

1. Introduction

In recent years, researchers have increasingly attempted to improve classical theoretical models by incorporating often neglected behavioural aspects. The growth in this non-traditional approach has been motivated by the need to explain regularly observed phenomena in financial markets which are incompatible with the predictions of classical financial models. Behavioural finance is a contemporary research stream, that studies human fallibility in competitive markets by integrating insights from psychology and sociology with neoclassical economic theory (Daniel, Hirshleifer & Subrahmanyam, 1998). Sentiment does not play any role in the classical financial framework, however, behavioural theorists suggest that waves of irrational sentiment - times of overly optimistic or pessimistic expectations - can persist and affect asset prices for significant periods of time (Schmelling, 2009). There is no single commonly accepted definition of investor sentiment however it can be defined as the component of investors' expectations about asset returns that are not justified by fundamentals (Black, 1986).

The relationship between sentiment and stock returns is at odds with classical financial theory that predicts that the stock price reflects the discounted present value of cash flows and there is no risk modification concerning investors' sentiment (Schmelling, 2009). Furthermore, classical financial theory contends that the influence of irrational investors on security prices is corrected by rational arbitrageurs who drive security prices back to their fundamental values (DeLong, Shleifer, Summers, Waldman, 1990). Thus, suboptimal trading behaviour such as paying attention to signals unrelated to fundamental value will be quickly eliminated in competitive financial markets. However, the inability of traditional asset pricing models to explain some of the most striking events in the history of the stock market has led to the emergence of a body of research which argues that some of the anomalies observed in the stock market can be attributed to noise created through trades which are motivated by sentiment (Black, 1986; Baker & Wurgler, 2006)

A number of studies have focused on the empirical relationship between investor sentiment and stock returns, however the results of these investigations have often

been mixed. Clarke and Statman (1998) note that the sentiment indicator published by Investors Intelligence provides no indication of future stock price changes. Fisher and Statman (2000) studied the sentiment of three groups of investors: Wall Street strategists, small investors and newsletter writers. The authors find that the sentiment of both small investors and Wall Street strategists were reliable contradictory indicators for future S&P 500 stock returns, but found no statistically significant relationship between the sentiment of newsletter writers and stock returns. Recently, Baker and Wurgler (2006) noted that investor sentiment has a significant impact on the cross-section of stock returns. The authors note that investor sentiment has larger effects on stocks whose valuations are highly subjective and difficult to arbitrage. Motivated by these findings, we construct a sentiment index to analyse the role that investor sentiment plays in the South African stock market.

1.1. Research problem and hypothesis

Baker and Wurgler (2006) note that sentiment based mispricing is based on both an uninformed demand shock and a limit to arbitrage. Regarding the first element, uninformed demand shocks, Brown and Cliff (2005) argue that sentiment is most likely a persistent effect, such that demand shocks of uninformed noise traders may be correlated over time thus giving rise to strong and persistent mispricing. However, the second component, limits of arbitrage, deters informed investors from eliminating the mispricing (Black, 1986; Shleifer & Vishny, 1997). It is difficult to determine how long buying or selling pressure from overly optimistic or pessimistic noise traders will persist, however, every mispricing has to eventually be corrected such that one would observe low long run returns after periods of high investor optimism (Lemmon & Portniaguina, 2006). Empirical evidence does indeed indicate that there is a negative relationship between sentiment and stock returns (Brown & Cliff, 2005). We investigate this relation for the South African market, which leads to our first hypothesis:

Hypothesis 1: Investor sentiment predicts future aggregate market returns. The relation between sentiment and expected returns is significantly negative and robust to controlling for fundamental factors.

Researchers have recently shown that sentiment has a significant impact on the cross section of stock returns. More specifically, sentiment disproportionately affects stocks whose valuations are highly subjective and difficult to arbitrage. Baker and Wurgler (2006) extend the approach of Daniel and Titman (1997) and find that when sentiment is low, stocks that are smaller, more volatile, unprofitable, non-dividend paying, extreme growth and distressed have higher subsequent returns, whereas the patterns largely reverse when sentiment is high. Kumar and Lee (2006) observe that retail investors, who are commonly believed to be noise traders, frequently overweight value stocks relative to growth stocks. Moreover, the authors note that shifts in the buy-sell balance of these retail investors are positively correlated with returns of value stocks.

Barber, Odean and Zhu (2008) investigate the returns of stocks that are heavily traded by individuals in the U.S. The authors provide direct evidence that individuals are noise traders. The authors note that stocks that are heavily sold by individuals outperform stocks that are heavily bought by a substantial 13.5% the following year. The authors furthermore document strong herding behaviour among individual investors. Correlated trading by irrational investors seems to be the likely cause for these return differentials (Schmelling, 2009).

We thus test for such-cross sectional effects in the South African market, which leads to our second hypothesis:

Hypothesis 2: The effect of sentiment on returns is stronger for stocks that are hard to value or hard to arbitrage.

A significant proportion of the body of research that analyses the role of investor sentiment in asset pricing has focused on developed markets. In contrast to emerging markets, developed markets are believed to be more efficient when it comes to pricing assets. Emerging market investors may be highly influenced by social and cultural factors while their counterparts are more likely to base their investment decisions on the information available (Kang, Liu & Ni, 2002). Furthermore, developed market investors are believed to bear lower risk as a result of the information efficiency of

these markets (Risso, 2008b). For these reasons, the degree of influence of investor sentiment in emerging markets may differ from those of developed markets. This study intends to fill the gap by exploring the role of investor sentiment in emerging markets utilising the framework employed by Baker and Wurgler (2006). There are no published studies that have constructed a sentiment index solely utilising the proxies mentioned in this paper. Additionally, prior research on investor sentiment did not taken transaction costs into account.

2. LITERATURE REVIEW

The chapter begins with a review of classical financial theory and inherently includes a discussion on the Efficient Market Hypothesis and financial market anomalies. Thereafter the literature surrounding behavioural finance (with a specific focus on human behavioural theories and biases) will be analysed. Subsequently, behavioural portfolio theory as well as the Adaptive Market Hypothesis is discussed. Finally extensive analysis of investor sentiment and its influence on financial markets is reviewed.

2.1. Investor sentiment in classical finance

In classical finance there is typically no room for investor sentiment. The standard argument is that in highly competitive financial markets, suboptimal trading behaviour such as paying attention to sentiment signals unrelated to fundamental value will be quickly eliminated by aggressive arbitrageurs. Arbitrage can be described as a means to bring under or overpriced assets back to their fundamental values and consequently market efficiency. It relates to the simultaneous purchase and sale of the same or essentially similar security in two different markets for advantageously different prices (Sharpe & Alexander, 1990).

Classical financial theory essentially revolves around two fundamental premises, which when taken together implies the lack of prolonged arbitrage opportunities.

1. Financial markets are informationally efficient; and
2. Market participants are rational

The cornerstone of modern financial economics, the efficient market hypothesis (EMH), asserts that prices should reflect all available information about the fundamental value of the underlying security (Fama, 1970). Assuming frictionless markets, the price of a security should equal its fundamental value, defined as the discounted sum of future cash flows. This rationale implies that no long-term risk-

adjusted abnormal returns are possible as new information is directly assimilated into the price of a security. EMH is associated with the idea of a “random walk”, which in financial literature characterises a price series where all subsequent price changes represent random departures from previous prices. The theoretical foundation of EMH is based on three key arguments:

1. Investors are rational and value securities rationally;
2. In case some investors are irrational, their trades are random and cancel each other out without affecting prices; and
3. Rational arbitrageurs eliminate the influence of irrational investors on the market.

Fama (1970) defined three distinct levels at which a market might actually be efficient. The weak form of market efficiency states that future prices cannot be predicted by analysing past prices. If a market is weak form efficient, there is no correlation between successive prices, so that excess returns cannot consistently be achieved through the study of past price movements.

The semi-strong form of market efficiency provides that share prices adjust quickly to public information. Neither a fundamental nor a technical analysis based strategy will earn excess returns. However, those that have access to private information may be able to obtain superior returns.

Lastly, under strong form efficiency, share prices fully reflect both public and private information. Thus, no sustainable superior returns, after costs, can be achieved in the long run.

Consistent with the paradigm of market efficiency is the presumption that individuals behave rationally and fully take into account all available information in the decision making process. Thus, when new information about a security becomes available, rational investors will quickly respond, leaving no room for excess risk-adjusted returns based on the information signal. Through the forces of arbitrage and

incentives of self-interest, modern finance has traditionally assumed that irrational investors will be quickly eliminated from the market, along with risk-free profit opportunities.

In reality however, there are limits to arbitrage that may prevent rational arbitrageurs from taking advantage of market mispricing. As real life financial markets are far from perfect, these frictions may make it difficult to find and take advantage of perfectly substitutable assets (Shiller, 2000).

Nonetheless, even after transaction costs and fundamental risk are taken into account, classical financial theories have difficulty in explaining prolonged mispricing and unexploited arbitrage opportunities such as initial public offering (IPO) underpricing and closed-end fund discounts (Shleifer & Vishny, 1997). These financial puzzles provide evidence that markets may not always be informationally efficient.

2.2. Financial market anomalies

Classical asset pricing models like the capital asset pricing model (CAPM) of Sharpe (1964) and Lintner (1965) have long been a basic tenet of modern finance. However, subsequent work by researchers such as Basu (1977), Banz (1981), Jegadeesh and Titman (1993) and Fama and French (1992) suggests that cross-sectional differences in average returns are determined not only by market risk, as prescribed by the CAPM, but also by firm-level market capitalisation, book-to-market, and prior return. These empirical results are referred to as anomalies. Financial market anomalies describes a situation in which the performance of securities deviate from maintained theories of asset pricing behaviour thus indicating market inefficiency (profit opportunities) or inadequacies in the underlying asset-pricing model (Kahneman & Tversky, 1986). Below is a summary of several anomalies that impact financial markets.

2.2.1. Size effect

Banz (1981) wrote what is arguably the first empirical paper presenting evidence on the anomaly known as the size effect. He analysed the relationship between the total

market value of all common stocks of firms listed on the New York Stock Exchange (NYSE) and their returns for the period 1936 to 1975. Banz (1981) noted that small firms, or firms with small capitalisations on the New York Stock Exchange (NYSE) earned higher average returns than is predicted by the CAPM. Banz's rationale for the results is related to the investor recognition hypothesis developed by Merton in 1987. This hypothesis states that investors only buy and hold securities of which they have enough information. Therefore investors are reluctant to hold small firm stocks because of lack of information, this results in higher returns for these securities. Given the findings of Banz (1981), Reinganum (1981) conducted several tests to ascertain whether the size effect was related to other unexplained factors in stock return data. He analysed a sample of 566 NYSE and AMEX firms over the period 1963-1977. He combined the securities into portfolios with different E/P ratios but similar market value and observed that small firms produced higher returns on average than large firms. Thereafter, Reinganum (1981) did the reverse and combined the securities into portfolios with different market values but similar E/P ratios, it was noted that there was no separate E/P effect. Reinganum (1981) concludes that there is a relationship between size and E/P ratios, and that both the size effect and E/P effect are indications of deficiencies in the CAPM.

2.2.2. The turn of the year effect

Rozeff and Kinney (1976) began examining stock market anomalies related to months in the year. They documented significantly higher returns in January than in other months. This anomaly has become known as the "turn of the year effect" or the "January effect". Keim (1983) demonstrated a relation between market size portfolios and the January effect. Using data from 1963 to 1979 across NYSE and the American Stock Exchange (AMEX) he observed a negative relation between the size of a company and risk adjusted returns. Keim (1983) noted that that the risk-adjusted returns to a portfolio of small firm stocks are significantly greater in the month of January. Keim (1983) interestingly observed that almost 50 percent of yearly company returns were accrued in January and moreover, more than 50 percent of the turn of the year effect was due to exceptionally large returns during the first week of trading.

Furthermore, Roll (1983) confirmed the findings of Keim (1983), utilising data from 1962 to 1980, he demonstrated that January was the only month with an abnormal premium for small firms. He also noted that the last trading day in December and first four trading days in January are the days with the highest returns. Reinganum (1983) agreed with Keim (1983) and Roll (1983) about higher profits of small firms in the beginning of January. However, his study was more important in a different aspect, as he attempted to connect the tax-loss selling hypothesis with size portfolios.

Kiem (1983), Reinganum (1983) and Roll (1983) argue that small capitalisation stocks experience greater volatility which may result in these securities experiencing substantial short term capital losses. Investors wishing to lessen their tax burden will sell these securities before the year-end and thereafter repurchase the shares in the new year. This selling pressure drives the price of small capitalisation stocks downwards in December and subsequently there is a rebound in prices in early January as investors re-establish their investment positions. Reinganum (1983) however, notes that the January size effect is not completely explained by the tax loss-selling hypothesis. The tax loss-selling hypothesis could explain high returns at the beginning of January however the hypothesis could not explain the high returns for the entire month of January (Schwert, 1983).

No explanation, which would entirely clarify the causes of the January effect, has been unearthed thus far. The tax-loss selling hypothesis could partly justify some patterns in stock returns, but the entire January effect has remained unexplained (Brown, Keim, Kleidon & Marsh, 1983). More researchers have inclined to behaviourism and suggested psychological effects as main causes of January effect in stock returns, (Malkiel, 2003).

