experience high positive returns around the event dates (eliminating skewness biases) (Barber and Lyon, 1997).

7.2 RECOMMENDATIONS

Market inefficiency created opportunities for active investors to earn superior returns by exploiting these market inefficiencies. It was critical for investors who developed an investment portfolio based on these market indicators to account for transaction costs when selecting the optimal investment period. An investment portfolio based on short selling shares of smaller companies that were the subject of cover stories, from the healthcare, general retail and general mining industries and buying of shares of companies from the control group, in the same proportions, from the same industries, similar company sizes and for the optimal investment period would yield the highest abnormal returns.

7.3 FUTURE RESEARCH

FinWeek and the *Financial Mail* were selected as secondary information sources for the research. These two magazines are the leading financial magazines in South Africa (SA Press, 2010), but are only published on a weekly basis. Future research could focus on alternative secondary information sources such as online financial magazines or daily newspapers that are more up to date with the latest news and developments in the market.

Industry, market capitalisation and price-to-earnings ratios were the three company-specific variables investigated in the research. Industry and market capitalisation were used for selecting the control companies. The inclusion of other company-specific variables would lead to a more refined investment model and potentially higher abnormal returns.

The difference in abnormal share trading volumes and BHRs was used as a proxy for attention-grabbing shares. The results from the BHR measurements were inconclusive and future research could investigate alternative proxies for attention-grabbing shares.

Transaction costs can have a significant impact on the ability to earn abnormal returns. A three per cent increase in transaction costs increased the optimal investment period for very optimistic cover story effects with 26 days compared to 412 days for optimistic cover stories. A detailed analysis of the effects of transaction costs and cover story categories on BHARs is required to improve investment returns by optimising the investment period.

The complexity of financial instruments and markets is continuously increasing over time while access to real-time financial information is improving. A study of changes in market inefficiency over time and market inefficiency in different market segments would give a better understanding of the causes of market inefficiency and identify larger investment opportunities.

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APPENDIX A1: DESCRIPTIVE STATISTICS

Table A5.1.1: Number of unique cover stories for five year intervals

	Positive		Neutral	Negative		Total	Recordings per year
Cover stories	1	2	3	4	5		
1985-1989	22	26	7	15	13	83	
	27%	31%	8%	18%	16%	7%	1%
1990-1994	17	53	32	35	25	162	
	10%	33%	20%	22%	15%	13%	3%
1995-1999	50	85	58	60	48	301	
	17%	28%	19%	20%	16%	25%	5%
2000-2004	64	104	78	79	75	400	
	16%	26%	20%	20%	19%	33%	7%
2004-2008	36	80	53	56	47	272	
	13%	29%	19%	21%	17%	22%	6%
Total	189	348	228	245	208	1218	
	16%	29%	19%	20%	17%		

	Positive		Neutral	Negative		Total	Recordings per year
Feature Stories	1	2	3	4	5		
1985-1989	4	6	1	3	1	15	
	27%	40%	7%	20%	7%	6%	1%
1990-1994	3	10	4	5	4	26	
	12%	38%	15%	19%	15%	11%	2%
1995-1999	9	20	9	9	11	58	
	16%	34%	16%	16%	19%	25%	5%
2000-2004	10	19	16	12	18	75	
	13%	25%	21%	16%	24%	32%	6%
2004-2008	4	13	14	18	12	61	
	7%	21%	23%	30%	20%	26%	6%
Total	30	68	44	47	46	235	
	13%	29%	19%	20%	20%		

Table A5.1.2: Size of companies (as measured based on market capitalisation)

Cover stories	Value	Positive		Neutral	Negative		Total
Percentiles	billion R	1	2	3	4	5	
0-10	≤0.40	4%	16%	14%	28%	37%	
10-20	0.40<x≤1.06	11%	27%	15%	17%	29%	
20-30	1.06<x≤2.17	20%	30%	13%	21%	16%	
30-40	2.16<x≤4.46	18%	26%	18%	16%	21%	
40-50	4.46<x≤7.75	13%	36%	18%	22%	11%	
50-60	7.75<x≤13.61	22%	32%	19%	14%	13%	
60-70	13.61<x≤22.86	15%	24%	26%	22%	13%	
70-80	22.86<x≤41.02	21%	32%	22%	15%	10%	
80-90	41.02<x≤72.71	17%	30%	26%	18%	8%	
90-100	>72.71	13%	38%	27%	12%	10%	
Market Capitalisation (billion R) – Mean							
Fin Week		26.0	28.3	31.3	15.4	11.0	29.9
FM		20.7	27.1	44.0	13.4	10.6	31.8
Total		23.0	27.7	37.5	14.3	10.8	30.9
Market Capitalisation (billion R) -Median							
Fin Week		15.7	10.2	10.6	6.5	1.7	8.1
FM		7.5	8.0	16.6	4.5	2.7	7.2
Total		11.4	9.0	14.6	5.7	2.3	7.8

Feature stories	Value	Positive		Neutral	Negative		Total
Percentiles	billion R	1	2	3	4	5	
0-10	≤0.36	13%	50%	0%	13%	25%	
10-20	0.36<x≤0.86	13%	50%	13%	25%	0%	
20-30	0.86<x≤2.76	13%	63%	0%	13%	13%	
30-40	2.76<x≤5.51	20%	60%	0%	20%	0%	
40-50	5.51<x≤8.64	0%	60%	20%	20%	0%	
50-60	8.64<x≤16.05	0%	40%	60%	0%	0%	
60-70	16.05<x≤25.14	0%	38%	25%	38%	0%	
70-80	25.14<x≤42.23	0%	29%	14%	43%	14%	
80-90	42.23<x≤80.27	13%	63%	13%	0%	13%	
90-100	>80.27	0%	57%	29%	14%	0%	
Market Capitalisation (billion R)-Mean							
Fin Week		26.5	33.0	27.7	19.4	7.8	27.9
FM		14.3	13.3	60.7	20.9	20.9	33.6
Total		23.0	27.7	37.5	14.3	10.8	30.8
Market Capitalisation (billion R)-Median							
Fin Week		44.1	10.9	66.2	8.1	0.6	8.2
FM		10.9	38.6	13.5	0.8	22.2	9.3
Total		10.9	7.5	15.8	7.4	3.2	8.6

Table A5.1.3: Industry distribution

Cover stories

	Positive		Neutral	Negative		0	Property	Total
Sector	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Broadcasting, Entertainment &Telecommunications	10	12	7	8	4	21	20	41
	24%	29%	17%	20%	10%	4%	3%	3%
Gambling	1	4	2	2	2	5	6	11
	9%	36%	18%	18%	18%	1%	1%	1%
Hotel Industry	0	3	2	0	1	3	3	6
	0%	50%	33%	0%	17%	1%	1%	1%
Property	0	4	6	3	5	7	11	18
	0%	22%	33%	17%	28%	1%	2%	2%
Services, IT	9	13	4	12	13	23	28	51
	18%	25%	8%	24%	25%	4%	5%	4%
Financial	49	70	66	55	46	160	126	286
	17%	24%	23%	19%	16%	27%	21%	24%
Retail	18	21	12	19	15	45	40	89
	20%	24%	13%	21%	17%	8%	7%	8%
Building, Construction & Engineering	8	11	3	6	6	9	25	34
	24%	32%	9%	18%	18%	2%	4%	3%
Chemical Industry	11	21	6	12	6	30	26	56
	20%	38%	11%	21%	11%	5%	4%	5%
Healthcare	6	3	4	1	3	7	10	17
	35%	18%	24%	6%	18%	1%	2%	1%
Electronic Equipment & Electrics	1	5	6	0	4	7	9	16
	6%	31%	38%	0%	25%	1%	2%	1%
Food	16	30	16	13	7	48	34	82
	20%	37%	20%	16%	9%	8%	6%	7%
Industrial	21	60	34	52	37	98	106	204
	10%	29%	17%	25%	18%	17%	18%	17%
Mining-Combined	35	84	55	47	47	120	148	268
	13%	31%	21%	18%	18%	21%	25%	23%
Total	185	341	223	230	196	583	592	1179

Table A5.1.3: Industry distribution (continue)

