The Human Investor: The Profile of Retail and Institutional Investors, and a Structural Equation Model of Investor Behavior in the Share Market.

A thesis in behavioral finance (aka economic psychology).

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Abstract

The share market has long been renowned for its volatility. Wyckoff (1922/2010, page 2054) and Graham (1949/1973) may have been the first to recognize the *human* element behind this volatility and developed investment strategies to profit from same. Using a variant of Graham's approach, Warren Buffett consistently enjoyed a premium in portfolio returns over what would have been obtained had his portfolio matched that of the S&P 500 (Berkshire Hathaway Inc., 2016). Academic interest in investor behavior did not really commence until the work of De Bondt and Thaler (1985, 1987). Past research had since debated whether Buffett's (contrarian) return premiums are due to market risk (e.g., Fama & French, 1995; 2000) or the attributes of other investors (e.g., Barber & Odean, 2000, 2001). Research on the *human* side of the investor garnered increasing interest throughout this debate. However, much of the research on investor behavior has been based on portfolio simulations or experimental research and considered only one or two constructs at a time. Consequently, very few psychometrically sound scales exist for use with investors. Recent studies on investor behavior have begun to take a multivariate perspective or use structural equation modeling. However, the structural equation models put forward to date have considered simple models of investor behavior or one of its antecedents. With the ease of performing structural equation modeling, it may now prove apt to take a multivariate approach to modeling investor behavior.

This thesis began by considering the psychometric properties of ten scales developed or adapted for use with investors. Upon modification, seven of the ten scales demonstrated good psychometric properties. This thesis also addressed five research questions. The first considered whether level of overconfidence could be predicted by the interaction between gender and marital status, such that single women would demonstrate the least overconfidence, followed by married women, married men, and single men in turn. Partial support was found for this research question. Single women did demonstrate the least overconfidence while men in general demonstrated the most overconfidence.

Research question two considered whether the count of "don't know" and/or the count of missing data could act as markers of underconfidence. The count of "don't know", along with the combined count of "don't know" and missing data were both found to act as markers of underconfidence but not the count of missing data alone. As the count of "don't know" proved to be a stronger marker of underconfidence, this variable was used for remaining analyses in this thesis.

Research question three explored the dimensions upon which retail investors differed from institutional investors. In relation to institutional investors, retail investors were older; less (financially) educated; and had fewer years of investment experience. Retail investors also spent fewer hours on their investments; as well as monitored (and invested in) fewer companies than did their institutional counterparts. Retail investors also reported less overreaction, less overconfidence and more underconfidence than their institutional peers.

Research question four identified the variables that could predict overreaction, overconfidence and underconfidence.

The final research question used structural equation modeling to predict the proportion of an investor's portfolio allocated to (a) defensive shares; (b) growth shares; (c) cyclical shares and (d) asset/turnarounds. Examination of the four models highlighted increasing levels of overconfidence as investors moved away from defensive shares and towards asset/turnarounds. In the models for growth shares, cyclical shares and asset/turnarounds, investors reported neither overreaction, nor anxiety, yet they engaged in the July effect; a variable for which anxiety was a significant predictor.

Based on the findings of this thesis, overconfidence (along with its inverse) may be useful in explaining investor behavior. Similarly, the combination of overreaction, the July effect and anxiety may also be useful in explaining investor behavior.

Dedication

This thesis is dedicated to the memory of my grandmother. It is through her insight and selfless action that my father, aunt and grandfather survived the Second World War.

Words can never do her noble courage justice.

Acknowledgements

A research project of this undertaking could not reach fruition without the input of able supervisors. Indeed, if my research shows any merit, it is due to the wisdom and capabilities of my supervision team: Dr. Bruce Findlay supervised the psychology component of my research. Professor Christine Jubb supervised the financial component as well as the later stages of my thesis. Dr. Denny Meyer supervised the statistical analyses. Professor Sheikh Rahman and Dr. Trish Buckley supervised the early to mid-stages of my research. If my research shows any faults, those faults are mine.

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"… the investor's chief problem --- and even his worst enemy --- is likely to be himself" (Graham, 1949/1973, p. xv).

Investors "… just drifted along, guided by hope of profit and pursued by fear of loss" (Wyckoff, 1922/2010, p. 34).

Signed Declaration

To the best of my knowledge, this thesis does not contain any material that has been published or written by another person, except where appropriately referenced in the body of this thesis.

This thesis does not contain any material that has been submitted for any other award, except where appropriately referenced in the body of this thesis.

Signed by me: ____

Rachel Abramson

Dated this day: 12th June, 2017

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Chapter 1 Introduction

1.1 Rationale for this research

It has long been known that share investors are not always rational (e.g., Graham, 1949/1973; Wyckoff, 1922/2010). Indeed, investor behavior may provide investment opportunities for others willing to invest contrarily (see Graham, 1949/1973). For the past 51 years, Warren Buffett has consistently achieved investment returns in excess of the S&P 500 by so doing (Berkshire Hathaway Inc., 2016).

It was not until the early work of De Bondt and Thaler (1985, 1987), however, that research became interested in contrarian investment (and ultimately investor behavior). While researchers appear unanimous in their understanding that contrarian profits may occur (e.g., Fama & French, 1995, 2000; Kothari, Shanken, & Sloan, 1995), some have concluded that the contrarian profits are a reward for taking on increased financial risk (e.g., Chan, 1988; Fama & French, 1995, 1998) or that it is merely an artifact of research design (Ball, Kothari, & Shanken, 1995).

Other researchers have concluded, however, that investors are “irrational”. The form of irrationality may stem from investor behaviors such as (a) overreaction (e.g., De Bondt & Thaler, 1985; 1987); (b) overconfidence (e.g., Barber & Odean, 2001); (c) January and/or July effects (Ciccone, 2011; Keim, 1983); (d) appetite for financial risk (Nguyen & Noussair, 2014); (e) psychological biases in investment decisions (Ates, Coskun, Sahin, & Demircan, 2016; Cheek, Coe-Odess, & Schwartz, 2015); and/or (f) social herding (Chang, 2014; Peress, 2014). Both retail and institutional investors may be prone to one or other sources of irrationality. (See, for example, Lai, Tan, & Chong, 2013).

Past research in behavioral finance has thus debated the benefits of contrarian investing within a market risk versus irrational investor framework (that is, an either/or approach).

It is possible, however, that market risk explanations of share market behavior, (e.g., Fama & French, 1995; 2000) may explain what *should* occur in share markets. Similarly, the explanations of the investor as irrational (e.g., Barber & Odean, 2000, 2001) may explain what *does* occur in share markets. The present thesis refers to the market risk view as the *rational* investor view and the irrational investor view as the *human* investor view.

It is possible that the Cannon (1914, 1922/1949) theory of fight/flight behavior, as well as its concomitants of anxiety and impulsivity (Gray, 1987, 1990), may explain underlying aspects of investor behavior. Consistent with this expectation, fear has been shown to be related to share sales (Lee & Andrade, 2011) and risk averse decisions (Nguyen & Noussair, 2014). Moreover, at the aggregate level, concurrent and prior societal moods were inversely related to portfolio returns (Choi, 2016).

It is the observation of this thesis that much of the research on investor behavior was based on portfolio simulation or, to a lesser extent, experimental research. Few investor behavior studies have surveyed share investors, be they individuals who might invest on their own behalf (i.e., retail investors) or those who might invest on behalf of others (i.e., institutional investors). Consequently, few psychometrically sound scales exist to measure key variables in investor behavior. Moreover, few investor surveys have taken a multivariate perspective; even fewer have considered structural equation models of investor behavior. This thesis notes that existing structural equation models of investor behavior have furnished simple models of investor behavior. (For example, Chin, Rasiah, and Lama (2016) provided a structural equation model for a generic measure of risk using two independent (predictor) variables while Kafayat (2014) provided a structural equation model for investor decision-making using three independent variables). Yet, from the literature introduced in this section, and which will be discussed in chapters 2 and 3, investor behavior might be expected to be more complex. While parsimony is to be applauded, it may be that a more complex multivariate model of investor behavior may be required to help flesh out the key variables influencing investor behavior. With the ease of ability to perform structural equation modeling, it may now prove apt to consider multivariate models of investor behavior.

1.2 Research aims and objectives

1.2.1 Research aims

The primary aim of this thesis is to provide an empirically-tested, theoretical and multivariate model of investor behavior in the share market. The purpose of doing so is to contribute to the explanation of investor behavior, guide future research and ultimately help inform investors and their financial advisors.

A secondary aim of this thesis is to build a profile of retail and institutional investors, as well as explore key variables in investor behavior.

1.2.2 Research objectives

The above two aims may be best served using a multivariate, survey methodology. However, with few existing investor surveys, the primary aim cannot be addressed without first developing and validating a set of scales measuring key variables in investor behavior. As part of the rationale for this thesis, Section 1.1 listed the key variables in investor behavior and the variables that may explain them. These constructs are discussed in chapters 2 and 3. The first objective is to thus assess the factor structure, reliability and discriminant validity of the following ten scales: (a) overreaction; (b) overconfidence; (c) January effect; (d) July effect; (e) appetite for financial risk; (f) information sources; (g) psychological biases; (h) social herding; (i) anxiety and (j) impulsivity.

The inverse of overconfidence may itself prove to be a useful variable in understanding investor behavior. Furthermore, “don’t know” responses are often treated as missing data in surveys. Yet in a survey of investor behavior, this variable, along with missing data, may act as markers of underconfidence. Both variables are easily obtained without necessarily extending the length of a survey questionnaire. Thus, the second objective is to determine whether the count of "don't know" and/or the count of missing data per respondent can act as markers of underconfidence.

In line with the secondary aim, the third objective is to explore key variables in investor behavior, as well as those that may distinguish retail from institutional investors.

In line with the primary aim, the final objective is to test whether the structural equation model put forward in this thesis (with or without modification) "fits" the sample of retail investors. Note that the structural equation model shown at the end of chapter 3 was also expressed as a multivariate theoretical model shown in figure 1.

1.3 A multivariate, theoretical model of investor behavior in the share market

In line with the primary aim, this thesis draws on a multivariate, theoretical model developed in Abramson (2003) and revised in Abramson, Rahman, and Buckley (2006). [Abramson (2003) is available through the Swinburne University of Technology library]. This model was further revised to take the form shown in Figure 1.

The *rational* investor component of the model delineated the five major investment methods available to investors. The investment methods included in the model were based on those commonly considered in the literature, e.g., (a) buy and hold investing; (b) dollar cost averaging; (c) contrarian investing; (d) index investing; and (e) momentum investing. Sections 2.2.4 to 2.2.8 discuss previous research on the five respective types of investment methods.

Lynch and Rothchild (1989) previously identified the major types of share investments. The financial component of the model adapted the Lynch and Rothchild (1989) to delineate four major types of share investments: (a) defensive shares; (b) growth shares; (c) cyclical shares; and (d) asset/turnarounds. The model combined the five major investment methods with four major types of shares to yield 20 possible investment combinations (Abramson, 2003; Abramson et al., 2006). The four major types of share investments are discussed in section 2.2.1.

The *rational* component of the model theorizes that certain combinations of investment method and type of share will be more effective in maximizing portfolio wealth than others (Abramson, 2003; Abramson et al., 2006). The model also theorizes market risk to indirectly affect portfolio wealth through its direct effect on choice of share investments. While past research in behavioral finance assessed the merits of one or two alternate investment methods alone (e.g., Assoe & Sy, 2003; Carosa, 2005; Leggio & Lien, 2001), the five major types of investment methods have yet to be simultaneously considered. Nor has the differential impact of the five major types of investment methods on the four major types of shares been considered.

The *human* investor component of the model delineated five behavioral variables. Once again, the variables included in the model were those commonly considered in the literature, i.e.: (a) overreaction; (b) overconfidence and underconfidence; (c) January effect and July effect; (d) psychological biases and (e) social herding. This literature has been discussed in sections 2.6.1 to 2.6.4 and 2.6.5 to 2.6.14 respectively. The *human* component of the model theorized that, when present, these five behavioral variables may affect investor behavior. More specifically, when present, these five variables were theorized to moderate investor capacity to consistently utilize their chosen investment method (Abramson, 2003; Abramson et al., 2006) as well as share selection. Moreover, it was theorized that the five behavioral variables might, in turn, be amplified or mitigated by demographic and other variables, including: (a) age; (b) gender; (c) marital status; (d) education; (e) financial education; (f) years of investor experience; (g) appetite for financial risk; (h) source of information; (i) anxiety; and (j) impulsivity

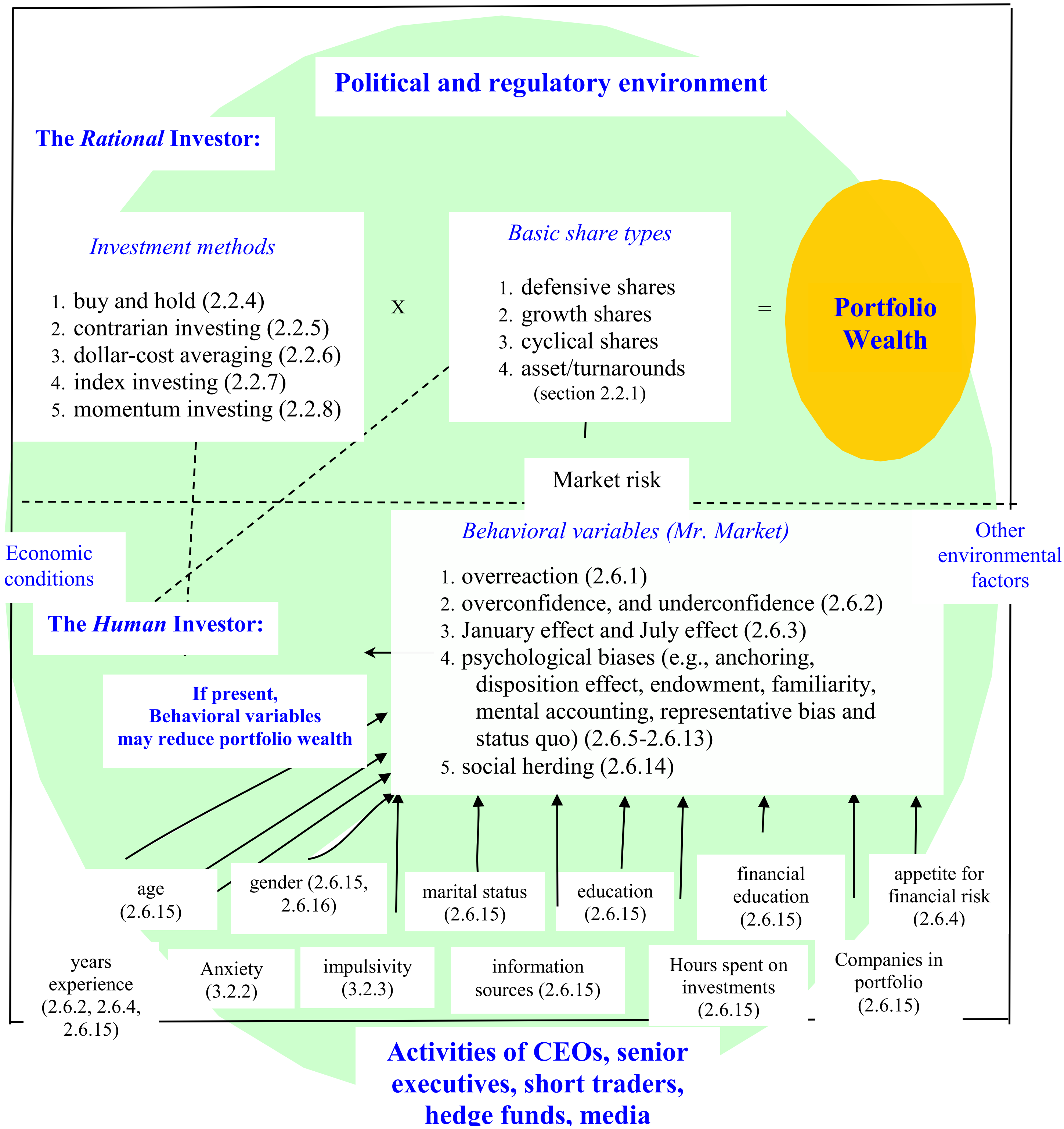

Figure 1. A theoretical model of investor behavior in the share market.

(Adapted from Abramson, 2003, p. 41; Abramson et al, 2006, p. 14)

(Abramson et al., 2006). This literature has been discussed in the remaining subsections of 2.6, along with sections 3.2.2 and 3.2.3. Finally, external variables were expected to have an impact on investor behavior, share types, and ultimately wealth changes through the share market (Mills, 2003).

Although previous research in behavioral finance considered each of the five behavioral variables separately (e.g., Caparrelli, D'Arcangelis, & Cassuto, 2004; De Bondt & Thaler, 1985, 1987; Kahneman, Knetsch, & Thaler, 1990; Kahneman & Tversky, 1972; Lakonishok & Smidt, 1984), none had considered their combined impact on investor behavior. Moreover, previous research considering the impact of demographic and other variables on the five behavioral variables had similarly considered each construct separately (e.g., Barber & Odean, 2001). It is therefore not yet known which of the demographic and other variables, when considered simultaneously, may be important in amplifying or mitigating the five behavioral variables. It is also not yet known which of the five behavioral variables, when considered simultaneously, may be important in moderating investor capacity to consistently utilize their preferred investment method when making share selections. In short, it is not yet known which, if any, of the five behavioral variables, when considered simultaneously, will be shown to be key drivers of investor behavior in the share market.

Figure 1 further refines Abramson (2003) and Abramson et al. (2006) to represent a multivariate, theoretical model of investor behavior used in this thesis. This thesis tests the *human* component of investor behavior. Figure 3, at the close of chapter 3 reproduces the *human* investor component of the model in the form of a structural equation model.

1.4 Contributions of the research

In line with the four objectives of this thesis described in section 1.2.2, this research makes four major contributions to the literature. Firstly, this thesis developed eight scales (i.e., (a) overreaction; (b) overconfidence; (c) January effect; (d) July effect; (e) information sources; (f) appetite for financial risk; (g) psychological biases; and (h) social herding). This thesis adapted a further two scales for use in investor surveys (i.e., (a) anxiety; and (b) impulsivity). This thesis also provided the factor structure, reliability and discriminant validity for the scales that demonstrated good factor structure. The development or adaption of these scales will facilitate multivariate research in behavioral finance (including the modeling of investor behavior), as well as the exploration of investor subgroups.

Secondly, this research considered the count of "don't know" per respondent and/or the count of missing data per respondent as three separate markers of underconfidence. As they are easily obtained measures of investor overconfidence, albeit expressed in the inverse direction, they can facilitate exploration of the construct of overconfidence (or underconfidence) without making survey questionnaires any longer for investors to complete.

Thirdly, this research considered the dimensions upon which retail investors differ from institutional investors. Understanding the distinction between both groups of investors can help flesh out key drivers of investor behavior in the share market. Moreover, by examining the differences between both groups of investors, the understanding of investor behavior becomes more nuanced than an examination of investor behavior as a whole.

Finally, four empirically tested theoretical models of investor behavior are provided; one for each of the four different types of share investments. The empirically tested theoretical models of investor represent the first such models to consider the key variables in investor behavior as a set, as well as the potential impact of anxiety and impulsivity on investor behavior.

The first two contributions reflect methodological contributions to the literature. By providing four tested models of a theoretical, multivariate model, the final contribution represents a theoretical contribution to the literature. The tested models, however, may also act as a guide for future research as well as inform investors and their advisors.

1.5 Methodology

The methodology of this research drew on the approach of a mail-out, mail-back survey. Over a six week period from mid-August 2010 to end of September 2010, investors completed a self-report questionnaire including demographic variables and questions about investment attitudes and practices overall and during the time of the Global Financial Crisis. It also asked questions about (a) overreaction; (b) overconfidence; (c) January effect; (d) July effect; (e) appetite for financial risk; (f) information sources; (g) psychological biases; (h) social herding; (i) anxiety; and (j) impulsivity.

1.6 Structure of the thesis

Chapter 2 discusses the literature contributing to the multivariate theoretical model. Chapter 3 introduces other variables that may help explain investor behavior. Chapter 3 also introduces the five research questions and their accompanying research hypotheses. Chapter 4 introduces the research philosophy, survey questionnaire and methodology for this research. Chapter 5 describes the factor structure, reliability and discriminant validity of the measures developed or adapted for use in this survey.

Chapters 6 to 9 provide the findings for the five research questions. More specifically, the first research question considered the interaction between gender and marital status on level of overconfidence. The findings of the first research question can be found in chapter 6. The second research question considers the count of “don’t know” and/or the count of missing data per respondent as markers of underconfidence. The findings of the second research question can also be found in chapter 6. The third research question considers the dimensions upon which retail and institutional investors differ. The findings of the third research question can be found in chapter 7. The fourth research question considered the variables that may help predict overreaction, overconfidence and the count of "don't know" as a marker of underconfidence. The findings of the fourth research question can be found in chapter 8. The final research question introduced a model of investor behavior. This research question can be found in chapter 9.

Chapter 10 discusses the findings reported in chapters 6 to 9. Chapter 11 draws conclusions. Chapter 11 considers the implications and limitations of this research. Chapter 11 also considers directions for future research. References and appendices follow.

Chapter 2 Literature Review: The Rational and Human Investor

2.1 Introduction

Chapter 2 considers the literature from both the *rational* and *human* investor perspectives. More specifically, this chapter begins with a discussion of the four major types of share investments and the five major types of investment strategies. This chapter continues with a discussion of the major bubbles in the history of the share market, leading into a discussion of the research on investor overreaction, and other *human* investor behavior. It is believed that the bubbles and crashes seen in the share market are extreme cases of investor overreaction. The literature discussed in this chapter (and indeed, the next chapter) informs the multivariate theoretical model of investor behavior introduced in the previous chapter.

2.2 Types of share investments, investment methods and the rational investor

2.2.1 Four major types of share investments

Lynch and Rothchild (1989) describe the major types of share investments: (a) defensive shares also known as slow to medium growers; (b) growth shares, also known as fast growers; (c) cyclical shares; and (d) asset plays and turnarounds; hereinafter referred to as asset/turnarounds. Abramson (2003) later adopted this framework as part of her own model development. Defensive shares are considered to be shares in companies that had stable earnings. Defensive shares provide the investor with a secure revenue stream (Lynch & Rothchild, 1989). At the time of writing, shares in Amcor, Australian Foundation Investment Corporation (AFIC) and Telstra may be considered examples of defensive shares.

Growth shares are considered to be shares in companies that have growing earnings. The companies may have greater needs for cash in order to manage their growth, and consequently, may have a greater risk for bankruptcy than those companies with stable earnings (Lynch & Rothchild, 1989). At the time of writing, shares in Wesfarmers and Commonwealth Bank may be considered examples of growth shares. Cyclical shares are considered to be shares in companies that have experienced periods of increasing and declining earnings in line with the industry in which those companies operate (Lynch & Rothchild, 1989). At the time of writing, shares in BlueScope Steel, Caltex and Qantas may be considered examples of cyclical shares.

Asset/turnarounds are a composite of the Lynch and Rothchild (1989) classifications of asset plays and turnarounds. Asset/turnarounds are considered to be shares in companies that previously had stable or growing earnings, but recently had poor earnings and/or were trading at 50 percent or less of net tangible assets. These companies may reflect the greatest risk to investor capital. They could also have the potential for the greatest return on investment (Lynch & Rothchild, 1989). Whilst normally considered cyclical shares, two good examples of asset/turnarounds are BlueScope Steel and Arrium (previously known as OneSteel). Shares in both companies had been previously oversold. Both companies had been working hard to turn their respective businesses around. Investing in either of these companies carried a high degree of risk, yet doing so also had the potential for high investment returns. With a change in fortune for the steel industry (Bluescope Steel Limited, 2017), BlueScope Steel profitability increased and its shares have returned to a cyclical classification. However, Arrium went into voluntary administration on the 7th April 2016. Arrium administrators since completed the sale of one of Arrium's businesses in January 2017, and are currently seeking buyers for its remaining business activities (Arrium Ltd, 2016; Korda Mentha Pty Ltd, 2016). The experience of Arrium demonstrates how risky this asset class can be.

2.2.2 Fundamental and technical analysis

There are approximately 2,400 publicly listed companies on the Australian Securities Exchange (ASX). The actual number varies daily. The ASX maintains a directory of the publicly listed companies on the ASX. This directory is updated daily at midnight eastern standard time (ASX Ltd, 2017). Consequently, there are many potential available share investments for an investor to choose from. The range of potential investment choices becomes even greater when one considers potential international investments. Investors may thus make use of fundamental and/or technical analysis to help identify potential future share investments. Fundamental analysis examines a company's business prospects and may include examination of the company's current earnings, non-earnings accounting numbers, future income prospects and dividend potential (Harvey, 2005). Technical analysis examines share price data over time with the intent of identifying and interpreting patterns within the share price time series (Harvey, 2005).

2.2.3 Five major investment methods

Investors have a range of investment methods available to them. The choice of investment method may also inform the type of share investments investors may ultimately make. Five major investment methods will be considered in this thesis (i.e., buy and hold investing, contrarian investing, dollar cost averaging, index investing and momentum investing). The five major investment methods can be considered to vary along a continuum of investor activity from passive to active. See Figure 2. In this framework, buy and hold investing is the most passive form of investing. Momentum investing is the most active.

Buy and hold investing	Buffett's Contrarian investing	Dollar cost averaging	Index investing	Grahamian contrarian investing	Momentum investing (hold 12 months)	. . .	Momentum investing (monthly rebalancing)
Passive							Active

Figure 2. A continuum of investment methods.
(Source: Abramson, 2003, p. 19)

Buy and hold investing is a method of investing whereby the investor buys shares in a company and holds those shares indefinitely (Harvey, 2005).