2.2.3. The Value Effect

Basu (1977) showed that stocks with high E/P ratios have higher average risk adjusted returns than stocks with low E/P ratios. This anomaly is known as the value effect. A number of papers thereafter have noted that portfolios with accounting values of measure, such as the book to market ratio or dividend yield produce positive abnormal returns. Ball (1978) concludes that this indicates deficiencies in the CAPM

rather than market inefficiency. He explains that the characteristics that would cause a trader following this strategy to add a firm to his or her portfolio would be stable over time and easy to observe. In other words, turnover and transactions costs would be low and information collection costs would be low. If such a strategy earned reliable abnormal returns, it would be available to a large number of potential arbitrageurs at a very low cost (Schwert, 2003).

2.2.4. The momentum effect

Jegadeesh and Titman (1993) observed what we now know as the momentum effect. They showed that past returns has a strong ability to predict future returns. A statistical analysis that they undertook indicated that a strategy of buying securities that performed well in the previous year and selling securities that did not perform so well resulted in abnormal returns of approximately 1% per month. DeBondt and Thaler (1985) observed the opposite of the momentum effect, termed the contrarian effect. They showed that securities that had low returns in the past three to five years (past losers) had on average greater returns than securities with high returns in the past three to five years (past winners). Fama and French (1996) test both these versions of momentum strategies using a three-factor model. They find no significant abnormal performance when testing the contrarian effect and they conclude that this is due to the similarities between past losers and small distressed firms. On the other hand they are unable to provide an explanation for the momentum effect that was observed by Jegdeesh and Titman (1993)

2.2.5. The weekend effect

Cross (1973) was one of the first researchers to report differences in returns on Fridays and Mondays compared to the rest of the week. With daily return data from 1953 to 1970 on the S&P 500, he found a statistically significant difference between Friday and Monday returns for almost every year in the sample period in both mean returns and in percentage of time that the index rose on that day. Subsequently French (1980) showed that the average returns to the S&P 500 composite portfolio exhibited relatively large returns on Fridays compared to Mondays for the period 1953 to 1977.

Utilising mean returns and variances for the S&P 500 from July 1962 to December 1978, Gibbons and Hess (1981) confirm the weekend effect found by Cross (1973). Moreover, Gibbons and Hess (1981) searched for possible explanations for the Monday effect and noted that the settlement period explains the more negative Monday returns before 1968 compared to the returns after 1968. The authors conclude that this is due to the settlement period being four business days prior to February 1968 and five business days after February 1968. Nonetheless, settlement period does not explain the negative Monday returns from February 1969 to December 1978.

French and Roll (1986) investigated the return variances of weekdays, weekends, holidays and holiday weekends by means of daily returns on the NYSE and AMEX from 1963 to 1982. They observed that the returns are more volatile during exchange trading hours compared to non-trading hours. The three possible explanations that were given by French and Roll (1986) for this are that public information (which causes the volatility) is announced more frequently during business days (weekdays), private information probably influences prices more when the stock markets are open and the process of trading itself causes volatility. French and Roll (1986) concluded that their results showed that only a small part of the difference in variances between trading hours and non-trading hours is caused by mispricing occurring during trading. The reason for this mainly lies in the difference in the quantity of information announced between trading hours and non-trading hours.

A number of researchers have postulated theories as to why this anomaly occurs; such as the tendency of corporations to release bad news after the market closes on Friday which depresses stock prices on Monday or that the effect is simply a reflection of traders' fading optimism over the weekend, but to date, no one has been able to come up with a satisfactory answer that explains this anomaly.

In an attempt to explain these financial market anomalies, researchers have increasingly relied on behavioural explanations that relax the strict rationality requisite of traditional financial theories. In particular, behavioural finance is a branch of research that studies human fallibility in competitive markets (Rabin, 1998). Behavioural finance analyses the impact that deviations in perfect rationality has on financial markets, security prices as well as the behaviour of other investors.

Furthermore, behavioural finance offers models that are much more flexible about investor behavior and in doing so, provides clarification for financial anomalies that traditional financial theories have not been able to explain. A brief summary of behavioural finance is provided in the following sub-section, with emphasis on its relevance to investor sentiment

2.3. Behavioural finance

Behavioural finance aims to integrate insights from psychology with neo-classical economic theories to explain pricing patterns that do not adhere to classical financial theories (Belsky & Gilovich, 1999). Behavioural finance relaxes the traditional assumptions of financial economics by incorporating observable, systematic and very human departures from rationality into standard models of markets (Barber & Odean, 1999). In essence, this financial theory contends that individuals do not always make investment choices on the basis of full rationality, and attempts to understand financial market phenomena by relaxing the following doctrines of the traditional paradigm, namely, (i) agents fail to update their beliefs correctly and (ii) there is a systematic deviation from the normative process in making investment choices. (Kahneman & Tversky, 1986).

Research in the field of behavioural finance examine emotions, biases and social norms in order to better understand an individual's decision-making process comprising the emotional and affective side in the dual process theory (Kahneman, 2003).

2.3.1. The Dual process theory and rationality

The idea of dual process theories in psychology dates back to Schneider and Shiffrin (1977a, 1977b) who used a series of experiments to contend that there are two processes that help in decision making, intuition and reasoning. Kahneman (2003) refers to this dual process theory as human behaviour following cognition on the one hand and affection on the other. Cognition and reasoning follows a rational way to form decisions contrasting with affection and intuition, which are emotion driven.

Due to an individual's bounded mental capacity, the importance of intuition and affection in decision making increases with task complexity. As intuitive decisions require less mental capacity, they are formed quickly, automatically and effortlessly (Khaneman, 2003). However, these decisions are also emotional, thus sentiment driven, and often forms the basis for financial decisions in security investments. Intuitive decisions are filled with biases and errors (Loewenstein, 1998). These biases and errors in human judgments lead to systematic irrationality in investing thus resulting in divergence from the EMH and forming the foundation for investor sentiment.

2.4. Human Behavioural Theories

Theories and models of human behaviour emanate from all disciplines of the social sciences..Human behaviour is influenced by a range of aspects, such as culture, attitudes, emotions, values as well as ethics (Watson, 1913). Evolutionary ideas of human behaviour have played an important role in economics as well as finance. A number of studies have been conducted exploring the connection between economics and human behaviour: economic extensions of sociobiology (Becker, 1976), evolutionary game theory (Smith, 1982), an evolutionary interpretation of economic change (Nelson & Winter, 1982), economies as complex adaptive systems (Anderson, Arrow & Pines, 1988), and the impact of uncertainty regarding the number of offspring on current consumption patterns (Arrow & Levin, 2009). Human behavioural theories that are pertinent to this study are discussed in the section below.

2.4.1. Expected utility theory

Expected utility theory refers to a hypothesis concerning people's preferences to choices that have uncertain outcomes (Schoemaker, 1982). Bernoulli (1954) introduced the notion of expected utility as the Saint Petersburg paradox. The Saint Petersburg paradox is a theoretical game used in economics, to represent a classical example were, by taking into account only the expected value as the only decision criterion, the decision maker will be misguided into an irrational decision. Expected utility theory consists of two components. The first component is that people use or

should use the expected value of the utility of different possible outcomes of their choices as a guide for making decisions. Bernoulli (1954) argues that individuals tend to maximise their wealth rather than maximise their expected monetary payoff. Hence, expected utility theory is able to describe realistic scenarios more accurately than expected value alone (Bernoulli, 1954). In the presence of risky outcomes, individuals could use the expected value of utility criterion as a rule of choice: higher expected utility investments are preferred.

The second component of expected utility theory is the idea that more of the same creates additional utility only at a decreasing rate. This insight is referred to as decreasing marginal utility. The combinations of these two components generate the theory of expected utility.

Von Neuman and Morgenstern (1944) develop the theory of rational decision making under uncertainty. Von Neuman and Morgenstern (1944) make several precise assumptions about an individual's behaviour and refer to these assumptions as axioms. The four axioms provide the minimum set of conditions for consistent and rational behaviour. The axioms are namely: completeness, transitivity, continuity and independence.

1. Completeness: An individual has well defined preferences;
2. Transitivity: An individual's preferences is consistent amongst any three options;
3. Continuity: there is a tipping point between being better than and worse than a given middle option; and
4. Independence: a preference holds independently of the possibility of another outcome

These axioms accompanied with the utility function formulae described by Von Neuman and Morgenstern (1944) serve to provide conditions describing when the expected utility hypothesis holds. Based on the work of Bernoulli (1954) and Von Neuman and

Morgenstern (1944), an individual will choose one gamble over another if, and only if, there is a utility function that shows that the expected utility of one gamble exceeds that of the other.

The expected utility theory has been very useful to economist and financial researchers, however the theorem does have several real life limitations. Rabin and Thaler (2001) criticise the theory's ability to explain real life choices. Rabin and Thaler (2001) assert that within the expected utility framework, for any concave utility function, even very little risk aversion over modest stakes implies an a significantly large degree of risk aversion over large stakes, which is simply not realistic.

Allais (1953) contends that the axiom of independence is commonly violated. The axiom of independence states that a choice (preference) will hold independent of the possibility of another outcome. Allais (1953) performed tests to see if the axiom of independence was violated in a set of lotteries. In the experiment, participants were asked to choose between two lotteries, each representing different potential payouts and their respective probabilities. Thereafter, the participants were asked to choose among another set of lotteries with differing payouts and probabilities.

Allais (1953) observed that the participants were not able to evaluate the lotteries independently from each other – choices were influenced by the outcome of another lottery. The main findings, of what is now known as the “Allais Paradox”, are that participants made inconsistent, irrational choices. These irrational choices could simply be due to errors in judgment made by individuals, but several researchers contend that outside factors not accounted for in the utility function, such as hope, fear and suspense could influence the decisions that individuals make (Markowitz, 1959).

Kahneman and Tversky (1979) maintain that there are two significant aspects that expected utility theory does not account for. Namely:

1. The isolation effect: investors usually disregard the common characteristics of the different prospects; and

2. The certainty effect: investors consider highly likely events as definite and disregard events that seem unlikely.

Kahneman and Tversky (1979) develop an alternative to expected utility theory called Prospect Theory. Prospect Theory seeks to compensate for the limitations of expected utility theory to better explain how individuals behave in reality when making decisions (Kahneman & Tversky, 1979).

2.4.2. Prospect theory

Prospect theory, in essence, attempts to describe the apparent irregularity in human behaviour when assessing risk under uncertainty. Kahneman & Tversky (1979) contend that human beings are not consistently risk-averse; rather they are risk-averse in gains but risk-takers in losses. Individuals place more weight on the outcomes that are perceived more certain than those that are considered merely probable, a feature known as the certainty effect. People's choices are also affected by the 'Framing effect'. Framing refers to the way in which the same problem is worded in different ways. Framing can influence the decisions of an individual in such a way that the classical axioms of rational choice do not hold.

There are two stages involved in prospect theory, namely: the editing phase and the evaluation phase.

1. Editing, this refers to how investors structure prospects according to a certain reference point by arranging and simplifying investment choices. The reference point for an investment's performance is usually the purchase price of a security. There are six distinctive steps related to editing
 - I. Coding – recognise whether an outcome is a gain or a loss
 - II. Combination – combine probabilities with identical outcomes
 - III. Segregation – segregate riskless from risky prospects
 - IV. Cancellation – cancel variables where probabilities and outcomes are the same in both prospects

- V. Simplify – round up or down
 - VI. Exclude dominated items – throw out choices strictly dominated by another
2. Once an individual has simplified their choices as much as possible, they move on to the evaluation phase. This is where individuals evaluate the prospects and choose the one comprising the highest value. An investor gives a certain weighting to each decision, calculates the value (decision tree), and chooses the decision with the highest expected outcome. The weight given to each decision is what ultimately determines the utility function and decision made. Investors at this stage tend to be risk averse in terms of gains and risk seeking in terms of losses. Additionally, investors may consider highly likely events as definite and ignore events that seem unlikely.

Prospect theory is not a solution in itself; rather it is a way to more accurately decipher an individual's utility curve by relaxing the tenets that underlie rationality (Barberis & Thaler, 2001).

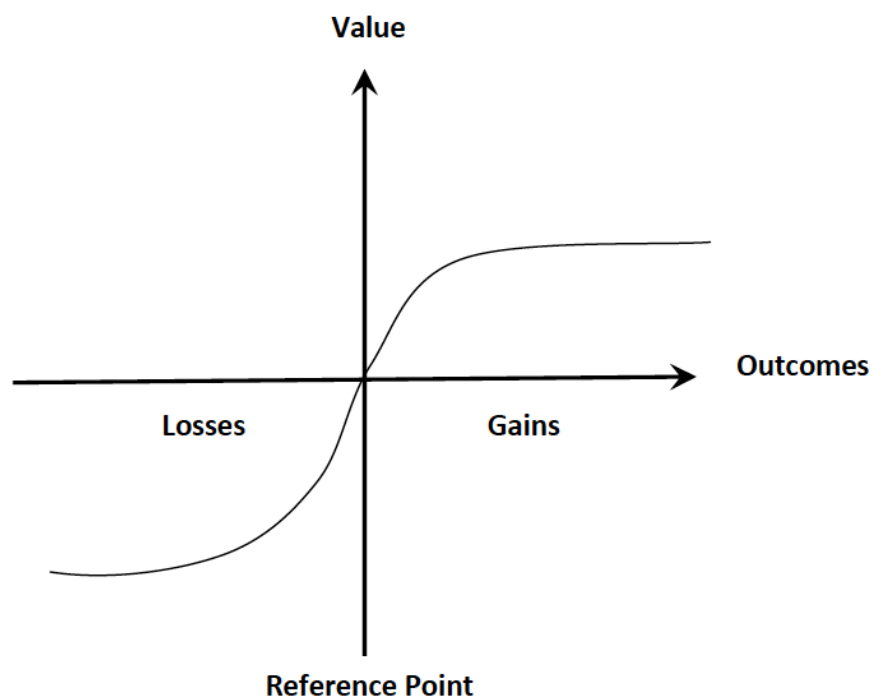


Figure 1 – Hypothetical value function.