Feature stories

	Positive		Neutral	Negative		0	0	Total
Sector	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Broadcasting, Entertainment &Telecommunications	3	3	2	3	1	6	6	12
	25%	25%	17%	25%	8%	6%	5%	5%
Gambling	0	1	0	1	0	0	2	2
	0%	50%	0%	50%	0%	0%	2%	1%
Hotel Industry	0	0	0	0	0	0	0	0
	0%	0%	0%	0%	0%	0%	0%	0%
Property	0	1	1	1	1	1	3	4
	0%	25%	25%	25%	25%	1%	3%	2%
Services, IT	0	0	0	2	1	2	1	3
	0%	0%	0%	67%	33%	2%	1%	1%
Financial	5	12	11	13	10	24	27	51
	10%	24%	22%	25%	20%	23%	23%	23%
Retail	5	7	3	2	6	15	8	24
	21%	29%	13%	8%	25%	14%	7%	11%
Building, Construction & Engineering	1	3	0	3	0	2	5	7
	14%	43%	0%	43%	0%	2%	4%	3%
Chemical Industry	2	9	3	2	1	8	9	17
	12%	53%	18%	12%	6%	8%	8%	8%
Healthcare	0	1	0	1	1	2	1	3
	0%	33%	0%	33%	33%	2%	1%	1%
Electronic Equipment & Electrics	0	2	0	0	0	0	2	2
	0%	100%	0%	0%	0%	0%	2%	1%
Food	5	5	4	4	0	11	7	18
	28%	28%	22%	22%	0%	11%	6%	8%
Industrial	4	14	12	8	7	20	25	45
	9%	31%	27%	18%	16%	19%	21%	20%
Mining-Combined	3	9	8	4	13	13	24	37
	8%	24%	22%	11%	35%	13%	20%	16%
Total	28	67	44	44	41	104	120	225

Table A5.1.4: Price-to-earnings distribution

Cover stories		Positive		Neutral	Negative		Total
Percentiles	Ratio	1	2	3	4	5	
0-10	≤6.1	11%	18%	6%	24%	40%	
10-20	6.1<x≤8.3	9%	33%	21%	17%	20%	
20-30	8.3<x≤10.0	16%	32%	26%	17%	9%	
30-40	10.0<x≤11.3	16%	37%	12%	23%	12%	
40-50	11.3<x≤12.8	17%	27%	26%	17%	13%	
50-60	12.8<x≤14.4	20%	34%	21%	15%	10%	
60-70	14.2<x≤16.7	18%	31%	27%	17%	6%	
70-80	16.7<x≤20.4	17%	33%	24%	17%	9%	
80-90	20.4<x≤29.4	19%	32%	16%	15%	17%	
90-100	>29.4	17%	28%	18%	22%	15%	
Price-to-earnings (ratio)-Mean							
Fin Week		14.8	12.3	15.8	12.8	48.6	27.4
FM		46.9	22.6	18.6	89.0	34.0	53.9
Total		33.0	17.5	17.1	54.5	42.5	41.0
Price-to-earnings (ratio)-Median							
Fin Week		13.7	12.8	13.3	12.5	10.8	12.8
FM		13.3	13.1	12.7	11.6	10.6	12.8
Total		13.5	12.9	13.2	12.0	10.8	12.8

Feature stories		Positive		Neutral	Negative		Total
Percentiles	Ratio	1	2	3	4	5	
0-10	≤0.36	0%	0%	0%	50%	50%	
10-20	5.3<x≤7.8	0%	50%	50%	0%	0%	
20-30	7.8<x≤9.4	17%	50%	33%	0%	0%	
30-40	9.4<x≤10.6	10%	40%	30%	20%	0%	
40-50	10.6<x≤12.1	10%	30%	30%	30%	0%	
50-60	12.1<x≤13.6	0%	43%	29%	29%	0%	
60-70	13.6<x≤15.3	0%	50%	50%	0%	0%	
70-80	15.3<x≤18.8	0%	60%	40%	0%	0%	
80-90	18.8<x≤22.2	20%	40%	40%	0%	0%	
90-100	>22.2	33%	0%	67%	0%	0%	
Price-to-earnings (ratio)- Mean							
Fin Week		7.87	11.47	11.19	10.94	7.30	12.9
FM		15.5	12.3	10.7	218.4	20.5	70.5
Total		12.7	11.9	10.9	119.0	13.9	43.8
Price-to-earnings (ratio)- Median							
Fin Week		14.9	10.1	13.0	12.8	10.7	11.2
FM		22.0	12.2	10.8	12.7	10.8	12.8
Total		15.1	12.1	12.7	12.1	7.8	12.1

Table A5.1.5: Industry categories

Category	Industry
1	Broadcasting, Entertainment &Telecommunications
2	Building, Construction & Engineering
3	Services, IT
4	Financial
5	Chemical Industry
6	Retail
7	Mining –Coal
8	Mining Diamonds
9	Healthcare
10	Electronic Equipment & Electrics
11	Food
12	Furnishings
13	Gambling
14	Mining-General
15	Mining – Gold
16	Hotel Industry
17	Industrial
18	Mining – Platinum
19	Property

APPENDIX A2: RESEARCH HYPOTHESES 1 & 2

Table A5.2.1: Statistics- Abnormal volumes traded

Cover stories	Positive		Neutral	Negative				Total
	1	2	3	4	5	*Fin Week*	*Financial Mail*	
Count	123	224	155	160	139	390	411	801
<u>Two days</u>								
Mean	1.3	0.3	-0.6	0.6	-1.0	0.1	0.2	0.2
Median	0.0	0.0	0.0	0.1	-0.2	-0.1	0.0	-0.1
Minimum	-2.3	-5.5	-9.3	-2.6	-20	-20.0	-9.3	-20.0
Maximum	16.8	7.2	3.2	8.5	4.0	15.2	16.8	16.8
Std-deviation	4.4	2.0	2.6	2.3	4.0	3.5	2.8	3.2
<u>Three days</u>								
Mean	-0.1	0.1	-0.3	-0.2	-0.1	0.2	-0.4	-0.1
Median	-0.2	-0.2	-0.3	-0.3	-0.2	-0.2	-0.3	-0.2
Minimum	-13.5	-6.6	-17.0	-8.4	-20	-20.0	-17.0	-20.0
Maximum	16.4	80.5	19.9	12.1	31.2	80.5	16.4	80.5
Std-deviation	3.4	6.1	3.2	2.2	4.3	5.4	2.7	4.3
<u>Four days</u>								
Mean	-0.2	0.2	-0.7	-0.1	-0.2	0.2	-0.5	-0.2
Median	-0.1	-0.1	-0.2	-0.2	-0.1	-0.1	-0.2	-0.1
Minimum	-18.1	-8.4	-49.4	-8.3	-25.6	-20.0	-49.4	-49.4
Maximum	9.9	37.9	25.4	8.7	31.2	37.9	21.6	37.9
Std-deviation	2.8	3.7	5.2	1.9	5.1	3.6	4.1	3.9
<u>Five days</u>								
Mean	-0.2	0.0	-0.7	-0.1	0.0	0.0	-0.4	-0.2
Median	0.0	-0.1	-0.1	-0.1	-0.1	0.0	-0.1	-0.1
Minimum	-18.1	-23.4	-49.3	-8.0	-22	-23.4	-49.3	-49.3
Maximum	10.2	23.2	18.0	6.6	31.2	31.2	19.6	31.2
Std-deviation	2.8	3.2	4.9	1.7	4.7	3.3	3.9	3.6
<u>One week</u>								
Mean	-1.7	0.1	-0.5	-0.4	0.0	0.1	-1.0	-0.4
Median	0.0	-0.1	-0.1	-0.1	-0.1	0.0	-0.1	-0.1
Minimum	-106.0	-11.7	-49.2	-23.2	-9.6	-21.1	-106	-106
Maximum	10.5	15.5	32.5	12.1	31.6	32.5	15.5	32.5
Std-deviation	13.5	2.4	5.4	3.6	3.8	3.4	8.3	6.4
<u>One month</u>								
Mean	-1.2	0.0	-0.5	0.3	-1.0	-0.4	-0.4	-0.4
Median	-0.1	0.0	0.0	0.0	-0.2	0.0	-0.1	0.0
Minimum	-83.0	-11.3	-49.5	-18.0	-84	-84.3	-83.0	-84.3
Maximum	3.2	9.8	13.9	76.5	13.9	13.9	76.5	76.5
Std-deviation	8.8	1.9	4.7	6.7	7.8	5.0	7.0	6.1