Contrarian investing involves buying shares at low prices and selling those same shares at higher prices (Lakonishok, Shleifer, & Vishny, 1992). The shares available at low prices are often referred to as value shares, losers or prior winners while those available at high prices are often referred to as glamour shares, winners or prior losers. (See, for example, Assoe & Sy, 2003; Athanassakos, 2009; Brouwer, van der Put, & Veld, 1997). Buffett varied the method of contrarian investing so as to buy shares at low prices and hold them indefinitely (Buffett & Clark, 1997). At the time of writing, many of the publicly listed companies in Australia might be considered to be value shares. During the highs of the internet bubble, technology and telecommunication shares might be considered glamour shares.

Dollar cost averaging involves outlaying a certain sum of money at set intervals in time to purchase shares in specified companies. This means that the investor will acquire more shares in the specified companies when the price per share is cheaper and fewer shares in those same companies when the price per share is more expensive. In so doing, the investor's average price per share for those same companies will be lower than the average price per share in those specified companies (Bierman & Hass, 2004; Knight & Mandell, 1993; Thorley, 1994). Investors may engage in dollar cost averaging when they set aside a certain portion of their fortnightly (or monthly) salary to purchase shares in specified companies.

Under index investing, no consideration is given to an investment's potential investment returns or risk profile. The investor simply buys shares in companies so as to match the same weighting those companies have in a specific benchmark share market index such as the S&P 500 or the ASX 200 (Gold, 2001; Harvey, 2005). If Telstra, for example, makes up 35 percent of the ASX 200, then an index based portfolio that is based on the ASX 200 would allocate 35 percent of its portfolio monies to the purchase of Telstra shares. If in the same example, Commonwealth Bank of Australia (CBA) made up 40 percent of the ASX 200, then 40 percent of the same portfolio monies would be used to purchase shares in CBA. Each of the other companies whose shares make up the ASX 200 would also be purchased using their respective weightings on the ASX 200. Once the initial index investment portfolio is established, it may be periodically adjusted to reflect changes to the selected benchmark index (Gold, 2001; Harvey, 2005). Such periodic adjustments involve purchasing more shares that have increased in value (the contrarian winners) since the previous periodic adjustment and selling down those shares that have declined in value (the contrarian losers) over the same period. This method effectively translates into momentum investing whereby winners are purchased in direct proportion to how much they are currently loved by the market place while losers are sold down in direct proportion to how little they are currently loved by the market place.

Momentum investing involves buying shares as they are rising in price and selling them as they decline in value (Lakonishok et al., 1992).

It is possible to construct portfolios using other investment strategies. Daniel and Hirshleifer (2015) discussed seven ways of constructing portfolios so as to take advantage of different share market anomalies. Two of these investment methods equate to contrarian and momentum investing. The remaining methods discussed by Daniel and Hirshleifer (2015) are outside the scope of this thesis. Sections 2.2.4 to 2.2.8 consider the research conducted on the five investment methods in turn.

2.2.4 Buy and hold investing

Portfolio returns using buy and hold investing and market timing methods have been constructed with share market data in a range of different countries, including those from Australian (Alcock & Gray, 2005); Swiss (Dische & Zimmermann, 1999); U.K. (Fong, 1992); or U.S. (Holloway, 1981; Pelaez, 1998; Pesaran & Timmerman, 1995;

Prather & Bertin, 1999) share markets. Market timing methods aim to predict growing and declining share market periods and make use of those predictions to time share trades (Chua, Woodward, & To, 1987). Some studies found the portfolio returns of buy and hold investing to be superior to that of market timing (Fong, 1992; Holloway, 1981), while others found the reverse (Alcock & Gray, 2005; Dische & Zimmermann, 1999; Pelaez, 1998; Pesaran & Timmerman, 1995; Prather & Bertin, 1999). In some studies, transaction costs had not been included (Dische & Zimmermann, 1999; Fong, 1992; Prather & Bertin, 1999). It is of concern that Prather and Bertin (1999) did not use significance tests. The findings of this study would need to be interpreted with caution.

The level of accuracy in market timing was not defined in the above-mentioned studies and may explain the discrepancy in findings across studies. Chua et al. (1987) constructed portfolio returns over a 34 year period from the Canadian Stock Market using buy and hold investing. The portfolio returns constructed with buy and hold methods were then compared to those constructed using market timing methods at different levels of market forecast accuracy. Portfolio returns from buy and hold investing were shown to be inferior to that of market timing when there was 100 percent forecast accuracy in those predictions. This relationship held when transaction costs were included. Chua et al. (1987) recognized that it would not be reasonable to expect investors to use market timing with 100 percent accuracy. The authors therefore calculated the odds ratio in generating superior returns to that of buy and hold investing at different levels of forecast accuracy. Chua et al. (1987) found that, before transaction costs, investors would need at least 80 percent accuracy in predicting growing (bull) share market runs, coupled with at least a 50 percent chance ability in predicting declining (bear) share market runs in order to generate superior returns to that of buy and hold investing. Investors would need 90 percent accuracy in predicting growing share market runs once transaction costs were factored into the equation.

From the research described in this section, it would appear that buy and hold investing will generate superior returns over that of market timing, unless the investor has superior prediction capabilities (i.e., able to predict at least 80 percent of bull runs and 50 percent of bear runs). Portfolio returns using buy and hold investing have also been compared to both dollar cost averaging and momentum investing. This literature is discussed in section 2.2.6 and 2.2.8 respectively.

2.2.5 Contrarian investing and the rational investor

Portfolios constructed using value shares generated consistent returns over those portfolios originally constructed using glamour shares in over 20 countries (see, for example, Assoe & Sy, 2003; Brouwer et al., 1997; Magnuson, 2011; Shi, Jiang, & Zhou, 2015). Moreover, one study found that the contrarian premium held in both bull and bear markets (Shi et al., 2015). An Australian study (Brailsford, 1992) and a Polish study (Zaremba, Okon, Nowak, & Konieczka, 2016) did not find evidence of a contrarian premium.

Using the book to market financial ratio to classify U.S. share market data into value and glamour shares, Fama and French (1995) confirmed contrarian profits. Fama and French (1998) repeated their analyses using book to market, earnings to share price, cash flow to share price and dividend to share price ratios to classify Australian, European and Far East share market data into value and glamour shares. Their second study also confirmed the benefits of contrarian investing (Fama & French, 1998). The Fama and French (1995, 1998) approach has been confirmed by other researchers. (See, for example, Daniel & Hirshleifer, 2015; Doeswijk, 1997; Dreman & Lufkin, 1997; Kothari et al., 1995).

Two studies found the difference between value and glamour portfolio returns to be more pronounced in January (Assoe & Sy, 2003; Li, 1987). Assoe and Sy (2003) found the January premium to be more pronounced where portfolios were constructed with small companies. Short term contrarian profits were also found (Galariotis, 2004; Otchere & Chan, 2003). Short term contrarian profits, however, may not be worthwhile pursuing after the impact of transaction costs has been considered (Assoe & Sy, 2003; Lee, Chan, Faff, & Kalev, 2003; Otchere & Chan, 2003; Park, 1995). Moreover, longer timeframes may be needed when using contrarian investing in smaller stock exchanges (Chin, Prevost, & Gottesman, 2002). Chung, Liu, and Wang (2016) found institutional investors engaged in short term contrarian investing. Moreover, short-term contrarian activity was undertaken by investment banks and mutual funds while other types of institutional investors engaged in more long term investing strategies. The authors also found short term contrarian investing to be profitable when investors used a one-week time frame (Chung et al., 2016).

The superior investment returns of the contrarian investment approach was considered the financial reward for taking on additional market risk associated with value shares (Chan, 1988; Fama & French, 1995, 1998). Some authors have argued that the contrarian profits were, in part, an artefact of research design (Ball et al., 1995; Chan, Jegadeesh, & Lakonishok, 1995; Kothari et al., 1995).

Others believed that contrarian profits are not compensation for taking on extra market risk. Indeed, they believed that contrarian investing is inherently less risky than other methods (Chan, Karceski, & Lakonishok, 2000; Chan & Lakonishok, 2004; Doeswijk, 1997; Dreman & Lufkin, 1997; Gregory, Harris, & Michou, 2001, 2003; Jegadeesh & Titman, 1993; La Porta, Lakonishok, Shleifer, & Vishny, 1997; Richards, 1997) or a consequence of naïve responsiveness to analyst forecasts (Dechow & Sloan, 1997; La Porta, 1996; Levis & Liodakis, 2001). Other reasons have been put forward to explain contrarian profits. For example, contrarian profits have been attributed to an extrapolation of past performance into the future (Lakonishok, Shleifer, & Vishny, 1994); mean reversion or regression to the mean effect (Badrinath & Kini, 2001; Balvers, Wu, & Gilliland, 2000; Gropp, 2004; Poterba & Summers, 1988); overreaction (Chang, McLeavey, & Rhee, 1995; Galariotis, 2004; Lee et al., 2003; Magnuson, 2011; Mun, Vasconcellos, & Kish, 1999; Otchere & Chan, 2003) and underreaction in the month of January (Galariotis, 2004).

Much of the research described in this section has been based on secondary data (portfolio simulation). The research described in this section consistently demonstrated the profitability of using contrarian investing with value shares over a three to five year investment horizon. The research described in this section has been divided, however, as to whether contrarian profits are due to market risk (and therefore, a function of the companies' financial merits), or whether contrarian profits are due to attributes of other investors. Portfolio returns using contrarian investing have been compared to those obtained when using momentum investing. This literature is discussed in section 2.2.8.

2.2.6 Dollar cost averaging

Past research has considered the portfolio returns of dollar cost averaging against those of buy and hold investing. Thorley (1994) calculated portfolio returns over a 66 year period, assuming the portfolio returns were constructed using dollar cost averaging and buy and hold investing. Average portfolio returns using dollar cost averaging were shown to be lower than those of buy and hold investing in market risk adjusted terms. Other studies confirmed portfolio returns from dollar cost averaging to be inferior to those of buy and hold investing (Knight & Mandell, 1993; Leggio & Lien, 2001, 2003; Rozeff, 1994; Williams & Bacon, 1993), albeit the reported results were not statistically significant in one study (Knight & Mandell, 1993) and statistically significant with small stocks only in another (Leggio & Lien, 2001). Two of the studies reported that portfolio returns were calculated before consideration of transaction costs (Knight & Mandell, 1993; Williams & Bacon, 1993). As the transaction costs for dollar cost averaging might be expected to be higher than those for buy and hold investing, the inclusion of transaction costs would be expected to further reduce the returns from dollar cost averaging over those of buy and hold investing (Knight & Mandell, 1993).

Using Monte Carlo simulations, buy and hold investing was shown to generate superior portfolio returns over those of dollar cost averaging. However, it was also shown to demonstrate higher market risk (Abeysekera & Rosenbloom, 2000). The proportion of time that portfolio returns from buy and hold investing would be superior to those of dollar cost averaging was shown to be dependent on the combination of the expected return from shares over those of government bonds, or other equivalent risk free interest bearing products. The greater the return from shares over those of government bonds or equivalent, the greater the superiority of portfolio returns from buy and hold investing over those of dollar cost averaging. Abeysekera and Rosenbloom (2000) concluded that there is a trade-off between buy and hold investing and dollar cost averaging such that the former generates greater investment returns while the latter generates greater protection from market risk.

Other studies using Monte Carlo simulations found buy and hold investing to generate superior returns over that of dollar cost averaging risk (Dichtl & Drobetz, 2011; Dubil, 2005). They also found buy and hold investing to demonstrate higher levels of market risk (Dichtl & Drobetz, 2011; Dubil, 2005).

Using a mean-variance analysis, Cho and Kuvvet (2015) confirmed that portfolio returns from buy and hold investing had superior investment returns over those of dollar cost averaging and that buy and hold investing is more risky than dollar cost averaging. Cho and Kuvvet (2015) concluded that risk averse investors may prefer dollar cost averaging returns for the sake of risk reduction in spite of its inferior portfolio returns.

Constructing portfolios at the beginning of both bull and bear markets, Grable and Chatterjee (2015) showed that portfolios constructed using buy and hold generated superior investment returns when undertaken at the beginning of bull markets while those generated using dollar cost averaging generated superior investment returns when undertaken at the beginning of bear markets. As Grable and Chatterjee (2015) noted, it may be difficult to ascertain when a bull or bear market is about to commence. The authors concluded that those with a higher risk tolerance may opt for buy and hold investing while those who are more risk averse may prefer to engage in dollar cost averaging.

Based on the research described in this section, it would appear that buy and hold investing consistently generated superior portfolio returns over those of dollar cost averaging, and these superior portfolio returns reflect increased financial risk.

2.2.7 Index investing

Index investing has been compared to actively managed funds (Carosa, 2005). As a proxy for index investing, 12 month rolling investment returns using the S&P 500 was compared with a pool of actively managed funds for a period of 29.5 years (Carosa, 2005). Using a paired two sample *t*-test, Carosa (2005) found that the portfolio returns from active funds significantly outperformed the S&P 500. It was not clear what method of investing was utilized by the active funds.

As a proxy for the method of index investing, the ASX All Ordinaries Accumulation Index was compared with the portfolio returns of 13 active funds against Australian benchmarks for a period of eight years (Gallagher, 2000). Gallagher (2000) found that only one of the 13 funds was able to significantly generate portfolio returns superior to that of the benchmark index. In a second study, active bond fund managers were shown to generate portfolio returns that matched their benchmark index. After management fees and expenses were taken into consideration, portfolio returns of active funds underperformed their benchmark index (Gallagher & Jarnecic, 2000). Again, it was not clear what investment method the active bond fund managers utilized.

From the research described in this section, it would appear that research is divided as to whether index investing is inferior or superior to more active fund management. The case in favor of index investing becomes clearer when transaction costs and management fees are taken into consideration. It is not clear, however, what method of investing the active funds had used. Moreover, past research has not compared the performance of index investing to those of buy and hold investing, contrarian investing, dollar cost averaging or momentum investing. It is therefore not yet known how portfolio returns using index investing compares with those of the remaining four methods. Yet, knowing the comparative performance of each investment method may help inform investor choice of investment methods.

2.2.8 Momentum investing

Momentum portfolios were constructed using share market data from 23 countries, i.e., Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Indonesia, Italy, Japan, Malaysia, The Netherlands, Norway, Singapore, South Africa, South Korea, Spain, Switzerland, Thailand, Taiwan, U.K. and U.S. (Chan, Hameed, & Tong, 2000). Significant momentum returns were found such that the longer the holding period (from 1 week to 26 weeks), the greater the momentum returns. Market risk could explain 12 and 26 week momentum returns but not two to four week momentum returns (Chan et al, 2000).

Momentum profits were also found in India over a seventeen year period. Momentum profits were enhanced for companies with small market capitalizations over those with large market capitalizations (Balakrishnan, 2016). A similar study of shorter duration (eight years) also found momentum profits in India. Momentum profits were evident for up to six months (Sehgal & Jain, 2015).

Other studies confirmed that momentum investing generated superior investment returns over short investment horizons (Chen, 2003; Cleary & Inglis, 1998). Moreover, momentum profits may be worth pursuing for investors who can access low transaction costs (Cleary & Inglis, 1998).

One study examined the portfolio returns of momentum investors in 401(k) accounts (Tang, 2016). The 401(k) plans are elective U.S. superannuation accounts that accept set employee pre-tax contributions. Funds are then available for investing in a range of cash or managed fund options at the employee's discretion (Internal Revenue Service, 2016).

The author found that the accounts of momentum traders consistently generated poor portfolio returns by buying funds that ultimately performed poorer than the average of the funds available and selling funds that performed better than the average of the funds available. The author believed that momentum traders did not select funds that matched their preference for momentum activity and that their trades reflected previous fund portfolio returns (Tang, 2016). This finding highlights the importance of having timely information when engaging in momentum investing.

Overconfident institutional investors were shown to generate superior momentum profits over those of underconfident institutional investors (Adebambo & Yan, 2016). The difference in momentum profits was not due to market risk. Nor could the difference in momentum profits be attributed to market capitalization, type of stocks, stock turnover or degree of analyst coverage. Later return reversals were evident in the stocks held by overconfident investors, but not for those held by underconfident investors (Adebambo & Yan, 2016).

Portfolio returns over a six year period using momentum investing were compared with those of buy and hold investing on the Jamaican Stock Exchange (Hunter, 1998). Transaction costs, fees and taxes were factored into the comparisons. Momentum investing demonstrated inferior investment returns to that of buy and hold investing. The author concluded that transaction costs make momentum investing unprofitable (Hunter, 1998).

Momentum and contrarian portfolios were also constructed using share market data from 19 countries (Bird & Whitaker, 2004; Chan, Jegadeesh, & Lakonishok, 1999; Forner & Marhuenda, 2003; Lee & Swaminathan, 2000; Mengoli, 2004; Rouwenhorst, 1998; Schiereck, De Bondt, & Weber, 1999). As might be expected from the literature on contrarian investing (see section 2.2.5), short term portfolio returns using momentum investing were found to be superior to those of contrarian investing (Bird & Whitaker, 2004; Chan et al., 1999; Forner & Marhuenda, 2003; Lee & Swaminathan, 2000;

Mengoli, 2004; Rouwenhorst, 1998; Schiereck et al., 1999), while contrarian investing had superior returns in the long term (Bird & Whitaker, 2004; Forner & Marhuenda, 2003; Lee & Swaminathan, 2000; Mengoli, 2004; Schiereck et al., 1999). Investors, however, would need to be mindful of transaction costs in practice (Chan et al., 1999). By contrast, one study found that short term portfolio returns using contrarian investing were superior to those of momentum portfolio returns, while longer term momentum portfolio returns were superior to those of contrarian portfolio returns (Kang, Liu, & Ni, 2002).

Momentum portfolio returns were not due to market risk (Schiereck et al., 1999). The benefits of momentum investing may eventuate because "investors are too pessimistic about the prospects of past loser companies and too optimistic about past winners. They cannot distinguish good (bad) companies from good (bad) shares and they do not perceive the general mean reversion in earnings" (Schiereck et al., 1999, page 112. Bracketed material in original).

The research, described in this section, has primarily used secondary data (portfolio simulation and 401(k) accounts). The research described in this section has demonstrated that momentum investing is profitable in the short term. However, investors planning to profit from momentum investing will need to factor in their costs of trading. In the long term, buy and hold or contrarian investing may prove superior to that of momentum investing.

From sections 2.2.4 to 2.2.8, it would appear that both buy and hold investing and contrarian investing strategies generate superior returns to those of dollar cost averaging and momentum investing in turn. It is not known whether index investing is inferior or superior to the other investment methods. In each of these studies, portfolio simulations compared only one or two methods of investing simultaneously. To date, there has not been a study that considered each of the five investment methods simultaneously. Moreover, none of these studies have considered which investment method is superior for different types of share investments. While it is outside the scope of this research, one might expect that certain types of investment methods may generate superior results with different types of share investments.

If the investor is purely *rational*, one need only determine the best combination of share investments and investment methods. However, if the investor is *human*, factors associated with the investor's *human*ity need be considered. Such factors include investor tendency towards overreaction, overconfidence, January and/or July effect, appetite for financial risk, information sources, social herding and psychological biases.

Sections 2.3 and 2.4 look at share market bubbles and crashes, as well as share market volatility. It is the belief of this thesis that share market bubbles and crashes represent extreme forms of investor overreaction. Sections 2.5 and 2.6.1 introduces the De Bondt (1985) concept of overreaction, and its accompanying research. The remainder of section 2.6 considers other research on the *human* investor, as well as research on investor profiles.

2.3 Share market bubbles, market crashes and the human investor

One may recognize a share market is a medium through which share trades can take place (Samuelson, Nordhaus, Richardson, Scott, & Wallace, 1948/1992). When share prices increase (or decrease) to a far greater extent than what might be expected based on a company's financial position and prospects, however, a financial bubble (or crash) may be in process (Fisher & Statman, 2002; Garber, 2000).

A number of share market bubbles and crashes have been observed in the history of share markets. Those known for pronounced upward momentum include the Tulip Bubble of 1634 to 1637, the Mississippi Bubble of 1719 to 1720, the South Sea Bubble of 1720 (Garber, 2000; Mackay, 1932) and the internet bubble of 1998 to 2000 (Bitmead, Durand, & Ng, 2004; Caginalp, 2001). Those known for the subsequent crashes include the share market crash of 1929 (Galbraith, 1979; Menschel, 2002) and the Global Financial Crisis of 2007 to 2010 (Anonymous, 2008a, 2008b; England, 2007; Goodway, 2007; Hale, 2008; Kopecki, 2008; Lekakis, 2008).

2.3.1 Share market bubbles

In the case of the Tulip Bubble, rare tulip bulbs were overbought. Much of the price momentum occurred late January/early February 1637. Little was known regarding prices for bulbs immediately following the February 1637 peak. However, five to six years later, rare bulbs were selling for $1/3^{rd}$ to $1/44^{th}$ of the February peak. One hundred years later, rare bulbs were selling for even smaller fractions of the February peak (Garber, 2000; Mackay, 1932).

The Mississippi Bubble is synonymously associated with John Law. He established a bank to manage royal French revenues after a period of financial distress. He established a company to trade on the Western side of the Mississippi River. This company later became known as *Compagnie des Indes*. Because of Law's banking reputation, investors held high expectations for the company. Consequently, its shares increased nine fold before the subsequent price reversal (Garber, 2000; Mackay, 1932).

Britain's South Sea company had sole rights to trade in the South Seas. It also had a reputation for money dealings. The company put forward a plan to bring British government debt under control and was permitted to issue shares in order to do so. The company made two issues of one million shares each. During the course of both issues, the company's share price rose nine fold. Thereafter, investors believed the share price to have reached its upper limits and sought to realize their gains. As more investors moved to sell their investments, sellers began to outnumber buyers, leading to a share price reversal. Director intervention and an issue of company bonds were unable to prevent this reversal (Garber, 2000; Mackay, 1932).

During the internet bubble of October 1998 to March 2000, the market value of technology shares rose five fold. Investment returns were seven times greater than that of the S&P 500 index while three times more volatile (Bitmead et al., 2004). Companies with *.com* in their name benefited from the share price momentum (Cooper, Dimitrov, & Rau, 2001). Moreover, the momentum exceeded fundamental value. In some instances, technology companies had yet to make a profit (Caginalp, 2001). Within three weeks from the March peak, technology shares dropped 40 percent. Investment returns of technology shares became four times poorer than that of the S&P 500 index. Technology shares became five times more volatile. Moreover, while trading volume for technology shares almost halved following momentum reversal, trading in the S&P 500 almost doubled (Bitmead et al., 2004).

2.3.2 Share market crashes

The late 1920s were renowned for a share market crash (Menschel, 2002). Prior to this crash, share prices demonstrated upward momentum. Several share price reversals occurred during 1927 and 1928. However, on each occasion, the share market rallied and the upward momentum continued. The three months prior to the crash showed consistent upward momentum. Trading volumes sustained levels not previously reported. The 1928 annual trading volume was almost double that of the 1927 trading volume. Margin lending was commonplace. Unit trusts increased eleven fold in value from early 1927 to autumn 1929 (Galbraith, 1979).

The turning point, known as "Black Thursday", took place on the 24th October 1929 (Galbraith, 1979; Menschel, 2002). Over a one hour period, sellers outnumbered buyers, actively traded shares demonstrated strong downward momentum. Inactive shares became unmarketable. The banks entered the market in an attempt to dampen downward momentum. While there was a minor rally, their combined efforts were insufficient to reverse the downward momentum (Galbraith, 1979; Menschel, 2002). The downward momentum continued for five days (Galbraith, 1979).

Finally, the Global Financial Crisis (GFC) began in 2007 with a series of defaults in the sub-prime lending market in the U.S. The U.S., U.K., European, Canadian and Asian banks acknowledged direct losses from this market, or indirect losses through their exposure to U.S. banks (e.g., England, 2007; Goodway, 2007). Fannie Mae and Freddie Mac, two of the largest U.S. mortgage lenders, had losses exceeding the value of their assets (Kopecki, 2008). Both lenders were bailed out by the U.S. government (Kopecki, 2009). However, the U.S. government did not extend its offer to other stressed companies. Consequently, Merrill Lynch was acquired by Bank of America, while Lehman Brothers went into liquidation (O'Shaughnessy, Johnston, Colebatch, & Martin, 2008). The Bush administration later bailed out American International Group (Martin, 2008) and took 40 percent equity in Citigroup (Dash, 2009).

The GFC had a negative impact upon consumer spending (e.g., Healy, 2009; Withers, 2009a); industry (e.g., Freed, 2009; Logue, 2009); employment (e.g., Goodman, Healy, & Stout, 2009; Withers, 2008b); liquidity (e.g., Nightingale, 2008; O'Shaughnessy, 2009a); and household wealth (Martin, 2009). The GFC also had a negative impact on mental health (e.g., Baumbach & Gulis, 2014; Gili et al., 2016). Gili et al. (2016) found an increase in the prevalence of depression, anxiety or psychosomatic disorders, during the period of the GFC. Moreover, the prevalence of these disorders were higher for men than they were for women (Gili et al., 2016). Baumbach and Gulis (2014) found an increase in fatal car accidents and suicide following the GFC.

Major governments took action to support their country's respective banking systems (e.g., Giles & Logutenkova, 2008; Livesey & Menon, 2008; Viscusi, 2008; Withers, 2008a). Moreover, Australia and the U.S. introduced several stimulus packages to reverse the downward economic trend (Davies, 2009; Murphy, 2008; Pittman & Ivry, 2008). Iceland, Hungary, Latvia, Pakistan and Ukraine received aid (Blomfield, 2009; Krasnolutska & Martens, 2008; Wilkinson, 2008; Ziffer, 2008). Latvia, however, remained at risk and was encouraged to devalue its currency (Blomfield, 2009). While some government interventions stimulated economic activity (see, for example, Colebatch, 2009), others had unintended consequences on market distributions (see, for example, Johnson, 2009).