The central element of prospect theory is the S-shaped value function curve depicted in Figure 1 above. The value function is defined in terms of change in wealth rather than final states. The shape of the function is concave in the region of gains and convex in the region of losses, reflecting risk aversion in the domain of gains and risk seeking in the domain of losses.

Prospect theory argues that when individuals choose between gambles, they compute the gains and losses for each one and select the one with the highest prospective utility. In a financial context this implies that an individual may choose a portfolio allocation by calculating, for each portfolio, the potential gains and losses in the value of their holdings, and then selecting the allocation with the highest prospective utility.

2.5. Heuristics

Heuristics are simple rules of thumb, which have been proposed to explain how people make decisions and solve problems, typically when facing complex problems or incomplete information (Kahneman & Tversky, 1981). They enable investors to reduce the complexity of decisions and quicken the decision making process. These rules of thumb may result in acceptable, economical and efficient solutions, but they often can lead to mental errors or cognitive biases (Kahneman & Tversky, 1981). Behavioural biases are generally classified as being of either a cognitive or emotional type. A summary of the most prominent biases are discussed below.

2.5.1. Cognitive biases

2.5.1.1. Availability bias

The availability deviation refers to the tendency of people to judge the likelihood of an event by the ease with which they are able to recall similar events (Kahneman & Tversky, 1974). Easily recalled events are considered more probable than those they can hardly imagine or perceive. Availability bias declares the person's tendency toward deciding and judging based on available and easily accessible information (Kahneman & Tversky, 1982). When sufficient information is not practically available, the investor's decisions face deficiency (Montier, 2002). An investor who does not dedicate the necessary time to understand all aspects of the information (both

good and bad) may make an incorrect decision based upon limited information.

2.5.1.2. Representativeness

The representative heuristic is used when making judgments about the probability of an event under uncertainty. The bias refers to investors determining the probability of an event by looking at comparable, known events and assuming that the probabilities are similar (Montier, 2002). Kahneman and Tversky (1972) defined representativeness as the degree to which an event (i) is similar in essential characteristics to its parent population, and (ii) reflects the salient features of the process by which it is generated. When people rely on representativeness to make judgments, they are likely to judge wrongly because the fact that something is more representative does not make it more likely (Kahneman & Tversky, 1982).

2.5.1.3. Disposition effect

The disposition effect relates to the tendency of individuals to sell securities that have risen in their portfolio since purchase, while keeping assets that have dropped in value (Shefrin & Statman, 1985). The disposition effect is one of the most robust behavioural regularities documented in studies of trading behaviour. It imposes substantial costs on investors and the market as a whole. Systematic disposition behaviour by many investors can affect trading volume and drive a wedge between market prices and fundamental values.

Shefrin and Statman (1985) compose a theoretical framework with four aspects that underlie the disposition effect. The first is prospect theory. An investor with preferences given by prospect theory would become more risk averse after experiencing gains and more risk seeking after experiencing losses (Kahneman & Tversky, 1979). This implies that holding on to the investment becomes more attractive than selling if the value of the investment decreases because the investor is willing to tolerate more risk.

The second aspect is mental accounting. It describes people's tendency to organise

some sources and uses of money in different psychological accounts in their mind. An individual may treat money received as a salary different from money received as a gift. This is often harmless, however, as people tend to consider these mental accounts separately, they may often lose sight of what is best for their overall financial well-being (Shefrin & Statman, 1985).

The third aspect that Shefrin and Statman (1985) propose is regret aversion. Closing a stock position at a loss and thus having to admit a mistake may cause regret over the initial decision to buy the stock.

The final aspect proposed by Shefrin and Statman (1985) is self-control. Self-control explains why the disposition effect is weaker at the end of the year. Investors may find getting rid of loss-making stocks easier when faced with explicit self-control mechanisms, such as the end of the tax year.

2.5.1.4. Confirmation bias

Confirmation bias (also called confirmatory bias) is a tendency for people to favour information that confirms their preconceptions or hypotheses regardless of whether the information is true (Baron, 2000). As a result, people gather evidence and recall information from memory selectively, and interpret it in a biased way. The biases appear in particular for emotionally significant issues and for deeply entrenched beliefs. An individual who decides upon a course of action or makes a decision will look for evidence to support their decision while either discounting or ignoring evidence to the contrary. This bias may influence another type of bias, anchoring.

2.5.1.5. Anchoring

The anchoring effect is a cognitive bias that describes the common human tendency to rely too heavily on the first piece of information received (Kahneman & Tversky, 1974). People who exhibit this bias are slow to adapt new information into future forecasts and expectations. This bias results in individuals weighting prior beliefs and knowledge more heavily than new information.

2.5.1.6. Conservatism

Conservatism bias is a mental process in which people cling to their prior views or forecasts at the expense of acknowledging new information. Once a position has been stated most people find it very hard to move away from that view even when they are presented with new data. When movement does occur it is only very slow which creates under-reaction to events. This slowness to revise prior probability estimates is known as conservatism. Anchoring and conservatism may be influenced by the status quo bias, which is an individual's preference for the current state rather than change (Kahneman, Knetsch & Thaler, 1991).

2.5.1.7. Illusion of money

In economics, money illusion, or price illusion, refers to the tendency of people to think of currency in nominal, rather than real, terms. For instance, a bond that is yielding 5% may be quite attractive in nominal terms, but if inflation were also at 5%, the real return would be 0%. This cognitive error could cause investors to overestimate the future purchasing power of their investments.

2.5.1.8. House money effect

The house money effect refers to the tendency of investors to take greater risks when investing with profits. The house money effect forecasts that investors are more prone to buy higher-risk stocks after a profitable trade (Thaler, 1990). The house money effect is an example of mental accounting, whereby capital is kept separate from recent profits, leading investors to view said profits as disposable. As a result, they are more inclined to take greater risks with the money.

2.5.1.9. Mental accounting

Mental accounting is the set of cognitive operations used by individuals and households to organise, evaluate, and keep track of financial activities. Mental accounting is an economic concept, which contends that individuals divide their current and future assets into separate, non-transferable portions (Thaler, 1980). The

theory purports that individuals assign different levels of utility to each asset group, which affects their consumption decisions and other behaviors.

2.5.1.10. Myopia

This bias is commonly combined with that of loss aversion, as they often occur together. Myopic investors require constant feedback with respect to the performance of their accounts, and are likely to view their account balances and security holdings often (Benartzi & Thaler, 1995). This could encourage an investor to make investment decisions based upon short-term portfolio performance in order to appease their emotions, even if the ultimate goal is years away.

2.5.1.11. Overconfidence

Individuals have a tendency to be overconfident about their own abilities and knowledge. A person with overconfidence bias has greater confidence in his judgments than his actual accuracy. This is dangerous because it hinders an investor's rational decision making. Nofsinger (2001) states that overconfidence causes people to overestimate their knowledge, underestimate risks, and exaggerate their ability to control events. Shefrin (2000) argues that there are two main implications of investor overconfidence.

First, investors take bad bets because they fail to realise that they are at an informational disadvantage. Second, overconfident investors trade more frequently than is prudent, which leads to excessive trading volume. Overconfident investors trade more, believe returns to be highly predictable and expect higher returns than what less confident people do (Lewellen, 1977). Barber and Odean (1999) conducted a study on the trading behaviour of households and found that households that trade frequently earn much lower net annualised geometric mean returns than those that trade infrequently. Barber and Odean (1999) conclude that overconfidence has a detrimental effect on an individual's financial well being.

2.5.2. Emotional biases

2.5.2.1. Loss aversion

Loss aversion refers to people's tendency to strongly prefer avoiding losses to acquiring gains (Kahneman & Tversky, 1979). This bias recognises that people interpret outcomes as gains and losses relative to a reference point and are more sensitive to losses than to absolutely commensurate gains. Loss aversion leads investors to take greater risks when facing losses, while locking in profits quickly when faced with gains to avoid potential future losses from that security. This emotional bias results in investors experiencing poor investment returns (Pompian, 2006).

2.5.2.2. Pride/Fear of regret

Investors exhibit this bias when their choices are driven by the delight and instant gratification they get from selling a security that has a gain, and the desire to not experience the pain from selling a security that has a loss (Graham & Sugden, 1982). Both pride and regret cause similar results to loss aversion but for different reasons. Similar to loss aversion, pride and regret cause investors to sell winners quickly to experience the pride of having made a profitable investment and hold on to losers as investors do not want to experience the regret of having made a poor investment decision. Studies have shown that individual who are quick to sell winners and slow to sell losers tend to have below average portfolio returns (Odean, 1998).

2.5.2.3. Optimism

The optimism bias (also referred to as unrealistic or comparative optimism) is a bias that causes a person to believe that they are less at risk of experiencing a negative event compared to others (Neil & Klein, 1996). An optimistic investor is one who believes that whatever decisions they make will turn out to be good ones. An optimist may choose to ignore bad news or negative information that they believe is just a pessimistic outlook. Additionally, an optimistic investor may also be subject to the bias of overconfidence. Optimism may cause an investor to fail to realise the potential

downside of their holdings, and therefore underestimate the risk of loss (Alexander, 1993).

2.5.2.4. Aversion to ambiguity

Aversion to ambiguity is very similar to the status quo bias. People who have this bias prefer the familiar to the unfamiliar, even if the familiar is not a favourable outcome (Shefrin, 2000). Ellsberg (1961) famously proposed an experiment the results of which have become known as the Ellsberg paradox. When making decisions under uncertainty people have been found to prefer options involving clear probabilities (risk) to options involving vague probabilities (ambiguity), even if normative theory (Savage, 1954) implies indifference. This phenomenon is referred to as ambiguity aversion (Ellsberg, 1961). Ambiguity aversion has been shown to be economically relevant and persistent in financial markets (Sarin and Weber, 1993).

2.5.2.5. Endowment effect

The endowment effect is the hypothesis that people ascribe more value to things merely because they own them. An investor would place a higher value on what they own than the market does. This leads to an investor not getting a fair price and holding onto an asset that may not be a good fit for their risk profile (Plott & Zeiler, 2005).

2.5.2.6. Hindsight bias

Hindsight bias, also referred to as creeping determinism, is the inclination to see events that have already occurred as being more predictable than they were before they took place. Fischhoff (1975) and Fischhoff and Beyth (1975) conducted the first studies on hindsight bias. Fischhoff (1975) noted that receipt of outcome knowledge affects individuals judgments in the direction predicted by the tendency to perceive reported outcomes as having been relatively inevitable. This tendency was referred to as creeping determinism. Fischhoff (1975) concluded that unperceived creeping determinism could seriously impair one's ability to judge the past or learn from it.

The effect of hindsight bias on learning has substantial consequences as hindered learning leads to increased overconfidence (Biais & Weber, 2008). Buksar and Conolly (1988) illustrate that hindsight bias hinders learning from past experience. Camerer, Lownstein and Weber (1989) contend that hindsight bias narrows the gap between what occurred and what predictions are recalled, reducing valuable feedback and inhibiting learning. Biais and Weber (2008) argue that hindsight bias hinders learning and leads individuals to underestimate volatility, which ultimately results in inefficient portfolio choice, loss making trades and poor risk management. An explanation provided for hindsight bias is the availability heuristic: the event that did occur is more salient in one's mind than the possible outcomes that did not.

Behaviour triggered by hindsight bias is also recognised in studies observing other biases. In a study on judgmental errors in economic settings, Camerer et al. (1989), discover that asymmetric information is not always beneficial for the better-informed agent, which violates the common assumption of economic analyses. This outcome is known as the curse of knowledge. According to Camerer et al. (1989), the curse of knowledge effect may influence an individual's decision making under uncertainty. Exaggerating the predictability of events intensifies the regret people feel when choices yield outcomes worse than those that would have resulted from forgone options. This is in line with hindsight bias, as people believe that they knew that the outcome would occur and question why they did not act correctly. In a similar vein, Bukszar and Conolly (1988) present that when outcomes are poor, then, people's evaluations of earlier decisions tend to be biased in an unflattering direction.

Hindsight bias additionally has an impact on performance evaluation in the principal agent relation. Mangelsdorff and Weber (1998) show that, in a principal agent relation, hindsight bias will prevent the principal from correctly evaluating the performance of the agent. According to Biais and Weber (2008), biased principals fail to remember what was known when the agents' decision was taken.