Table A5.2.1: Statistics- Abnormal volumes traded (continue)

Six months

Mean	-0.9	-0.1	-0.4	0.6	-0.7	-0.2	-0.3	-0.2
Median	0.0	0.0	0.0	-0.1	-0.1	-0.1	0.0	0.0
Minimum	-68.5	-11.1	-49.6	-9.3	-34	-33.3	-68.5	-68.5
Maximum	4.3	7.6	13.2	79.5	8.2	57.5	79.5	79.5
Std-deviation	6.7	1.3	4.2	8.0	4.5	3.7	6.3	5.2

t-test statistics- Cover Story

	Skewness	Kurtosis	p-value	Reject Ho
2 days	3.7	18.2	0.23	No
3 days	32.2	19.9	0.71	No
4 days	-10.6	17.7	0.86	No
5 days	-19.5	17.7	0.93	No
1 week	-32.2	19.6	0.97	No
1 month	-25.2	19.1	0.97	No
6 months	12.8	19.1	0.90	No

Anova- Tukey-Kramer's Simultaneous Confidence Intervals

	Skewness	Kurtosis	p-value	Reject Ho	
2 days	-0.1	7.0	0.04	Yes	Category 1 different from 5
3 days	29.0	18.2	0.91	No	
4 days	-9.1	16.6	0.38	No	
5 days	-18.2	16.8	0.39	No	
1 week	-31.1	19.1	0.17	No	
1 month	-24.6	18.7	0.17	No	
6 months	12.5	19.0	0.13	No	

t-test statistics for Category 1 and 5

p-Values	1	2	3	4	5
Ha	>0	>0	<0	<0	<0
2 days	0.06	0.93	0.13	0.84	0.10
3 days	0.60	0.38	0.12	0.19	0.40
4 days	0.77	0.22	0.06	0.31	0.34
5 days	0.81	0.51	0.04	0.35	0.49
1 week	0.91	0.32	0.11	0.07	0.45
1 month	0.93	0.40	0.10	0.69	0.07
6 months	0.94	0.89	0.14	0.82	0.05

Table A5.2.1: Statistics- Abnormal volumes traded (continue)

Feature stories	Positive		Neutral	Negative				Total
	1	2	3	4	5	*Fin-Week*	*Financial Mail*	
Count	23	49	33	33	36	84	90	174
Two days								
Mean	5.7	0.2	-0.2	0.3	-0.1	0.1	0.2	0.2
Median	1.3	0.0	0.2	0.1	0.0	-0.1	0.0	-0.1
Minimum	0.8	-1.5	-4.3	-2.0	-1.1	-20.0	-9.3	-20.0
Maximum	15.2	3.8	3.2	3.9	1.0	15.2	16.8	16.8
Std-deviation	8.2	1.4	2.8	1.7	0.9	3.5	2.8	3.2
Three days								
Mean	-0.1	-0.5	-0.3	-0.6	1.0	0.2	-0.4	-0.1
Median	-0.1	-0.5	-0.2	-0.6	-0.4	-0.2	-0.3	-0.2
Minimum	-13.3	-4.7	-5.7	-5.3	-6.1	-20.0	-17.0	-20.0
Maximum	15.3	6.3	3.2	4.2	31.2	80.5	16.4	80.5
Std-deviation	4.8	1.9	1.5	1.7	7.0	5.4	2.7	4.3
Four days								
Mean	0.1	-0.2	-0.3	-0.3	0.9	0.2	-0.5	-0.2
Median	0.0	-0.1	-0.2	-0.6	-0.4	-0.1	-0.2	-0.1
Minimum	-10.1	-8.4	-5.1	-3.9	-4.2	-20.0	-49.4	-49.4
Maximum	9.6	8.6	3.2	3.7	31.2	37.9	21.6	37.9
Std-deviation	3.3	2.2	1.4	1.4	6.3	3.6	4.1	3.9
Five days								
Mean	0.1	-0.3	-0.3	-0.2	1.2	0.0	-0.4	-0.2
Median	0.1	-0.2	-0.1	-0.1	-0.2	0.0	-0.1	-0.1
Minimum	-10.1	-8.6	-4.5	-3.9	-4.8	-23.4	-49.3	-49.3
Maximum	10.2	8.6	2.3	2.5	31.2	31.2	19.6	31.2
Std-deviation	3.4	2.1	1.2	1.4	6.4	3.3	3.9	3.6
One week								
Mean	-8.4	-0.3	-0.3	-0.6	0.3	0.1	-1.0	-0.4
Median	0.1	-0.1	-0.1	-0.4	-0.4	0.0	-0.1	-0.1
Minimum	-106.0	-11.7	-5.4	-9.5	-6.5	-21.1	-106	-106
Maximum	10.5	6.4	1.9	2.1	31.6	32.5	15.5	32.5
Std-deviation	30.2	2.6	1.4	1.9	5.8	3.4	8.3	6.4
One month								
Mean	-5.6	0.3	-0.2	0.2	-3.4	-0.4	-0.4	-0.4
Median	0.0	0.0	0.1	-0.1	-0.3	0.0	-0.1	0.0
Minimum	-83.0	-8.7	-5.6	-3.4	-84	-84.3	-83.0	-84.3
Maximum	1.9	9.8	1.5	5.8	2.1	13.9	76.5	76.5
Std-deviation	19.8	2.3	1.2	1.5	14.7	5.0	7.0	6.1

Table A5.2.1: Statistics- Abnormal volumes traded (continue)

Six months								
Mean	-4.3	-0.2	-0.3	1.7	-1.1	-0.2	-0.3	-0.2
Median	0.0	0.1	-0.1	-0.1	-0.2	-0.1	0.0	0.0
Minimum	-68.5	-11.1	-7.1	-3.5	-33	-33.3	-68.5	-68.5
Maximum	1.9	1.7	3.1	57.5	5.4	57.5	79.5	79.5
Std-deviation	15.1	1.7	1.5	10.1	5.8	3.7	6.3	5.2

t-test statistics- Feature Story

	Skewness	Kurtosis	p-value	Reject Ho
2 days	3.6	18.2	0.23	No
3 days	32.2	19.9	0.71	No
4 days	-10.6	17.7	0.86	No
5 days	-19.5	17.7	0.93	No
1 week	-32.2	19.6	0.97	No
1 month	-25.2	19.1	0.97	No
6 months	12.8	19.1	0.90	No

Kruskal-Wallis One-Way Anova- Tukey-Kramer's Simultaneous Confidence Intervals

	Skewness	Kurtosis	p-value	Reject Ho	
2 days	2.9	3.2	0.25	No	1 from 2 and 3
3 days	10.3	8.0	0.65	No	
4 days	11.5	8.6	0.39	No	
5 days	11.3	8.6	0.54	No	
1 week	-13.2	9.1	0.54	No	1 from 5
1 month	-13.2	9.0	0.43	No	
6 months	-7.4	9.1	0.50	No	1 from 4

Wilcoxon Signed-Rank Test for Difference in Medians

p-Values	1	2	3	4	5
Ha	<0	<0	<0	<0	<0
2 days	0.05	0.40	0.55	0.61	0.45
3 days	0.91	1.00	0.06	0.01	0.08
4 days	0.29	0.93	0.03	0.05	0.06
5 days	0.15	0.98	0.13	0.28	0.19
1 week	0.42	0.96	0.22	0.05	0.04
1 month	0.50	0.21	0.38	0.53	0.02
6 months	0.69	0.32	010	0.27	0.07