In spite of government efforts, investors returned to cash, bonds (Bajaj & Grynbaum, 2008; Buhrer, 2008; Patten, 2008) and gold (FitzGerald, 2009a, 2009b; Hirst, 2009; Kirby, 2009; Williams, 2008; Wray, 2008). The run on non-bank assets led many institutions to freeze funds. Almost twelve months later, the freeze on non-bank assets was lifted only for those who could demonstrate financial difficulty (Battersby, 2009a). At the time of writing, the freeze on non-bank assets remains in Australia.

Finally, global share market indices trended downwards, with periods of sharp declines (e.g., Battersby, 2009b; England, 2007; Healy, 2008; Lindstroem, 2008; Liondis, 2008; O'Shaughnessy, 2008; O'Shaughnessy, 2009b). In Australia, the ASX 200 index reached a five-and-a-half year low of 3145.5 points on 6th March 2009 (Ciampa, 2009). Consistent with this trend, the proportion of Australians invested in shares declined from a high of 55 percent in 2004 to 46 percent in 2006 and to a low of 41 percent as at December 2008 (ASX Ltd, 2009).

By the 1st of May, 2009, the ASX 200 increased by 18 percent, while the S&P 500 increased 28 percent (Bassanese, 2009). The ASX 200 index rose through to 8th May before experiencing further declines (Battersby, 2009c). While there was evidence of share price volatility (e.g., Bailey, 2009c; Battersby, 2009d; Wells, 2009a), the ASX 200 reached progressive highs (Bailey & Baker, 2009; Battersby, 2009e; Ciampa & Liondis, 2009; Wells, 2009b). It had reached an eleven month high of 4596.1 on the 11th September 2009 (Bailey, 2009a). The S P 500 also reached progressive highs (Bailey, 2009b; Hughes, 2009). In the latter half of 2009, France, Germany (Dougherty, 2009), Japan (Tabuchi, 2009) and New Zealand (Withers, 2009b) showed signs of economic recovery. The GFC officially ended in April 2010 (Martin, 2010).

On examining market bubbles (and subsequent crashes) Kindleberger (1978) made the following observations: (a) Investors believe in the wealth potential of specific financial assets, and consequently, switch from cash to those assets. Investors may also engage in margin lending to obtain them. The general movement into those assets leads to an upward price momentum; (b) The price momentum of those assets exceeds fundamental value; and (c) At a later stage one or more events may contribute to a movement from those assets back to cash, (or payment of debt). The general movement away from those assets leads to a price reversal of those assets (Kindleberger, 1978).

It would also appear that the time horizon between one bubble (and its subsequent crash) and the next is sufficiently great that those who have lost a significant sum of money from one event are physically not around to experience the next one. Consequently, one might also conclude that each new bubble (and subsequent crash) occurs in the presence of a new set of investors. It is possible that the new group of investors are not aware of the previous bubbles or that they discount lessons from the past, believing the current event differs from those of the past. Regardless of the reason for the recurring nature of share market bubbles and crashes, it would appear that they represent extreme manifestations of share market volatility, or indeed, investor overreaction. The next two sections consider the literature on share market volatility and overreaction.

2.4 On share market volatility: From Bachelier to Buffett

It was not until 1900, after three major bubbles had occurred, that the first mathematician (Bachelier, 1900/2006) modeled the distribution of share market prices, as well as futures and option prices. In modeling share market data, he assumed the time series followed an identical and independent normal distribution, with an average price change of zero and a variance dependent on the length of the time series (Bachelier, 1900/2006; Sullivan & Weithers, 1991). Bachelier's distributional assumptions implied the presence of a random walk, and hence, that share price movement over time is random. His approach became known as Brownian Motion (Courtault et al., 2000; Sullivan & Weithers, 1991).

Some subsequently showed support for Bachelier's approach (Granger & Morgenstern, 1963; Kendall, 1953; Osborne, 1959; Samuelson, 1965), albeit Osborne (1959) identified log-normality. Others had shown the distribution of share market prices to demonstrate nonnormality (Brealey, 1970; Fama, 1963; Mandelbrot, 1963a, 1963b, 1967, 1971) as well as seasonality (Boness, Chen, & Jatusipitak, 1972; Mandelbrot, 1971). This line of research led to later research on the January effect. See section 2.6.3.

Wyckoff (1922/2010) may have been the first to recognize that share markets can be volatile, irrespective of intrinsic value or earning capacity. He attributed share price fluctuations to three factors: (a) share market manipulation; (b) technical factors in the share market; and (c) share market trends. He observed that most investors had little interest in learning about the investment world and reacted to current market activities. They preferred to receive quick tips from others. These same investors were allowing emotions such as fear and greed to eclipse sound financial judgment. Wyckoff (1922/2010) also observed that financially successful investors tended to: (a) learn about share market activity before making investments; (b) use foresight; (c) buy sound investments, at undervalued prices; (d) use stop loss orders; (e) act contrarily to other investor speculations; and (f) grow their wealth slowly and steadily.

Wyckoff (1922/2010) combined trading and investment practices. He traded to provide the cash flow for his future investment opportunities. For this reason, he sought out highly liquid financial products that could be immediately sold when he identified another investment opportunity. Wyckoff (1922/2010) was proactive in identifying good investments. He began with examination of the long term market trends, followed by industry analyses and company prospects. He examined the quality of the company's management team, its financial position and long term earnings potential. From there he examined share price data. He sought out shares: (a) with growth potential; (b) in companies that reinvested capital and/or income in their own future; (c) that were undervalued by the marketplace; and/or (d) in companies that provided essential or semi essential services (such as gas, electricity, food or steel). In cases where companies were being sold down in anticipation of a future disaster or future litigation, Wyckoff would wait until the anticipated event occurred before buying the company's shares. He reinvested dividends and took up rights issues. He also sought out undervalued bonds in good companies.

Graham (1949/1973) also recognized that share markets demonstrate volatility. He introduced *Mr. Market* to personify share market behavior. *Mr. Market* was willing to trade shares based on his own valuations. On some occasions those valuations represented fair value. On other occasions, *Mr. Market* became fearful or euphoric and would consequently under- or over- value those shares. Rather than succumb to *Mr. Market*'s mood swings, Graham recommended valuations be based on sound, independent analyses. He also recommended taking advantage of *Mr. Market* by buying a diverse cross section of undervalued shares and selling them when they become overvalued (Graham, 1949/1973; Graham, Dodd, Cottle, & Tatham, 1962).

A number of investors followed Graham's approach. While they had each selected different investments and had their own style, they all adopted Graham's concept of purchasing undervalued shares. In each case, their investment returns exceeded that of the S&P 500. (See appendix to Graham, 1949/1973). Warren Buffett is perhaps the most renowned of Graham's followers. Buffett amassed a fortune solely through his investment initiatives (Heller, 2000; Vick, 2001). In his early investment days, Buffett sought out undervalued companies, with no distinction between companies that had fair financial prospects and those that had excellent prospects (Heller, 2000; Vick, 2001). Buffett later refined his investment method so as to seek out businesses that: (a) he understands; (b) has sustainably growing earnings; and (c) has capable, honest management. Once identified, he acquires these businesses (wholly or in part) if they can be obtained at undervalued or fair prices. Buffett prefers to pay cash for these investments and hold them indefinitely (Berkshire Hathaway Inc., 2016; Heller, 2000; Vick, 2001).

Over a 51 year period Buffett's investment vehicle, Berkshire Hathaway, generated an after tax compounded annual return of 19.2 percent (book value) and 20.8 percent (market value). Over the same fifty-one year period, the S&P 500 generated a before tax compounded annual return of 9.7 percent (Berkshire Hathaway Inc., 2016).

From the literature described in this section, it would appear that while the share market may follow a random walk, there may be seasonality or non-normality evident in share prices over time. Moreover, the share price volatility observed by Wyckoff (1922/2010) and Graham (1949/1973) has enabled investors like Warren Buffett to enjoy superior investment returns.

It was not, however, until the work of De Bondt (1985) that academic interest in investor behavior emerged. Indeed, De Bondt (1985), through the seminal publications of De Bondt and Thaler (1985, 1987), led to interest in investor overreaction, the method of contrarian investing and ultimately the debate on whether or not the investor is rational. It is therefore believed that Wyckoff (1922/2010), Graham (1949/1973) and De Bondt (1985) sequentially contributed to the development of the field now known as behavioral finance with a view of the investor as *human*. These three authors may thus be considered the grandfathers of behavioral finance. Bachelier (1900/2006) may have laid the foundation for the alternate view of the investor as *rational*. The work of De Bondt (1985) will be considered in section 2.5.

2.5 Glamour and value shares, the De Bondt (1985) concept of overreaction

De Bondt (1985) introduced the concept of investor overreaction. He believed overreaction occurs when the price of a company's shares overcompensates for new information by moving in one direction (or the other) to a greater extent than may be warranted by the nature of that new information. Underlying this overreaction is the tendency for investors to overweight new information over that of older information. This tendency is more likely to occur when the new information stands out or is unforeseen (De Bondt, 1985).

De Bondt (1985) defined value shares (also known as losers or prior winners) as those shares that had negative returns over the preceding two to five years. Conversely, glamour shares (also known as winners or prior losers) had positive returns over the same period.

Portfolio returns based on value shares outperformed those based on glamour shares by as much as 19.6 percent two years after portfolio formation and displayed significantly less financial risk (De Bondt, 1985). Moreover, the difference between value based and glamour based portfolios was not equal, with value based portfolios gaining far more than glamour based portfolios lost (De Bondt, 1985). Much of the difference in portfolio returns occurred in January. Return differences could be observed up to five years following portfolio formation (De Bondt, 1985). This research was later published in the seminal publications of De Bondt and Thaler (1985, 1987).

2.6 The dimensions of the human investor

As noted at the end of section 2.4, the work of De Bondt and Thaler (1985, 1987) has opened up academic interest in investor behavior. The dimensions of the *human* investor include overreaction; overconfidence and its inverse; the January effect and its July effect counterpart; appetite for financial risk; psychological biases and social herding.
Sections 2.6.1 to 2.6.13 consider the research on overreaction, along with the remaining dimensions of the *human* investor. Section 2.6.14 considers the profile of investors.

2.6.1 Research on overreaction

When constructing value and glamour portfolios to match those of De Bondt (1985), value portfolios demonstrated superior returns in market risk-adjusted terms (Zarowin, 1990). However, value portfolios were based on companies with smaller market capitalizations (that is, company size) in thirteen of the seventeen periods under examination. When matched on market capitalization, value portfolios had superior returns in January alone. When small value portfolios were compared with large glamour portfolios, small value portfolios had superior returns. Yet, when comparing large value portfolios with small glamour portfolios, small glamour portfolios had superior returns (Zarowin, 1990).

Similarly, in relation to glamour portfolios, value portfolios were shown to have superior monthly returns one month after portfolio formation on risk adjusted terms (Zarowin, 1989). This finding was evident across all months. It was, however, most pronounced in January when value portfolios had smaller market capitalizations than those of glamour portfolios (Zarowin, 1989).

Using book to market financial ratios to classify portfolios, value portfolios were shown to outperform glamour portfolios by 1.9 percent to 10.5 percent per annum (Bauman & Miller, 1997; Capaul, Rowley, & Sharpe, 1993; Lakonishok et al., 1994). This relationship held when adjusting for market capitalization (Bauman & Miller, 1997; Lakonishok et al., 1994) and market risk (Capaul et al., 1993). Similar return differences were obtained when constructing portfolios on the basis of cash flow to share price or earnings per share to share price (Bauman & Miller, 1997; Lakonishok et al., 1994). Five year return differences were more pronounced than annual return differences (Lakonishok et al., 1994). Return differences could not be attributed to market risk. Rather, they were attributed to investor extrapolation of past performance into the future (Lakonishok et al., 1994).

It has been shown that value portfolios outperformed glamour portfolios for up to five years from portfolio construction. However, the reverse was true 10 to 14 years from portfolio formation (Beneda, 2002).

It was of interest to note that institutional investors were found to be net buyers of glamour shares while retail investors were net buyers of value shares (Sharma, Hur, & Lee, 2008). It has been shown that the greater the proportion of institutional investors that make up the share ownership of a particular company, the greater that company's share price volatility (Windolf, 2016). Moreover, on days when there were high volume trading, leading to significant market increases or decreases of at least two percent, it would appear that it was institutional investors (not retail investors) who were active in the share market (Dennis & Strickland, 2002). The trading activities of institutional investors were shown to buy up or sell down beyond the inherent value of the shares being traded. Moreover, those institutional investors that were mutual funds or pension funds followed the direction of the market movement while the trading activities of institutional investors associated with banks traded in the opposite direction (Dennis & Strickland, 2002).

Overreaction was not limited to investor behavior. Using recent earnings per share (EPS) as a guide, analyst forecasts of future EPS were too optimistic and too extreme (De Bondt & Thaler, 1990). Analyst forecasts may not fully represent all the information available to them (Trueman, 1990).

Much of the research described in this section has drawn on secondary data (portfolio simulation). The research described in this section conveys the hypothesis that shares in previously loved companies may fall out of favor and become value shares for up to a five year period, but not of longer horizons. Conversely, shares in previously disliked companies may become favored, glamour shares over a similar time frame. In general, the difference between value and glamour portfolio performance holds across market capitalization and market risk. Retail investors appear to be net buyers of value shares while institutional investors appear to be net buyers of glamour shares. It is possible that the volume of institutional trades may be such that they help “move markets”. In so doing, the share market as a whole may appear to overreact on value and glamour shares. Finally, it would seem that analysts also overreact in their expectations about the future earnings of the companies they research.

2.6.2 Overconfidence and underconfidence

Overconfidence occurs when investors consider themselves to be more capable investors than they actually are (Barber & Odean, 1999, 2001). Overconfidence may occur when investors believe “too strongly” in their own “mistaken valuations” and expect to extensively profit from same (Daniel & Hirshleifer, 2015, page 61). Overconfidence may also occur when level of confidence exceeds level of financial knowledge (Asaad, 2015). Overconfidence may also occur when decisions are made impulsively rather than decisions made following deep reflection on the surrounding issues pertaining to the decision (Noori, 2016).

In data obtained from U.S. brokerage accounts, overconfidence was shown to lead to increased trading activity (Asif, 2016; Barber & Odean, 1999, 2000, 2001; Glaser & Weber, 2003). It also led to poorer investment returns than might otherwise have been the case had investors retained their original holdings (Barber & Odean, 1999, 2000, 2001). Men have demonstrated a greater propensity towards overconfidence than women (Barber & Odean, 2001; Pompian & Longo, 2004). Men also demonstrated poorer investment returns due to their increased trading (Barber & Odean, 2000, 2001). Barber and Odean (2000) concluded that active trading has a detrimental effect on portfolio wealth. See also section 2.6.15, on the interaction between marital status and gender on level of overconfidence.

Using the market data for six Asian countries (Japan, Hong Kong, Malaysia, Singapore, South Korea, Taiwan) along with that of U.S. market data, the negative impact of overconfidence on portfolio returns has been confirmed (Huang, Heian, & Zhang, 2011). The link between overconfidence and excess trading has also been confirmed in Finland (Grinblatt & Keloharju, 2009) and Taiwan (Lin, 2005). Overconfidence may also have been at work when a sample of 45 retail investors reported more optimistic expectations of their own portfolios while concurrently reporting more realistic expectations of the Dow Jones' performance (De Bondt, 1998).

Overconfidence could be predicted by a combination of (a) financial literacy; (b) gender; and (c) marital status, but not age, education, investment experience or source of information about their investments (Ates et al., 2016). Together with self-attribution bias and over-optimism, overconfidence was shown to inversely predict quality of decision making (Kafayat, 2014). Overconfidence may also lead to detrimental financial decisions (Asaad, 2015). Interestingly, positive mood was shown to lead to overconfidence, and subsequent poor quality decisions. Awareness of the impact of positive mood on overconfidence could mitigate the negative impact of overconfidence on the quality of decisions ultimately made (Koellinger & Treffers, 2015).

Overconfidence may have some positive benefits: Using share market modeling, overconfident investors have been shown to do well in comparison to rational traders on investment opportunities borne about by market liquidity or activities of noise traders (i.e., those who trade on minor fluctuations in share prices that can be attributed to "noise"). Overconfident investors may do so by mispricing market risk as well as misestimating the size of potential financial rewards for acting on those opportunities (Hirshleifer & Luo, 2001). For these reasons, Hirshleifer and Luo (2001) concluded that overconfident investors may remain active share market participants. As discussed in section 2.2.8, overconfident institutional investors were shown to generate superior momentum returns over those of underconfident institutional investors. Portfolio return differences were not due to other factors. Later return reversals were found for the securities that overconfident institutional investors had previously invested in

(Adebambo & Yan, 2016). Finally, overconfidence may lend itself to persistence with solving difficult problems (Bi, Dang, Li, Guo, & Zhang, 2016).

While not many studies have considered underconfidence, it is conceivable that investors could also display underconfidence in their investment decisions. Griffin and Tversky (1992), for instance, found a relationship between the quality of the information and tendency towards either overconfidence or underconfidence in a series of six experiments using 25 to 298 students. The tendency towards overconfidence or underconfidence depended on the strength and credibility of the information. To the extent that the strength of information was strong and credibility of the source was weak, a tendency towards overconfidence may be evident. Conversely, when the strength of the information was weak and credibility of the source was strong, there may be a tendency towards underconfidence. This relationship was noted because individuals formed judgments more on the strength of the information, than the credibility of its source (Griffin & Tversky, 1992).

In summary, the research described in this section suggests that men may be more inclined towards overconfidence than women. Moreover, overconfidence may lead to increased share trading with consequent reductions in portfolio returns than might otherwise have been the case had they not engaged in those trades. Interestingly, positive moods may evoke overconfidence, with the subsequent negative impact on the quality of decisions made. Yet knowledge of the impact of mood on overconfidence may help mitigate this effect. Finally, the tendency towards overconfidence or underconfidence may be dependent on the strength of information investors have access to, irrespective of the source of that information.

2.6.3 January effect and its Australian counterpart --- the July effect

As discussed in section 2.4, research on the January effect grew out of research on distributional properties of share market prices (Boness et al., 1972; Brealey, 1970;

Fama, 1963; Granger & Morgenstern, 1963; Kendall, 1953; Mandelbrot, 1963b, 1967, 1971; Officer, 1975; Osborne, 1959; Rozeff & Kinney, 1976; Samuelson, 1965; Wachtel, 1942). Some found no evidence of seasonality (Granger & Morgenstern, 1963; Kendall, 1953; Osborne, 1959; Samuelson, 1965). Others did find evidence of seasonality (Boness et al., 1972; Mandelbrot, 1971; Rozeff & Kinney, 1976; Wachtel, 1942) while others specified that the seasonality specifically occurred in January (Rozeff & Kinney, 1976; Wachtel, 1942).

In a series of U.S. studies using secondary data (i.e., share market data of publicly listed companies), shares trading towards their twelve month lows in December, demonstrated an increase the following January. This increase was more pronounced in the first two weeks of January (Branch, 1977). Superior returns for companies with small market capitalizations occurred on the last day of December trading, plus the subsequent first four (Lakonishok & Smidt, 1984; Roll, 1983) or five days of January trading (Keim, 1983). The trend was most pronounced on the first day of January (Keim, 1983) and was still evident in the second week of January (Roll, 1983). Superior returns for larger companies were found before and after Christmas as well as on the turn of the calendar year (Lakonishok & Smidt, 1984). Trading volume for poorly performing securities was higher in December while trading volume for well performing securities was higher in January (Lakonishok & Smidt, 1986).

On the last day of December trading, there was a shift from trades at the buyers' offered price to trades at the sellers' asking price. This trend was coupled with overnight increases in the sellers' asking price (Lakonishok & Smidt, 1984). This trend became known as the January effect.

Further studies using secondary data have consistently confirmed the presence of a January effect. (See, for example, Beller & Nofsinger, 1998; Bentzen, 2009; Chan, 1986; Ciccone, 2011; De Bondt, 1985; Gultekin & Gultekin, 1983; Jones, Pearce, & Wilson, 1987; Jones, Lee, & Apenbrink, 1991; Klock & Bacon, 2014; Reinganum, 1983; Ritter, 1988; Ritter & Chopra, 1989; Schultz, 1985; Zarowin, 1990). The January effect was also present in other countries, including Australia, Belgium, Denmark, Germany, Holland, Japan, Norway, Spain and Sweden (Gultekin & Gultekin, 1983). However, two studies did not find evidence of a January effect (Pandey & Samanta, 2016; Patel, 2016).

One study considered the quarterly and annual trading activity of institutional investors (Hu, McLean, Pontiff, & Wang, 2014). Of interest in relation to the January effect, the authors found that institutional trading was lower at the end of the year. Institutional investors made fewer buy and sell transactions in the lead up to the end of the calendar year. However, the decline in sell transactions was greater than the decline in buy transactions (Hu et al., 2014). With the volume of trading that one might expect of institutional investors, the study may explain the December decline component of the January effect phenomenon.

The January effect could not be attributed to market risk in the U.S. (Beller & Nofsinger, 1998; De Bondt, 1985), but was associated with increased financial risk in Romania (Stancu & Geambasu, 2012).

One study found the January effect to account for only three percent of the variance in excess portfolio returns (Bentzen, 2009). A larger portion of the excess returns was accounted for by the interaction of year and month on portfolio returns. From 1964 to 2008, fourteen year by month combinations were shown to have positive excess returns; only one of them included a January. Of the sixteen negative excess returns; only one was a December (Bentzen, 2009). Consistent with expectations of a January effect, a Nigerian study found negative returns in December as well as positive returns in January (Ogieva, Osamwonyi, & Idolor, 2013). However, they also found evidence of negative returns in February, March, April and May. The months of August, September, October and November were also shown to have positive returns.

As is the case in the U.S., Canada's financial year aligns with the calendar year for both companies and individual tax payers (Berges, McConnell, & Schlarbaum, 1984). A January effect was found for Canada both before and after the introduction of capital gains taxation (Berges et al., 1984; Tinic, Barone-Adesi, & West, 1987).

Other studies using secondary data found evidence of a January effect in Australia (Brown, Keim, Kleidon, & Marsh, 1983; Gultekin & Gultekin, 1983); Belgium (Gultekin & Gultekin, 1983); Canada (Berges et al., 1984; Tinic et al., 1987); Denmark (Gultekin & Gultekin, 1983); Egypt (Mlambo & Biekpe, 2006); Germany (Gultekin & Gultekin, 1983); Holland (Gultekin & Gultekin, 1983); Japan (Gultekin & Gultekin, 1983; Kato & Schallheim, 1985); Mauritius (Mlambo & Biekpe, 2006); Norway (Gultekin & Gultekin, 1983); Romania (Stancu & Geambasu, 2012); Spain (Gultekin & Gultekin, 1983); Sweden (Gultekin & Gultekin, 1983); Tunisia (Mlambo & Biekpe, 2006); and Zimbabwe (Mlambo & Biekpe, 2006).

In Japan, companies can set their own financial years. Fifty percent of those companies have set their financial years to end on the 31st March (Kato & Schallheim, 1985). Both a January and June effect were found in Japan (Kato & Schallheim, 1985). While Kato and Schalheim (1985) do not report the financial years of individual Japanese taxpayers, they note that individual Japanese taxpayers do not pay capital gains tax, nor do they receive a tax benefit on capital losses (Kato & Schallheim, 1985). While the authors do not draw any causal links, they noted that Japanese companies traditionally pay employee bonuses in January and June. They also noted that the January and June effects may be related to quarterly reporting seasons for publicly listed companies (Kato & Schallheim, 1985).

In Australia, where the financial year typically ends on the 30th June for most Australian taxpayers (Brown et al., 1983), both a January and July effect were found (Brown et al., 1983; Henker & Paul, 2012). A later study found a June effect, which was attributed to tax loss selling (Brown, Ferguson, & Sherry, 2010). Henker and Paul (2012) explored whether retail investor activities could explain the January seasonal and found that their investment activities could not explain this effect. They wondered whether the January seasonal in Australia may be a function of institutional investor activities or a “spill over” effect from U.S. trading activities (Henker & Paul, 2012, page 1098).

The January effect has been attributed to tax loss selling (Wachtel, 1942) for companies with small market capitalization (Branch, 1977; Reinganum, 1983; Roll, 1983). Consistent with this hypothesis, changes to U.S. taxation law influenced retail investor behavior (Bentzen, 2009; Ivkovic, Poterba, & Weisbenner, 2004; Poterba & Weisbenner, 2001). The July effect in Australia appears similarly influenced by Australian capital gains taxation laws (Brown et al., 2010). Moreover, the July premium may be a consequence of investors reinvesting the proceeds from tax loss selling (Brown et al., 2010).

The January effect was found with both long term and short term capital losses (Chan, 1986). Moreover, after accounting for market capitalization and tax loss selling, the January effect disappeared (Johnston & Cox, 1996). Under this hypothesis, one might expect the presence of a January effect after the introduction of capital gains taxation on securities, but not before. Research, however, was mixed in this regard. (See Jones et al., 1987; compared with Jones et al., 1991; and Schultz, 1985).

In perhaps the only experimental test of the January effect, two pairs of auctions using student populations were undertaken. The first of each pair took place in December and the second in January. For each pair of auctions, students were shown to be willing to pay more in January than they were in December (Anderson, Gerlach, & DiTraglia, 2007). The authors acknowledge that students have a longer holiday period than do Wall Street professionals. However, they note that students may have a “change in mindsets across the winter holidays” (Anderson et al., 2007, page 6).