2.5.2.7. Self-attribution bias

Self-attribution bias occurs when people attribute successful outcomes to their own skill but blame unsuccessful outcomes on bad luck (Shefrin, 2000). People are prone

to attribute success to their own dispositions and failure to external forces. Self-attribution bias affects the perception about one's own capabilities as it hinders the evaluation of past performance. This leads to overconfidence. According to Gervais and Odean (2001), who studied the effects of past results in traders' behaviour, success leads to increased overconfidence. When a trader is successful, he attributes a significant proportion of his success to his own ability and revises his beliefs about his ability upward too much, which increases overconfidence. Gervais and Odean (2001) additionally find that both volume and volatility increase with the degree of a trader's learning bias. As a result overconfident traders behave sub-optimally, thereby lowering their expected profits.

Deaves, Lüders, and Schröder (2005) study overconfidence in making stock market expectations among German financial professionals. Deaves et al. (2005) observe that the professionals are not just overconfident but their level of overconfidence increases after a successful forecast measured by a 90% confidence interval. Furthermore, the adjustment to a wider confidence interval after failure is smaller than the adjustment to narrower interval after success. This results in a psychological phenomenon named cognitive dissonance, which suggests that people prefer to forget their failures and rather remember their successes.

2.5.2.8. Snakebite effect

An investor who has a negative experience and reverts to a strategy that no longer reflects their needs and goals exhibits the snakebite bias (Kahneman & Tversky, 1979). An investor who makes poor decisions and has a bad investment experience may become more averse to risk or loss, thus reducing the probability that they reach their initial goals.

A behavioural trait that is not directly listed as a bias but is equally important in the decision making process, is how individuals act in the face of uncertainty. Investors do not only react to the current state of information, but they make decisions based upon what they perceive the future to be. Anticipatory feelings such as hope, optimism, fear, anxiety and suspense play a significant role in the decisions investors make. Caplin and Leahy (1997) conduct a study on the impact of anticipatory feelings

and find that conventional measures of risk underestimate the effect of uncertainty on asset prices. This could result in an investor making a decision contrary to the expected utility theory, not because of the current situation or any predictable bias, but due to the anxiety they feel about what may happen in the future.

2.6. Factors that influence people's exposure to behavioural biases

There are a number of demographic, socioeconomic as well as individual factors that influence individuals' cognitive biases. The two most studied and natural demographic factors are gender and age. Psychological research has established that men are more prone to overconfidence than women, particularly so in male-dominated realms such as finance. Barber and Odean (1999) find that men are more active traders, which serves as a proxy for overconfidence. These findings are supported by Lewellen, Lease and Schlarbaum (1977), who find that men have a stronger tendency to overconfident behaviour than women have. Korniotis and Kumar (2011) observe that older investors have better knowledge about investing and hold less risky and more diversified portfolios. Thus implying that overconfidence decreases with age. This observation however is found to be less apparent in the group of individuals with higher education and higher income.

2.6.1. Expertise

In economics literature, it is commonly believed that sophisticated individuals behave fundamentally differently, as they learn from past experiences to avoid biases. Furthermore, the behaviour of sophisticated individuals is believed to be influenced by higher incentives. However, there is no fully coherent evidence in financial and economic literature about the effects of expertise on behavioural biases.

Studies' comparing the decision making of financial market professionals to ordinary people find that whether or not professionals are less biased depends on the specific context of the study. Törnngren and Montgomery (2004) compared the overconfidence of stock market professionals and the general public. The authors concluded that both groups exhibit overconfidence, however stock market professionals overestimated

their ability by a greater margin. The results suggest that the information-based predictions of professionals do not outperform the simple heuristics used by the general public.

Haigh and List (2005) find that students more closely follow Bayes' rule, whereas floor traders at the Chicago Board of Trade are better at assessing the quality of public information and thus earning higher returns. Kaustia, Alho and Puttonen (2008) find that the expertise of professionals significantly attenuates behavioural biases. On a study analysing the anchoring effect, Kaustia et al. (2008), find that anchoring significantly impacts students' more than financial professionals.

2.6.2. Cognitive ability and individual thinking style

Similar to expertise, an individual's intellectual ability is found to decrease behavioural bias. Frederick (2005) analysed how the score of the cognitive reflection test (CRT)¹ explains an individual's decision-making process. Frederick (2005) concluded that CRT scores are predictive of the types of choices that feature prominently in tests of decision-making theories, such as expected utility theory and prospect theory.

In tests of time preference, Frederick (2005), observed that people who scored higher on the CRT were generally more patient. Indicating that their decisions implied lower discount rates. For tests assessing short-term choices between monetary rewards, the high CRT group was much more inclined to choose the later larger reward. Hence, implying that greater cognitive reflection fosters the recognition or appreciation of considerations favouring the later larger reward. In the test of risk preference Frederick (2005) found that in the domain of gains, the high CRT group was more willing to gamble, particularly when the gamble had higher expected value. For items involving losses, the high CRT group was less risk seeking; they were more willing

¹ The cognitive reflection test (CRT) refers to a test which is designed to measure an individuals cognitive ability using simple tasks for which intuition usually offers wrong answers but which can be solved by systematic thinking. An example of such a task is the 'bat and ball' problem (see Nagin and Pogarsky, 2003). A High CRT score refers to a tendency to think (rational system) whereas a low CRT score refers to impulsive decision making (experiential system).

accept a sure loss to avoid playing a gamble with lower (more negative) expected value. The observations of Frederick (2005) indicate that people with higher cognitive ability are capable of making more optimal decisions².

Psychological literature commonly states that people process information by two parallel, interactive systems: a rational system and an experiential system (Kahneman & Tversky, 1983; Weinberger & McClelland, 1990). Based on cognitive experiential self-theory, Epstein, Pacini, Denes-Raj and Heier (1996), present a test for cognitive ability called rational experiential inventory (REI). The test contains two dimensions, one measuring analytic-rational processing, and the other measuring intuitive-experiential processing.

The intuitive-experiential processing is measured using a scale called faith in intuition (FI). According to Epstein et al. (1996), strong experientiality (a high FI score) may interfere with logical thinking; that is, people who are strongly experiential tend to accept their heuristic thinking as rational. However, the use of heuristics does not necessarily lead to rational behavior (Kahneman & Tversky, 1974). Thus people with high FI scores are expected to be more exposed to behavioural biases.

Analytic-rational processing is measured using the need for cognition (NFC) scale of Cacioppo and Petty (1982). According to Cacioppo, Petty, Feinstein and Jarvis (1996) people with higher NFCs are found to do better on arithmetic problems, anagrams, trivia tests and university coursework, to be more knowledgeable, more influenced by the quality of an argument, to recall more of the information to which they are exposed, to generate more task relevant thoughts and to engage in greater information-processing activity. Hence, people with high NFC scores can be expected to be less exposed to behavioral biases.

2.7. Behavioural portfolio management

² For example Frederick (2005) found that only 31% of low CRT sample chose 15% change of \$1,000,000 (expected value \$150,000) over certain \$500. The respective proportion of high CRT sample was 60%.

Markowitz (1952) wrote the seminal paper on modern portfolio theory. Markowitz (1952) expanded on the work undertaken by Williams (1938), who asserted that the value of a security should be the same as the net present value of future dividends. Markowitz (1952) argued that since the future dividends of most securities are known, the value of a security should be the net present value of expected future returns. Markowitz (1952) focused on the portfolio as a whole rather than individual security selection. He noted that when forming a portfolio of financial securities, one should not only take into account the characteristics of the individual assets, but investors should consider the co-movements between the assets as well. Markowitz (1952) states that if one takes into account covariance's of assets when forming portfolios, investors will be able to construct portfolios that generate a higher expected return at the same level of risk or a lower level of risk with the same level of expected return (Mankert, 2006). Markowitz (1987) defines these portfolios that have the best possible expected levels of return for its level of risk as efficient portfolios. The expected value is often referred to as the mean value, as a result this type of optimisation is called the mean-variance optimisation (Salomons, 2007).

Modern portfolio theory contends that even though there are numerous irrational investors, rational investors arbitrage away any price distortions. This implies that prices fully reflect all available information. Behavioral portfolio management (BPM), a concept within the broader paradigm of behavioral finance, assumes most investors make decisions based on emotions and shortcut heuristics. It posits that there are two categories of financial market participants: emotional crowds and behavioral-data investors (BDIs). Emotional crowds are made up of investors who base decisions on anecdotal evidence and emotional reactions to unfolding events (Howard, 2013). Rational investors or BDIs are investors who base their investment decisions on the fundamentals of an asset.

Howard (2013) contends that emotional crowds dominate the determination of both prices and volatility, with fundamentals playing a small role. This means that more often than not prices reflect emotions rather than underlying value, a consequence of arbitrage failing to keep prices in line with fundamentals. As a result, price distortions are the rule rather than the exception to building superior investment portfolios. The impact of emotions and sentiment is present in every corner of the market, and should

be taken into account when forming investment portfolios (Howard, 2013).

2.8. Adaptive Market Hypothesis

The question of market efficiency has been a theoretical debate since the naming of the EMH by Fama (1965). Numerous studies conclude that markets are efficient and yet many others conclude that markets are inefficient. A new paradigm of thought emerged in Lo (2004, 2005) who introduced an alternative to the EMH. This Adaptive Market Hypothesis (AMH) would describe efficiency as the interaction of market participants. Hence, efficiency would be cyclical, limited by the nature of said participants and the environment this interaction occurs within.

The AMH emerged from principles in evolutionary biology, psychology and sociology. Although no definition akin to the EMH has been formalised, the AMH contends: “Prices reflect as much information as dictated by the combination of environmental conditions and the number and nature of ‘species’ in the economy” (Lo, 2005, p. 19). Species refers to market participants such as traders, asset managers and hedge funds. Thus, the efficiency of the market at any point in time is related to the factors of evolution and competition present.

The AMH presents a simple and pleasantly intuitive view of market efficiency. Market efficiency can be seen as cyclical. There are times of inefficiency and efficiency. For a market to become efficient, it must first be inefficient and vice versa. The influence of market participants (through trading or financial product innovation) influences this efficiency.

2.9. Investor sentiment and the noise trader model

Classical financial models argue that investor sentiment has no impact on security prices. Such theories mostly assume away or ignore investor sentiment, contending that cognitive biases and misguided beliefs that lead to suboptimal trading decisions will immediately be arbitrated away by aggressive arbitrageurs. However, recent empirical findings have shown that this is not always the case. In particular, individual investors are prone to biases, and in certain instances are likely to display

over-confidence, herding behavior, and speculation (Barberis & Thaler, 2001). This implies that even in highly competitive financial markets with a large number of participants, investors with suboptimal biases may not be completely eliminated through the process of arbitrage.

These findings directly challenge the concept of market efficiency. The EMH asserts that investors are rational and they value securities rationally. Rationality means two things. First, investors update their beliefs correctly by following Bayes' law when receiving new information. Second, investors make choices that are normatively acceptable in the sense that they are consistent with Savage's (1954) notion of Subjective Expected Utility (Barberis and Thaler, 2003). Hence, the EMH predicts that security prices are always correct, as they equal their fundamental value.

However, behavioural theorists argue that investors are not always rational. Investors often exhibit excessive optimism or pessimism in assessing asset values (De Long et al, 1990), and have the propensity to speculate (Baker and Wurgler, 2006). Black (1986) noted that noise traders trade on the basis of noisy sentiment rather than information, as if it is vital knowledge that would provide them with an advantage on the trading floor. Noise denotes information that has no fundamental component and hence it should not be utilised by rational investors to value financial assets. De Long et al (1990) describe two groups of investors in their noise trader model: noise traders and rational arbitrageurs. Noise traders form erroneous beliefs about the future distribution of returns on a risky asset.

Noise traders have the following characteristics:

1. They are subject to a number of behavioural biases such as overconfidence, conservatism, under reaction or overreaction in processing information and forecasting stock returns;
2. They form portfolios based on noise rather than information; and
3. They perceive risks incorrectly

As a result, noise traders may drive prices away from their fundamentals. In contrast, rational arbitrageurs are sophisticated investors who have rational expectations. They are assumed to be risk averse and have reasonably short investment horizons. Rational arbitrageurs particularly take into account the behaviour of irrational investors who may be prone to exogenous sentiment. Trading of rational arbitrageurs may bring prices back to their fundamentals and keep markets efficient.

The second assumption underlying the EMH is that investors' errors are uncorrelated. Proponents of the EMH argue that the trading behaviour of investors' is random and that they cancel each other out without affecting security prices. However, researchers have observed that investing in risky assets could be a social activity, investors' transactions are systematically correlated, and investors are subject to a number of judgment errors (De Long et al, 1990; Black, 1986).

Shiller (1984) emphasises the importance of social influences on an individual's investment decisions. Investors are exposed to information, often rumours or noise, provided by their family, friends, colleagues, and neighbours in casual chats, thus it is possible that an investor's behaviour would be influenced by social movements. Social influence could impact investor behaviour in two aspects. First, investor sentiment may impact the decisions of investors and drive up asset price. Second, the transactions of investors could be systematically correlated.