Table A5.2.2: Statistics- Difference BHRs

Cover Stories	Positive		Neutral	Negative		Fin Week	FM	Total
	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Count	189	350	227	242	196	587	608	1204
<u>Two days</u>								
Mean	-0.5	0.1	0.0	0.4	0.2	0.1	0.0	0.1
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-15.8	-11.8	-12.5	-12.9	-17.1	-17.1	-12.5	-17.1
Maximum	6.3	31.7	11.1	53.5	20.0	53.5	13.0	53.5
Std-deviation	2.6	3.3	2.5	4.5	3.9	4.3	2.4	3.5
<u>Three days</u>								
Mean	-1.0	0.1	0.1	0.4	0.7	0.3	-0.2	0.1
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-24.9	-12.8	-12.5	-24.2	-25.0	-25.0	-24.2	-25.0
Maximum	8.2	66.1	11.7	53.5	40.0	53.5	66.1	66.1
Std-deviation	3.5	5.4	3.5	5.8	5.9	5.5	4.6	5.0
<u>Four days</u>								
Mean	-0.8	-0.3	0.0	0.1	0.0	0.2	-0.6	-0.2
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-24.9	-32.5	-20.0	-61.7	-95.2	-95.2	-61.7	-95.2
Maximum	12.4	66.1	15.0	53.5	31.7	53.5	66.1	66.1
Std-deviation	4.2	6.2	4.6	7.5	10.1	7.1	6.5	6.8
<u>Five days</u>								
Mean	-0.6	-0.2	-0.3	0.0	0.1	0.2	-0.6	-0.2
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-22.5	-32.5	-57.8	-49.7	-31.6	-57.8	-49.7	-57.8
Maximum	12.4	70.0	14.1	79.6	27.1	79.6	70.0	79.6
Std-deviation	4.7	6.8	6.3	8.6	7.5	7.3	6.6	7.0
<u>One week</u>								
Mean	-1.1	-1.0	-0.2	-0.7	2.9	0.7	-1.1	-0.2
Median	-0.3	-0.4	0.0	0.0	0.0	0.0	-0.3	0.0
Minimum	-28.0	-46.8	-27.0	-74.7	-50.0	-74.7	-50.0	-74.7
Maximum	14.6	82.8	21.2	79.6	525.0	525.0	82.8	525.0
Std-deviation	6.5	8.6	7.3	11.5	39.0	23.6	9.1	17.8
<u>One month</u>								
Mean	-1.6	-3.9	-3.4	-15.4	15.4	-4.2	-1.2	-2.7
Median	-0.7	-3.1	-1.9	-0.3	0.0	-1.8	-0.9	-1.5
Minimum	-88.7	-70.5	-121.1	-2900.0	-51.4	-2900.0	-164	-2900
Maximum	217.6	240.8	104.9	78.6	1732.5	1732.5	240.8	1732.5
Std-deviation	22.7	20.8	20.2	188.1	133.5	143.6	24.3	102.2

Table A5.2.2: Statistics- Difference BHRs (continue)

Six months

Mean	-4.3	-6.8	-5.2	-7.6	-0.8	-7.2	-3.6	-5.4
Median	0.8	-1.8	0.0	0.0	0.0	-1.5	0.4	-0.7
Minimum	-201.4	-346.0	-358.4	-367.8	-238.4	-358.4	-367.8	-367.8
Maximum	150.4	266.4	96.9	89.3	320.0	320.0	266.4	320.0
Std-deviation	41.9	43.5	41.9	50.3	52.5	47.4	44.8	46.3

t-test statistics- Cover Story

	Skewness	Kurtosis	p-value	Hypothesis	Reject Ho
2 days	-5.0	22.7	0.411	Ha>0	No
3 days	24.2	19.9	0.260	Ha>0	No
4 days	-19.7	20.6	0.833	Ha>0	No
5 days	13.6	19.0	0.811	Ha>0	No
1 week	46.4	25.4	0.648	Ha>0	No
1 month	-41.9	25.3	0.815	Ha>0	No
6 months	-17.5	16.6	0.999	Ha>0	No

Anova-Tukey-Kramer's Simultaneous Confidence Intervals

	Skewness	Kurtosis	p-value	Reject Ho	
2 days	-2.20	11.45	0.123	No	Different from from 6 months
3 days	-5.98	12.16	0.000	Yes	Different from from 6 months
4 days	-7.30	12.53	0.013	Yes	
5 days	-3.24	11.40	0.595	No	Different from from 6 months
1 week	6.62	11.47	0.200	No	
1 month	6.20	13.97	0.000	Yes	
6 months	-5.30	10.10	0.001	No	Different from from 2,3, and 5 days

t-test statistics for Category 1 and 5

p-Values	1	2	3	4	5
Ha	<0	<0	<0	>0	>0
2 days	0.00	0.75	0.49	0.00	0.26
3 days	0.00	0.64	0.68	0.73	0.06
4 days	0.01	0.18	0.54	0.14	0.50
5 days	0.04	0.31	0.25	0.41	0.39
1 week	0.01	0.01	0.32	0.51	0.15
1 month	0.16	0.00	0.01	0.84	0.05
6 months	0.08	0.00	0.03	0.90	0.59

Table A5.2.2: Statistics- Difference BHRs (continue)

Feature Stories	Positive		Neutral	Negative		FM	FM	Total
	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Count	30	67	44	47	43	0	0	231
Two days								
Mean	-0.2	-0.1	-0.5	0.5	-0.2	0.1	0.0	0.1
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-12.5	-11.8	-4.5	-8.3	-9.8	-17.1	-12.5	-17.1
Maximum	6.3	5.0	3.4	8.8	12.0	53.5	13.0	53.5
Std-deviation	3.0	2.9	1.7	2.7	3.5	4.3	2.4	3.5
Three days								
Mean	-0.3	-0.3	-0.2	0.1	1.1	0.3	-0.2	0.1
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-12.5	-11.3	-8.8	-24.2	-9.8	-25.0	-24.2	-25.0
Maximum	7.5	8.8	6.0	12.8	15.9	53.5	66.1	66.1
Std-deviation	3.8	3.6	2.9	5.8	4.6	5.5	4.6	5.0
Four days								
Mean	-0.9	-0.5	-0.2	-1.7	1.4	0.2	-0.6	-0.2
Median	-0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	-13.3	-12.8	-14.0	-61.7	-9.8	-95.2	-61.7	-95.2
Maximum	6.3	8.9	7.5	12.2	17.9	53.5	66.1	66.1
Std-deviation	4.3	4.3	4.1	10.8	5.5	7.1	6.5	6.8
Five days								
Mean	-0.8	-0.6	0.4	-1.5	0.4	0.2	-0.6	-0.2
Median	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0
Minimum	-16.3	-15.5	-13.5	-49.7	-14.1	-57.8	-49.7	-57.8
Maximum	6.3	8.1	10.3	15.8	21.0	79.6	70.0	79.6
Std-deviation	5.4	4.9	4.4	9.6	6.2	7.3	6.6	7.0
One week								
Mean	-2.6	-1.2	0.5	-0.2	0.5	0.7	-1.1	-0.2
Median	-1.5	0.0	0.5	0.0	0.0	0.0	-0.3	0.0
Minimum	-24.3	-19.8	-13.5	-29.2	-19.9	-74.7	-50.0	-74.7
Maximum	9.8	13.3	17.0	24.7	26.2	525.0	82.8	525.0
Std-deviation	7.5	6.0	6.9	9.5	8.4	23.6	9.1	17.8
One month								
Mean	3.5	-7.2	-1.3	-69.3	2.1	-4.2	-1.2	-2.7
Median	-4.8	-4.2	0.1	-6.0	4.2	-1.8	-0.9	-1.5
Minimum	-69.4	-53.6	-38.8	-2900.0	-47.8	-2900	-164	-2900
Maximum	217.6	30.6	81.0	64.1	49.5	1732.5	240.8	1732.5
Std-deviation	43.9	16.3	19.1	422.9	23.0	143.6	24.3	102.2

Table A5.2.2: Statistics- Difference BHRs (continue)

Six months

Mean	-6.5	-8.6	-5.3	-15.1	-8.9	-7.2	-3.6	-5.4
Median	-8.3	-6.2	0.5	-1.6	-7.1	-1.5	0.4	-0.7
Minimum	-145.3	-85.4	-358.4	-367.8	-215.8	-358.4	-367	-367.8
Maximum	150.4	52.1	96.9	65.3	77.8	320.0	266.4	320.0
Std-deviation	49.0	27.2	60.4	61.4	51.8	47.4	44.8	46.3

t-test statistics- Feature Story

	Skewness	Kurtosis	p-value	Hypothesis	Reject Ho
2 days	-4.2	5.8	0.708	Ha>0	No
3 days	-5.4	6.5	0.435	Ha>0	No
4 days	-12.7	9.7	0.812	Ha>0	No
5 days	-9.8	8.4	0.859	Ha>0	No
1 week	-1.1	4.2	0.859	Ha>0	No
1 month	-19.2	11.7	0.890	Ha>0	No
6 months	-11.3	8.8	0.990	Ha>0	No