The January effect has also been attributed to parking of the proceeds (Ritter, 1988) and portfolio rebalancing (Ritter & Chopra, 1989). Under the parking of the proceeds hypothesis, retail investors retain proceeds from December tax loss selling until January. Proceeds would then be supplemented with those from capital gains and bonuses. Thereafter, retail investors act in unison to make share acquisitions. This pattern of activity contributes to the upward share price pressure typically seen in January (Ritter, 1988). Similarly, under the portfolio rebalancing hypothesis, institutional investors sell out of high risk securities in December and purchase new securities, including high risk ones, in January (Ritter & Chopra, 1989). While retail investors may be motivated by confirmation of available funds for future investment (Ritter, 1988), institutional investors may be governed by the appearance of their year-end balance sheets (Ritter & Chopra, 1989). The result would be one where both retail and institutional investors act in concert to sell down securities traded in December and buy up securities traded in January (Ritter, 1988; Ritter & Chopra, 1989), albeit for different reasons.

A more recent hypothesis attributed the January effect to investor optimism each January, followed by disappointment in remaining months of the same year (Ciccone, 2011). Ciccone (2011) anticipated that those publicly listed companies with greater dispersion in analyst forecasts would have superior investment returns in January, followed by inferior returns in latter months of the year. By marrying (secondary) share market data with degree of variability in analyst forecasts, Ciccone (2011) was able to provide support for his hypothesis.

As Ciccone (2011) acknowledges, the optimism/disappointment hypothesis may explain a part of the presence of the January effect. From the research described in this section, it is possible that the presence of the January effect, and indeed the July effect, may result from a combination of factors including (a) optimism/disappointment; (b) portfolio rebalancing by institutional investors; (c) parking of the proceeds by retail investors; and (d) tax loss selling. Other factors yet to be researched may also contribute to the presence of the January effect.

In summary, from the research described in this section, it would appear that investors sell down shares in the lead up to the end of the calendar (or financial) year and buy up new shares in the new (financial) year. As with overreaction and overconfidence, much of the research on the January (and July) effects is based on portfolio simulations using secondary data. Whilst there are hypotheses as to why the January (and July) effects occur, the underlying antecedents are not yet known.

2.6.4 Appetite for financial risk

Appetite for financial risk may depend on previous investment returns (Nofsinger, 2001). Following a capital loss, investors may become risk averse, demonstrating conservative investment decisions. Alternatively, they may try to break even on high risk investments, even if their probability of a good return is low (Nofsinger, 2001). By contrast, following a financial gain, investors may feel as if they are playing with other people's capital and may consequently be willing to take on more risk with those "wins" (Nofsinger, 2001).

In a share market competition, men demonstrated greater appetite for financial risk than women. In some instances, the differences could be attributed to gender alone. In other instances, it could be attributed to the interaction between gender and degree of optimism (Felton, Gibson, & Sanbonmatsu, 2003). Optimistic men were more inclined to use futures and options. Optimistic men were also less likely to trade on the New York Stock Exchange (NYSE). Overall, men engaged in more transactions on the National Association of Securities Dealers Automated Quotations, (commonly referred to as the NASDAQ) (Felton et al., 2003). Felton et al. (2003) suggests that men in general, and particularly optimistic men, have a preference for share investments that have a higher risk profile, and consequently, favor securities listed on the NASDAQ over those of the NYSE. Consistent with what might be expected with a greater appetite for financial risk, portfolio results for men demonstrated greater variability than those of women (Felton et al., 2003).

The gender differences in appetite for financial risk may have a physiological base (Apicella, Dreber, & Mollerstrom, 2014). One study found changes in level of testosterone influence, following a prior win or loss, influenced later appetite for financial risk. More specifically, a prior win led to increased levels of testosterone. In turn, higher levels of testosterone led to greater appetite for financial risk than when the reverse was true. Moreover, when the competition for the prior win was strong, the increase in testosterone was greater (Apicella et al., 2014).

Using a database of 3551 Canadians, appetite for financial risk was shown to decrease with age (Morin & Suarez, 1983). Appetite for financial risk was also shown to increase when considering wealth effects (Morin & Suarez, 1983). In a sample of 742 retail investors, investor appetite for financial risk was shown to decline with age (Charles & Kasilingam, 2015). In this sample, the youngest investors had either a high appetite for financial risk or a low appetite (Charles & Kasilingam, 2015).

Using a sample of 2166 retail investors from a Tunisian brokerage house, appetite for financial risk was shown to be predicted by gender, age, income, education and whether or not the investor worked in the finance sector (Sebai, 2014). As might be expected, age and income were shown to inversely predict appetite for financial risk while level of education and working in the finance sector predicted appetite for financial risk (Sebai, 2014). Contrary to what one might expect, however, being male in this sample was predictive of less appetite for financial risk (Sebai, 2014). Sebai (2014) noted that Tunisian society is primarily patriarchal. It is therefore possible that the lower appetite for financial risk in Tunisian males may be an artifact of Tunisian societal norms.

While Morin and Suarez (1983), Charles and Kasilingam (2015) and Sebai (2014) found appetite for financial risk to decline with age, it is also possible that the relationship between age and appetite for financial risk may lie with years of investment experience. The authors of these three studies did not consider the role of investment experience on appetite for financial risk.

In two experiments with 25 to 32 administrative staff at the University of Southern California, participants were willing to invest less of their retirement savings allocated to shares when shown the potential twelve month returns, but willing to invest more of their retirement savings when shown the expected returns over longer time horizons (Benartzi & Thaler, 1999).

In a sample 128 Malaysian investors, a preference for investing in familiar companies inversely predicted propensity for general risk-taking, while positive self-attributions of investor acumen was positively related to propensity for general risk-taking (Chin et al., 2016). A study that also considered generic risk preferences, found that those who used more cognitive reflection had a greater risk appetite on gains, and lower risk appetite on losses, than did those who used a more impulsive cognition (Noori, 2016). While both studies did not consider appetite for financial risk *per se*, but rather, a more general measure of propensity for risk, one might expect the research findings of both studies to extend to appetite for financial risk. If this proves to be the case, then appetite for financial risk may be moderated by other factors such as familiarity bias, self-attribution bias and the depth of thinking about a particular problem before reaching an investment decision.

In a series of 40 lottery trials, propensity for making risky decisions amongst 30 university students was considered. Facial recognition software was used to identify six major types of emotion (fear, surprise, happiness, anger, disgust and sadness). The six emotions were selected by the authors because the accompanying facial expressions are universal across cultures, and blind people show the same expressions as do sighted people (Nguyen & Noussair, 2014). The authors found that prior facial expressions of fear, happiness, anger and surprise were associated with later risk aversion in lottery decisions. Moreover, the authors also found a gender difference in propensity for making risky decisions, with female students in their study showing greater risk aversion than did male students. The authors concluded that strong emotions may trigger risk averse decisions (Nguyen & Noussair, 2014). While this study used lotteries to evoke decision making under uncertainty, the Nguyen and Noussair (2014) findings are consistent with other studies that considered appetite for financial risk in financial markets.

In a second lottery experiment, participants made riskier gambles following negative experiences than they did following positive experiences (Schneider, Kauffman, & Ranieri, 2016).

Based on the research described in this section, it would appear that men, and especially optimistic men, may have an appetite for financial risk while women, or older investors, may be more risk averse. Moreover, it would appear that investors can be encouraged to increase their appetite for financial risk by being educated in the long term benefits of investing in the share market. By contrast, one might expect prior strong emotion to trigger risk aversion. Whilst not considered by the research described in this section, it is also possible that years of investment experience may play a role in the degree of appetite for financial risk an investor might display.

2.6.5 Psychological biases

According to Kahneman and Tversky (1979), prospect theory predicts how decisions are made under uncertainty. In particular, there is a tendency to underweight probable outcomes in comparison to those that are more certain. This tendency leads to risk averse decisions regarding gains such that a smaller, but certain, gain is preferred over a potentially larger uncertain gain. This tendency also leads to risk tolerant decisions over losses such that a potentially larger loss is preferred to a smaller, but certain one. Information that is constant across alternative options tends to be ignored, leading to inconsistent results when problems are framed differently. Ultimately this theory predicts that decisions are made so as to seek out certain gains, while avoiding certain losses.

Prospect theory thus implies that decisions made under uncertainty do not follow statistical weighting of probabilities, but rather, are subject to psychological biases. Sections 2.6.6 to 2.6.12 describe several psychological biases that may be evident in investor decisions.

2.6.6 Anchoring bias

Anchoring bias occurs when an investor tags share securities to a set price. The price at which the anchor is set may be associated with the investor's purchase price or some other key event in the investor's experience (Brabazon, Idowu, & Menyah, 2004). The anchoring bias may lead to less extreme investment decisions than might otherwise have been made (Czaczkes & Ganzach, 1996). Investors may be subject to the anchoring bias when they consider their own purchase price for a particular company's shares, rather than company, industry or structural factors, when making decisions as to whether or not to sell that particular company's shares.

Using a series of six experiments in samples ranging between 92 and 181 undergraduate students, Cheek et al. (2015) showed that student judgments were influenced by the presence of anchors. Student judgments were influenced by anchors irrespective of whether or not those anchors were plausible to the task at hand; and irrespective of whether the judgments were of their own performance, or that of another participant in the study (Cheek et al., 2015).

2.6.7 Disposition effect

The disposition effect has been described as the tendency to capitalize gains early and hold onto unrealized losses too long (Baker & Ricciardi, 2014; Nofsinger, 2001; Shefrin & Statman, 1985). Prospect theory, mental accounting, regret aversion and self-control jointly explain this effect: An investor frames investment decisions into gains and losses. In each case, gains are preferred over losses (prospect theory). When shares are purchased a new account is established and the performance of those shares is monitored against that of the share purchase price (mental accounting). The investor is reluctant to close off an account at a capital loss as it elicits feelings of regret. The investor much prefers to close off an account at a capital gain, eliciting feelings of pride (regret aversion). Capitalizing a loss requires self-control strategies such as pre-determined trading rules, including pre-determined points at which share sales are triggered (Shefrin & Statman, 1985). Investors may be subject to the disposition bias when they sell a particular company's shares for a capital gain soon after that company's shares begin rising (Shefrin & Statman, 1985). Investors may also be subject to the disposition bias when they have a number of different company's shares in their portfolio that are trading at prices below their own purchase price and those company's shares are continuing to drop in price (Shefrin & Statman, 1985).

Empirical research (Chui, 2001; Das, 2012; Oehler, Heilmann, Lager, & Oberlander, 2003; Rubaltelli, Pasini, Rumiati, Olsen, & Slovic, 2010; Shafran, Benzion, & Shavit, 2009; Weber & Camerer, 1998), share market data (Ferris, Haugen, & Makhija, 1988; Goetzmann & Massa, 2008) and investor trading activity (Barber & Odean, 1999; Odean, 1998) were consistent with the presence of a disposition effect.

Lehenkari and Perttunen (2004) also analyzed investor trading activity. Consistent with the disposition effect, they found that Finnish investors held onto losing shares. However, they found no evidence of Finnish investors selling winning shares too quickly. The authors concluded that Finnish investors were loss averse (Lehenkari & Perttunen, 2004).

2.6.8 Endowment effect

Endowment effect occurs when an investor seeks a higher sale price for an investment already owned than the investor would have paid to purchase that same investment if they had not already owned it (Kahneman et al., 1990; Nofsinger, 2001; Sevdalis, Harvey, & Bell, 2009; Shefrin & Caldwell, 2001). The endowment effect was found to be affected by consideration of probability and size of return or liability (Shefrin & Caldwell, 2001). The endowment effect may arise as a consequence of anticipating future regret (Ratan, 2014). This effect may also arise as a consequence of creating an expectation of ownership in study participants (Heffetz & List, 2014). There may be a gender difference in the presentation of this effect, with women willing to pay less than men (Wieland, Sundali, Kemmelmeier, & Sarin, 2014). However, the gender difference is not evident when men and women determine how much they are willing to sell for an owned item (Wieland et al., 2014).

2.6.9 Familiarity bias

Familiarity bias (also known as home bias) occurs when investors demonstrate a preference for investments in known, local companies (Baker & Ricciardi, 2014; Nofsinger, 2001). One might expect that investors may also be subject to the familiarity bias when they invest in companies with whom they are a customer. Familiarity bias was shown to inversely predict propensity for general risk-taking (Chin et al., 2016).

Investors may also be displaying the familiarity bias when they invest in local or national companies over international ones (Nofsinger, 2001). Indeed, fund managers were shown to invest in local and international securities that were geographically closer than those that formed part of their benchmark index (Coval & Moskowitz, 1999). French and Poterba (1991) reported preferences for national investment at the rate of 79 percent (Germany), 89.4 percent (France), 92 percent (U. K), 92.2 percent (U. S.), and 95.7 percent (Japan). A preference for investing in companies that are familiar was also found in Finland (Grinblatt & Keloharju, 2001). Germany, Japan and U.S. (Hasan & Simaan, 2000).

Familiarity bias may occur due to greater investor confidence with local/national investments over international investments (Kilka & Weber, 2000). Familiarity bias was also more pronounced in the equity markets of emerging economies over those of developed economies (Kim, Yun, Cin, & Kim, 2014). However, investment decisions based on familiarity may lead to poor portfolio returns in bear markets (Boyd, 2001).

Decision makers judged events to be more likely to the extent that they were familiar with those events. However, the effect of familiarity dissipated when decision makers were asked to make probability judgments (Fox & Levav, 2000).

2.6.10 Mental accounting

Mental accounting occurs when each financial transaction is placed into a separate account. The tendency to do so may come from a need to control one's finances. However, when one mentally locks funds into separate accounts, there is a lack of flexibility across accounts that may ultimately lead to poor overall financial decisions (Brabazon et al., 2004; Nofsinger, 2001; Thaler, 1985, 1999). Investors may thus be engaging in mental accounting when they mark out separate funds for spending on Christmas presents, planned holidays, investing and superannuation.

In a semester-long share market exercise with 84 accounting and finance students, a gender difference was found in the prevalence of mental accounting. More specifically, mental accounting was more prevalent with male students than it was with female students (Lee, Miller, Velasquez, & Wann, 2013).

2.6.11 Representative bias

Representativeness occurs when an object is considered to be an example of a specific type on their most prominent attributes (Kahneman & Tversky, 1972; Tversky & Kahneman, 1974). Representative bias may thus occur when investors extrapolate from a set of common, observable dimensions to other (non-observable) dimensions (Nofsinger, 2001). This bias may occur when investors regard current circumstances to be a manifestation of something they have seen before. It may occur when investors think they see patterns, but those perceived patterns are little more than random variations. It may occur when investors extrapolate past trends into the future (Brabazon et al., 2004). It may also occur when investors equate the prospects of a company's profit performance with that of its financial securities (Nofsinger, 2001). It may also lead to more extreme investment decisions than might otherwise have been made (Czaczkes & Ganzach, 1996). Investors may thus be engaging in representative bias when they treat a company's share performance as being the same as the company's profit over the same period of time. Representative bias was shown to be predicted by education and financial literacy (Ates et al., 2016).

2.6.12 Status quo bias

Status quo bias reflects a "do nothing" approach and occurs when investors prefer to stay with their current investment position (Baker & Ricciardi, 2014; Nofsinger, 2001). Using a series of experiments, W. Samuelson and Zeckhauser (1988) demonstrated the tendency for individuals to seek the status quo. Degree of cognitive reflection has no significant influence on the tendency towards this bias (Noori, 2016).

As can be seen from the discussion in sections 2.6.5 to 2.6.12, psychological biases may influence investment decisions. More specifically, psychological biases have the capacity to unnecessarily restrict investment options (e.g., familiarity bias and mental accounting) as well as to lead to poor or extreme investment decisions (anchoring, disposition effect, endowment effect, status quo) than might otherwise have been the case.

2.6.13 Other psychological biases

Other biases include ambiguity aversion, availability bias, cognitive dissonance, confirmation bias, conservatism bias, framing, hindsight bias, illusion of control, loss aversion, optimism bias, regret, recency bias, self-attribution bias and self-control bias (Pompian, 2008). Overconfidence is often considered a psychological bias (see, for example, Pompian, 2008). This thesis, however, conceptualizes overconfidence as a personality construct. It has therefore been discussed in section 2.6.2 above.

2.6.14 Social herding

Social herding is the tendency of investors to act in concert with others (Lakonishok et al., 1992; Nofsinger & Sias, 1999; Prechter, 2001). Investors may be engaging in social herding when they purchase shares in the same company as their friends, neighbors or colleagues (Hong, Kubik, & Stein, 2004). Herding behaviors are likely when retail investor social networks are strong. Moreover, even small swings in share market behavior can elicit social herding in the share market (Chang, 2014).

Prechter (2001) suggested that social herding may occur when investors lack sufficient knowledge to form their own judgments and believe that they can best protect their financial assets by following the actions of others. Prechter (2001) believed that social herding may occur when investors want to preserve their intellectual image amongst their peers and believe they can best accomplish this by demonstrating they hold views similar to those of the majority. Indeed, in modeling the behavior of portfolio managers, Scharfstein and Stein (1990) found that institutional investors were more inclined to ignore their own research in favor of following the herd. In so doing, institutional investors could preserve their reputation as being as intelligent as their colleagues (Scharfstein & Stein, 1990). Institutional investors were also shown to be more inclined to social herding than were retail investors (Nofsinger & Sias, 1999; Trenca, Pece, & Mihut, 2015). Social herding may be related to momentum activity (Nofsinger & Sias, 1999). Prechter (2001) believed there may be a biological basis for social herding.

As Prechter (2001) suggested, acting in concert with others in financial markets may reduce investor wealth. It may lead investors to buy securities at increasingly inflated prices or sell securities at increasingly deflated prices. Moreover, as investors have access to the same information, social herding may act to feed on itself, leading to successive periods of prolonged positive and negative overreaction. This may, in turn, generate successive periods of share market bubbles and crashes.

The decision to participate in the share market may be determined by investor sociability, where the more sociable the investor, the more likely that investor will invest if his/her peers do (Hong et al., 2004). Once in the share market, social herding may influence choice of information to inform investment decisions. The information sought may not necessarily be relevant to the investment decision (Froot, Scharfstein, & Stein, 1992).

In one study examining social herding in France, Germany, Japan, Mexico, Spain, U.K. and U. S., social herding was found to be present in Spain, but not the remaining six countries (Blasco & Ferreruela, 2008). In a separate study, social herding occurred in both growing (bull) and declining (bear) Italian share markets (Caparrelli et al., 2004). It also occurred in South Korean and Taiwanese markets, and to a lesser extent in Japanese markets, but not U.S. or Hong Kong markets (Chang, Cheng, & Khorana, 2000). On the whole, social herding was not influenced by market capitalization (Chang et al., 2000). Social herding was not evident in two separate U.S. studies (Christie & Huang, 1995; Lakonishok et al., 1992). In one of these studies, however, herding became apparent when considering companies with small market capitalization (Lakonishok et al., 1992).

Herding was present in Korean institutional investors (Chung et al., 2016). Herding was also present in analyst forecasts (Baddeley, 2013; Clement & Tse, 2005; Olsen, 1996; Stickel, 1990). Moreover, analyst tendency to herd was positively related to the degree of difficulty in forecasting a company's future earnings (Olsen, 1996). Similarly, when investment club members were asked to make forecasts, their tendency to herd was negatively related to their own perceived forecasting abilities and positively related to the perceived credibility of the majority view (Cote & Sanders, 1997). The tendency to herd was positively related to the number of industries the analyst followed, employment by smaller brokerage houses as well as inexperience or infrequency of making forecasts (Clement & Tse, 2005). The tendency to herd may be due to a need to manage one's reputation amongst professional peers (Baddeley, 2013). Yet, those who made their own independent forecasts were more accurate than those who aligned with consensus forecasts (Clement & Tse, 2005; Rulke, 2013).

Barber and Odean (2008) used share price data trading volume, the previous trading day's share price movements, and Dow Jones news feeds as markers of attention attractors. Using trading activities from U.S. retail and institutional investors, the authors found retail investors to be net buyers when these markers were present and concluded that retail investors made share purchase decisions based on what attracted their attention (Barber & Odean, 2008). As institutional investors were net sellers under these same conditions, the authors concluded that institutional investors were not as influenced by these markers (Barber & Odean, 2008). If this is indeed the case, it would appear that retail investors may appear to be herding on share market data, whether it is share market data itself, or news reports of same.

The direction of media sentiment was found to predict short term trading volume and short term direction of trading activity in U.S. share markets (Tetlock, 2007). The proportion of negatively couched language in a news article was predictive of future investor trading activity. If that news article was related to a specific company's financial performance, the negative media sentiment was more likely to be predictive of that company's future financial performance than it was if the negative media sentiment was of a more general nature (Tetlock, Saar-Tsechansky, & Macskassy, 2008). Moreover, it would appear that retail (but not institutional) investors did not distinguish between new information and revisited old information (Tetlock, 2011).

In a related study, the trading records of retail investor accounts in 19 separate U.S. cities were compared with local media coverage of events (Engelberg & Parsons, 2011). The authors found that share buying and selling activities were significantly increased on the same day as local media coverage. The authors noted that this relationship was not affected by retail investor current holdings at the time of media coverage. Moreover, if there were severe weather events that may have delayed physical delivery of the local newspapers, the impact of media on retail investor trading activities was lost (Engelberg & Parsons, 2011). The authors believed that the impact of the media on investor trading did not come from the contents of media coverage, but rather, the very presence of media coverage itself. The authors concluded "… the media is at least … likely to drive trade than information. If these generalize … to the aggregate level, they easily are capable of influencing prices and allocations" (Engelberg & Parsons, 2011, page 96). If the conclusion of Engelberg and Parsons (2011) is indeed correct, media may also be responsible, either wholly or in part, for the appearance of social herding in share markets.

In a second related study, Ahern and Sosyura (2015) considered 501 newspaper articles that were first to disclose a potential merger (rumor) within the period under investigation (i.e., 2000 to 2011). Approximately one-third of the 501 rumored mergers later took place or were involved in merger, but failed, negotiations (Ahern & Sosyura, 2015). Moreover, only 9 percent of all mergers that took place in the period of analysis received media coverage. Thus, not all mergers were reported and not all rumored mergers turned out to be genuine (Ahern & Sosyura, 2015). The authors found that companies that were subject of rumored mergers experienced superior investment returns. However, those that turned out not to be genuine experienced return reversals back to the levels seen prior to the rumored mergers (Ahern & Sosyura, 2015). The authors found that rumored mergers were more likely to be genuine when (a) the subject of the rumor was not a large publicly listed company with a recognized brand; (b) the journalists were older; (c) the journalists had appropriate training in journalism; (d) the journalists specialized in the field in which the article was reported; and (e) there were specific details outlined within the text of the article (Ahern & Sosyura, 2015). The authors also found retail investors were buyers following rumored mergers while institutional investors were sellers following the same rumors (Ahern & Sosyura, 2015). Moreover, the authors found that "sophisticated short sellers" were better able to assess the veracity of rumored mergers (Ahern & Sosyura, 2015, page 2053). The authors concluded that "media impacts asset prices … (and) introduces noise through speculative articles" (Ahern & Sosyura, 2015, page 2054).

A third study along this line of research considered the impact of media on share trading volume during nation-wide strikes (Peress, 2014). The author found the volume of trading on the day of a strike was significantly lower than non-strike days (Peress, 2014). The reduction in trading volume was pronounced for companies with smaller market capitalizations. Declines in trading volume dissipated in companies with large market capitalizations. Availability of online news services mitigates this effect (Peress, 2014). The author surmised the reduction in trading to be driven by retail investors as retail investors do not have access to other sources of media to inform their investment decisions (Peress, 2014).

In general, the research described in this section suggests that investors may feel safe by investing in the same direction as the rest of an investment crowd. Moreover, it would appear that media has the capacity to move the direction of herding behavior. The impact of media on social herding may take place, irrespective of the degree of accuracy of media content. Moreover, in relation to institutional investors, retail investors may be less discerning over the quality of media content.

2.6.15 Investor profile

Thus far, the literature considered characteristics of the investor that may affect investor behavior in the share market. However, the demographic profile of investors may also influence share market behavior. This section describes the demographic profile of the share investor, along with how such demographic characteristics may influence investor behavior.

The Australian Securities Exchange (ASX) has conducted fourteen surveys of Australian investors since 1986 (ASX Ltd, 2015). The November 2014 survey randomly surveyed 4,009 Australians aged 18 years or over. Thirty-three percent of those surveyed had direct exposure to publicly listed shares through the ASX and/or overseas security exchanges. Moreover, direct participation in the share market had increased over previous years while indirect participation through managed funds had decreased. The 2014 ASX survey found retail investors more likely to be (a) male; (b) tertiary educated; (c) aged 45 to 64; and (d) residing in capital cities. Retail investors in this survey were also more likely to use an online platform to enact their trades (ASX Ltd, 2015). Not surprisingly, the proportion of respondents with direct participation in the share market increased with level of education or salary: Twenty-five percent of those with a year 12 education or less were directly exposed to the share market. This figure increased to 51 percent for those with a post graduate education. Similarly, 33 percent of those earning \$50,000-\$70,000 per annum were directly exposed to the share market. This figure increased to 51 percent for those earning over \$200,000 per annum (ASX Ltd, 2015).

Forty-nine percent of respondents in the ASX 2014 survey considered themselves to be knowledgeable investors and 46 percent sought ongoing investment education (ASX Ltd, 2015). Retail investors used six to seven sources of information to inform their investment decisions. The most popular source of information came from personal networks (family, friends and colleagues), followed by social or print media and financial advisors. Thirty percent of those who had direct exposure to the share market did not seek information to guide investment decisions (ASX Ltd, 2015).