The final assumption of the EMH is that there are no limits to arbitrage. Mispricing cannot occur because arbitrageurs, who form fully rational expectations about security prices, can always bring prices back to their fundamental value. If the price of a security falls below that of the substitute portfolio, arbitrageurs sell the substitute portfolio and buy the stock until these two assets reach the same price, and vice versa. The noise trader model predicts that the impact of noise traders on asset prices would not be entirely countered by rational arbitrageurs because rational arbitrageurs face fundamental as well as noise trader risk. These risks would deter the willingness of arbitrageurs from betting against noise traders and limit the size of the arbitrageurs' initial positions, leaving the price deviating from its fundamental value.

Fundamental risk denotes the risk that new fundamental information may

unexpectedly arrive after an arbitrageur has taken his initial position. For example, an arbitrageur may sell short a particular security if he believes the security is selling above its expected value of future dividends. The arbitrageur hopes to make a profit when closing his position by buying back the security at a lower price in the future. The arbitrageur bears the risk that the realisation of dividends may turn out to be better than expected, thus he is responsible for the payment of the dividends to the investor from whom he borrowed the security for short selling. Miscalculation of the future dividends would result in an additional cash crunch for the arbitrageur

Additionally, the arbitrageur also bears the risk that new positive fundamental information may suddenly arrive. If new fundamental information unexpectedly arrives, the arbitrageur is likely to suffer a loss if this new information is positive and causes the price to rise above his short-selling price for his initial position. Fear of such a loss may limit arbitrageurs trading against noise even if an arbitrageur believes that current market prices are not in line with fundamental values.

The second risk that deters arbitrageurs from taking positions against noise traders is the noise trader risk. Noise trader risk is the risk incurred by arbitrageurs from the unpredictability of noise traders (De Long et al, 1990). If an arbitrageur short sells a security and plans to liquidate his position in the future, he bears the risk that the security may be even more overpriced in the future than today due to the increased bullishness of noise traders. The arbitrageur would suffer a loss if for some reason he has to liquidate his position before the price returns to fundamental value. The more unpredictable the future resale price is, the more noise trader risk is introduced to the market. The possibility that the mispricing being exploited by the arbitrageur worsens in the short run limits the arbitrageur's initial position and hence keeps him from driving the price entirely back to its fundamental value (De Long et al, 1990).

Noise traders' expectations of asset returns are sensitive to fluctuations in sentiment. Expected returns are over estimated in certain periods and under estimated in others, such that their trades are not randomly distributed across assets. Due to the correlation of sentiment across noise traders, this risk cannot be diversified away. This simply implies that limits to arbitrage may persist due to noise trader risk.

There are a number of additional real world factors that further limit arbitrage. The first factor is the length of the arbitrageur's horizon (De Long et al, 1990). Noise trading can more effectively drive prices away from fundamentals when arbitrageurs have shorter horizons. Generally, arbitrageurs have finite horizons due to the cost implications associated with arbitrage. Arbitrageurs pay fees in order to borrow cash or securities to implement their trades. The longer they take to close out their positions, the more fees they have to pay. Costly real-world arbitrage discourages arbitrageurs to trade and hence they fail to completely eliminate the long-term price divergence from fundamental values caused by noise trading.

The second factor is the ownership of the money that arbitrageurs use to engage in arbitrage (Shleifer and Vishny, 1997). Professional managers who engage in arbitrage usually act as agents for their investors. Investors quite often allocate their money to the funds managed by such arbitrageurs based on their past returns – performance-based arbitrage. When prices further diverge from fundamental values, the performance of arbitrageurs can get worse. It is at this time that arbitrageurs require additional capital to exploit such profit opportunities. However, investors might withdraw their money because of the observed bad performance of the arbitrageurs. This results in arbitrageurs becoming more constrained when they have the best opportunities to bet against this mispricing. Performance-based arbitrage amplifies the effect of noise trading in the market, especially when prices are significantly out of line and arbitrageurs are fully invested.

Lastly, market structure can also influence the effect of investor sentiment on the behaviour of security prices. In a market with a specialist market maker, investor sentiment does not affect return continuation because there is no under reaction to information in the order flow while in a market without a specialist market marker, higher investor sentiment is associated with higher return continuation because noise traders underreact to the information in the order flow (Deuskar, 2008).

As opposed to the traditional view that only changes in fundamental value or the discount rate explain stock return co-movements, the noise trader model implies that the correlated trading activities of unpredictable noise traders can additionally induce return co-movements. Thus indicating that security prices are determined by the

interaction of sophisticated arbitrageurs and unpredictable noise traders, in addition to macroeconomic variables and standard risk factors. In this manner, the noise trader theory provides leeway for the presence of investor sentiment.

Researchers however have noted that noise trading could have a severe impact on financial markets (De Long et al, 1990). Specifically if expectations about a persistent imbalance of the intrinsic value of an asset are widespread, this could result in a herding behaviour, which may not be outweighed by rational traders who attempt to restore prices to fundamental values. Excess optimism would result in increased trading, and subsequently prices would be pushed even further away from their fundamental values. The same principle applies when excess pessimism drives security prices far below their intrinsic value. Through the process of herding, noise traders could drive the price of securities unrealistically low or high and generate bubbles and crashes (Hirshleifer, 2001).

Nevertheless, despite the noise trader theory's implication on how market participants may respond to irrational noise traders, the model does not provide an explicit definition of investor sentiment or how sentiment as opposed to noise in general can impact market outcomes.

2.10. Defining investor sentiment

Researchers have broadly agreed that sentiment can be economically significant but the concept itself is still largely regarded as abstract. The crux of the problem is that, to date, there is no single commonly accepted definition of investor sentiment. Existing definitions of sentiment range from vague statements about investors' mistakes to specific psychological biases that are model-specific (Shefrin, 2007). Additionally, the term itself is subject to a wide spectrum of classifications and used in different ways by academic researchers, financial analysts and the media (Barberis, Shleifer & Vishny, 1998; Baker & Wurgler 2007).

Zweig (1973) contends that investor sentiment comes from investors' biased expectations on asset values. Black (1986) refers to investor sentiment as the noise in

financial markets. Lee, Shleifer and Thaler (1991) define investor sentiment as the component of investors' expectations about asset returns that are not justified by fundamentals. Baker and Wurgler (2004) note that investor sentiment generally refers to investors' propensity to speculate, or investors' optimism (pessimism) about stocks. Baker and Stein (2004) define investor sentiment as investors' misvaluation of an asset. Central to these definitions is that investor sentiment reflects the difference between what asset prices are and what asset prices should be. In a market with two groups of investors, assuming one holds rational expectations on an asset's value and the other makes biased valuations, investor sentiment reflects the valuation difference between the two groups of investors (Lee, Shleifer and Thaler, 1991; Baker and Stein, 2004; Brown and Cliff, 2005)

2.11. Sentiment proxies

Despite a growing body of literature on the influence of investor sentiment over the last two decades, there is still no consensus on the best method to measure investor sentiment. There are several proxies that researchers utilise to capture sentiment, but thus far there is no consensus about which one provides the best results (Baker and Wurgler, 2007). Investor sentiment measures employed generally fall into two categories: survey based and market based sentiment indices. Survey-based indices are obtained by directly polling the opinions or perceptions of investors through surveys and questionnaires. In contrast, market based indices seek to glean sentiment indirectly from financial proxies. Presented below is a review of several proxies that are utilised to measure sentiment.

2.11.1. Closed end fund discount

Zweig (1973) and DeLong et al. (1990) contend that if closed-end funds are partly held by individual investors, the average discounts of closed-end funds (measured as the average difference between the Net Asset Value (NAV) and the trading price of the fund) can effectively measure the degree of investor sentiment. When investors are optimistic about the fund's future, they will sell the fund with a premium or smaller discount, as they believe their holdings may be worth more in the future. However, if fund holders are pessimistic, they will sell their funds with a large discount as

compensation for the buyers. For these reasons, large discounts observed in a given period suggest that investors are bearish and small discounts indicate that investors are bullish. Consistent with this argument, Lee et al. (1991) indicate that fluctuations in these discounts are driven by changes in individuals' investor sentiments.

2.11.2. Trading volume

Jones (2001) and Baker and Stein (2004) suggest that turnover may reflect the sentiment of investors if short selling is constrained. Trading volume or market liquidity, measures the amount of funds available on the market. Unsophisticated traders are willing to add additional liquidity to markets only when they are optimistic about the future performance of the market. Thus irrational traders are more likely to trade when investor sentiment is high. Higher trading volume increases market liquidity and may induce overvaluation, which results in abnormally low subsequent returns. Hence, high turnover may have a negative influence on market returns.

2.11.3. Dividend premium

Baker and Wurgler (2004) define dividend premium as the difference between the average market-to-book ratios of dividend payers and non-dividend payers. Generally, dividend-paying stocks are perceived as less risky with more predictable future cash flows, as they are associated with larger and more profitable firms. As a result, demand for stocks with these characteristics is inversely related to the prevailing sentiment (Zaharieva, 2012).

2.11.4. Initial public offerings, first day returns and volume

The IPO market is often regarded as a reflection of the expectations and beliefs of investors with high first day returns reflecting investors' enthusiasm (Loughran and Ritter, 1997). Baker and Wurgler (2006, 2007) contend that firms are more likely to offer an IPO when investor sentiment is high. In such periods, investors are generally over-optimistic on the newly issued shares which may induce greater first day returns and provide additional benefit for newly listed firms. Hence, the underlying demand

for IPOs is perceived to be extremely sensitive to the prevailing sentiment in the stock market.

2.11.5. Equity issue over total new issues

Baker and Wurgler (2000) argue that the share of equity issues in total equity and debt issues could be utilised to capture investor sentiment. The authors contend that this measure indicates that rational managers take advantage of temporary mispricing in the stock market by issuing equity when stocks are overpriced. In their empirical study, the authors observe that high values of the equity share predict low market returns.

2.11.6. Consumer confidence index

A consumer confidence index reflects the combined expectations and the beliefs of investors on the fundamentals of the economy and markets (Li, 2010). Lemmon and Portniaguina (2006) and Qiu and Welch (2007) assert that a confidence index forms a direct measure of the general feelings of investors, and changes can measure the fluctuation of stock returns especially for small firms. A common approach in the literature is to use a combined sentiment index consisting of several sentiment proxies. Utilising such an index, Baker and Wurgler (2006) observe that investor sentiment has a significant effect on the cross section of stock returns.

2.12. Sentiment in the financial market

In a frictionless market, sentiment should have no impact on asset prices. Even if investor sentiment could cause asset prices to deviate from their fundamental values, arbitrageurs would eliminate the discrepancies immediately (Baker & Wurgler, 2006). However, in reality, there exist transaction cost and short-sales constraints. Such frictions limit arbitrage activities leading to investor sentiment affecting asset prices (Black, 1986; Schleifer & Vishny, 1997).

Researchers have utilised a multitude of factors to proxy investor sentiment. Zweig (1973) utilised close-end fund discounts as the measure of individual investor

sentiment, as individual investors are the major traders of closed-end funds. The author models two types of investors on the market: professionals and non-professionals. Non-professionals use unjustified information to form their expectations and affect security prices accordingly. As security prices deviate from their intrinsic values, professionals profit from the deviations and bring the security prices back to their fundamental values. Utilising weekly discount data of 24 closed-end funds over the period 1966 to 1970, Zweig (1973) notes that buy (sell) signals generated on the discount data can be used to form trading strategies that lead to superior returns on the Dow Jones Industrial average.

De Long, et al. (1990) contends that there are two types of investors: rational arbitrageurs who are sentiment free and irrational (noise) traders who are prone to exogenous sentiment. The trading of irrational investors creates risk (noise trader risk), and deters the arbitrage activities of rational investors. As a result, stock prices can diverge significantly from fundamental values even in the absence of fundamental risk. Moreover, noise traders, bearing a disproportionate amount of risk that they themselves create earn higher expected returns than rational investors. Lee, Shleifer and Thaler (1991) examine the proposition that fluctuations in discounts of closed-end funds are driven by changes in an individual investor's sentiment. The theory implies that discounts are high when investors are pessimistic about future returns and low when investors are optimistic. Average discounts exist because the unpredictability of investor sentiment creates a risk to holding a closed end fund in addition to the risk inherent in the fund's portfolio (Lee, Shleifer & Thaler, 1991). The authors employ monthly discount data in the period from July 1956 to December 1985, and construct a value-weighted index of discounts based on 20 closed-funds. The authors observe that discounts on closed end funds are indeed a proxy for changes in individual investor sentiment and that the same sentiment affects returns on smaller capitalisation stocks that are traded by individual investors.

Neal and Wheatley (1998) examine the forecasting power of three popular measures of individual investor sentiment: the level of discounts on closed-end funds, the ratio of odd-lot sales to purchases and net mutual fund redemptions. The authors confirm the results obtained by Lee, Shleifer and Thaler (1991) as they observe a positive relation between fund discounts and small firm expected returns, but no relation

between discounts and large firm expected returns. This is consistent with the investor sentiment hypothesis as small firm stocks are generally held by individuals, while large firm stocks are mostly held by institutions (Lee, Shleifer & Thaler, 1991). Additionally the authors find reliable evidence that net redemptions predict the size premium whereas there is no indication that the odd-lot ratio predicts either small or large firm returns.