Kruskal-Wallis One-Way Anova-Tukey-Kramer's Simultaneous Confidence Intervals

2 days	2.9	3.1	0.254	No
3 days	10.3	8.0	0.648	No
4 days	11.5	8.6	0.387	No
5 days	11.3	8.6	0.542	No
1 week	-13.2	9.1	0.541	No
1 month	-13.2	9.0	0.431	No
6 months	-7.4	9.1	0.504	No

Wilcoxon Signed-Rank Test for Difference in Medians

p-Values	1	2	3	4	5
Ha	<0	<0	<0	<0	<0
2 days	0.42	0.81	1.00	0.93	0.29
3 days	0.36	0.46	0.04	0.78	0.90
4 days	0.15	0.29	0.62	0.11	0.94
5 days	0.50	0.46	0.73	0.09	0.66
1 week	0.06	0.13	0.80	0.35	0.65
1 month	0.23	0.00	0.69	0.01	0.16
6 months	0.17	0.01	0.24	0.08	0.16

APPENDIX A3: RESEARCH OBJECTIVE 3 & 4

Table A5.3.1: Statistics- Pearsons correlations

Pearson correlations section (Row-Wise Deletion)

	Category	Industry	Market_Cap	PE_Ratio
Category	1.000	0.046	-0.022	0.070
Industry_catx	0.046	1.000	-0.030	0.085
Market_Cap	-0.022	-0.030	1.000	0.003
PE_Ratio	0.070	0.085	0.003	1.000

Pearsons correlation category

	Category	Industry	Market_Cap	PE_Ratio
Category	1	5	5	4
Industry_catx	5	1	5	4
Market_Cap	5	5	1	5
PE_Ratio	4	4	5	1

Test for normal distribution

Industry	Skewness	Kurtosis	p-value	Reject H0
2 years prior	42.4	22.9	0.277	No
1 year prior	45.2	23.4	0.976	No
6 months prior	37.3	21.9	0.924	No
1 month prior	42.7	23.0	0.002	Yes
1 week prior	3.9	16.3	0.000	Yes
1 week after	0.2	7.2	0.011	Yes
1 month after	0.9	4.0	0.007	Yes
6 months after	2.7	3.1	0.123	No
1 year after	5.4	3.0	0.000	Yes
2 years after	7.4	22.5	0.000	Yes
Market Capitalisation				
2 years prior	48.9	25.8	0.344	No
1 year prior	52.1	26.3	0.352	No
6 months prior	41.6	24.5	0.240	No
1 month prior	49.5	26.0	0.841	No
1 week prior	6.9	18.2	0.686	No
1 week after	-2.2	10.7	0.880	No
1 month after	7.6	12.0	0.718	No
6 months after	3.9	2.8	0.886	No
1 year after	8.7	4.9	0.909	No
2 years after	11.4	5.2	0.005	Yes

Table A5.3.1: Statistics- Pearsons correlations (continue)

Price-to-earnings Ratio				
2 years prior	49.0	25.8	0.762	No
1 year prior	52.1	26.3	0.540	No
6 months prior	41.7	24.5	0.005	Yes
1 month prior	49.5	26.0	0.923	No
1 week prior	7.0	18.2	0.397	No
1 week after	-2.2	10.6	0.411	No
1 month after	7.7	12.0	0.640	No
6 months after	4.0	3.0	0.126	No
1 year after	9.2	5.6	0.000	Yes
2 years after	10.9	5.3	0.000	Yes

Pearson correlations Section (Row-Wise Deletion)

	Industry_catx	Market_Cap	PE_Ratio
2 years prior	0.056	-0.008	-0.001
1 year prior	0.015	0.008	0.009
6 months prior	0.000	0.005	0.005
1 month prior	-0.014	0.031	-0.014
1 week prior	-0.005	-0.010	0.007
1 week after	0.024	0.049	0.011
1 month after	-0.062	-0.032	0.011
6 months after	-0.017	-0.015	0.018
1 year after	-0.071	-0.064	0.049
2 years after	-0.045	-0.074	-0.025

Pearsons correlation sategory

	Industry_catx	Market_Cap	PE_Ratio
2 years prior	4	5	5
1 year prior	5	5	5
6 months prior	5	5	5
1 month prior	5	5	5
1 week prior	5	5	5
1 week after	5	5	5
1 month after	4	5	5
6 months after	5	5	5
1 year after	4	4	5
2 years after	5	4	5

APPENDIX A4: RESEARCH HYPOTHESES 5 & 6

Table A5.4.1: Calculated BHARs

Cover stories	Positive		Neutral	Negative		Fin Week	FM	Total
	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Count	189	348	228	245	209	603	615	1218
2 years prior								
Mean	35.8	32.3	4.4	-8.9	-11.0	13.7	10.8	12.3
Median	23.1	19.6	4.3	-3.3	-9.7	9.5	3.5	7.2
Minimum	-583	0.0	0.0	0.0	0.0	-583.2	-389.4	-583.2
Maximum	466.7	753.0	445.5	608.3	766.7	766.7	753.0	766.7
Std-deviation	98.4	114.0	91.5	110.2	124.7	108.2	112.6	111.1
1 year prior								
Mean	20.4	12.9	6.9	-5.0	-10.8	4.3	6.6	5.5
Median	13.2	10.3	6.7	-3.6	-6.5	4.5	4.2	4.8
Minimum	-379	0.0	0.0	0.0	0.0	-342.6	-379.0	-379.0
Maximum	379.1	246.3	286.5	326.7	250.9	379.1	326.7	379.1
Std-deviation	69.8	58.4	55.8	61.9	64.3	61.8	62.9	62.6
6 months prior								
Mean	10.6	5.7	3.7	-4.2	-8.1	-0.3	3.9	1.9
Median	7.8	3.3	4.2	-2.4	-5.0	0.2	2.2	1.7
Minimum	-262	0.0	0.0	0.0	0.0	-262.8	-234.2	-262.8
Maximum	169.7	223.4	150.0	186.0	190.3	186.0	223.4	223.4
Std-deviation	39.4	37.2	36.5	43.8	55.1	41.6	43.3	42.7
1 month prior								
Mean	0.8	0.4	1.3	-0.4	-2.5	0.4	-0.4	0.0
Median	0.4	0.6	0.4	0.0	0.0	0.0	0.0	0.0
Minimum	-99.2	0.0	0.0	0.0	0.0	-99.2	-88.8	-99.2
Maximum	49.1	55.1	45.9	109.8	61.4	100.0	109.8	109.8
Std-deviation	15.3	16.8	14.7	23.3	18.2	18.3	17.7	18.0
1 week prior								
Mean	1.3	1.0	0.1	0.1	-1.1	0.3	0.5	0.4
Median	0.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	0.0	-54.9	0.0	0.0	0.0	-52.1	-54.9	-54.9
Maximum	36.9	19.8	20.0	39.5	25.0	39.5	35.7	39.5
Std-deviation	6.9	5.5	5.8	10.1	8.2	7.7	7.0	7.4
1 week after								
Mean	0.0	0.0	0.1	0.8	-1.1	0.5	-0.5	0.0
Median	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Minimum	0.0	-54.5	0.0	0.0	0.0	-49.8	-54.5	-54.5
Maximum	18.0	45.0	38.4	49.5	50.0	50.0	49.5	50.0
Std-deviation	6.4	7.7	7.0	8.5	9.3	7.8	7.9	7.9

Table A5.4.1: Calculated BHARs (continue)