In a Malaysian study, respondent race and education were shown to determine whether investors choose to invest in shares or other forms of investments (Jamal, Ramlan, Pazim, & Budin, 2014).

In a mail-out, mail-back survey of 200 retail and 51 institutional investors in Malaysia (Lai et al., 2013), respondents were found to be between 25 and 45 years of age and tertiary educated. Fifty-seven percent of institutional investors, however, reported themselves to be confident with their investment skills, while only twenty percent of retail investors reported themselves to be confident in their own investment skills. Moreover, both retail and institutional investors in this sample reported overconfidence and herding activities in both bull and bear markets. However, retail investors reported significantly lower levels of overconfidence and significantly higher levels of social herding in both bull and bear markets (Lai et al., 2013).

A mail-out, mail-back survey was undertaken with 972 randomly selected U.S. investors who were customers at a large, unnamed stock broker from the 1st January 1964 to 31st December 1970 (Cohn, Lewellen, Lease, & Schlarbaum, 1975; Lease, Lewellen, & Schlarbaum, 1974). This study found that retail investors typically: (a) were married men aged 45 years or older; (b) were tertiary educated; (c) were employed in professional or managerial roles or not employed; (d) earned a high salary; (e) used fundamental analysis exclusively or as part of their overall investment plan; (f) subscribed to investment periodicals; (g) spent up to five hours per month making investment decisions; (h) focused on capital growth; (i) held six or more share securities; (j) used margin lending; and (k) purchased warrants (Lease et al., 1974). A greater proportion of retail investor wealth allocated to risky assets (including shares) was associated with being single, older and earning higher levels of income (Cohn et al., 1975).

A survey of 742 Indian retail investors explored the relationship between age and investor behavior (Charles & Kasilingam, 2015). The authors found that there were significant age differences in (a) reasons for investing in shares; (b) length of investment holding periods; and (c) the proportion of their investments allocated to share investments. The authors found that while investors had increasingly lower levels of risk as they aged, the youngest group of investors had either a high appetite for risk or a low appetite for risk. Finally, the authors found that while 79 percent of respondents preferred to draw on their own savings to invest in the share market, younger investors were also willing to obtain loans to invest (Charles & Kasilingam, 2015).

In a sample of 596 Turkish retail investors, significant differences in financial literacy were found based on marital status and age (Ates et al., 2016). The authors found that financial literacy contributed to the prediction of overconfidence, cognitive dissonance, confirmation bias, framing, loss aversion, over-optimism, and representative bias. Gender was shown to contribute to the prediction of overconfidence, illusion of control, confirmation bias and framing. Marital status was shown to contribute to the prediction of overconfidence, over-optimism and cognitive dissonance. Age was shown to contribute to the prediction of loss aversion while education was shown to contribute to the prediction of representative bias (Ates et al., 2016).

Finally, using an Estonian sample of 10,555 retail investors, it was found that those with a tertiary education traded more frequently than those that without a tertiary education (Liivamagi, 2016). Liivamagi (2016) found that men traded more frequently than did women and that those who traded more frequently held their share investments for shorter periods of time than did those who traded less frequently. Liivamagi (2016) also found that trading frequency had a positive impact on risk-adjusted portfolio returns and that risk-adjusted portfolio returns increased with the frequency of trading.

Using multivariate analyses with 527 to 550 retail investors, Dobni and Racine (2016) found that younger men, who are both sociable and financial literate, were more likely to regard the share market as a good avenue for wealth creation. Similarly, trusting and financially literate respondents were more likely to regard the share market as an indicator of economic health. By contrast, distrustful and financially illiterate men were more likely to consider the share market as morally corrupt. Once again using multivariate analyses with 421 to 430 retail investors, Dobni and Racine (2016) found that investors who considered the share market a good vehicle for wealth creation were more likely to invest for either wealth creation or as a hobby. They were also more likely to be satisfied with their portfolio performance, engage in portfolio diversification, as well as feel in control and excited by share market activity. The authors found, by contrast, that respondents who considered the share market to be morally corrupt were more likely to treat share investing as a hobby or speculative activity. They were also more likely to feel out of control and panicky regarding share investing (Dobni & Racine, 2016).

2.6.16 Gender

In a survey of 100 U.S. investors, male investors were found to be more overconfident than female investors (Pompian & Longo, 2004). Moreover, as discussed in section 2.6.2, male overconfidence translated into higher trading activity and consequently, poorer portfolio performance than they might otherwise have been the case (Barber & Odean, 2001). Higher trading activities negatively affected the portfolio returns of both male and female investors. However, in relation to female investors, male investors traded more frequently and had greater declines in portfolio performance (Barber & Odean, 2001). Investment portfolios of single women showed the least decline in portfolio performance, followed by those of married women and married men respectively. Single men showed the greatest decline in portfolio performance (Barber & Odean, 2001). Degree of overconfidence showed the same profile, where single women demonstrated the least overconfidence and single men the greatest overconfidence (Barber & Odean, 2001).

Male investors have been found to have a greater appetite for financial risk than female investors (Pompian & Longo, 2004). Consequently, they invested in riskier assets (Barber & Odean, 2001; Felton et al., 2003; Lee et al., 2013). Felton et al. (2003)

attributed preference for riskier assets to male optimism. It is noted, however, that the Felton et al. (2003) and the Lee et al. (2013) findings were based on two separate student samples taking part in a semester-long share market exercise. Semester grades may not adequately reflect share market conditions where investors effectively put their own wealth at risk in order to secure investment returns. It is therefore conceivable that respondent attitudes and behaviors in their respective studies may differ from those of typical investors.

2.6.17 Investor types

Several studies have introduced alternate ways of describing the types of investors in the share market. A mail-out, mail-back survey of 361 investors (sourced from members of the Australian Shareholders Association, members of investment clubs and attendees at ASX courses) found four types of investors (Clark-Murphy & Soutar, 2005). The most common type of investor was risk averse and selected share investments, not for capital gain, but for dividend yield. The second type of investor sought capital gains and was more likely to focus on speculative investments. This second type of investor was more inclined to engage in fundamental analysis. The third type of investor sought investments with growth potential. In order to find such investments, the third type of investor was willing to follow tips and rumors. The least common type of investor was that of the contrarian investor. The contrarian investor sought to profit from undervalued share investments. The contrarian investor also sought dividend yield and was likely to engage in fundamental analysis (Clark-Murphy & Soutar, 2005).

Using a snowball and convenience sampling technique (sourced through friends, colleagues and MBA students), a paper based survey of 90 investors also found four types of investors (Wood & Zaichkowsky, 2004), albeit with different attributes. Wood and Zaichkowsky (2004) found retail investors to be one of four investor types, which they described as: (a) conservative; (b) risk intolerant; (c) loss averse; or (d) confident investors. Conservative investors monitored investments less than once a month and traded less than five times per annum. Conservative investors preferred managed funds. They bought investments based on growth potential, or based on financial advice. Investments were sold on the basis of poor performance. Proceeds were reinvested (Wood & Zaichkowsky, 2004). Risk intolerant investors monitored investments several times a week and traded less than five times per annum. Risk intolerant investors preferred blue chip investments. They bought investments based on growth potential or advice from friends. Investments were sold based on poor management, to capitalize profits or cash needs (Wood & Zaichkowsky, 2004). At the time of writing blue chip investments in Australia include shares in Australia and New Zealand Bank, Commonwealth Bank, National Australia Bank and Westpac (commonly referred to as the "big four" banks), BHP Billiton or Wesfarmers. Loss averse investors were younger and had smaller portfolios. They were prepared to take risks, but personalized losses. Loss averse investors traded more than fifteen times per annum. Loss averse investors preferred a combination of technology investments and mutual funds. They bought investments based on growth potential. Investments were sold because of poor performance or cash needs. Proceeds were reinvested (Wood & Zaichkowsky, 2004). At the time of writing, technology investments in Australia include shares in Computershare. Australian mutual funds include Colonial First State Choice Investments and Perpetual Wealth Focus Investment Advantage. Confident investors were older and had larger portfolios. Confident investors monitored investments at least weekly and traded more than fifteen times per annum. Confident investors spread their investments across blue chip, technology, mid-sized investments and mutual funds. They bought investments on the basis of growth potential. Investments were sold to capitalize gains or because of poor performance. Proceeds were reinvested (Wood & Zaichkowsky, 2004). At the time of writing, mid-sized investments in Australia include Qantas and Fairfax.

The ASX studies also found four types of investors (ASX Ltd, 2009, 2013), albeit using a different framework from that of either Wood and Zaichkowsky (2004) or Clark-Murphy and Soutar (2005). In the ASX (2009, 2013) studies, investors differed in level of knowledge and engagement with the share market. Thus, confident investors or confident traders were both knowledgeable and enthusiastic about the share market. Diligent investors or informed diligents were knowledgeable, but somewhat more detached from the share market than confident investors. Aspirational investors or self-reliant dabblers were less knowledgeable but enthusiastic about the share market. Finally delegators or unsure delegators were neither knowledgeable nor engaged with the share market. Both diligent investors and delegators were found to rely on expert advice (ASX Ltd, 2009, 2013). Twenty-five percent of respondents in the ASX 2014 survey with direct exposure to the share market could be described as confident investors, 32 percent were dabblers, 24 percent were diligent investors while the remaining 19 percent could be described as delegators (ASX Ltd, 2015).

Finally, Pompian (2008) conceptualized four types of investors: Passive preserver, friendly followers, independent individualists and active accumulators. Passive preservers were considered to be those who were cautious with their wealth (Pompian, 2008). Friendly followers were expected to follow the latest investment trends and lacked their own investment plan (Pompian, 2008). Independent individualists were considered to be those who had a high appetite for financial risk, engaged in their own research, but were reluctant to change their views when market conditions had subsequently changed (Pompian, 2008). Finally, active accumulators were considered to be those investors who have made their wealth outside the share market and expect to be able to transfer their skills to investing (Pompian, 2008). Pompian (2008) believes this group of investors may be confident to the point of being overconfident.

From the literature described in subsections 2.6.14 and 2.6.15, it would appear that retail investors are typically tertiary-qualified middle-aged men on high salaries. They seek information about their investments. Men also tend to be more overconfident and have a greater appetite for financial risk than do women. Moreover, institutional investors tend to be more overconfident than their retail counterparts. Overconfident investors trade more frequently than those less confident. Their increased trading results in poorer portfolio returns.

2.7 Conclusion

This chapter discussed the literature describing both the *rational* and *human* investor. This literature informs the model of investor behavior put forward in chapter 1. The next chapter discusses additional variables that may inform investor behavior. It also provides the *human* component of the model in structural equation form.

Chapter 3 Towards a Model of the *Human* Investor

3.1 Introduction

It has been said that economists, supporting the view that markets are efficient, are reluctant to consider psychological explanations of share market behavior (Read, 2009). Doing so may mean shedding their own tools (Read, 2009). However, this reluctance implies an either/or approach to modeling share market behavior such that either the *rational investor* or the *human investor* explanation of share market behavior is the "correct" view. While no one model or theory can be truly correct, it may be that both views can offer theoretically useful explanations of share market behavior; albeit at different times or under different conditions. It may thus be the case that *rational investor* views may explain what *should* occur in share markets while *human investor* views may explain what *does* occur in share markets.

This chapter considers other research that may increase understanding of the *human* side of the investor. It also introduces the *human investor* component of the model in structural equation model format, along with the five research questions.

3.2 The human investor: Research that may help explain investor behavior

3.2.1 Fight – flight theory

Observations from the Global Financial Crisis (GFC) (2007 to 2010) suggest that investors removed their funds from the share market and placed them in cash or bonds (e.g., Buhrer, 2008; Kirby, 2009), consumers held their cash (e.g., Healy, 2009; Withers, 2009a), while employers reduced their staff (e.g., Burnett, 2009; Cauchi, 2009; Withers, 2008b). Governments were one of the few groups to take action to reduce the impact of the GFC on the economy (e.g., Davies, 2009; Giles & Logutenkova, 2008; Grattan &

O'Shaughnessy, 2008; Livesey & Menon, 2008; Pittman & Ivry, 2008; Viscusi, 2008; Withers, 2008a). Kindleberger's (1978) description of investor behavior in periods of share market bubbles and crashes, along with Graham's (1949/1973) personification of share market behavior as *Mr. Market*, seem an apt description of events that took place in response to the events of the GFC. Indeed, it may be that investors overreacted negatively during this period.

Actions taken during the GFC were consistent with the Cannon (1914, 1922/1949) theory of fight/flight behavior. Under this theory, strong emotions such as fear or rage immediately lead to an autonomic increase in adrenaline, oxygen and blood sugar to the brain, heart, lungs and major muscle groups. Bronchial tubes are also widened to facilitate the extra oxygen flow in and out of the lungs, and blood clotting ability is enhanced. These physiological changes invigorate large muscle groups and prepare the body for survival so that the individual can fight off predators or flee from danger (Cannon, 1914, 1922/1949). As this process is autonomic, it occurs regardless of whether the strong emotion emanates from seeing "a wild beast" or major share price declines (Cannon, 1922/1949, p. 156). Moreover, even "trifling worries or anxieties" may prepare an individual's body for fight or flight (Cannon, 1922/1949, page 157).

Fight/flight behavior is triggered by the amygdala (LeDoux, 1996, 2002). The amygdala, which resides in the limbic brain, is often referred to as the brain's "danger detector". It can override the neocortex in times of potential or actual danger. It prepares the body for fighting or fleeing. It also engages emotions such as anxiety and impulsivity to ensure that the body does indeed fight or flee (LeDoux, 1996, 2002).

Gray (1987, 1990) developed a model which combines (a) a fight/flight mechanism; (b) a behavioral inhibition system; and (c) a behavioral activation system. Individuals may be expected to differ in their inclination towards each of these three mechanisms (Gray, 1987).

The behavioral inhibition system is a punishment avoiding mechanism and is manifested through the presence of anxiety. The behavioral inhibition system may be activated by the threat of punishment, novel stimuli or fear provoking stimuli. The behavioral inhibition system may seek to avoid these threats by inhibiting behavior, increased arousal and/or increased attention (Gray, 1990). Thus, individuals who are more inclined towards anxiety might be expected to withdraw from an activity in the face of repeated failures. If withdrawal is not an option, they may act more slowly and cautiously. Those inclined to anxiety can plan to avoid anxiety provoking environments (Gray, 1987). The behavioral inhibition system may become dampened if the individual takes anxiolytic (anti-anxiety) medication (Gray, 1990).

By contrast, the behavioral activation system is a reward seeking mechanism and is manifested through the presence of impulsivity (Gray, 1990). The behavioral activation system may be activated upon the potential for reward. The behavioral activation system may seek to tap into those potential rewards by evoking approach behaviors. Those more inclined towards impulsivity may be quick to take action and in so doing, may be inclined to making more mistakes. However, by the very nature of impulsivity, those prone to impulsivity may be unable to avoid environments that typically lead to impulsive behaviors (Gray, 1987).

Consistent with the earlier work of Cannon (1914, 1922/1949), the fight/flight mechanism is alert to the potential for negative events and if detected, will trigger fight or flight behavior (Gray, 1990). There may be cases where anxiety does not lead to more slow and cautious behaviors. Moreover, the fight/flight mechanism does not necessarily evoke anxiety if that individual later comes across similar circumstances (Gray, 1987).

A set of three experiments was one of the few studies to draw a link between fear and share trading activities (Lee & Andrade, 2011). Student participants were allocated to either a control condition or a treatment condition. In the treatment condition, participant fears were evoked on an unrelated (prior) task. No emotions were elicited in the control condition. Both groups of participants then took part in a simulated share market game (Lee & Andrade, 2011). Evoked fear on the prior task was shown to lead to subsequent selling activities in the simulated share market activity (Lee & Andrade, 2011). Selling activities following fear were more likely to be triggered when participants thought they were playing against other participants in the simulated share market activity and less likely to be triggered when they thought they were playing against a computer (Lee & Andrade, 2011). Moreover, when participants were told their risk profile was common, they were more likely to trigger share sales under fear than when they were told their risk profile was unique (Lee & Andrade, 2011).

Using facial recognition software, a related study found prior fear to lead to risk averse decisions (Nguyen & Noussair, 2014). Moreover, as a proxy for societal mood, suicide rates (concurrent and one-month lags) were shown to inversely predict monthly portfolio returns at the aggregate level (Choi, 2016).

From the research described in this section, it would appear that strong emotion may signal future directions of share market returns. Cannon's (1914, 1922/1949) fight/flight mechanism may help explain investor overreaction during periods of extreme market volatility (such as those seen in market bubbles and crashes). Anxiety may be the responsible mechanism underlying the flight (avoidance) behavior seen in market crashes (including that of the GFC). Impulsivity may be the responsible mechanism underlying fight (approach) behavior seen during periods of market bubbles. One might therefore expect both anxiety and impulsivity to play a role in share market behavior. Sections 3.2.2 and 3.2.3 flesh out what those roles might be.

3.2.2 Anxiety

Anxiety has been defined as an emotional state in response to threat of pain, failure or novel circumstances. In turn, this state results in cessation of current actions, increased vigilance and preparation for alternate actions (Gray, 1988). It is also the emotional state manifested within the behavioral inhibition system described by Gray (1987, 1990).

Research on investor anxiety has been sparse. One study considered investor online monitoring activity following bull and bear runs (Gherzi, Egan, Stewart, Haisley, & Ayton, 2014). The authors found that investors were more inclined to monitor their investments in both bull and bear periods. However, the tendency to monitor their investments was greater for bull runs than it was for bear runs (Gherzi et al., 2014). This finding was even more pronounced for investors with higher levels of neuroticism in bear markets, but not in bull markets (Gherzi et al., 2014).

In a set of three experiments using 63 to 138 U.S. undergraduate students, anxiety was shown to be associated with little appetite for financial risk (Maner et al., 2007). In a set of two experiments using 51 and 60 Italian participants, anxiety was shown to be associated with a tendency to gather less information and reach quicker decisions when making decisions under uncertainty (Bensi & Giusberti, 2007). An experiment with 140 Italian participants demonstrated that level of anxiety could predict the tendency to gather less information (Bensi, Giusberti, Nori, & Gambetti, 2010). Bensi and Giusberti (2007) believed that anxious individuals were motivated to reach decisions quickly in order to reduce discomfort with uncertainty and that reducing their discomfort was more important to them than was reaching a correct decision. Anxiety was also shown to have a deleterious impact on decision making in a gambling experiment (Leonello & Jones, 2016).

In an experiment using 48 U.S. undergraduate students, participants were asked to report preferences for one of four different pens (De Los Reyes, Aldao, Kundey, Lee, & Molina, 2012). In comparison to those with lower levels of anxiety, it was shown that those with higher levels of anxiety experienced prolonged dissonance over choice options not taken. This relationship held even for those who engaged in a ritual designed to leave their choice behind them (De Los Reyes et al., 2012).

In a survey of 100 British students, anxiety was shown to contribute to the prediction of (a) the tendency to pass the problem onto others; (b) procrastination; and (c) hypervigilance (Umeh & Omari-Asor, 2011).

The research described in this section suggests that those experiencing anxiety may seek ways of quickly reducing their discomfort. In so doing, they may seek less information, and indeed, may try to distance themselves from unfamiliar (and potentially risky) events. Their decisions may consequently be suboptimal. As Cannon (1922/1949) suggested, it does not matter whether the source of one's strong emotions is a hungry tiger or a marked share market decline. One might therefore expect anxiety to play an important role in share market behavior.

3.2.3 Impulsivity

Impulsivity has been defined as spontaneous action without consideration of the potential consequences of that action (Gulec et al., 2008). It is also the emotional state manifested within the behavioral activation system described by Gray (1987, 1990).

Impulsivity has been studied with a range of populations, including criminal populations (Haden & Shiva, 2008), U.S. war veterans (Suris, Lind, & Kashner, 2005), clinical populations (Black et al., 2009) and students (Xu, Korczykowski, Zhu, & Rao, 2013).

Little research, however, has considered investor impulsivity. In studies considering impulsiveness and decision making, impulsive individuals have been shown to (a) take riskier choices, focusing on the potential for gain rather than loss (Dretsch & Tipples, 2011; Martin & Potts, 2009; Xu et al., 2013); (b) be insensitive to loss (Dretsch & Tipples, 2011); and (c) seek out the smaller, but more immediate reward over the larger but delayed reward (Lyke & Spinella, 2004; Mitchell, 1999). There may be an age effect on impulsivity (Lyke & Spinella, 2004). There may also be a gender effect (Dretsch & Tipples, 2011; Perkins et al., 2008).

One study, found that financial education reduced impulsive decisions. This relationship was even more pronounced for those who had higher levels of neuroticism or appetite for financial risk (DeHart, Friedel, Lown, & Odum, 2016).

From the research described in this section, it would appear that those prone to impulsivity are more willing to make riskier choices with a focus on potential gains and insensitivity to potential losses. Moreover, those prone to impulsivity may seek out more immediate short term gains over larger future gains. One may therefore expect impulsivity to play a role in share market behavior.

3.3 Scale development and five research questions

3.3.1 Absence of scales

Much of past research in behavioral finance has been based on portfolio simulation. (See, for example, Caparrelli et al., 2004; De Bondt & Thaler, 1985, 1987; Lakonishok & Smidt, 1984, 1986). Experimental research has also been used with investors. (See, for example, Kahneman et al., 1990; Kahneman & Tversky, 1972; Weber & Camerer, 1998).

Few studies in behavioral finance have surveyed investors. Consequently few scales have been developed. While previous research has developed scales for overconfidence, (e.g., Ates et al., 2016; Iqbal, Ahmad, Abrar, & Hassan, 2014; Kafayat, 2014); appetite for financial risk (Chin et al., 2016; Iqbal et al., 2014; Rajagopalan & Gurusamy, 2014) and psychological biases (e.g., Ates et al., 2016) their complete psychometric properties have not been provided. Moreover, each of these scales was published after data was collected for this thesis. Consequently, there is an absence of adequate scales available for use in investor surveys and the scales that were available in the literature were not available in time to be utilized in this thesis. Yet, the development of scales with sound psychometric properties for use with share investors would facilitate multivariate analyses, structural equation modeling of investment behavior, as well as exploration of investor subgroups.

As discussed in section 1.2.2, the first objective of this thesis is to address the absence of scales for use in surveys of share investors by putting forward scales to measure the constructs of (a) overreaction; (b) overconfidence; (c) January effect; (d) July effect; (e) appetite for financial risk; (f) information sources; (g) psychological biases; (h) social herding; (i) anxiety; and (j) impulsivity. The outcomes for this objective are addressed in chapter 5.

3.3.2 Overconfidence

The research on overconfidence has shown that overconfident investors trade more and that the trading results in poorer portfolio performance than would have been the case had they not traded. Moreover, men are more inclined to overconfidence than are women (Barber & Odean, 2000, 2001). Indeed single men were shown to be the most active traders (and most overconfident), while single women the least active traders (and least overconfident (Barber & Odean, 2001).

The Barber and Odean (2000, 2001) finding is an interesting one, especially as level of overconfidence was shown to have an impact on long term portfolio wealth. Their research was on U.S. brokerage data. It is not yet known whether the degree of overconfidence shown in Barber and Odean (2000, 2001) extrapolates to Australian investors, especially when using a different research methodology. If the finding does prove to be the case in an Australian sample, training could be provided to men (and single men in particular) on the link between overconfidence and declines in portfolio wealth over time.

Recall that the third objective of this thesis is to explore key variables in investor behavior, as well as consider those variables that may distinguish retail from institutional investors. See section 1.2.2. Overconfidence may be expected to be a key driver of investor behavior. Drilling down to examine this component of investor behavior may partially address the third objective of this thesis. It has been formulated as the first research question.

Research question 1 therefore asks: Does level of overconfidence depend on the interaction of gender and marital status in a manner that is consistent with the findings of Barber and Odean (2001); that is, where single women demonstrate the least amount of overconfidence, followed by partnered women, partnered men and single men in turn.

More specifically, research hypothesis, h_1, states there is a difference in means across the four groups such that single women report the least overconfidence, followed by partnered women and partnered men in turn. This research hypothesis also states that single men would report the greatest levels of overconfidence. The first research question is addressed in chapter 6.

3.3.3 Missing data as research 'data'

Missing data has often been considered as problematic for survey and experimental research (Cohen & Cohen, 1983). Data has been considered to be more easily analyzed when its missing values are missing completely at random (MCAR) or missing at random (MAR). Missing data would be of most concern when it is non-ignorable; that is, missing not at random (MNAR). Indeed, a dataset's missingness could be ignored if there are minimal missing values interspersed throughout the dataset (Cohen & Cohen, 1983; Little & Rubin, 1987; Tabachnick & Fidell, 2014). However, the very presence of missing data may prove to be useful data in and of itself (Cohen & Cohen, 1983). Missing data may reflect a multitude of factors, including carelessness in questionnaire completion, refusal to complete specific questions, as well as unfamiliarity with the object of questioning. If the latter were the case, the extent of items left blank per respondent may equate with degree of underconfidence.

Moreover, where respondents have been given the option to endorse “don’t know” within a questionnaire, such options have often been treated as missing data by the researcher. (See, for example, Cohen & Cohen, 1983). Indeed, a “don’t know” response does not typically ‘fit’ within the range of the ‘real’ alternatives along a Likert scale. Yet, in a survey of investor behavior, the number of items a respondent endorsed with “don’t know” may reflect the respondent’s unfamiliarity with investment matters. This variable may similarly act as a marker of underconfidence and may thus represent important data in and of itself. In a similar vein, a combined count of the number of items a respondent left blank or endorsed with “don’t know” may also act as a third marker of underconfidence.

As one might expect underconfidence to be the inverse of overconfidence, markers of this kind may prove to be valuable data in investor research, whilst not adding to the length of survey questionnaires.