Swaminathan (1996) confirms the relationship between closed-end fund discounts and small firm returns but additionally notes that the information contained in closed-end fund discounts is related to expectations on future earnings growth and inflation. Thus suggesting that investor sentiment may not be the sole reason explaining the relation between closed-end fund discounts and small firm returns. Elton, Gruber and Busse (1998) observe that sentiment index computed from closed-end funds over the period 1969 to 1994 are not priced factors in the return generating processes, suggesting that investors do not care about sentiment.

Baker and Stein (2004) contend that in a world with short sales constraints, market liquidity can be utilised as a sentiment indicator. The authors contend that an unusually liquid market is one in which pricing is being dominated by irrational investors, who under react to information contained in equity issues. Thus high liquidity is an indication that the sentiment of these irrational investors is positive, and that expected returns are therefore abnormally low. Since there are short sales constraints on the market, rational investors cannot counteract the overconfident investors' transactions.

Recently studies have begun to focus on the characteristics of firms that are affected by sentiment. Baker and Wurgler (2004) argue that investor sentiment affects asset prices through two distinct channels: I) cross-sectional variation in sentiment, and II) variation in the difficulty of arbitrage. The authors construct a composite sentiment index based on the following proxies: The closed-end fund discount, the number of IPOs, turnover, the initial returns of IPOs, the equity shares in new issues and the dividend premium. The authors posit that the time-series relation between investor sentiment and expected stock returns is greater on stocks that are vulnerable to

sentiment waves and are difficult to arbitrage. The authors hypothesise that stocks of low capitalisation, unprofitable, non-dividend paying, young, distressed, high volatility or growth are likely to be disproportionately sensitive to broad waves of investor sentiment. These stocks are difficult value, and furthermore, are rarely monitored by arbitragers (Shleifer & Vishny, 1997; Baker & Wurgler, 2007). For this reason, such stocks are more likely to be influenced by changes in sentiment. Consistent with their predictions, the authors observe that these stocks earn high future returns when their beginning of period proxies for investor sentiment are low, and the patterns attenuate when the beginning of period sentiment proxies are high.

Baker, Wurgler and Yuan (2009) apply the methodology developed by Baker and Wurgler (2006) to a study of global markets. The authors include both global and local factors to determine the impact that sentiment has across various countries, and to measure the contribution of the global component of sentiment on the stock pricing mechanism of highly integrated markets. Consistent with previous research, the study supports the theory that stocks that are difficult to value and arbitrage tend to be more influenced by the fluctuation of sentiment.

Additionally, researchers have observed that information contained in survey results are useful predictors of stock returns. Fisher and Statman (2003) study the confidence measures of the Conference Board and University of Michigan as well as the investor sentiment measures of the American Association of Individual Investors and Investor's Intelligence. The authors find that an increase in the consumer confidence index is associated with an increase in the bullishness of individual investors.

Utilising survey data, Brown and Cliff (2004) examined the forecasting power of several investor sentiment proxies proposed in prior research. In contrast with previous studies, the authors constructed a single sentiment index, employing principle component analysis to abstract the correlated among several sentiment proxies. Moreover, the authors employ Vector Auto Regression (VAR) methods to investigate the casual relationship between expected returns and a sentiment index. The authors find that many commonly cited indirect measures of sentiment are related to direct measures (surveys) of investor sentiment. Furthermore, the authors note that

even though changes of sentiment levels are strongly correlated with contemporaneous market returns, the predictive power in a sentiment index for near-term future stock returns is relatively weak. The evidence presented in this study does not support the conventional wisdom that sentiment primarily affects individual investors and small stocks.

Brown and Cliff (2005) provide evidence that sentiment affects asset valuation. The authors indicate that excessive investor optimism leads to periods of market overvaluation followed by low cumulative long run return as valuation levels return to intrinsic value. Verma and Soydemir (2006) studied the contagion effects of U.S. institutional and individual investor survey sentiment on international stock market returns. The authors find that U.S. investor sentiment has significant influence on international stock market returns, however the effect of sentiment on stock market returns differs according to a country's trade ties with the U.S. and its institutional structure. Lemmon and Portniguina (2006) noted that the consumer confidence index is useful in forecasting both small cap stocks returns as well as the returns of stocks with disperse ownership. The author's utilised information obtained through surveys of the Conference Board and the University of Michigan Survey Research Center to construct a sentiment index. The empirical results revealed that a sentiment index could significantly forecast the returns of small and disperse stocks and that sentiment was negatively correlated with stock returns. Consistent with the findings of Lemmon and Portniguina (2006), Qiu and Welch (2006) find a consumer confidence index to be a useful predictor of excess returns on small decile stocks.

Schmelling (2009) examined the effect of consumer confidence index on stock returns of 18 industrialised countries and found that expected stock returns are negatively related to the consumer confidence index. Furthermore, the authors note that the effect of sentiment is greater for countries that have less institutionalised stock markets, low market integrity and where investors are more prone to herd-like behavior. Zouaoui, Nouyrigat and Beer (2011) examine the influence of investor sentiment on the probability of a stock market crisis over the period 1995 to 2009. The empirical analysis reveals that investor sentiment increases the probability of occurrence of a stock market crisis within a one-year horizon. The impact of investor sentiment on stock markets is found to be more pronounced in countries that are

culturally more prone to herd like behavior and overreaction or in countries with low institutional involvement.

2.13. Conclusion

This chapter covered a number of aspects related to finance literature - some of which seem unrelated. However, under closer examination, it is found that these aspects are intertwined. The chapter began with an analysis of classical financial theories and a brief summary of the financial market anomalies that do not adhere to classical financial models. The emergence of behavioural finance is discussed with a focus on human behavioural theories and specific biases that influence an individual's decision making. Further, behavioural portfolio theory illustrated the prominence of emotion in financial markets and the importance of accounting for sentiment when constructing investment portfolios. The AMH presents a simple, philosophical and intuitive alternative to the EMH. The AMH contends that market efficiency is cyclical, and that market participants determine the efficiency. Lastly, a review of sentiment is undertaken, with a focus on its influence on investors and financial markets.

3. Data and methodology

This chapter involves a discussion of the analytical framework adopted to meet the objectives set out in Chapter 1. The methodology describes the framework of constructing the aggregate sentiment index and how to analyse the relationship between consumer sentiment and stock prices. Additionally, the chapter will provide an in-depth discussion of the proxies utilised to construct the sentiment index as well as reasons why the relevant proxies were chosen.

3.1. Basic approach

To analyse the impact that sentiment has on stock returns, this study utilises the following empirical design. We develop an aggregate measure of investor sentiment by employing a number of sentiment proxies that we hypothesise contain some component of investor sentiment and some component of non-sentiment related idiosyncratic variation. To isolate the sentiment component of the proxies from business cycle components, we orthogonalise each proxy with respect to several macroeconomic variables. The residuals from the regressions are taken as a cleaner proxy that is independent of major business cycle effects. The sentiment series is then estimated as the first principle component of the orthogonalised sentiment proxies.

We organise our empirical work around the following model:

$$E_{t-1}[R_{it}] = \alpha + b_1'X_{it-1} + b_2'T_{t-1}X_{it-1} \quad (1)$$

Where i indexes firms or securities, t is time, X is a vector of firm or security characteristics and T is a time series conditioning variable that proxies for investor sentiment. The null hypothesis is that b_2 is zero or, more precisely, that any nonzero effect is due to rational compensation for bearing systematic risk. The alternative is that b_2 is nonzero and reflects the correction of mispricing's. We use Eq. (1) as an organising framework to test for conditional characteristic effects, not as a structural model.

3.2. Share price data

Share price data is obtained from I-Net Bridge and McGregor BFA. The data consisted of closing monthly prices of all firms listed and subsequently delisted on the Johannesburg Securities Exchange (JSE) for the period December 1999 to July 2009. It is important to note that the inclusion of delisted firms is done to prevent any look ahead³ bias. Furthermore, the closing prices of the JSE All Share Index (ALSI) over the same 10 year period is obtained from McGregor BFA. The ALSI will be compared with the aggregate sentiment index. This index is specifically chosen as it is likely to be representative of the entire South African securities market.

3.3. Firm data

McGregor BFA as well as the Findata@Wits database is utilised to obtain data on the characteristics of all companies listed as well as delisted on the JSE over the analysis period. The age of a company, volatility, BE/ME and size are the firm characteristics that are assessed in the study. This data is used to observe the impact that sentiment has on shares with these varying characteristics.

3.4. Herding data

Herding behaviour can be described as a mimicking of actions by investors. Herding is characterised by a lack of decision making or thoughtfulness, causing people to think and act in the same way as the majority of those around them (Seetharam & Britten, 2013). Herding behaviour can be due to a variety of reasons, the most common being that of investor irrationality. Herding data is obtained directly from Seetharam and Britten (2013). The authors conducted a study on herding behaviour during market cycles in South Africa. This data will be utilised in conjunction with the ALSI to analyse the aggregate sentiment index.

³ Bias created by the use of information in a study or simulation that would not have been known or available during the period being analysed. This may lead to inaccurate results in the study or simulation.

3.5. Transaction costs

Transaction costs consist of two components – explicit costs, such as brokerage fees and taxes; and implicit costs, such as bid-ask spreads and the price impact of the trade (Boussema, Bueno & Sequier, 2001). As implicit costs are difficult to quantify, many studies instead deduct a fixed percentage of the value of each trade to account for trading costs. This value is referred to as unconditional trading costs.

Studies that have utilised unconditional trading costs range from 0.5% (Jegadeesh & Titman, 1993) to 1.5% (Grundy and Martin, 2001). However, there are no published studies of investor sentiment that take transaction costs into account. This study uses an amount of 1% per share per month for transaction costs.

3.6. Sentiment proxies: Motivation

The first proxy we employ to construct our sentiment index is volatility premium. This simply identifies times when valuations on high idiosyncratic volatility stocks are high or low relative to valuations on low idiosyncratic stocks. The motivation for this variable derives from the theoretical prediction that sentiment has its strongest effects on hard to value and hard to arbitrage stocks (Baker & Wurgler, 2011). Volatile stocks are inherently riskier to trade – volatility brings with it fundamental risk as well as arbitrage risk (Wurgler & Zhuravskaya, 2002). Furthermore, volatile stocks are particularly unattractive to arbitrageurs, which in turn increase the potential for such stocks to be affected by noise trader sentiment.

The volatility premium is the year end log ratio of the value-weighted average market-to-book ratio of high volatility stocks to that of low volatility stocks. High (low) volatility denotes one of the top (bottom) three deciles of the variance of the previous year's monthly returns. Total volatility is defined as the standard deviation of the 12 trailing months of monthly returns.

The second and third proxies employed are derived from initial public offering (IPO) data. They are the total volume of IPOs and their initial first day returns. The theoretical motivation for using the volume of IPOs is simply that insiders and long

run shareholders have strong incentives to time the equity market for when valuations are greatest, which presumably is when sentiment is highest. Low long-run returns to IPOs have been noted by Ritter (1991) and Loughran, Ritter, and Rydkvist (1994), which is ex post evidence of successful market timing relative to a market index. Additionally, researchers have widely noted that the initial returns on IPOs increase in hot markets, and that the worst future returns occur for IPOs and equity issues from hot market cohorts with high total issuance volume (Baker & Wurgler, 2011).

The number of IPOs (NIPO) is the log of the total number of IPOs that year. The initial returns on IPOs (RIPO) are the average initial return on that year's offering. The returns are equally weighted across firms. Data will be obtained from the Johannesburg Securities Exchange and McGregor BFA.

The final sentiment proxy employed is market turnover. Researchers such as Bagehot (1873) and Kindelberger (1978) have noted that high trading volume in the overpriced asset is a pattern that goes back to the tulip bubble. Cochrane (2002) asserts that the association of volume and price is a generic feature of historical bubbles while Smith, Suchanek and Williams (1988) indicate that bubbles are associated with high turnover. Furthermore, there is ample evidence in financial literature to connect sentiment with trading volume. Barker and Stein (2004) observe that when shorting is relatively costly, sentimental investors are more likely to trade when they are optimistic, and overall volume will increase. Barber, Odean and Zhu (2009) argue that abnormal trading volume can be considered a signal of irrational investor sentiment. Scheinkman and Xiong (2003) provide a complimentary argument based on overconfidence for using turnover as a proxy for sentiment. As with the other three measures, we expect a positive relationship between the observed proxy and the underlying sentiment. Market turnover (TURN) is the log of total market turnover – total rand volume over the year divided by total capitalisation at the end of the prior year. To my knowledge, there are no published studies of investor sentiment that utilise the above stated proxies to construct an aggregate sentiment index.

Finally to remove information about expected returns that may be contained in our sentiment proxies that is not related to sentiment, we adopt the methodology noted by Baker and Wurgler (2006) and orthogonalise each proxy to three macro-economic series. These are inflation (Fama & Schwert, 1977), employment growth (Santos &

Veronesi, 2006) and industrial production growth (Chen, Roll & Ross, 1986). This data is obtained from the Johannesburg Securities Exchange, Statistics South Africa (Stats SA) and the International Monetary Fund (IMF) database.