<u>1 month after</u>								
Mean	-0.2	-0.3	-0.5	-0.2	-1.3	-0.8	-0.1	-0.5
Median	0.2	0.0	0.0	0.1	0.0	0.0	0.0	0.0
Minimum	0.0	-133	0.0	0.0	0.0	-133.3	-131.3	-133.3
Maximum	41.7	65.7	58.2	72.4	61.5	72.4	61.5	72.4
Std-deviation	16.3	12.7	12.7	16.8	17.9	16.2	14.0	15.1
<u>6 months after</u>								
Mean	-4.5	-4.1	-0.6	-7.9	-17.5	-8.0	-4.9	-6.5
Median	2.8	-1.6	1.5	-0.8	-0.4	0.0	0.0	-0.1
Minimum	0.0	-691	0.0	0.0	0.0	-691.1	-533.3	-691.1
Maximum	151.1	169.8	116.7	102.5	156.7	169.8	151.1	169.8
Std-deviation	73.2	48.6	38.7	52.3	90.5	67.9	53.1	61.0
<u>1 year after</u>								
Mean	-4.9	-7.9	-3.7	-18.2	-21.1	-13.0	-8.8	-10.9
Median	4.1	-2.7	1.3	-6.3	-4.9	0.0	-3.1	-1.7
Minimum	0.0	-675	0.0	0.0	0.0	-675.0	-587.5	-675.0
Maximum	221.4	208.7	121.6	230.5	263.9	208.7	263.9	263.9
Std-deviation	91.4	80.6	56.0	91.2	93.3	88.2	77.8	83.4
<u>2 years after</u>								
Mean	5.7	-14.7	-2.2	-12.2	-37.2	-2.1	-22.1	-12.5
Median	1.4	0.0	1.4	-1.6	-1.5	0.0	-5.4	0.0
Minimum	0.0	-970	0.0	0.0	0.0	-894.8	-970.2	-970.2
Maximum	299.0	364.4	289.0	339.9	273.3	364.4	299.0	364.4
Std-deviation	84.4	124.6	75.2	97.3	138.9	102.9	113.6	109.8

<u>t-test statistics- Cover Story</u>			Ha >0		Ha < o	
	Skewness	Kurtosis	p-value	Reject Ho	p-value	Reject Ho
2 years prior	9.6	13.9	0	Yes	1	No
1 year prior	1.3	12.7	0	Yes	1	No
6 months prior	-6.1	13.1	0.09	No	0.99	No
1 month prior	-7.1	13.5	0.5	No	0.5	No
1 week prior	-13.3	15.6	0.04	Yes	0.96	No
1 week after	-1.8	15.9	0.49	No	0.5	No
1 month after	17.7	17	0.82	No	0.18	No
6 months after	-29.9	20.8	1	No	0	Yes
1 year after	-25.3	17.8	1	No	0	Yes
2 years after	-22.2	17	1	No	0	Yes

Table A5.4.1: Calculated BHARs (continue)

Anova- Tukey-Kramer's Simultaneous Confidence Intervals

	Skewness	Kurtosis	p-value
2 years prior	13.1	15.3	0.00
1 year prior	19.7	18.6	0.00
6 months prior	-4.8	13.3	0.00
1 month prior	-10.1	14.9	0.13
1 week prior	-11.1	16	0.03
1 week after	-1.3	15.9	0.25
1 month after	-17.9	17.1	1.00
6 months after	-29.9	20.2	0.15
1 year after	-26.7	18.3	0.04
2 years after	-29.5	19.7	0.23

t-test statistics for Category 1 and 5

	Ha>0					Ha<0				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
p-Values	1	2	3	4	5	1	2	3	4	5
2 years prior	0.00	0.00	0.23	0.90	0.86	1.00	1.00	0.77	0.10	0.14
1 year prior	0.00	0.00	0.03	0.90	0.99	1.00	1.00	0.97	0.11	0.01
6 months prior	0.00	0.00	0.06	0.93	0.99	1.00	1.00	0.94	0.07	0.01
1 month prior	0.23	0.34	0.08	0.61	0.97	0.77	0.66	0.92	0.40	0.03
1 week prior	0.00	0.00	0.39	0.42	0.95	1.00	1.00	0.61	0.58	0.05
1 week after	0.50	0.51	0.39	0.07	0.95	0.50	0.49	0.61	0.93	0.05
1 month after	0.58	0.67	0.72	0.59	0.74	0.42	0.33	0.28	0.41	0.26
6 months after	0.80	0.94	0.60	0.99	0.99	0.20	0.06	0.40	0.01	0.01
1 year after	0.77	0.97	0.40	1.00	1.00	0.23	0.03	0.60	0.00	0.00
2 years after	0.18	0.99	0.67	0.97	0.99	0.83	0.01	0.33	0.03	0.01

Table A5.4.1: Calculated BHARs (continue)

Feature	Positive		Neutral	Negative				Total
Stories	1	2	3	4	5	*FinWeek*	*Financial Mail*	
Count	30	68	44	48	46	110	126	236
2 years prior								
Mean	23.3	38.4	-12.6	6.9	-28.1	4.6	10.0	7.5
Median	19.4	27.7	9.5	4.9	-9.8	11.9	10.5	11.2
Minimum	-75.6	-227	-336.8	-108.7	-360.6	-360.6	-348.7	-360.6
Maximum	138.8	410.9	231.7	238.6	138.0	200.9	410.9	410.9
Std-deviation	59.6	94.1	86.9	58.0	105.7	84.2	91.7	88.2
1 year prior								
Mean	20.0	8.1	-0.3	-1.9	-13.4	3.9	-0.7	1.4
Median	18.7	2.2	-4.5	3.2	-4.7	4.5	1.2	1.9
Minimum	-129	-126	-94.6	-93.4	-140.5	-140.5	-137.4	-140.5
Maximum	130.8	140.0	177.6	114.3	100.0	177.6	140.0	177.6
Std-deviation	49.8	45.2	44.8	49.0	56.2	48.7	50.4	49.6
6 months prior								
Mean	17.5	5.2	-0.9	0.2	-12.9	2.7	0.4	1.5
Median	12.8	3.5	2.1	-0.4	-9.7	0.6	-0.1	0.0
Minimum	-81.7	-73.6	-84.6	-108.4	-113.9	-113.9	-108.4	-113.9
Maximum	135.5	102.8	139.1	145.0	150.0	150.0	145.0	150.0
Std-deviation	40.5	30.6	31.3	40.7	46.7	38.2	39.7	39.0
1 month prior								
Mean	2.4	1.8	1.0	3.4	-3.6	1.7	0.3	0.9
Median	0.8	1.3	-0.7	0.5	-2.8	-0.6	1.1	0.2
Minimum	-34.1	-41.2	-24.0	-61.8	-69.7	-69.7	-61.8	-69.7
Maximum	20.9	37.9	27.8	44.4	38.6	44.4	37.9	44.4
Std-deviation	11.5	13.6	10.3	19.8	19.6	15.1	16.3	15.7
1 week prior								
Mean	1.2	0.8	-0.1	-0.3	-1.0	-0.1	0.0	0.0
Median	1.1	0.0	0.2	0.0	0.0	0.0	0.0	0.0
Minimum	-12.0	-16.5	-18.9	-45.3	-52.1	-52.1	-45.3	-52.1
Maximum	9.0	19.8	14.6	30.5	25.0	30.5	25.0	30.5
Std-deviation	5.0	5.3	6.6	10.9	10.4	7.9	8.3	8.1
1 week after								
Mean	-1.1	0.5	1.6	1.6	0.5	0.8	0.6	0.7
Median	0.0	0.0	0.6	0.0	0.0	0.0	0.0	0.0
Minimum	-31.4	-10.1	-13.6	-11.5	-14.8	-14.8	-31.4	-31.4
Maximum	12.7	19.6	20.0	18.5	26.6	19.6	26.6	26.6
Std-deviation	8.7	5.2	5.8	5.4	8.5	5.5	7.5	6.6

Table A5.4.1: Calculated BHARs (continue)

1 month after								
Mean	-2.6	-0.9	3.6	1.6	-2.6	-1.8	1.4	-0.1
Median	0.0	0.5	1.5	1.8	0.0	0.0	1.7	0.9
Minimum	-68.2	-38.2	-11.4	-31.5	-91.9	-91.9	-68.2	-91.9
Maximum	41.7	22.7	58.2	27.1	35.7	58.2	41.7	58.2
Std-deviation	17.7	11.3	11.8	11.8	19.4	16.0	12.5	14.3
6 months after								
Mean	-21.2	-0.5	6.3	-5.3	-12.0	-2.1	-6.9	-4.7
Median	-7.6	-0.4	4.2	-0.8	0.0	0.0	1.0	0.0
Minimum	-533	-51.9	-56.0	-90.6	-294.7	-122.0	-533.3	-533.3
Maximum	102.5	58.7	64.8	47.5	83.6	75.5	102.5	102.5
Std-deviation	104.1	23.0	28.8	25.2	57.9	30.6	61.6	49.6
1 year after								
Mean	-31.4	-10.4	3.0	-11.4	-26.3	-12.8	-12.5	-12.6
Median	-14.3	-0.1	1.4	-5.0	-8.4	-1.3	-7.0	-3.0
Minimum	-587	-675	-195.0	-180.0	-363.2	-675.0	-587.5	-675.0
Maximum	119.0	84.2	120.3	52.0	109.0	109.0	263.9	263.9
Std-deviation	114.8	93.6	49.7	37.3	79.0	82.6	78.5	80.3
2 years after								
Mean	-19.3	-12.4	5.0	-11.4	-64.0	-9.4	-26.7	-18.7
Median	0.0	3.8	3.4	-8.0	-26.6	0.8	-11.9	0.0
Minimum	-257	-806	-142.9	-115.1	-970.2	-806.4	-970.2	-970.2
Maximum	68.8	180.3	208.5	110.6	134.9	134.9	273.3	273.3
Std-deviation	63.3	122.6	63.8	45.8	172.8	102.3	119.5	112.0