As discussed in section 1.2.2, the second objective of this thesis was to determine whether the count of “don’t know” and/or the count of missing data could act as markers of underconfidence. It has been formulated as the second research question.

Research question 2 thus asks: Can the count of “don’t know” and/or the count of missing data per respondent act as markers of underconfidence in investor behavior? If these three variables are indeed markers of underconfidence, one might expect overconfidence and financial education to be predictors of these three variables. One might also expect their beta coefficients to be negative, such that the more financial education and/or the more overconfidence, the fewer the items endorsed with “don’t know” and/or left blank.

More specifically, research hypothesis h_{2a} states: overconfidence and financial education would predict the count of “don’t know” and that their respective beta weights would be negative. Research hypothesis h_{2b} states: overconfidence and financial education would predict the count of missing data and that their respective beta weights would be negative. Finally, research hypothesis h_{2c} states: overconfidence and financial education would predict the combined count of "don't know" and missing data and that their respective beta weights would be negative. Research question 2 is also addressed in chapter 6.

3.3.4 Profile of retail and institutional investors

Few studies have explored the demographic profile of investors. Those studies that have provided demographic profiles did so using retail investors, but not institutional investors. (See, for example, ASX Ltd, 2015; Cohn et al., 1975; Lease et al., 1974). It is therefore not known whether institutional investors have a similar demographic profile to those of retail investors, and if not, on what dimensions they might differ. To the author's knowledge, no comparative research is available on a range of key variables such as (a) overreaction; (b) underconfidence; (c) January and July effects; (d) appetite for financial risk; (e) information sources; (f) psychological biases; and (g) social herding. Only one study compared retail and institutional investors on overconfidence (Lai et al., 2013). To the author's knowledge, no comparative research has been undertaken regarding anxiety or impulsivity. Yet, based on the Cannon (1914, 1922/1949) fight/flight theory, one might expect anxiety and impulsivity to mobilize investors into the kinds of actions observed within share market data. An exploration of investor subgroups might therefore provide a more nuanced understanding of investor behavior, as well as key drivers of investor behavior.

Such a nuanced understanding of investor behavior, along with key drivers of investor behavior, would address the balance of the third objective of this thesis. This objective has been formulated as the third and fourth research questions.

Research question 3 therefore asks whether retail investors can be distinguished from institutional investors, on (a) demographic profile; (b) investment practices; (c) investment strategies; (d) emotional presentation; (e) personality variables; (f) behavioral practices; and (g) changes to portfolio wealth over the period of the GFC.

More specifically, research hypothesis h_{3a}, states that retail investors can be discriminated from institutional investors on demographic profile (i.e., age, education, financial education and years of investor experience). Research hypothesis h_{3b} states that retail investors can be discriminated from institutional investors on the basis of investment practices (i.e., hours spent on investments, number of companies followed and number of companies in the investment portfolio). Research hypothesis h_{3c} states that retail investors can be discriminated from institutional investors on the basis of investment strategies (i.e., the proportion of the investment portfolio allocated to defensive shares, growth shares, cyclical shares and asset/turnarounds).

Research hypothesis h_{3d} states that retail investors can be discriminated from institutional investors on the basis of emotional presentation (i.e., overreaction, overconfidence and count of “don’t know” as a marker of underconfidence,). Research hypothesis h_{3e} states that retail investors can be discriminated from institutional investors on the basis of personality variables (i.e., anxiety, lack of attention, lack of planning and motor activity). Research hypothesis h_{3f} states that retail investors can be discriminated from institutional investors on the basis of behavioral practices (such as January and July effects, appetite for financial risk, and information sources). Finally, research hypothesis h_{3g} states that retail investors can be discriminated from institutional investors on the basis of one-year, two-year and three-year changes to portfolio wealth during the GFC. Research question 3 is addressed in chapter 7.

Research question 4 asks: Can the key variables that distinguished retail investors from institutional investors themselves be predicted? Thus, research hypothesis, h_{4a}, states that overreaction can be predicted from demographic profile (age, education, financial education, years of investor experience); investor practices (hours spent on investments, number of companies followed and number of companies in investment portfolio);

personality variables (anxiety, and impulsivity); and behavioral practices (January and July effects, appetite for financial risk, and information sources). Similarly, research hypothesis, h_{4b}, states that overconfidence can be predicted from demographic profile (age, education, financial education, years of investor experience); investor practices (hours spent on investments, number of companies followed and number of companies in investment portfolio); personality variables (anxiety, and impulsivity); and behavioral practices (January and July effects, appetite for financial risk, and information sources).

Finally, research hypothesis, h_{4c}, states that count of "don't know" (as a marker of underconfidence) can be predicted from demographic profile (age, education, financial education, years of investor experience); investor practices (hours spent on investments, number of companies followed and number of companies in investment portfolio); personality variables (anxiety and impulsivity); and behavioral practices (January and July effects, appetite for financial risk, and information sources). The fourth research question is addressed in chapter 8.

3.3.5 Towards a multivariate structural equation model of investor behavior

Past research on share market behavior considered whether investors were inclined towards (a) overreaction (e.g., De Bondt & Thaler, 1985; 1987); (b) overconfidence (e.g., Barber & Odean, 2001); (c) the January effect (e.g., Keim, 1983; Lakonishok & Smidt, 1984, 1986); and/or the July effect (e.g., Brown et al., 1983; Gultekin & Gultekin, 1983); (d) appetite for financial risk (Nofsinger, 2001); (e) psychological biases (e.g., Brabazon et al., 2004; Kahneman et al., 1990; Kahneman & Tversky, 1972); or (f) social herding (e.g., Caparrelli et al., 2004; Chang et al., 2000).

Most of the past research in behavioral finance, however, has considered only one or two variables simultaneously. Moreover, past research has not considered the impact of anxiety or impulsivity on investor behavior. Moreover, while Abramson (2003) developed a theoretical model based on the literature, this model was not formalized for testing through structural equation modeling. This research, will thus provide the first tested multivariate structural equation model, integrating key variables in investor behavior, as well as consider the impact of both anxiety and impulsivity on investor behavior.

More specifically, the research on overreaction suggests that investing in companies that have fallen out of favor (value shares) lends itself to improved portfolio returns over companies that are currently considered ‘market darlings’ (glamour shares). When there are two groups of investors (perhaps institutional investors) who trade significant volumes of shares, in opposite directions, there is the potential to ‘move markets’. When this happens, it appears that the share market is overreacting on value and glamour shares. Moreover, analysts may themselves overreact. (See section 2.6.1).

Past research has yet to identify antecedents that may exacerbate or ameliorate the propensity for overreaction. It is not known, for instance, if those prone to overreaction are of a certain age, level of investment experience or avid use of investment research. It is also not yet known whether they have an appetite for financial risk. However, one might expect that if investors view the research of overreacting analysts, they may themselves become more likely to overreact. As was shown in section 3.2, the Cannon (1914, 1922/1949) theory of fight/flight and its concomitants of anxiety and impulsivity (Gray, 1987, 1990) may help explain investor overreaction. One might therefore expect information sources, coupled with a tendency towards anxiety or impulsivity, to predict investor overreaction.

Past research has also not yet identified those factors that are more likely to occur as a consequence of investor overreaction. However, one might suspect that those prone to overreaction may be more likely to invest in cyclical shares and asset/turnarounds over those of defensive or growth shares.

The research on overconfidence suggests that access to information leads to overconfidence and that overconfidence leads to increased share trading with a subsequent reduction in long term portfolio wealth. Moreover, there is a marital status by gender effect on level of overconfidence. (See section 2.6.2).

Once again, past research has yet to identify the antecedents that may exacerbate or ameliorate the tendency towards overconfidence. The relationship between overconfidence and other variables (including information sources, financial education, investment experience or appetite for financial risk) is not yet known. However, one might expect information sources, financial education, years of investment experience, hours spent on investments, number of companies followed, number of companies in portfolio, and appetite for financial risk to predict overconfidence. Similarly, one might expect underconfidence and age to inversely predict overconfidence. In addition, the Cannon (1914, 1922/1949) theory of fight/flight and its concomitants of anxiety and impulsivity (Gray, 1987, 1990) may help explain investor overconfidence. (See section 3.2). As underconfidence is conceptually the inverse of overconfidence, one might expect any marker of underconfidence to display an inverse relationship with the same set of predictors to those of overconfidence.

Past research has also not yet identified the variables that may be more likely to occur as a consequence of overconfidence. However, one might expect that as investors become increasingly more overconfident, they move increasingly out of defensive and growth shares in favor of cyclical shares and asset/turnarounds.

The research on the January effect suggests that share market data shows a decline in the latter part of December followed by an increase in the early days of January. A similar effect has been found in July. This finding was initially found in the U.S., where the taxation reporting season is based on a calendar year. It has also been found evident in many other countries. In Australia, where the taxation reporting season ends on the 30^{th} June each year, both a January and July effect were found.

Many hypotheses have been put forward to explain the presence of this phenomenon, including portfolio rebalancing by institutional investors and parking of proceeds by retail investors. (See section 2.6.3). However, research has yet to identify the antecedents that may exacerbate or ameliorate the tendency towards the January effect.

One might expect information sources to inform the optimism/disappointment observed by Ciccone (2011). Moreover, the Cannon (1914, 1922/1949) theory of fight/flight and its concomitants of anxiety and impulsivity (Gray, 1987, 1990) may also help explain the tendency towards the January and July effects. One might therefore expect information sources, appetite for financial risk and anxiety to inform the January (or July) effect.

Past research has also not considered the variables that may be more likely to occur in the presence of the January effect. However, one might expect that those that engage in the January (and July) effects might choose growth shares, cyclical shares and asset turnarounds over defensive shares. In so doing, they may be more inclined to the swings of moods from optimism to disappointment recognized by Ciccone (2011) during the course of the calendar (or financial) year.

As discussed in section 1.2.2, the final objective of this thesis was to test a structural equation model of investor behavior with a sample of retail investors. It has been formulated as the final research question. The final research question thus asks: Does the structural equation model shown in Figure 3 at the end of this chapter (with, or without modification) fit the data from a sample of retail investors? Research hypothesis h_{5a} states: Overreaction can be predicted by (a) information sources; (b) anxiety; and (c) impulsivity. All three variables are expected to show positive relationships with overreaction.

Research hypothesis h_{5b} states: Overconfidence can be predicted by (a) financial education; (b) years of investor experience; (c) C4: hours spent on investments; (d) C18:

companies followed; (e) C19: companies in portfolio; (f) appetite for financial risk; (g) information sources; (h) impulsivity; (i) age; and (j) anxiety. It is further hypothesized that the first eight of these variables will have a positive pathway to overconfidence and the remaining two variables will have a negative pathway to overconfidence.

Research hypothesis h_{5c} states: Count of "don't know" and/or count of missing data as a marker of underconfidence can be predicted by (a) financial education; (b) years of investor experience; (c) C4: hours spent on investments; (d) C18: companies followed; (e) companies in portfolio; (f) appetite for financial risk; (g) information sources; (h) impulsivity; (i) age; and (j) anxiety. It is further hypothesized that the first eight of these variables will have a negative pathway to the count of "don't know" and/or count of missing data as a marker of underconfidence and the remaining two variables will have a positive pathway to the count of "don't know" and/or count of missing data as a marker of underconfidence.

Research hypothesis h_{5d} states: January and July effects can be predicted by (a) appetite for financial risk; (b) information sources; and (c) anxiety. All three variables are expected to show positive relationships with the January and July effects.

Research hypothesis h_{5e} states that overreaction, overconfidence, count of "don't know" and/or count of missing data and the January and July effects can contribute to the prediction of defensive shares. Moreover, it is expected that overreaction, overconfidence and the January and July effects will have negative pathways while the count of "don't know" and/or count of missing data as a marker of underconfidence will have a positive pathway to defensive shares.

Research hypothesis h_{5f} states that overreaction, overconfidence, count of "don't know" and/or count of missing data and the January and July effects can contribute to the prediction of growth shares. Moreover, it is expected that overreaction and overconfidence will have negative pathways while the count of "don't know" and/or count of missing data as a marker of underconfidence and the January and July effects will have a positive pathway to growth shares.

Research hypothesis h_{5g} states that overreaction, overconfidence, count of “don’t know” and/or count of missing data and the January and July effects can contribute to the prediction of cyclical shares. Moreover, it is expected that overreaction, overconfidence and the January and July effects will have positive pathways while the count of “don’t know” and/or count of missing data as a marker of underconfidence and will have a negative pathway to cyclical shares.

Finally, research hypothesis h_{5h} states that overreaction, overconfidence, count of “don’t know” and/or count of missing data and the January and July effects can contribute to the prediction of asset/turnarounds. Moreover, it is expected that overreaction, overconfidence and the January and July effects will have positive pathways while the count of “don’t know” and/or count of missing data as a marker of underconfidence and will have a negative pathway to asset/turnarounds. The final research question is addressed in chapter 9.

3.4 Conclusion

This chapter introduced the theoretical model of investor behavior in the share market in structural equation form. It also put forward five research questions. Chapter 4 introduces the research philosophy. Chapter 4 also describes the survey questionnaire and research method.

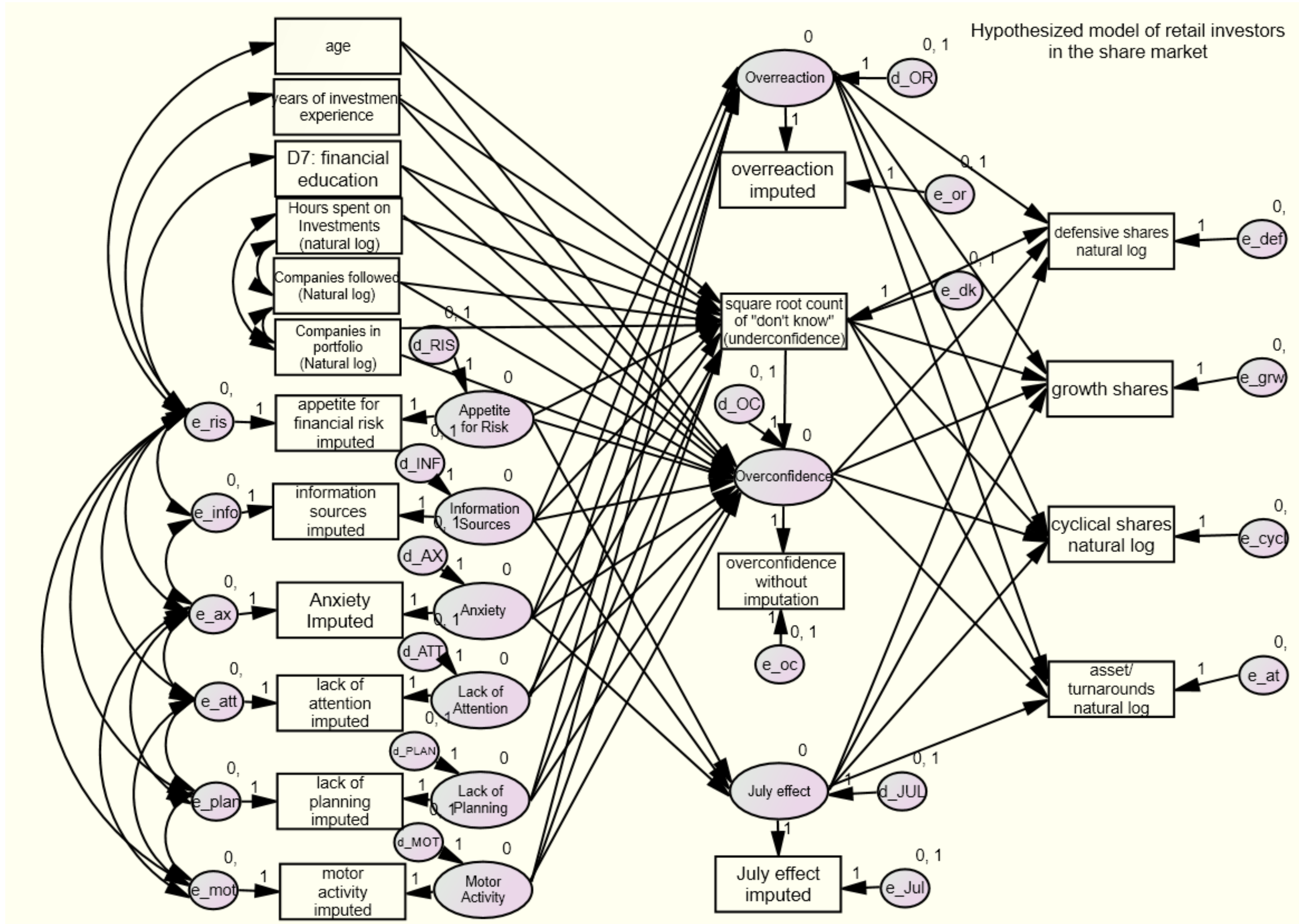

Figure 3. The hypothesized structural equation model of investor behavior in the share market.

Chapter 4 Methodology

4.1 Introduction

Chapter 4 introduces the research philosophy underlying this thesis. It also describes the sample, survey questionnaire and method used in this research.

4.2 Scientific philosophy

This thesis was modeled on Popper's (1972a, 1972b, 1972c) concept of falsifiability. It also drew on the quantitative and objective methodology associated with a postpositivist perspective (Guba & Lincoln, 1994). Moreover, model development was guided by an imperative to seek factors underlying surface observations (Marshall, 1890/1961). However, it is also recognized that model development cannot fully explain the phenomenon under investigation. Models can only approximate that phenomenon. As such, the primary objective of the research was to refute the model proffered in chapter 3 using structural equation modeling. If it survived testing with or without modification, it may be considered worthy of inclusion within the existing body of behavioral finance knowledge until such time as it is superseded by a model with greater explanatory power.

4.3 Sample

A random sample of Australians who reported that they were shareholders was drawn from publicly available lists yielding 3,713 potential investors (1,463 institutional and 2,250 retail investors). More specifically, the drawn retail sample of 2,250 (791 male; 1,459 female) was randomly drawn from a database of 26,581 Australian people aged 18 years or more, who had purchased shares through brokers (internet, phone) or public floats of Australian companies (i.e., Initial Public Offering). The institutional sample was drawn from a mix of financial databases. The drawn institutional sample of 1,463

(1,244 male; 219 female) represents the population of those who reported themselves to be superannuation fund managers, fund managers or money managers. It also included owners of superannuation or fund companies where those companies had less than 20 staff. Fund/money managers invested across all industries and were employed in either listed or unlisted companies. While it is noted that these individuals represent institutional investors, they will hereinafter be referred to as institutional investors as they are the individuals that effect the trade on behalf of the institutions that employ them.

The drawn sample accommodated the rule of thumb of ten cases for every model parameter and statistical power (Kline, 2011; MacKinnon, Lockwood, Hoffman, West, & Sheets, 2002). The drawn sample size accommodated an expected response rate of 40 percent (Lease et al., 1974).

The final sample size of 521 cases (including 56 institutional investors), represented an overall response rate of 14.03 percent. As the response rate was lower than the anticipated 40 percent, the sample could not be randomly divided in two. Consequently, the structural equation model could not be tested on one half of the sample and validated on the second half as per the recommendation of Breckler (1990).

4.4 Procedure

The 3713 retail and institutional investors were mailed a cover letter, questionnaire and reply paid envelope mid-August 2010. No identifying information was requested of the potential respondents, nor was any identifying information retained after the preparation of both sets of address labels used in this mail-out. In this way, respondents could be assured of the anonymity of their responses.

A reminder letter was sent to 3275 potential respondents three weeks after the initial mail out. A second copy of the questionnaire and reply paid envelope was included in the follow up mail out. This number was less than that of the initial mail out for two reasons. Firstly, it excluded those who had expressed an interest in receiving summary results by the time of the follow up mail out (100 cases). It was assumed that they had already returned their completed survey. Secondly, the follow up mail out excluded return-to-senders received by the time of the follow up mail out (178 cases). A courtesy summary was provided to the 100 investors, who had expressed an interest in receiving this summary, upon completion of the structural equation modeling.

The study had the approval of the Swinburne University research ethics committee as project 2010/111. A copy of the ethics clearance and final report to the Swinburne University Research Ethics Committee can be found in Appendix 1.

See appendices 2 to 4 for a copy of the cover letter, sample (blank) questionnaire, and reminder letter respectively. A copy of the summary of the early research findings prepared for interested respondents can be found in Appendix 5.

4.5 Questionnaire

A questionnaire was developed for use in the survey. Questions were developed based on theory and past research. A draft version of this survey was piloted with eight retail investors. Those responding in the pilot phase were specifically targeted because they had little to moderate levels of expertise in the share market. It was hoped that by seeking their input during the pilot phase, the questionnaire could be made clear for all investors who might take part in the survey. Based on investor feedback during the pilot phase, amendments were made to questionnaire layout, instructions given, estimation of time to complete the survey, and wording of individual questions.

The final form of the questionnaire had four major sections. Section A of the questionnaire sought investor opinions. Section A included questions that were intended to measure overconfidence and appetite for financial risk. Section B of the questionnaire sought information about investor perceptions. Section B included questions intended to measure overreaction, January effect, July effect, psychological biases and social herding anxiety and impulsivity. Section C of the questionnaire sought information about investor practices. Section C included questions about their investment method, share investments, information sources as well as financial ratios used in buy and sell decisions. Section D of the questionnaire sought information about investor demographic backgrounds. Sections 4.5.1 to 4.5.13 describe the final form of the questionnaire. The questionnaire was expected to take between 20 and 30 minutes to complete. A copy of the questionnaire can be found in appendix 3.

4.5.1 Overreaction

No prior overreaction scales were available in the literature. Therefore two questions, B25 and B26, were developed by the researcher to measure overreaction. Both questions are shown in Table 1. Questions were completed using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Higher scores on this construct would equate with greater levels of reported overreaction.

Table 1 *Questions Measuring Overreaction*

Overreaction	B25	When a company's share price performance has done badly, I sell out, no matter how little I get for selling them
(2 questions)	B26	When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them

A minimum of three questions are needed in order for a factor (or indeed a latent variable) to be considered theoretically meaningful (Brown, 2006). The constructs of January effect, July effect and social herding each contained three questions. If each set of questions were analyzed separately, they could do no more than load on a single factor. Consequently both questions developed to measure overreaction were considered simultaneously with those of the January effect, July effect, psychological biases and social herding. In this way, the factorability of each variable could be properly assessed.

The factor structure, Cronbach's alpha and discriminant validity for the overreaction scale developed in this thesis can be found in chapter 5.

4.5.2 Overconfidence

There have been previous attempts to develop measures of overconfidence. (As will be seen in section 4.5.5, 4.5.7 and 4.5.8, there have also been attempts to develop measures for appetite for financial risk, psychological biases and social herding).

The Lee et al. (2013) measure of overconfidence was originally developed by Pompian (2012). While Lee et al. (2013) did not provide a list of the questions used to measure overconfidence in their study, the questions were available through Pompian (2012). The questions included six multiple choice items (four of which directly tapped into finance and investment concepts, one item was of a general knowledge nature and the remaining multiple choice item tapped into self-perception of driving ability (Pompian, 2012). Pompian (2012) also included two questions asking respondents to provide estimates of weight (sperm whales) and distance (to the moon) with 90% confidence intervals. It would thus appear that Pompian (2012) sought to tap into investor overconfidence as well as a more general tendency towards overconfidence. However, the psychometric properties of the Pompian (2012) scale have not been reported in either Pompian (2012). or Lee et al. (2013).

Iqbal et al. (2014) developed three questions to measure overconfidence. The first question Iqbal et al developed to measure overconfidence, "I am confident of my ability to do better than others in picking stocks", addressed overconfidence in relation to share selection ability (Iqbal et al., 2014, page 35). The second question Iqbal et al developed to measure overconfidence, "I am fully responsible for the results of my investment decisions", addressed investor degree of self-control (Iqbal et al., 2014, page 35). The third question developed by Iqbal et al, "I have complete knowledge of stock market", was intended to measure the knowledge aspects of overconfidence (Iqbal et al., 2014, page 35). Iqbal et al. (2014) did not report the psychometric properties of their measure of overconfidence.

Kafayat (2014) also developed a measure of overconfidence. However, the individual questions making up the overconfidence scale were not provided. The scale appeared to demonstrate good factor structure and internal reliability. However, a discriminant analysis was not performed.

Ates et al. (2016) did not provide the two questions used to measure overconfidence. Consequently, no comparison can be made between the seven questions developed in this thesis to measure overconfidence against the two questions developed by Ates et al. (2016). The overall 30-question scale (including two questions measuring overconfidence) developed by Ates et al. (2016) had a Cronbach's alpha of .78.

Finally, one further study made use of a nine item measure of overconfidence that had been adapted from an unpublished Masters thesis (Asif, 2016). While the nine questions were not provided, the measure had a reported Cronbach's alpha of .91 (Asif, 2016).

Each of the above studies (i.e., Asif, 2016; Ates et al., 2016; Iqbal et al., 2014; Kafayat, 2014; Lee et al., 2013) took place after the data collection phase of this thesis. The questions developed to measure the construct of overconfidence in this thesis were therefore developed independent of previous attempts to measure this construct.

Seven questions were developed by the researcher to measure overconfidence. Questions included A18: how knowledgeable do you consider yourself to be about investing; A19: in comparison to other investors, how more or less knowledgeable do you consider yourself to be about investing; and A20: how knowledgeable do you consider yourself to be about share price indices. Table 2 provides the full list of questions developed to measure overconfidence. Questions were completed using a five point scale. A '1' answer for questions A18 to A20 mean *completely unknowledgeable* whereas a '5' for the same questions mean *completely knowledgeable*. A '1' answer for questions A21 to A24 means a decrease by 10 percent or more while a '5' answer for the same questions means an increase of 10 percent or more. Higher scores on this construct would equate with greater levels of reported overconfidence.