3.7. Conclusion

This chapter set out the empirical framework that is used to analyse the relationship between investor sentiment and stock returns. . We develop an aggregate measure of investor sentiment by employing a number of sentiment proxies that we hypothesise contain some component of investor sentiment and some component of non-sentiment related idiosyncratic variation. To isolate the sentiment component of the proxies from business cycle components, we regress each proxy with respect to several macroeconomic variables – inflation, employment growth, and growth in industrial production – and use the residuals from these regressions as our sentiment proxies.

The four sentiment proxies will have a common sentiment component, especially given that major macroeconomic influences have been removed. The sentiment series is then estimated as the first principle component of the orthogonalised sentiment proxies. Stocks are sorted according to several firm characteristics and their logarithmic returns are calculated. The sentiment index is analysed against the logarithmic returns of company characteristics to analyse the differential effects of investor sentiment across firms.

4. Results

This chapter presents the results of the aggregate sentiment index and its influence on stock price returns.

4.1. Principal component analysis

The principal axis method was used to extract the components and this was followed by a varimax (orthogonal) rotation⁴. Principal component analysis (PCA) is a multivariate technique that analyses a data table in which observations are described by several inter-correlated quantitative dependent variables. The goal of PCA is to extract the important information from the table and to express this information as a set of new orthogonal variables called principal components (Abdi & Williams, 2010). A varimax solution means that each component has a small number of large loadings and a large number of zero (or small) loadings. This simplifies the interpretation because, after a varimax rotation, each original variable tends to be associated with one (or a small) number of the components, and each component represents only a small number of variables (Abdi & Williams, 2019). Each of the components were cleaned of macroeconomic factors and standardised.

This procedure led to the following index:

$$\text{SENTIMENT} = 0.623\text{NIPO} + 0.420\text{TURN} + 0.451\text{RIPO} + 0.482\text{PREMIUM} \quad (2)$$

All, but one of the proxies (PREMIUM) enter the equation with the expected signs. The correlation matrix, given in Table 1 below, indicates that RIPO and NIPO have the highest correlation closely followed by TURN and NIPO. TURN and RIPO are negatively correlated; either of the two variables could have been removed without impacting on the quality of the results.

⁴ An oblimin (Kaiser normalization) rotation is additionally conducted and the results are reported in Appendix B

Table 1 – Pearson correlation matrix

Variables	Premium	NIPO	TURN	RIPO
Premium	1	0.154	0.151	0.101
NIPO	0.154	1	0.189	0.247
TURN	0.151	0.189	1	-0.026
RIPO	0.101	0.247	-0.026	1

Values in bold are different from 0 with a significance level $\alpha=0.05$

Table 2 below shows the output for the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy. The KMO measure of sampling adequacy is used to compare the magnitudes of the observed correlation coefficients in relation to the magnitudes of the partial correlation coefficients. The KMO statistic varies between 0 and 1. A value of 0 indicates that some partial correlations are large relative to the sum of correlations, indicating diffusion in the pattern of correlations (hence, factor analysis is likely to be appropriate). A value of close to 1 indicates that patterns of correlations are relatively compact, thus factor analysis should yield distinct and reliable factors. Kaiser (1974) recommends accepting values greater than 0.5 as reliable (values below you either collect more data or rethink which variables to include). The KMO sampling adequacy test provides a value of 0.530, indicating that factor analysis is likely to be appropriate.

Table 2 – Kaiser-Meyer-Olkin measure of sampling adequacy

Premium	0.623
NIPO	0.532
TURN	0.502

RIPO	0.494
KMO	0.530

Table 3 below displays the output for Bartlett's sphericity test. Bartlett's test of sphericity is used to test the hypothesis that the original correlation matrix is an identity matrix (all diagonal terms are one and off diagonal terms are zero). We are looking for significance (a significance level of less than 0.05), as we want the variables to be uncorrelated. The computed p-value of 0.010 is less than the significance level, thus we accept the alternate hypothesis that at least one of the correlations between the variables is significantly different from zero.

Table 3 – Bartlett's sphericity test

Chi-square (Observed value)	16.887
Chi-square (Critical value)	12.592
DF	6
p-value	0.010
alpha	0.05

Test interpretation;

H0: There is no correlation significantly different from 0 between the variables

Ha: At least one of the correlations between the variables is significantly different from 0

As the computed p-value is lower than the significance level $\alpha = 0.05$, one should reject the null hypothesis H0,

And accept the alternative hypothesis Ha.

The risk to reject the null hypothesis H0 while it is true is lower than 0.97%

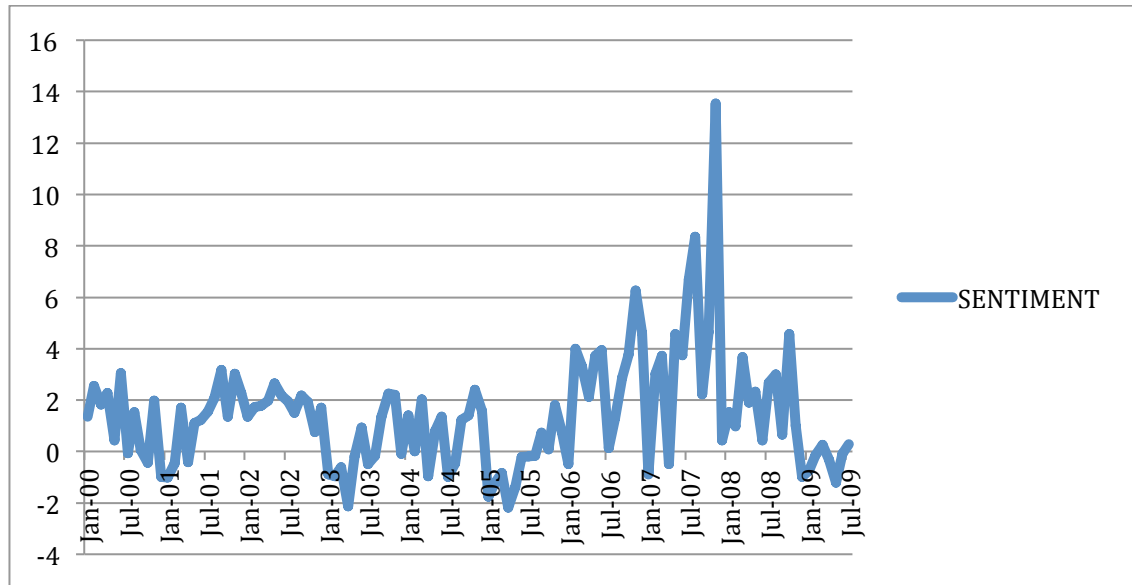


Figure 2 – Sentiment

Figure 2 above indicates that the sentiment index constructed lines up well with anecdotal accounts of sentiment over the analysis period. In particular the sentiment proxies clearly capture the decline in sentiment at the turn of the century due to the Internet bubble and the subsequent rise in investor sentiment as market conditions improved. The sharp decline in sentiment in the year 2008 coincides with the collapse of the investment bank Lehman Brothers, during financial market crises. Sentiment is generally low through this period reflecting the uncertainty and pessimism that existed in the market at the time.

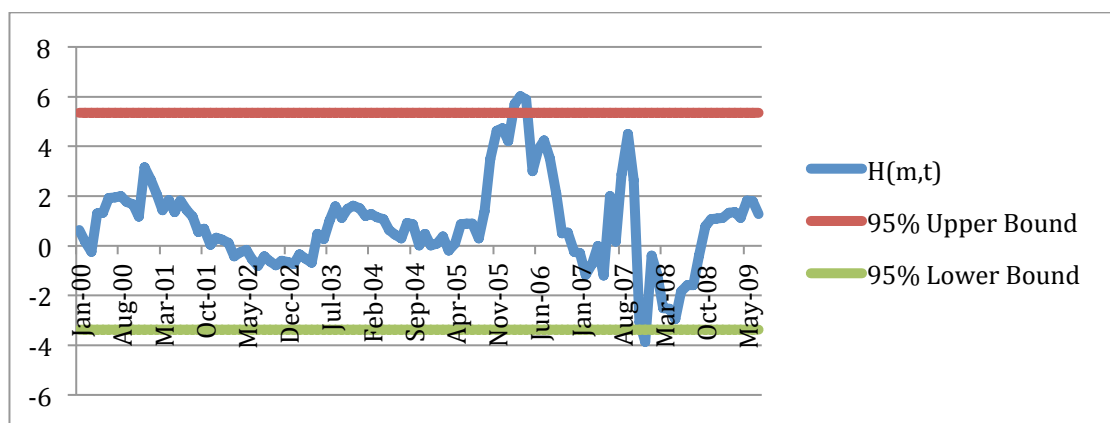


Figure 3 – Herding behaviour

Figure 3 presents a graphical representation of herding behaviour, denoted as $H(m,t)$. Any increase in $H(m,t)$ relative to its previous value, is indicative of herding

(Seetharam & Britten, 2013). Thus, it can be seen that herding was mildly volatile for the period January 2000 to July 2009. The notable exceptions are the latter half of 2005 and the middle of 2008. These periods have $H(m,t)$ values above or close to the 95% confidence level, indicative of a possible real-world anomaly. The sentiment index in Figure 2 clearly denotes a significant fall in investor sentiment over these periods, thus implying that there is a close relation between investor sentiment and herding behaviour. The 2005 period coincides with political instability in South Africa and general risk aversion of investors towards emerging markets. The 2008 period coincides with the global financial crises. Both events are depicted by an abrupt increase and subsequent quick decrease in herding during that period.

4.2. Portfolio sorts

Table 4 analyses the conditional characteristics effects. Each monthly return observation is placed into a bin according to their portfolio rank that a characteristic takes at the beginning of that month, and then according to the level of a sentiment proxy from the end of the previous calendar year. Portfolios are constituted according to the methodology advocated by Fama and French (1993). Portfolio 1 represents the first three deciles, portfolio 3 is composed of the top three deciles and portfolio 2 is the intermediate portfolio. We compute the average monthly return for that bin and analyse the results. We report sorts on TURN in table 3a and SENTIMENT in table 3b. For brevity we omit sorts on the three other sentiment proxies as they provide similar results.

Table 4A – Two-way sorts: TURN and firm characteristics

TURN _{t-1}		Portfolio			Overall			T-Stat
		1	2	3	3-1	3-2	2-1	
ME	Positive	5.97	5.65	4.28	-1.69	-1.37	-0.32	0.00*
	Negative	1.12	1.38	1.80	0.62	0.42	0.26	
	Difference	4.85	4.27	2.48	-2.31	-1.79	-0.58	
Age	Positive	6.00	5.95	5.06	-0.94	-0.89	-0.05	0.01*
	Negative	2.88	2.93	1.96	-0.92	-0.97	0.05	

	Difference	3.12	3.02	3.1	-0.02	0.08	-0.1	
Volatility	Positive	4.28	4.89	5.92	1.64	1.03	0.61	0.07*
	Negative	2.42	1.89	0.93	-1.49	-0.96	4.97	
	Difference	1.86	3.01	4.99	0.15	0.07	-4.36	
BE/ME	Positive	4.87	5.42	6.01	1.14	0.59	0.55	0.02*
	Negative	-0.18	1.52	2.46	2.64	0.94	1.7	
	Difference	5.05	3.90	3.55	-1.50	-0.35	-1.15	

*Denotes p-values that are statistically significant at the 5% level of significance

**Transaction costs of 1% are employed

Table 4A above indicates two-way sorts for market turnover and firm characteristics. Table 4B below illustrates two-way sorts of the sentiment index and firm characteristics. For both tables we report average portfolio returns over months where the standardised SENTIMENT and TURN from the previous year is positive negative and the difference between the two.

Table 4B – Two-way sorts: SENTIMENT and firm characteristics

SENTIMENT _{t-1}		Portfolio			Overall			T-Stat
		1	2	3	3-1	3-2	2-1	
ME	Positive	1.79	2.05	2.68	0.69	0.37	0.26	0.01*
	Negative	5.46	4.38	3.17	-2.29	-1.21	-1.08	
	Difference	-3.67	-2.33	-0.49	2.98	1.58	1.34	
Age	Positive	2.40	3.61	3.29	0.89	-0.32	1.21	0.02*
	Negative	5.34	4.88	4.02	-1.32	-0.87	-0.46	
	Difference	-2.94	-1.27	-0.73	2.21	0.55	1.67	
Volatility	Positive	3.61	3.27	2.42	-1.19	-0.85	-0.34	0.04*
	Negative	3.68	4.89	5.33	1.65	0.44	1.21	
	Difference	-0.07	-1.62	-2.91	-2.84	-1.29	-1.55	
BE/ME	Positive	2.07	3.19	3.71	1.64	0.52	1.12	0.01*

Negative	4.18	3.88	3.76	-0.42	-0.13	-0.3
Difference	-2.11	-0.69	-0.05	2.06	0.65	1.42

*Denotes p-values that are statistically significant at the 5% level of significance

**Transaction costs of 1% are employed

The first rows of Table 4 illustrate the effect of size conditional on sentiment. Specifically, the cross-sectional effect of size exists when TURN is positive or when SENTIMENT is negative. When sentiment is negative the portfolio 1 provides a return of greater than 5% while portfolio 3 provides an average return of 3.17% per month. A similar pattern is observed when conditioning on TURN. When TURN is positive portfolio 1 delivers a return of approximately 6% while portfolio 3 returns a monthly average of 4.28% respectively.