t-test statistics- Feature Stories			Ha>0		Ha<0	
	Skewness	Kurtosis	p-value	Reject Ho	p-value	Reject Ho
2 years prior	-1.8	5.9	0.04	No	0.96	No
1 year prior	0.2	2.7	0.29	No	0.71	No
6 months prior	3.5	4.3	0.28	No	0.72	No
1 month prior	-3.6	4.7	0.18	No	0.82	No
1 week prior	-7.6	7.6	0.50	No	0.50	No
1 week after	1.0	5.1	0.05	No	0.95	No
1 month after	-7.0	7.2	0.53	No	0.47	No
6 months after	-14.5	10.3	0.92	No	0.08	No
1 year after	-12.8	9.4	0.99	No	0.01	Yes
2 years after	-12.9	9.5	0.99	No	0.01	Yes

Table A5.4.1: Calculated BHARs (continue)

Categories	Ha>0					Ha<0				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
p-Values	1	2	3	4	5	1	2	3	4	5
Ha	>0	>0	>0	>0	>0	<0	<0	<0	<0	<0
2 years prior	0.08	0.00	0.81	0.30	0.89	0.92	1.00	0.19	0.70	0.11
1 year prior	0.01	0.07	0.78	0.61	0.92	0.99	0.93	0.22	0.39	0.08
6 months prior	0.01	0.14	0.50	0.78	0.97	0.99	0.86	0.50	0.23	0.03
1 month prior	0.06	0.06	0.41	0.07	0.93	0.94	0.94	0.59	0.93	0.07
1 week prior	0.06	0.18	0.45	0.50	0.82	0.94	0.82	0.55	0.50	0.18
1 week after	0.51	0.52	0.04	0.09	0.62	0.49	0.48	0.96	0.91	0.38
1 month after	0.58	0.54	0.09	0.09	0.62	0.42	0.47	0.91	0.91	0.38
6 months after	0.83	0.48	0.09	0.87	0.88	0.18	0.53	0.91	0.13	0.12
1 year after	0.97	0.36	0.25	0.98	0.97	0.03	0.64	0.75	0.02	0.03
2 years after	0.79	0.47	0.29	0.97	1.00	0.21	0.53	0.71	0.03	0.01

APPENDIX A5: RESEARCH OBJECTIVE 7

Table A5.5.1: Optimal Investment Time Periods

Transaction costs	Cover stories					Feature stories				
	Positive		Neutral	Negative		Positive		Neutral	Negative	
	1	2	3	4	5	1	2	3	4	5
0%	2	2	2	2	2	3	2	2	8	2
1%	28	36	7	12	6	6	16	716	15	33
2%	28	414	7	19	30	14	16	716	19	33
3%	28	414	147	19	117	14	16	716	19	33
4%	56	666	147	8	727	14	19	716	19	37
5%	714	679	147	19	728	14	679	716	19	728

Table A5.5.2: BHARs per Company size

Percentiles		Positive		Neutral	Negative		Total
		1	2	3	4	5	
0-25	1 week after	-0.5	0.0	2.7	0.4	-1.2	0.0
	1 month after	0.3	-1.8	0.0	-0.7	-1.9	-1.2
	6 months after	-5.3	-7.6	-4.4	-14.2	-14.9	-10.7
	1 year after	5.6	-6.3	-13.0	-11.6	-7.6	-7.8
	2 years after	30.3	-26.3	-22.7	-1.7	-39.3	-19.6
25-50	1 week after	0.0	0.3	-0.3	0.2	-0.1	0.1
	1 month after	0.3	0.5	-0.1	0.1	0.6	0.8
	6 months after	0.0	0.5	-1.1	-0.8	0.3	-0.7
	1 year after	0.7	1.3	-0.6	-2.2	-0.9	-0.9
	2 years after	0.7	0.3	-0.7	-2.6	-2.0	-2.5
50-75	1 week after	0.0	0.0	0.1	-0.1	-0.1	0.0
	1 month after	0.0	0.2	0.1	0.0	0.1	0.3
	6 months after	-0.2	-0.3	0.3	-0.4	0.0	-0.5
	1 year after	0.4	-0.9	0.4	-0.6	-0.3	-0.8
	2 years after	0.5	-0.5	0.2	0.2	0.5	0.7
75-100	1 week after	0.0	0.0	-0.1	0.0	0.0	-0.1
	1 month after	0.1	0.0	0.0	-0.1	0.0	0.0
	6 months after	0.1	-0.4	0.0	-0.5	0.1	-0.6
	1 year after	0.1	-0.5	0.0	-0.7	0.0	-0.9
	2 years after	0.6	-0.7	0.3	-0.2	0.2	0.3

Table A5.5.3: BHARs per P/E Ratio

		Positive		Neutral	Negative		Total
Percentiles		1	2	3	4	5	
0-25	1 week after	0.5	0.6	-0.2	-0.6	-1.6	-0.6
	1 month after	1.0	1.8	0.0	-0.1	-1.2	0.4
	6 months after	2.9	-1.2	1.5	1.7	-10.6	-3.2
	1 year after	6.3	-3.9	0.8	3.0	-5.6	-1.0
	2 years after	5.4	-4.7	-4.7	-0.7	-26.1	-13.3
25-50	1 week after	-0.1	0.0	0.2	0.2	-0.3	0.0
	1 month after	0.4	0.0	0.3	0.3	-0.3	0.4
	6 months after	0.2	-1.0	0.0	-3.1	-0.8	-2.9
	1 year after	1.2	-0.4	0.0	-4.3	-0.4	-2.3
	2 years after	1.8	-2.2	-1.0	-1.9	0.9	-1.6
50-75	1 week after	0.0	0.0	-0.1	0.0	0.1	0.0
	1 month after	0.3	0.1	0.0	0.1	0.0	0.3
	6 months after	0.4	-0.3	-0.2	0.5	0.4	0.5
	1 year after	0.8	-0.9	-0.5	0.4	0.3	0.0
	2 years after	0.7	-1.5	-0.1	0.7	1.0	0.6
75-100	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	-0.2	-0.2	0.0	-0.1	0.2	-0.2
	6 months after	-0.6	-0.1	-0.4	-1.1	0.0	-1.8
	1 year after	-0.5	0.2	-0.1	-1.3	-0.6	-1.7
	2 years after	0.7	-0.3	0.4	0.3	-0.9	0.2