Table 2 *Questions Measuring Overconfidence*

Overconfidence (7 questions)	A18	How knowledgeable do you consider yourself to be about investing?
	A19	In comparison to other investors, how more or less knowledgeable do you consider yourself to be about investing?
	A20	How knowledgeable do you consider yourself to be about share price indices
	A21	By the end of 2010, do you expect your portfolio you own or manage to decrease by 10% or more … to increase by 10% or more
	A22	By the end of 2010, do you expect the All Ordinaries Index to decrease by 10% or more … to increase by 10% or more
	A23	What percent return do you expect your portfolio to earn by the end of the year?
	A24	What percent return do you believe other investors to earn on their portfolios by the end of the year?

The factor structure, Cronbach's alpha and discriminant validity for the overconfidence scale developed in this thesis can be found in chapter 5.

4.5.3 January effect

No prior scales for the January effect were available in the literature. Three questions, B4 to B6, were therefore developed by the researcher to address investor tendency towards the January effect. Table 3 provides a full list of questions developed to measure this construct. Questions were completed using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Higher scores on this construct would equate with greater tendency towards behaviors associated with the January effect.

Table 3 *Questions Measuring the January Effect*

January effect (3 questions)	B4	At the end of each year, I sell shares for less than I had paid for them
	B5	At the end of each year, I sell shares for more than I had paid for them
	B6	At the beginning of each year, I buy more shares

As can be seen from Table 3, only three questions were developed to measure this construct. Yet a minimum of three questions are needed in order for a factor (or indeed a latent variable) to be considered theoretically meaningful (Brown, 2006). Consequently, the three questions measuring the January effect could do no more than load on a single factor. The constructs of overreaction, July effect and social herding also contained two or three questions each. For this reason, questions developed to measure these four constructs were considered simultaneously with those for psychological biases. The factor structure, Cronbach's alpha and discriminant validity for the January effect developed in this thesis can be found in chapter 5.

4.5.4 July effect

No prior scales for the July effect were available in the literature. Thus, three questions (B7 to B9) were developed by the researcher to measure the July effect. These questions mirrored those developed to measure the January effect. The first three questions shown in Table 4 represent the three questions developed to measure the July effect. Remaining questions shown in Table 4 represent plausible reasons investors may engage in behavior akin to the January effect and/or July effect. Questions were completed using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Higher scores on this construct would equate with greater tendency towards behaviors associated with the July effect.

As discussed in sections 4.5.1 and 4.5.3, the three questions of the July effect were considered in conjunction with those of overreaction, January effect, psychological biases and social herding. Factor structure, Cronbach's alpha and discriminant validity for the July effect developed in this thesis can be found in chapter 5.

Table 4 *Questions Measuring the July Effect, Plus Plausible Reasons for Same*

July effect (3+8 questions)	B7	Towards the end of June each year, I sell shares for less than I had paid for them
	B8	Towards the end of June each year, I sell shares for more than I had paid for them
	B9	At the beginning of July each year, I buy more shares
	B10	I use the tax time of year to sell shares at a capital loss
	B11	I use the tax time of year to sell shares at a capital gain
	B12	I use the proceeds from share sales to buy more shares
	B13	I use the proceeds from holidays pay to buy more shares
	B14	I use the proceeds from annual bonuses to buy more shares
	B15	I use the proceeds from dividend income to buy more shares
	B16	I use the proceeds from tax refunds to buy more shares
	B17	I use reporting seasons as an opportunity to sell my high risk shares and purchase more conservative, 'blue chip' shares

4.5.5 Appetite for financial risk

Rajagopalan and Gurusamy (2014) and Iqbal et al. (2014) developed a three- or four-question scale to measure appetite for financial risk. More specifically, the three questions developed by Rajagopalan and Gurusamy were "I do not prefer to take risk"; "I avoid risk totally"; and "I choose low risk-steady return over high risk high returns" (Rajagopalan & Gurusamy, 2014, page 107). The four questions developed by Iqbal et al were "I make riskier investments for maximum gain"; "I usually invest in companies I am familiar with"; "I am a risk taker"; and "I invest mostly in companies with stable expected returns" (Iqbal et al., 2014, page 39). The questions loading on the Rajagopalan and Gurusamy (2014) demonstrated good factor structure. Iqbal et al. (2014) did not provide the factor structure for their construct. Neither study provided Cronbach's alpha or the discriminant validity for their respective scales.

Chin et al. (2016) developed a three-question scale to measure a more generic propensity for risk-taking. Questions included “I would never go hang-gliding or bungee jumping”, “I would stick to the rules”, and “I would avoid dangerous situations”. (Chin et al., 2016, page 3909). The authors reported good psychometric properties for their scale. Once again, this scale was published after data was collected in this thesis. It could thus not be adapted for use with share investors.

Finally, Dobni and Racine (2016) developed a single question to measure retail investor appetite for financial risk By its very nature of being a single question, no psychometric properties are available on the question.

Each of the above studies (i.e., Chin et al., 2016; Iqbal et al., 2014; Rajagopalan & Gurusamy, 2014) were published after data was collected in this thesis and therefore could not be used in this thesis. Fifteen questions (A3 to A7, A11 to A17 and C74 to C76) were developed by the researcher to measure appetite for financial risk. A3, A6 and A7 were reverse-scored so that when questions that form part of this scale were summated, higher scores would reflect a greater appetite for financial risk.

More specifically, A3 to A7 asked about the importance of investing safely; share price growth; taking risks to earn good returns; spreading investments across share market sectors; and spreading investments across asset classes respectively. A11 to A17 asked about investor use of ‘stop loss’ and high risk investment products. C74 to C76 asked about investor use of margin lending; options, warrants and/or derivatives; and bank loans or mortgage redraw facilities during the Global Financial Crisis. Table 5 provides the full list of questions measuring appetite for financial risk.

Table 5 *Questions Measuring Appetite for Financial Risk*

Appetite for financial risk (15 questions)	A3R	Investing safely (reverse-scored)
	A4	Share price growth
	A5	Taking risks to earn good returns
	A6R	Spreading investments across share market sectors (reverse-scored)
	A7R	Spreading investments across asset classes (reverse-scored)
	A11	Automatic 'stop loss' or 'sell' orders
	A12	Automatic 'buy' orders
	A13	Margin lending
	A14	Options trading
	A15	Warrants
	A16	Derivatives
	A17	Bank loans or home mortgage redraw facilities to buy shares
	C74	During the GFC, I used margin lending
	C75	During the GFC, I used options, warrants, derivatives or other financial products
	C76	During the GFC, I used bank loans or redraw facilities on my home loan to buy shares

Questions were completed using a five point scale. For A3R to A17, a '1' answer meant completely unimportant while a '5' answer meant completely important. Similarly, a '1' answer on C74 to C76 meant not at all while a '5' answer meant every transaction. Higher scores on this construct would equate with greater levels of reported appetite for financial risk. Factor structure, Cronbach's alpha and discriminant validity for the appetite for financial risk scale developed in this thesis can be found in chapter 5.

4.5.6 Information sources

Once again, no prior scales for information sources were available in the literature. Questions to measure information sources were developed by the researcher. Investors were asked to report where they sourced information for future investments (C40 to C60). Responses to C40 to C60 were summed to form information sources. Questions asked to what extent investors drew on these sources of information to guide their investment decisions. Six subscales were formulated. Subscales included professional advice (C40: accountant; and C41: financial advisor); broker advice (C42: internet brokers; and C43: full service brokers); research (e.g., C44: the Australian Securities Exchange; and C46: company annual reports); media (e.g., C49: newspapers in general; C51: television; C52: radio); experiential (e.g., C55: your experience as a customer of the company and C56: your experience as an employee of the company); and social network (e.g., C58: friend; and C59: a family member).

Questions were completed using a five point scale ranging from completely unimportant (1) to completely important (5). Table 6 provides a full list of questions developed to measure information sources. Higher scores on this construct would equate with greater reliance on information sources. Factor structure, Cronbach's alpha and discriminant validity for the information sources scale developed in this thesis can be found in chapter 5.

Table 6 *Questions Measuring Information Sources*

Information Sources (21 questions)	C40	Your accountant
	C41	Your financial advisor
	C42	Internet brokers
	C43	Full service brokers
	C44	The Australian Stock Exchange (ASX) website
	C45	IPO prospectus
	C46	Company annual reports
	C47	Company websites
	C48	Other websites
	C49	Newspapers in general
	C50	Business newspapers and/or business supplements
	C51	Television
	C52	Radio
	C53	Financial magazines
	C54	Financial trade journals
	C55	Your experience as a customer of the company
	C56	Your experience as an employee of the company
	C57	Your neighbor
	C58	A friend (outside work)
	C59	A family member
	C60	A work friend or colleague

4.5.7 Psychological biases

There were three previous attempts to measure psychological biases (Ates et al., 2016; Lee et al., 2013), or several of its components (Asif, 2016). Asif (2016) made use of a three-question measure of anchoring as well as a single item measure of the disposition effect. The three-question measure of anchoring was an adaptation of an unpublished Masters thesis (Asif, 2016). However, the thee questions used to measure anchoring were not reported in Asif (2016). Ates et al. (2016) provided the reliability of a combined measure of overconfidence and psychological biases (Cronbach's alpha was .78), Asif (2016) provided the reliability for three questions measuring anchoring (Cronbach's alpha was .67). However, the reliability of the measure used in Lee et al. (2013) was not provided.. Nor was it available in Pompian (2012). Neither study provided the factor structure or discriminant validity of their respective measures.

Once again, each of these measures was published after the data collection phase of this thesis and could not be used in this thesis. B18 to B24 and B27 were developed by the researcher to measure psychological biases. More specifically, B18 (I keep separate accounts [e.g., car, home, income, investment, savings "windfalls"] for different kinds of activities) asked about investor tendency towards mental accounting. Section 2.4.11 describes mental accounting. B19 (A company's profit performance has the same prospects as that of its share price performance) asked investors about their tendency towards representative bias. Section 2.4.12 describes representative bias.

B20 (When I buy or sell shares, I consider the original purchase price of those shares I already have) asked investors about their tendency towards anchoring. Section 2.4.7 describes anchoring bias. B21 (I prefer to capitalize gains quickly) and B22 (I prefer to hold on to losing stocks in the hope that they will eventually make a capital gain) asked investors about their tendency towards the disposition effect. Section 2.4.8 describes the disposition effect.

B23 (I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income) asked investors about their tendency towards the status quo bias. Section 2.4.13 describes the status quo bias. B24 (I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares) asked investors about their tendency towards the endowment effect. Section 2.4.9 describes the endowment effect.

B27 (Of the different company shares in your portfolio, what proportion are listed on … [a] the Australian Stock Exchange only, [b] dually listed on the Australian Stock Exchange and other stock exchanges, [c] approximately 70 percent listed/dual listed on the ASX, 30 percent on other stock exchanges … [f] all listed on other exchanges) addressed investor tendency towards familiarity bias. Investors endorsed one of six ordinal categories. This question was reverse-scored so that the higher the score, the greater the tendency towards familiarity bias. Section 2.4.10 describes the familiarity bias.

Table 7 summarizes the eight questions developed to measure psychological biases. Questions B18 to B24 were completed using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Question B27 was completed on a six point ordinal scale. Thus, higher scores on this construct would equate with greater propensity for psychological biases in respondent investment activities. The factor structure for the psychological biases developed in this thesis was considered together with that of overreaction, January effect, July effect and social herding. See chapter 5.

Table 7 *Questions Measuring Psychological Biases*

Psychological biases (10 questions)	B18	I keep separate accounts (mental accounting)
	B19	A company's profit performance has the same prospects as that of its share price performance (representative bias)
	B20	When I buy or sell shares, I consider the original purchase price of those shares I already have (anchoring)
	B21	I prefer to capitalize gains quickly (disposition effect)
	B22	I prefer to hold on to losing stocks in the hope that they will eventually make a gain (disposition effect)
	B23	I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income (status quo bias)
	B24	I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares (endowment effect)
	B27	Of the different companies in your portfolio, what proportion are listed on the Australian stock exchange … and what proportion are listed on other stock exchanges (reverse-scored) (familiarity bias)

4.5.8 Social herding

Asif (2016) used a three question measure of social herding. The three-question measure was adapted from an unpublished Masters thesis (Asif, 2016). While the three questions used in Asif (2016) were not provided, the measure had a Cronbach's alpha of .80. This measure was reported after the data collection phase of this thesis and could therefore not be used in this thesis.

Three questions, B1 to B3, were developed by the researcher to measure social herding. Table 8 provides a full list of the three questions developed to measure social herding. Questions were completed using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). Higher scores on this construct would equate with greater tendency towards social herding in the share market.

As discussed in sections 4.5.1 and 4.5.3, the factor analysis, for this scale was considered in conjunction with that of overreaction, January effect, July effect and psychological biases. See chapter 5.

Table 8 *Questions Measuring Social Herding*

Social herding (3 questions)	B1	The best way to protect one's wealth is to do as others do in the share market
	B2	Most of my friends are also investors
	B3	It is important to look at the same information that fellow investors look at

4.5.9 Anxiety

The NEO Personality Inventory (Revised) is a "big five" measure of personality, measuring introversion/extroversion, neuroticism, openness, agreeability, and conscientiousness (Costa & McCrae, 1992). The NEO Personality Inventory (Revised) neuroticism scale includes the subscale of anxiety. The anxiety subscale measures a propensity for apprehension, fearfulness, nervousness and worrying (Costa & McCrae, 1992). Past research has shown Cronbach's alpha to be in the range of .78 and .82 for two different versions of the subscale of anxiety (Costa & McCrae, 1992).

Costa and McCrae (1992) summarized a series of studies that showed the big five dimensions of personality, along with each of its subscales (including that of anxiety) demonstrated discriminant validity.

The International Personality Item Pool (IPIP) provides readily available free alternatives to standardized psychometric tests such as the NEO Personality Inventory (Revised). The IPIP website provides (a) psychometric properties of the IPIP scales; (b) individual test questions; and (c) scoring guides. Researchers can mix and match individual IPIP scales or questions according to their research needs (Goldberg et al., 2006).

The ten question IPIP version of the NEO Personality Inventory (Revised) subscale of anxiety has a reported Cronbach's alpha of .83 (IPIP, 2010). Questions included B28: I am relaxed most of the time; B30: I fear for the worst; and B36: I don't worry about things that have already happened. Discriminant analyses were not reported for the IPIP questions measuring anxiety. The IPIP anxiety scale was shown to have a correlation of .75 with the NEO Personality Inventory (Revised) subscale of anxiety (IPIP, 2010).

The ten IPIP questions were adopted for use in this survey using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5). The ten questions can be found in Table 9. B28, B33 and B35 to B37 were reverse-scored so that responses to these questions may be interpreted in the same way as positively-worded questions. Thus higher scores on this construct would equate with greater levels of reported anxiety.

Table 9 *Questions Measuring Anxiety*

Anxiety (10 questions)	B28R	I am relaxed most of the time (reverse-scored)
	B29	I worry about things happening
	B30	I fear for the worst
	B31	I get stressed easily
	B32	I get caught up in my problems
	B33R	I am not easily bothered by things (reverse-scored)
	B34	I am afraid of many things
	B35R	I am not easily disturbed by events (reverse-scored)
	B36R	I don't worry about things that have already happened (reverse-scored)
	B37R	I adapt easily to new situations (reverse-scored)

Chapter 5 reports the factor structure, Cronbach's alpha and discriminant validity for the scale of anxiety in this research.

4.5.10 Impulsivity

Patton et al. (1995) performed a principal component analysis on the tenth version of the Barratt Impulsivity Scale (34 questions) and found it to contain six primary factors and three second order factors. The three higher order factors were ultimately labeled attentional impulsivity, motor impulsivity and non-planning impulsivity. Full scale scores for the 34 questions (tenth version) had an association with that of the resultant version 11 of .98.

Version 11 of the Barratt Impulsiveness Scale (commonly referred to as the BIS30), is a 30 question measure of impulsivity with three subscales measuring lack of attention (eight questions), lack of planning (11 questions) and motor activity (11 questions). This measure used a four point Likert scale. Eleven of the BIS30 questions were worded in the non-impulsive direction and were reverse-scored before calculating impulsivity or its subscale scores (Patton et al., 1995).

A short form of the BIS30 was developed by Spinella (2007). The short form was also constructed using a four point Likert scale. Using factor analysis with varimax rotation, the five questions with the strongest loadings on the three respective subscales were selected to form the short form of the scale. This short form has been referred to as the BIS15 (Spinella, 2007). The correlation between the BIS15 and the BIS30 was .94. Cronbach's alpha for the overall scale was .79 (Spinella, 2007). Spinella (2007) did not report Cronbach's alpha coefficients for the three BIS15 subscales. Spinella (2007) also did not report the discriminant validity for the BIS15, or its subscales.

To be consistent with the other questions asked in this survey (described in 4.5.1 to 4.5.9 above), the BIS15 was adopted for use in this survey using a five point Likert scale ranging from *strongly disagree* (1) to *strongly agree* (5) (B38 to B52). Using the BIS15 over the BIS30 would reduce the number of questions investors would be asked to complete, while still obtaining scores on the construct of impulsivity for each investor.

B38 to B42 contribute to the first component of impulsivity, referred to as lack of attention. B38 was reverse-scored so that a higher score related to higher levels of impulsivity. Questions in this subscale included B38: I concentrate easily; B39: I am restless at lectures or talks; and B41: I don't pay attention.

B43 to B47 contribute to the second component of impulsivity, referred to as lack of planning. All five questions on this subscale were reverse-scored prior to summation so that, once again, higher scores equated with higher levels of impulsivity. Questions included in this subscale were: B44: I plan for the future; B46: I plan tasks carefully; and B47: I am a careful thinker.

B48 to B52 contribute to the third component of impulsivity, referred to as motor activity. Questions included in this subscale were: B48: I act on impulse; B49: I act on the spur of the moment; and B52: I buy things on impulse.

In each case, higher scores equate with greater levels of reported lack of attention, lack of planning, and/or motor activity components of impulsivity. See Table 10 for a full list of questions measuring impulsivity.

Table 10 *Questions Measuring Impulsivity*

Impulsivity (15 questions)	Lack of attention (5 questions)	B38R	I concentrate easily (reverse-scored)
		B39	I am restless at lectures or talks
		B40	I squirm at plays or lectures
		B41	I don't pay attention
		B42	I get easily bored when solving problems
	Lack of planning (5 questions)	B43R	I plan for job security (reverse-scored)
		B44R	I plan for the future (reverse-scored)
		B45R	I save regularly (reverse-scored)
		B46R	I plan tasks carefully (reverse-scored)
		B47R	I am a careful thinker (reverse-scored)
	Motor activity (5 questions)	B48	I act on impulse
		B49	I act on the spur of the moment
		B50	I do things without thinking
		B51	I say things without thinking
		B52	I buy things on impulse

Chapter 5 reports the factor structure, Cronbach's alpha and discriminant validity for impulsivity.

4.5.11 Investor profile

The researcher developed questions to examine respondent profile. Questions were asked regarding investor years of investment experience (C1); whether investors were retail or institutional investors (C2); C18: how many different companies investors followed, researched or analyzed; and C19: how many different company's shares investors currently had in the share portfolio they owned and/or managed. Questions were also asked regarding which country's stock exchanges respondents invested on (C3 to C16) and which set of financial ratios were used for buying or selling shares (C24 to C39). Demographic variables were also requested, (including, D1: age; D2: gender; D3: marital status; D6: education; D7: financial education; and D8: occupation).

4.5.12 Investment method and types of shares held

The researcher developed questions to survey investors on their primary investment method (C17), along with the type of share investments they hold in their portfolio (C20: defensive shares; C21: growth shares; C22: cyclical shares; and C23: asset/turnarounds).

4.5.13 Global Financial Crisis (GFC)

The researcher developed questions C62 to C76 to survey investors on their activities during the GFC (i.e., C62: During the recent GFC, I bought shares for less than those I already owned; C63: During the recent GFC, I bought shares for the same price as those I already owned; C64: During the recent GFC, I bought shares for more than those I already owned; C65: During the recent GFC, I sold shares for less than I had paid for them; C66: During the recent GFC, I sold shares for the same price I had paid for them; C67: During the recent GFC, I sold shares for more than I had originally paid for them; C68: During the recent GFC, I bought bonds, gold or term deposits; C69: During the recent GFC, I sold bonds, gold or term deposits; C70: During the GFC, I increased my cash holdings; C71: During the GFC, I decreased my cash holdings; C72: During the recent GFC, I used automatic 'stop loss' or 'sell' orders; C73: During the recent GFC, I used automatic 'buy' orders; C74: During the recent GFC, I used margin lending; C75:

During the recent GFC, I used options, warrants, derivatives or other financial products; and C76: During the recent GFC, I used bank loans or redraw facilities on my home loan to buy shares. C65, C68 and C70 measured flight in fight/flight theory. Questions were completed using a five point Likert scale.

4.5.14 Portfolio wealth

The researcher also developed questions to survey investors on the value of their investment portfolio for the period ended 30th June 2007 (C61d) to the period ended 30th June 2010 (C61a).

4.6 Data preparation

Upon receipt of completed questionnaires, data was entered into Statistical Package for the Social Sciences (SPSS), Version 19, data file. Missing values were left blank.

While the researcher entered all the data into a SPSS data file, she did so over three different laptops; each had different keyboard sensitivities. It was therefore decided to manually check the accuracy of data entry for each case. Detected data entry errors were then corrected. In cases #99 and #144, investors reported that they commenced share trading on the demutualization of AMP. The year of demutualization was then entered for C1. In case #289, the investor reported owning 315 shares in Suncorp Metway. The investor's share portfolio was calculated at cost for C61a to C61d. Case #519 reported commencing share trading when "IGA" floated. However, the researcher could find no listing date for this company. While it was possible the investor meant IAG, case #519's response to C1 was left blank.

Some investors had reported the total number of different companies' shares held that were C20: defensive shares; C21: growth shares; C22: cyclical shares; or C23: asset/turnarounds. However, other investors reported the percentage of their portfolios that were allocated to either defensive shares, growth shares, cyclical shares or asset/turnarounds.

For the sake of consistency, all responses to questions C20: defensive shares to C23: asset/turnarounds were converted to percentages before data entry. As C19 asked investors to report the total number of different companies' shares held in their portfolios, responses to this question were used to convert C20: defensive shares to C23: asset/turnarounds responses to percentage scores. However, it is recognized that this method was not without its own problems. In several cases, responses to C19 did not appear to reflect the total of the combined responses to C20: defensive shares to C23: asset/turnarounds. In several other cases, investors reported their companies' shares as belonging to more than one of the four types of shares and double counted them accordingly. While the researcher expected the theoretical range for C20: defensive shares to C23: asset/turnarounds to total 100 percent, they may exceed 100 percent in practice. As these discrepancies were few in number, and may have added 'noise' (that is, increased the error variance) in the four variables, these discrepancies were not expected to have a significant impact on significance tests. No other alterations were made to the data file.

The following preliminary variables were calculated:

a) "Don't know" responses were summed per respondent to yield the count of "don't know" per respondent.
b) "Don't know" responses were then recoded to system missing. In this way, SPSS did not distinguish between respondents endorsing "don't know" or those who left questions unanswered. As SPSS cannot perform a count of scale, nominal and string variables within the same count, the summation of all the missing values per respondent was undertaken in four steps. Firstly a count of missing values was obtained for all the scale questions in the first three sections of the questionnaire. Secondly, a count was taken of the remaining numeric (nominal)

questions in the questionnaire (i.e., C2, which asked investors whether they were retail and/or institutional investors; C3, which measured preference for fundamental and/or technical analysis; and C17, which measured investment methods). Thirdly, a count was taken of missing values in the string item (C5: Do you monitor the movements of a share price index: daily, weekly, monthly, annually, (or) never). The final step involved collating tallies obtained in the first three steps, using SPSS mean command. The summation of missing values per respondent thus reflected the count of "don't know" and count of missing data per respondent.

c) To distinguish whether investor profiles differed between those who endorsed "don't know" options versus those who left questions unanswered in the first three sections of the questionnaire, the count of "don't know" per respondent was subtracted from the count of "don't know" and count of missing data per respondent. Thus, this third variable reflected the count of missing data per respondent.

d) Overreaction was obtained by summing responses on B25: When a company's share price performance has done badly, I sell out, no matter how little I get for selling them; and B26: When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them.

e) Overconfidence was obtained by summing responses on A18 to A21 and A23. Questions sampled investor belief about their own level of investment knowledge (e.g., A18: how knowledgeable do you consider yourself to be about investing). Questions also sampled investor expectations about portfolio performance (e.g., A23: what percentage return do you expect your portfolio to earn by the end of the year).

f) January effect was obtained by summing responses on B4: At the end of each year, I sell shares for less than I had paid for them; B5: At the end of each year, I sell shares for more than I had paid for them; and B6: At the beginning of each year, I buy more shares.

g) July effect was obtained by summing responses on B7: Towards the end of June each year, I sell shares for less than I had paid for them; B8: Towards the end of June each year, I sell shares for more than I had paid for them; and B9: At the beginning of July each year, I buy more shares.

h) A3, A6 and A7 were reverse-scored. Score on appetite for financial risk was then obtained by summing responses on A3 (reverse-scored), A4, A5, A6(reverse-scored) and A7(reverse-scored), A13 to A17, and C74 to C76. These questions sampled investor propensity for risk generally (e.g., A3: Investing safely; and A13: margin lending) as well as propensity for risk during the period of the global financial crisis (e.g., C71: during the GFC, I decreased my cash holdings; and C74: during the GFC, I used margin lending).

i) Scores on information sources were obtained by summing scores on C40 to C60.

j) Six subscales were calculated for use of information sources (Information - Professional advice was the summation of C40 and C41. Information – Broker advice was the summation of C42 and C43. Information – Research was the summation of C44 to C48. Information – Media was the summation of C49 to C54. Information – Experiential was the summation of C55 and C56. Information – Social network was the summation of C57 to C60).

k) B27 was reverse-scored. Scores on psychological biases were then obtained by summing responses on B18 to B24, and B27 (reverse-scored). These questions measured mental accounting, anchoring, disposition effect, endowment effect, familiarity bias, representative bias and status quo bias.

l) Social herding was obtained by summing responses on B1: The best way to protect one's wealth is to do as others do in the share market; B2: Most of my friends are also investors; and B3: It is important to look at the same information that fellow investors look at.

m) B28, B33, and B35 to B37 were reverse-scored. Anxiety was then obtained by summing scores on B28 (reverse-scored), B29 to B32, B33 (reverse-scored), B34 and B35 (reverse-scored) to B37 (reverse-scored).

n) B38 and B43 to B47 were reverse-scored. Impulsivity was then obtained by summing scores on B38 (reverse-scored), B39 to B42, B43 (reverse-scored) to B47 (reverse-scored) and B48 to B52.
o) Marital status (D3) and gender (D2) were combined to create a nominal variable, with its coding aligned to the finding of Barber and Odean (2001). Thus single men were coded “4”, partnered men were coded “3”, partnered women “2” and single women “1”. This grouping variable was used with the first research question.
p) Years_experience (at the time of the survey) was calculated by subtracting C1 from the year 2010. This variable will be referred to as years of investor experience.
q) Twelve month changes in portfolio wealth was calculated by subtracting the 2009 portfolio value from the 2010 portfolio value. The difference was divided by the 2009 value, which in turn was multiplied by 100. Equivalent calculations were undertaken for two year changes in portfolio wealth and three year changes in portfolio wealth.