The conditional cross sectional effect of Age reveals that investors tend to demand young stocks when SENTIMENT is positive and older stocks when SENTIMENT is negative. When SENTIMENT is pessimistic, the top Age firms achieve a return of 1.32% lower than the bottom Age firms, but return an average of 0.89% more when SENTIMENT is optimistic.

The third row indicates that the cross-sectional effect of return volatility conditional upon sentiment. Table 4B indicates that high volatility stocks are out of favour when SENTIMENT is positive. High volatility firms achieve a return of 2.42% as opposed to an average return of 3.61% for low volatility firms. However, similar to Age, the cross sectional effect of volatility fully reverses in low sentiment conditions.

The last row displays the effect of BE/ME conditional on SENTIMENT. Table 4B illustrates that when SENTIMENT is positive, average returns of portfolios sorted on BE/ME increase and similarly average returns broadly decrease when SENTIMENT is negative. This simply implies that average returns are generally greater for securities with high BE/ME values.

A closer look at the conditional pattern in the BE/ME variable reveals a U-shaped configuration in the conditional difference of average returns. When SENTIMENT is high there is a U-shaped pattern across BE/ME portfolios, which is illustrated in the

3-1 and 2-1 portfolio contrasts. When SENTIMENT is negative however, this becomes an inverted U configuration. This pattern is only present in the BE/ME variable. Baker and Wurgler (2004) comment that BE/ME may identify extreme growth opportunities and distress stocks. However, Baker and Wurgler (2004) further note that BE/ME may simply just serve as a generic valuation indicator.

The U-shaped conditional difference pattern observed in the BE/ME variable, suggests that investors demand both high growth and distressed firms when they are optimistic, or when their propensity to speculate is high. Furthermore, investors avoid these extreme stocks when their propensity to speculate is low, or when they are pessimistic.

The implication that sentiment has a greater impact on distressed firms is consistent with theoretical predictions that both rapidly growing firms and firms that are extremely distressed are difficult to value and have high idiosyncratic risk (Baker & Wurgler, 2004). Theory predicts that such securities, which are more subjective to value and harder to arbitrage, tend to be more sensitive to swings in sentiment.

4.3. Conclusion

In classical financial theory there is typically no room for investor sentiment. The standard argument is that in highly competitive financial markets, suboptimal trading behaviour such as paying attention to sentiment signals unrelated to fundamental value will be quickly eliminated by aggressive rational arbitrageurs. However the rise in non-traditional financial concepts, such as investor sentiment, demonstrates that classical financial theories may not be capturing the basic intuition of what people know all along— that individuals are imperfect, they believe things that seem objectively irrational, and may not make decisions in a rational manner.

This thesis explores two fundamental questions regarding investor sentiment: does investor sentiment have an impact on the South African market and is the influence of sentiment greater on securities that are hard to value and arbitrage. To test the hypothesis, we construct a composite sentiment index as the linear combination of four indirect measures, namely, volatility premium, total volume of IPOs, average

initial first day returns of IPOs and market turnover. The main empirical finding is that sentiment has a rich and broad cross-sectional impact on securities in the South African market. More specifically, when investor sentiment is relatively high, young stocks, small firm stocks, highly volatile stocks, and extreme growth experience low future returns relative to other securities. These securities are likely to be attractive to speculators and optimists and at the same they are unattractive to arbitrageurs. On the other hand, conditional on low sentiment, these cross-sectional patterns in returns attenuates or reverses. This result gives credence to the argument by financial researchers, that often-neglected behavioural aspects, such as sentiment, should be incorporated into classical financial theories to improve traditional asset pricing and risk models.

4.4. Limitations of the study

After preparatory reading of financial literature concerning investor sentiment, it became clear that there are various interpretations as well methodological procedures to analyse investor sentiment. The author uses a concept described by Baker and Wurgler (2006) to construct an aggregate sentiment index from several proxies. The results of the analysis could be different if additional proxies were utilised to construct the sentiment index. Furthermore, the results of the analysis are sensitive to the economic series that are used to orthogonalise the sentiment proxies.

A time bias in the analysis can occur if the period used to conduct the analysis is either too short or either too long. If a lengthy period is used to conduct the analysis, the fundamental economic behaviour underlying the results may change. Likewise, if the time period used to conduct the analysis is very brief, the effects captured may only hold for that short period and subsequently may have no explanatory power of future results. The analysis in this dissertation is conducted over a 9 year period. This seems like a reasonable time period to capture the fundamental economic relationships underlying security price returns, however, the time period can be extended to include previous financial anomalies. This would provide us with a clearer picture of how investor sentiment impacts stock market returns over time.

4.5. Recommendations for future research

An interesting area of future research would be to examine if investor sentiment could be utilised to predict stock market crashes. Given the difficulty caused by the global financial crises it would be appealing to analyse if investor sentiment provides an indication as to when a financial market crash may occur.

A further avenue of future research relates to incorporating investor sentiment into portfolio selection. MPT is dominated by rational investors and arbitrageurs who select stocks based on their fundamental values. However, Howard (2013) indicates that in reality, stock prices reflect emotions rather than underlying value. It would be interesting if investor sentiment could be incorporated into an asset allocation model to construct portfolios that generate superior returns.

5. References

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Appendix A

Appendix A provides a graphical representation of the performance of the ALSI over the analysis period.

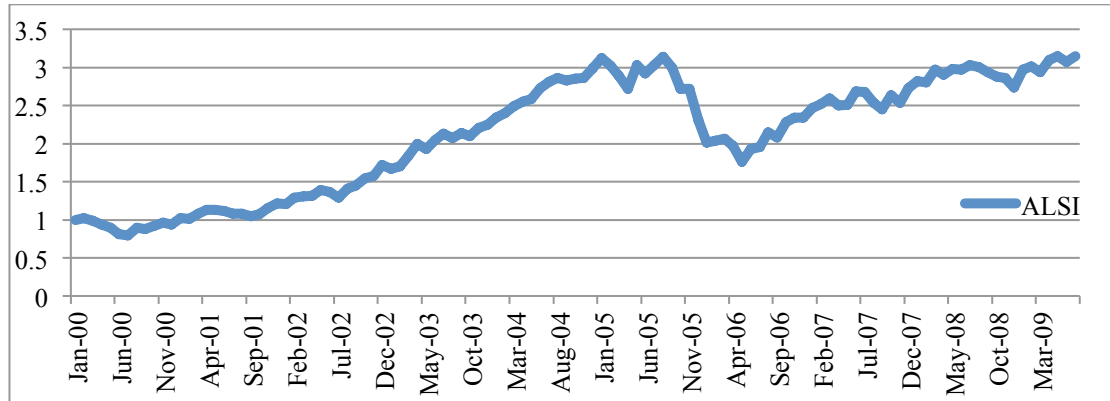


Figure A1 – Performance of ALSI

Figure A1 above illustrates the return an investor would receive if R1 were invested in the ALSI index over the analysis period. The graph clearly indicates a decrease in returns in the year 2005 and the latter part of the year 2008. This coincides with evidence from the sentiment index as well as $H(m,t)$. Both investor sentiment and herding behaviour decreased over this period.

Appendix B

Appendix B display the output for the oblimin rotation. Direct oblimin rotation is the standard method when one wishes a non-orthogonal (oblique) solution – that is, one in which the factors are allowed to be correlated. This will result in higher eigenvalues but diminished interpretability of the factors.

Table B1 – Rotation matrix

	D1	D2
D1	1.757	1.452
D2	0.013	-0.989

Table B2 – Factor loadings after the oblimin rotation

	D1	D2
Premium	1.008	1.080
NIPO	1.308	0.936
TURN	0.871	1.405
RIPO	0.955	0.089

Factor loadings are the weights and correlations between each variable and the factor. The higher the load the more relevant in defining the factors dimensionality. A negative factor value indicates an inverse impact on the factor.

Figure B1 – Correlation between variables after Oblimin rotation

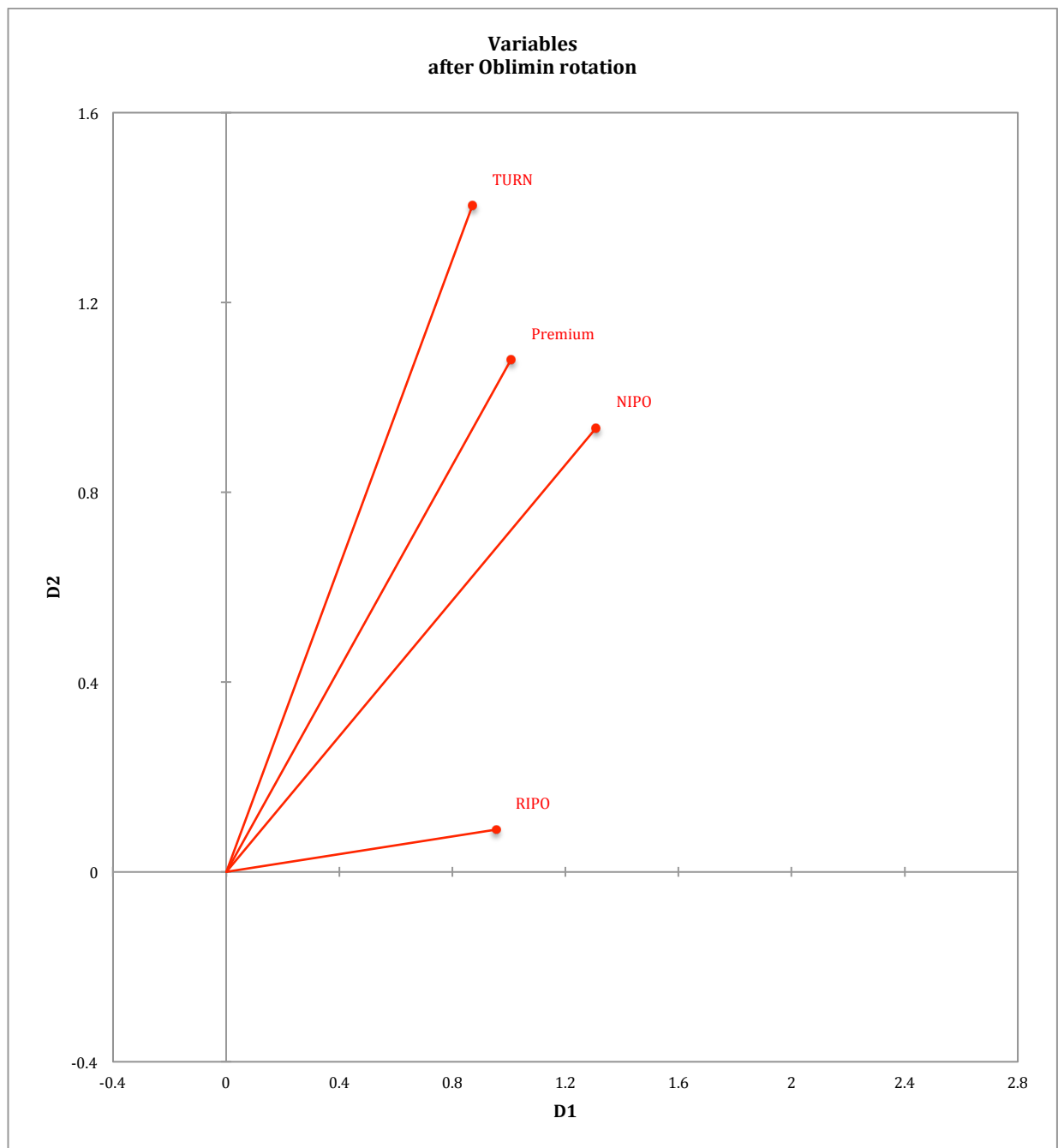


Figure B1 illustrates the correlation between the variables after the oblimin rotation. The diagram indicates that TURN and PREMIUM have the highest correlation while RIPO has the lowest correlation with the variables.

Table B3 – Correlation between variables and factors after Oblimin rotation

	D1	D2
Premium	0.120	0.251
NIPO	0.539	-0.140
TURN	-0.284	0.688
RIPO	0.882	-0.696

Table B4 – Contribution of variables after oblimin rotation

	D1	D2
Premium	23.105	28.995
NIPO	38.901	21.762
TURN	17.254	49.045
RIPO	20.740	0.198

Table B5 – Squared cosiness of the variables after the Oblimn rotation

	D1	D2
Premium	0.364	0.418
NIPO	0.568	0.291
TURN	0.252	0.655
RIPO	0.800	0.007

Values in bold correspond for each variable to the factor for which the squared cosine is the largest

The squared cosine shows the importance of the cosine for a given observation. The squared cosine indicates the contribution of a component to the squared distance of the observation to the origin.

Table B6 – Component score coefficients after the oblimin rotation

	D1	D2
Premium	0.031	0.240
NIPO	0.409	-0.136
TURN	-0.346	0.660
RIPO	0.769	-0.670

Table B7 – Correlation between factors after Oblimin rotation

	D1	D2
D1	1.000	-0.822
D2	-0.822	1.000

Figure B2 – Observation after Oblimin rotation