Table A5.5.4: BHRs per Industry

Cover Stories		Positive		Neutral	Negative		Total
Sector		1	2	3	4	5	
1	1 week after	-0.7	-0.4	0.3	-0.2	-0.1	-0.5
	1 month after	-0.4	0.6	0.0	-0.3	1.0	0.4
	6 months after	-3.7	2.1	2.2	-6.3	2.9	-1.3
	1 year after	-2.5	2.7	3.7	-3.4	7.3	3.2
	2 years after	-2.8	1.9	0.2	-1.8	4.1	0.7
2	1 week after	-0.2	-0.1	-0.2	0.3	0.1	0.0
	1 month after	-0.6	-0.1	-0.5	-0.4	-0.2	-1.0
	6 months after	0.4	-3.2	-0.4	-4.5	0.8	-4.2
	1 year after	5.3	-0.4	-1.5	-7.0	-0.7	-2.6
	2 years after	1.7	-1.0	-4.0	-3.1	-6.8	-7.7
3	1 week after	-0.2	0.3	-0.6	0.2	0.0	-0.1
	1 month after	0.5	1.2	-0.6	-0.2	-0.8	0.1
	6 months after	1.9	-2.0	-0.2	-0.3	-1.3	-0.8
	1 year after	5.1	-1.5	0.6	-3.2	-3.9	-1.2
	2 years after	4.7	-1.1	-5.1	-1.4	-4.5	-3.0
4	1 week after	-0.1	0.4	-0.3	0.1	-0.2	0.0
	1 month after	0.7	1.4	-0.3	0.1	-0.4	0.8
	6 months after	1.2	0.0	-1.1	0.7	-0.6	0.1
	1 year after	2.6	-0.5	-0.5	0.6	-1.8	0.2
	2 years after	4.2	-0.3	-1.8	1.6	0.5	1.9
5	1 week after	0.3	4.1	2.3	-0.5	0.0	5.2
	1 month after	0.1	0.2	0.0	-0.2	0.0	0.2
	6 months after	-0.1	0.4	-0.2	-0.2	0.1	-0.1
	1 year after	0.2	0.1	-0.4	0.6	-1.1	-0.4
	2 years after	-0.1	0.4	1.1	0.5	-2.8	-0.8
6	1 week after	0.0	0.0	0.0	0.1	0.0	0.1
	1 month after	0.0	0.0	0.0	-0.2	0.0	-0.2
	6 months after	-0.3	0.3	0.3	-0.2	0.0	0.1
	1 year after	-0.4	-0.2	0.3	0.3	-1.1	-0.9
	2 years after	-1.1	-0.2	0.5	-0.1	-2.7	-3.2
7	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.0	0.1	0.0	0.0	0.0	0.1
	6 months after	0.0	0.4	0.0	0.0	0.0	0.4
	1 year after	0.0	0.3	0.0	0.0	-0.1	0.1
	2 years after	0.0	-0.1	0.0	0.0	-0.1	-0.2

Table A5.5.4: BHRs per Industry (continue)

		Positive		Neutral	Negative		Total
Sector		1	2	3	4	5	
	1 month after	0.0	0.1	0.1	0.0	-0.3	-0.1
	6 months after	0.1	0.1	0.1	0.0	-0.5	-0.3
	1 year after	0.2	0.1	0.2	-0.1	-0.2	0.2
	2 years after	0.4	0.0	0.4	-0.1	-1.7	-1.1
9	1 week after	0.1	0.0	0.0	0.0	-0.1	-0.1
	1 month after	0.1	0.0	0.0	0.0	-0.2	-0.2
	6 months after	0.1	-0.1	-0.1	0.0	-0.6	-0.6
	1 year after	0.3	0.1	0.1	-0.1	-0.3	0.1
	2 years after	0.6	0.0	0.7	-0.1	-2.1	-0.9
10	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.2	-0.1	-0.1	0.0	0.1	0.1
	6 months after	0.1	-0.1	0.1	0.1	0.1	0.2
	1 year after	0.3	0.0	0.0	0.2	0.0	0.5
	2 years after	0.3	0.4	0.4	0.2	0.0	1.1
11	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.2	-0.1	0.0	0.0	0.0	0.1
	6 months after	0.1	-0.2	0.3	0.1	0.1	0.4
	1 year after	0.3	-0.1	0.2	0.2	0.2	0.7
	2 years after	0.2	0.3	0.2	0.2	0.4	1.2
12	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.0	-0.1	0.0	0.0	0.0	0.0
	6 months after	-0.1	0.0	0.1	0.1	0.0	0.1
	1 year after	0.0	0.1	0.2	0.2	-0.1	0.4
	2 years after	-0.1	0.2	0.2	0.1	0.0	0.4
13	1 week after	0.0	0.0	0.0	0.0	-0.1	-0.1
	1 month after	-0.2	-0.1	0.1	0.0	0.0	-0.2
	6 months after	-1.2	-0.2	-0.2	-1.4	0.0	-2.8
	1 year after	-1.4	0.2	-0.5	-1.7	-0.2	-3.3
	2 years after	-0.3	0.3	-0.4	0.2	0.1	-0.1
14	1 week after	0.0	-0.1	0.0	0.0	-0.1	-0.1
	1 month after	-0.2	-0.3	0.1	0.2	0.2	0.0
	6 months after	-1.1	-0.3	-0.3	-1.5	-0.2	-2.8
	1 year after	-1.3	-0.4	-0.4	-1.8	0.0	-3.2
	2 years after	0.2	-0.7	-0.5	0.5	-0.9	-1.2
15	1 week after	-0.1	0.0	0.1	0.0	0.0	-0.1
	1 month after	-0.1	-0.2	0.0	0.2	0.2	0.1
	6 months after	0.0	-0.2	-0.2	0.0	-0.1	-0.5
	1 year after	-0.1	-0.4	-0.2	0.1	0.0	-0.5
	2 years after	0.2	-1.0	-0.7	0.3	-0.9	-1.9

Table A5.5.4: BHRs per Industry (continue)

Sector		Positive		Neutral	Negative		Total
		1	2	3	4	5	
16	1 week after	0.0	0.1	0.0	0.0	0.0	0.1
	1 month after	0.1	0.0	0.0	0.0	0.1	0.2
	6 months after	0.3	-0.5	-0.3	-0.5	-0.8	-1.6
	1 year after	0.4	-0.9	-0.6	-0.9	0.0	-1.7
	2 years after	0.2	-2.4	-1.0	-1.4	0.1	-3.9
17	1 week after	0.0	0.1	0.0	0.0	0.0	0.1
	1 month after	0.1	0.0	0.0	0.0	0.1	0.2
	6 months after	0.4	-0.6	-0.3	-0.4	-0.7	-1.4
	1 year after	0.5	-0.8	-0.4	-0.9	0.1	-1.3
	2 years after	0.7	-2.5	-0.2	-1.4	0.2	-2.8
18	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.0	0.0	0.1	0.0	0.0	0.0
	6 months after	0.1	-0.1	0.0	0.0	0.0	-0.1
	1 year after	0.1	0.0	0.0	0.0	0.0	0.0
	2 years after	0.4	-0.3	0.3	0.0	0.1	0.5
19	1 week after	0.0	0.0	0.0	0.0	0.0	0.0
	1 month after	0.0	0.0	0.1	0.0	0.0	0.0
	6 months after	0.0	0.0	0.1	0.0	-0.1	0.0
	1 year after	0.0	0.0	0.1	0.0	0.0	0.0
	2 years after	0.0	0.1	0.2	0.0	0.0	0.3

APPENDIX A6: RESEARCH HYPOTHESES 8

Table A5.6.1: Optimal BHARs

Daily BHARs - Cover Stories

	Positive		Neutral	Negative		FM	FM	Total
	1	2	3	4	5	*FinWeek*	*Financial Mail*	
+2 days								
Mean	-0.2	0.0	-0.0	-0.1	0.1	-0.1	-0.1	-0.0
Median	0.0	0.0	0.00	0.0	0.0	0.0	0.0	0.0
Minimum	-27	-28.0	-4.1	-14.9	-5.0	-28.0	-28.0	-28.0
Maximum	3.5	12.5	6.3	6.3	12.5	12.5	12.5	12.5
Std-deviation	2.2	1.8	0.8	1.3	1.4	1.9	1.9	1.6
+28 days								
Mean	0.0	-0.1	-0.2	0.1	-0.0	-0.1	-0.1	-0.1
Median	0.0	0.0	0.0	-0.0	0.0	0.0	0.0	0.0
Minimum	-1.4	-35.8	-36.1	-1.6	-8.0	-36.0	-36.0	-36.0
Maximum	3.1	11.7	2.5	9.8	1.6	11.7	11.7	11.7
Std-deviation	0.5	2.1	2.5	0.9	0.8	1.8	1.8	1.7

t-test statistics-

	Skewness	Kurtosis	p-value	Reject Ho	
1 week after	-1.4	15.9	0.627	No	Different from 1- , 2 years after
1 month after	0.4	18.8	0.437	No	Different from 1- , 2 years after
6 months after	-30.0	20.3	0.001	Yes	Different from 1- , 2 years after
1 year after	-28.4	19.3	0.000	Yes	Different from2- ,28 days, 1 week and 1 month after
2 years after	-32.3	21.1	0.006	Yes	Different from2- ,28 days, 1 week and 1 month after
+2 days	30.0	21.7	0.086	No	Different from 1- , 2 years after
+28 days	24.7	20.5	0.010	Yes	Different from 1- , 2 years after

Anova	Skewness	Kurtosis	p-value	Hypothesis
	-73.7	52.8	0.000	Yes

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