Question C17 asked investors about their preferred investment method. Five major types of investment methods were provided as options, (i.e., buy and hold investing, contrarian investing, dollar cost averaging, index investing, and momentum investing). However, respondents primarily endorsed buy and hold investing, and to a lesser degree, contrarian investing. Very few respondents endorsed the remaining three options. For this reason, preferred investment method was excluded from the analyses.

In order to test for differences between early and late responders, the first 100 cases were coded ‘1’ and the last 100 cases were coded ‘0’. Independent *t*-tests were then calculated for the 18 variables used in the structural equation model, along with three-year wealth change. No significant difference was found between early and late responders on any of these variables.

Finally, the sample was split into two in order to test and validate the factor structure of the ten scales developed or adapted for use in this study. Case numbers with odd values formed part of the "training sample" (n = 260) whilst case numbers with even values formed part of the "validation sample" (n = 261). In so doing, it was expected that there would be no real (significant) difference between the two sub-samples; that is, both sub-samples could be expected to be random samples drawn from the same population from which the full sample was drawn.

Independent *t*-tests were calculated on 19 variables on the training and validation subsamples in turn to test whether there were any differences between early and late responders. Once again, no significant difference was found between early and late responders on any of these variables in either the training or validation subsamples.

4.7 Scale development

As can be seen from sections 4.5.1 to 4.5.14, (and Tables 1 to 10), each of the questions used in this research were developed or adapted for use with investors. Questions measuring anxiety (described in 4.5.9) and impulsivity (described in 4.5.10) were adapted for use with investors. Remaining questions were all developed by the researcher. A composite of 97 questions measured the ten constructs.

The questions shown in Tables 1 to 10 are attitudinal in nature and most of these questions were measured on a Likert scale. If a subset of the questions were dropped from any one construct, it would not detract from the full meaning of the construct the questions were developed to measure. Indeed, examination of the correlation matrix amongst questions intended to measure each construct demonstrate modest correlations. Based on the work of Jarvis, Mackenzie and Podsakoff (2003) one might conclude these questions to be reflective indicators.

Brown (2006) noted that confirmatory factor analyses can only be performed after constructs have already been refined through exploratory factor analyses. Moreover, exploratory factor analysis is preferred over principal components analysis when constructs have been based on theory or past research (Blunch, 2013).

Exploratory factor analysis represents a range of extraction methods. Of these methods, Jarvis, Mackenzie and Podsakoff (2003) recommend using principal axis factoring when questions intended to measure a particular construct are reflective indicators of that construct. Principal axis factoring makes no statistical assumptions (Brown, 2006). Varimax rotation is the most commonly used orthogonal rotation method (Tabachnick & Fidell, 2014). Varimax rotation simplifies factors. In so doing, it makes factors more readily interpretable (Tabachnick & Fidell, 2014). As an orthogonal rotation method, varimax rotation has the added advantage that the factor loading between a variable and the factor it loads upon can be interpreted as one interprets a correlation coefficient. The size of the factor loading thus reflects the contribution of a variable to the factor it loads upon (Brown, 2006).

Note, that this questionnaire makes use of positively- and negatively-worded questions. Historically, the inclusion of both positively and negatively worded questions formed part of questionnaire design to reduce respondent biases in questionnaire completion (such as respondent endorsement of socially acceptable alternatives or of 'yes' alternatives). Underlying this research practice, however, is the assumption that both positively-worded and negatively-worded items tap into the same construct domain (Marsh, 1996).

It is noted, however, that both exploratory and confirmatory factor analytic techniques may attempt to extract additional factors so that positively worded items fit on one factor, while their negatively-worded counterparts fit on a separate factor. The creation of a separate factor due to the direction of item wording is known as a method effect (Brown, 2006; Marsh, 1996). Marsh (1996) has empirically shown such a division into separate factors has no theoretical or empirical meaning. Confirmatory factor analytic models can fit associations between error terms to account for method effects (Brown, 2006). Marsh (1996) recommends (a) the removal of negatively-worded items; (b) to ensure positive and negatively worded items are equally represented on each factor; and/or (c) retain negative items (so as to test for response biases), but exclude the negatively-worded items when obtaining a score on the resultant scales.

The full sample was divided into two sub-samples for the sole purpose of testing and validating the factor structure for the ten constructs (i.e., overreaction; overconfidence; January effect; July effect; appetite for financial risk; information sources; psychological biases; social herding; anxiety; and impulsivity). [Upon completion of the scale development work, the two half samples were recombined for remaining analyses]. Exploratory factor analyses, using principal axis factoring with varimax rotation, were performed with the first sub-sample, the "training sample" (n = 260). Confirmatory factor analyses were then performed using the second sub-sample, the "validation sample" (n = 261). Where any scale modifications were undertaken, they were based on theoretical grounds or past research. If a method effect becomes evident, the first recommendation of Marsh (1996) was utilized.

4.7.1 Training sample: Exploratory factor structure of proposed scales

Principal axis factoring with varimax rotation was used with the training sample (n = 260). Pairwise deletion of missing data was also used to preserve as much data as possible. As discussed in 4.7, any modifications undertaken to the factor model were done so based on theoretical grounds and past research. Exploratory factor models were accepted if they demonstrated Thurstone's (1935, 1940) concept of simple structure. Simple structure has been said to exist when (a) each factor has a set of variables with salient loadings and remaining variables have negligible loadings; (b) each variable has a salient loading on one factor and negligible loadings on remaining factors (Thurstone, 1935, 1940); and (c) there are at least three salient loadings for each factor. Loadings are considered salient if they are at least |.3| in magnitude (Brown, 2006; Gorsuch, 1983; Tabachnick & Fidell, 2014).

As there were only three questions measuring the January effect, July effect and social herding, and only two questions measuring overreaction, their factor structure were considered simultaneously with the questions measuring psychological biases. In this way, their unique factorability could be more adequately assessed. See also discussion in sections 4.5.1, 4.5.3, 4.5.4 and 4.5.8. Separate exploratory factor analyses were obtained for the remaining five constructs. Chapter 5 reports the factor structure that best approached simple structure.

4.7.2 Validation sample: Confirmatory factor analyses of final scales

Confirmatory factor analyses were undertaken using the validation sample (n = 261). Once again, modifications undertaken to the factor model were based on theoretical expectations and past research. The final model for each construct can be found in chapter 5.

Confirmatory factor analysis models are assessed using the chi squared (Barrett, 2007) or normed chi squared test; comparative fit index (CFI) (Bentler, 1990); Tucker-Lewis Index (TLI), which is also known as the non-normed fit index (NNFI) (Bentler, 1990); and root mean square error of approximation (RMSEA) (Steiger, 2000). A confirmatory factor analytic model can be considered to be a good fit to the data when the chi squared is not significant. However, the chi squared test statistic is affected by model complexity and sample size (Barrett, 2007). Hence, where the chi squared test is significant, the chi squared value will be divided by its degrees of freedom (df) to arrive at a normed chi squared value (Blunch, 2013). Normed chi squared values should approach a value of one (Blunch, 2013). The confirmatory factor analytic model is often considered to be a good fit to the data when the normed chi squared value is less than a value of three.

The model is also considered a good fit to the data when the CFI, TLI and comply with a certain critical value. Different opinions exist regarding what the critical values for CFI, TLI and RMSEA should be. Some authors consider values in excess of 0.90 (CFI and TLI) (Byrne, 2010; McDonald & Ho, 2002; Schumacker & Lomax, 1994) and less than 0.08 (RMSEA) indicative of a good model fit to the data (Byrne, 2010; McDonald & Ho, 2002). Other authors consider values in excess of 0.95 (CFI, TLI) and less than 0.05 or 0.06 (RMSEA) indicative of a good model fit to the data (Blunch, 2013; Brown, 2006; Kline, 2011; Schumacker & Lomax, 1994; Ullman, 2014). In this research, the model was considered a good fit to the data when CFI and TLI were both in excess of 0.90, and the RMSEA was less than 0.08.

The exploratory and confirmatory factor analyses led to the development of the following scales: (a) overreaction; (b) overconfidence; (c) July effect (d) appetite for financial risk; (e) information sources; (f) anxiety; and (g) the three independent dimensions of impulsivity (i.e., lack of attention, lack of planning; and motor activity). Note that overconfidence had two subscales: investor knowledge and investor expectation about portfolio performance. Similarly, information sources had two subscales: investor research and social network. Factor structure for the eight scales, along with the subscales for overconfidence and information sources, can be found in chapter 5.

4.7.3 Reliability and discriminant validity of final scales

Cronbach's alpha coefficients were obtained for each of the final scales. Where applicable, Cronbach's alpha was also obtained for subscales. Listwise deletion of missing data was used. Cronbach's alpha coefficients were considered adequate for exploratory research if the coefficients were greater than 0.60 (Hair, Anderson, Tatham, & Black, 2005).

Tests for model reliability and discriminant validity were also undertaken using the method described by Fornell and Larcker (1981). Results of the tests for model reliability and discriminant validity can be found in chapter 5.

Full scale scores were calculated for the eight scales along with both the subscales for information sources and overconfidence. In each case, scales and subscale scores were a summation of the questions loading on the final model for each construct. Chapter 5 provides the correlation matrix for the eight scales and both sets of subscales. Cronbach's alpha coefficients were provided down the leading diagonals in both correlation matrices.

4.8 Missing data analysis and statistical assumptions

4.8.1 Missing data analysis

Missing value analyses were then performed and the data was found to be missing completely at random (MCAR) (*Little's MCAR Chi square* = 7223.4; *df* = 6388; *normed chi squared* = 1.13; $p > .05$). The Expectation Maximization (E.M.) algorithm was used to impute values for missing values for each of the eight scales and subscales. The E.M. algorithm iterates between computing the expected value for a missing datapoint and the maximum likelihood of that expected value being obtained (SPSS Inc., 2010a). This method assumes that the data is MCAR (SPSS Inc., 2010a). It is noted that analyses based on covariances using imputed values may underestimate those covariances. This underestimation may be in direct proportion to the number of "jointly unobserved" datapoints to be imputed (SPSS Inc., 2010a, page 9).

Scale and sub-scale scores were then recalculated using imputed values. Cronbach's alpha coefficients were recalculated. As might be expected with data that is MCAR, the coefficients obtained using imputed values were almost identical to those obtained using listwise deletion. Imputed scale and subscale scores were merged into the original data file.

Missing items per respondent were also examined. The count of missing data per respondent had already been obtained. See section 4.6. The percent of missing data per respondent were obtained by dividing the count of missing data by the total number of items in the questionnaire (164 items). Thirty-four respondents had at least 20 percent missing data. These cases were removed from the datafile, yielding a sample size *n* of 487 cases, and consequently, reducing the useable response rate to 13.9 percent.

The correlation matrix and descriptive statistics using imputed values are reported towards the end of chapter 5. Cronbach's alpha for imputed values were obtained for the sample of 487 cases. Cronbach's alpha has also been reported down the leading diagonal of the correlation matrix. See chapter 5.

4.8.2 Statistical assumptions

Multivariate statistical tests typically assume that residuals are independent and follow multivariate normality, linearity and homoscedasticity. Multivariate statistical tests are also affected by the presence of outliers, multicollinearity and singularity (Tabachnick & Fidell, 2014). Moreover, both analysis of variance and discriminant analysis assume that each level of a grouping variable demonstrate normality (or multivariate normality), linearity and homoscedasticity (Tabachnick & Fidell, 2014).

4.8.3 Multivariate normality, linearity, homoscedasticity and absence of outliers

To check for multivariate normality, linearity and homoscedasticity of residuals, plots of standardized residuals were plotted against predicted values using the SPSS regression module. As the discriminant analyses and analysis of variance also assumed (multivariate) normality, linearity and homoscedasticity at each grouping variable, the assumption checks were undertaken for each level of their respective grouping variables. All assumption checks were undertaken before addressing the first research question.

Deviations from this assumption were addressed by transforming twelve variables, followed by the removal of seven outlying cases. The following variables were transformed using a natural log transformation: (a) How many hours per week do you typically spend thinking, reading, researching or discussing investments (C4); (b) How many different companies do you research, follow or analyze (C18); (c) How many different company's shares do you currently have in the share portfolio (C19); (d) Defensive shares (C20); (e) Cyclical shares (C22); (f) Asset/turnarounds; (g); one-year wealth changes; (h) two-year wealth changes; and (i) three-year wealth changes. As the four different share types and three wealth change variables could contain zero values, a constant was added prior to the log transformation.

The remaining three variables were transformed using a square root transformation: (a) Count of "don't know"; (b) Count of missing data; and (c) the combined count of "don't know" and missing data. The seven outlying cases removed from the data file were cases 453R, 166I, 417I, 053I, 311R, 181R and 306R. The sample size, *n,* for remaining analyses is thus 480 cases, further reducing the usable response rate to 13.7 percent.

4.8.4 Multicollinearity and singularity

Computer programs automatically exclude variables that contribute too severely to multicollinearity and singularity (Tabachnick & Fidell, 2014).

In the case of this dataset, however, overconfidence and information sources both have two subscales each. Inclusion of the full scale and their respective subscales would lead to multicollinearity and singularity. The count of "don't know" and the count of missing data were summed to determine scores on the combined count of "don't know" and the count of missing data. Including all three variables in any one analysis would similarly lead to multicollinearity and singularity.

Consequently, full scales were not considered simultaneously with one or both of its subscales. Similarly, the combined count of "don't know" and missing data were not considered concurrently with either the count of "don't know" or the count of missing data.

Chapter 5 concludes with descriptive statistics for the eight scales and subscales using imputed values. Further descriptive statistics were provided for remaining variables. Where appropriate, variables were transformed using a natural log or square root transformation.

4.9 Research question 1: Overconfidence and gender/marital status

Following assumption checks as discussed in section 4.8.3, a one way analysis of variance, along with a Bonferroni post-hoc test, was performed. This analysis examined whether the level of overconfidence was influenced by the interaction between marital status and gender. As the dependent variable had more than 20 percent of its data missing, this variable was considered in its original form (that is, without imputation). Thus, this analysis is based on a sample of 313 cases.

Following on from the research of Barber and Odean (2001), it was hypothesized that single women would report the least overconfidence, partnered women would report the second-least overconfidence, partnered men would report the second-most overconfidence and single men would report the most overconfidence. Results of these analyses can be found in chapter 6.

4.10 Research question 2: Identifying markers of underconfidence

As previously noted in section 4.6, "don't know" responses were recoded to missing. It is possible, however, that different forms of missing data may add valuable information. Indeed, one might expect that endorsing "don't know" and/or leaving items blank on an investor survey, may be indicators of underconfidence. Three measures were therefore developed (a) the count of "don't know" per respondent; (b) the count of missing data per respondent and (c) the combined count of "don't know" and missing data per respondent. The count of "don't know" was a tally of the number of questions endorsed as "don't know" by an investor. The count of missing data tallied the number of questions an investor left blank. The third variable, the combined count of "don't know" and missing data thus represented a combined tally of the number of questions an investor endorsed with "don't know" as well as the number of questions an investor left blank.

Following the assumption checks in section 4.8.3, three separate multiple regression analyses were performed. In each case, the natural log transformations of (a) the count of "don't know; (b) count of missing data and (c) the combined count of "don't know" and missing data were treated as the dependent variable in turn. Overconfidence (without imputation) and financial education were treated as independent (predictor) variables in each analysis. Pairwise deletion of missing data was used in each analysis. As hypothesized in h_{2a} to h_{2c}, both predictors were expected to have significant negative beta weights. Chapter 6 summarizes these analyses.

4.11 Research question 3: Profile of investor

The sample of 480 investors included both retail (n = 378) and institutional investors (n = 53). Forty-nine investors did not indicate whether they were retail or institutional investors. Of those 49 investors, 39 endorsed that they did not know to which group they belonged. The remaining 10 investors left the question blank.

It was of interest to explore on what dimensions could one group of investors be distinguished from those of the other. In this regard, seven discriminant analyses were performed. Tabachnick and Fidell (2014) note that predictor variables can be selected for discriminant analyses on practical or theoretical grounds. Of the seven planned discriminant analyses, variables selected for the first two analyses were selected on practical grounds while those selected for the remaining five analyses were selected on theoretical grounds: (a) demographic profile; (b) investment practices; (c) investment strategies; (d) overreaction, overconfidence, and underconfidence; (e) anxiety and impulsivity; (f) July effect; information sources and appetite for financial risk; and (g) changes in portfolio wealth over time. The 49 investors that did not indicate whether they were retail or institutional investors were not included in the discriminant analyses. However, they were included in the classification procedures arising from each discriminant analysis.

Discriminant analysis assumes (a) multivariate normality; (b) absence of outliers; (c) linearity; (d) homogeneity of the variance – covariance matrix; as well as (e) an absence of multicollinearity and singularity (Tabachnick & Fidell, 2014). Tabachnick and Fidell (2014) note that discriminant analysis is robust to deviations from multivariate normality when those deviations are due to skewness, but not the presence of outliers. Discriminant analysis is also robust from deviations from multivariate normality when groups are equal in size and two-tailed tests of significance are used (Tabachnick & Fidell, 2014). If sample sizes are unequal, as it is in the case of the present samples, discriminant analysis will be robust from departures from multivariate normality when the smallest group has at least 20 cases and there are no more than five predictors being used in the discriminant analysis (Tabachnick & Fidell, 2014).

As the smallest group in each analysis exceeds 20 cases, and all seven planned discriminant analyses used less than five predictors, it was expected that the discriminant analyses would be fairly robust to deviations from this assumption. However, tests for multivariate normality, linearity, homoscedasticity, multicollinearity

and singularity were routinely performed on completion of scale development. See section 4.8.3 above. At this point, nine variables were transformed using a natural log transformation, while a further three variables were transformed using a square root transformation. These twelve variables form part of the second, third and final discriminant analyses. Moreover, seven outlying cases were removed from the datafile.
It was expected that these assumption checks had ensured homogeneity of the variance – covariance matrix used in discriminant analysis. However, three of the seven discriminant analyses had a significant Box's M statistic. Box's M is known to be sensitive to other factors. Consequently, researchers may obtain a significant Box's M result when the variance – covariance matrix is actually homogenic. If the researcher obtains a significant Box's M result, the alternatives are to (a) use separate covariance matrices in the classification procedure; (b) run the risk that the classification procedure favors the group with the greater dispersal of scores; (c) perform a non-parametric discriminant analysis; or (d) perform a quadratic discriminant analysis. The first option may result in overfitting the classification equation to the present sample. The second option may result in a biased classification equation. The latter two options are only available through SAS (Tabachnick & Fidell, 2014). In the former case, moreover, the researcher may not be able to extrapolate research findings to the populations from which the samples were drawn.

In SPSS, the researcher has the option of setting options in the discriminant classification procedure to model the ratio of different sample sizes *a priori*. However, doing so in the present survey would mean, all else being equal, cases would be more likely to be classified as retail investors. It was of greater interest to assess the merits of the set of predictors without the advantage of *a priori* knowledge of the ratio between group sample sizes. For this reason, equal weighting of group membership was used for the seven discriminant analyses.

Perusal of each variable's standard deviation showed that in some instances, retail investors had the greater dispersal of scores, and institutional had the greater dispersal of scores in others. The dispersal of scores in the second discriminant analysis favored the institutional investors. However, the classification equation favored the retail investor, with an 85.6 percent success rate. As the classification equation favors the group with the tighter dispersal of scores, it would appear that this result can also be accepted as a valid result (Tabachnick & Fidell, 2014). Tabachnick and Fidell (2014) believe classification equations that yield success rates in the order of 95 percent success are always welcomed, irrespective of any problems with deviations from statistical assumptions.

Where available, multiple imputation is the preferred method of handling missing data. Multiple imputation does not make any assumptions about the form of a data's missingness (Tabachnick & Fidell, 2014). However, only listwise deletion is available in discriminant analysis. Consequently, each discriminant analysis reports on the sample size of each group for that analysis. Results for the seven discriminant analyses can be found in chapter 6.

4.12 Research question 4: Predicting emotional presentation

Analyses for the fourth and final research question were based on the sample of retail investors (including the 49 investors who did not indicate to which group they belonged), that is, a sample of 427 retail investors. These findings can be found in chapter 8. The analyses for the fourth research question were also repeated without the originally ungrouped investors (that is, a sample of 378 retail investors). The repeated analyses can be found in appendix A6. Assumptions for hierarchical regression were addressed in section 4.8.3.

Three hierarchical regressions were performed using (a) overreaction; (b) overconfidence; and (c) count of "don't know", as a marker of underconfidence as the dependent variables in turn.

Four blocks were entered into the hierarchical regression models in turn. Demographic variables (age, gender, marital status, education, financial education and years of investor experience) entered the model in the first block. These variables are both easily obtained and represent relatively enduring characteristics of a respondent. The investor practices (Natural log of C4: Hours spent on investments; Natural log of C18: Companies followed; and Natural log of C19: Companies in portfolio) were entered into the model second. These three variables are also easily obtained. One might expect personality attributes (such as impulsivity) to precede behaviors (such as appetite for financial risk). Thus, personality variables entered the model in the third block and the behavioral practices entered the model in the final step. See chapter 8.

4.13 Research question 5: Modeling investor behavior

Structural equation modeling was used to test the hypothesized model as shown in Figure 3 at the close of chapter 3.

Structural equation modeling is an *a priori* tool that combines factor analytic and multiple regression techniques (Kline, 2011; Ullman, 2014). Its default estimation tool, maximum likelihood, assumes: (a) asymptotic large sample size; (b) multivariate normality approaching a chi squared distribution; (c) linearity; (d) homoscedasticity; (e) an absence of multicollinearity or singularity; (f) correctly specified model as evidenced by independent residuals with a mean of zero and symmetrical variance; (g) manifest variables measured on an interval scale and (h) random sampling (Arbuckle, 2010; Byrne, 2010; Kline, 2011; Ullman, 2014).

While maximum likelihood estimation assumes that the data is at least missing at random (Arbuckle, 2010; Ullman, 2014), it produces the best results when the data is missing completely at random (Byrne, 2010).

4.13.1 Asymptotically large sampling

With a sample size of 427 cases and 84 parameters to be estimated, the first assumption has been minimally met. To ensure that the sample remained asymptotically large, structural equation modeling was performed using the Munck (1979) single indicator latent variable method. In so doing, this method keeps the number of parameters to be estimated at a minimum while accounting for each scale's (manifest variable) error variance (Munck, 1979). By accounting for each scale's error variance, scale parameters will have more explanatory power than they would have had the model been put forward as a simple path analysis (Blunch, 2013).

Breckler (1990) recommended randomly splitting the sample in two such that the first sample be used to test the model and the second sample be used to validate the model. This approach has been put forward to prevent overfitting of the model to a single sample (Markland, 2007). However, doing so with a sample of 427 and 84 model parameters, would mean the sample no longer remains asymptotically large. For this reason, it was decided to use the full sample to test the model. It is left to future research to validate the model with other samples of investors.

4.13.2 Multivariate normality, linearity and homoscedasticity

The second, third and fourth assumptions were previously addressed. See section 4.8.3. As discussed in section 4.8.3, checks for these three assumptions resulted in the transformation of 12 variables. Eight of these variables were used in this analysis. Of the eight variables, the count of "don't know" was transformed using a square root transformation. Remaining seven variables were transformed using a natural log transformation (i.e., C4: How many hours per week do you typically spend thinking, reading, researching or discussing investments; C18: How many different companies do you follow, research or analyze; C19: How many different company's shares do you currently have in the share portfolio; C20: defensive shares; C22: cyclical shares; C23:

asset/turnarounds; and three-year wealth change). Seven outliers were also removed from the data.

4.13.3 Absence of multicollinearity and singularity

The fifth assumption was previously addressed in section 4.8.4. The only potential source of multicollinearity and singularity in this model would be the use of full scales (overconfidence and information sources) and their respective subscales. Full structural equation models can incorporate subscales. However, this thesis drew on the Munck (1979) method in order to reduce the number of pathways being predicted. For this reason, the Munck (1979) method was used with full scale scores only.

4.13.4 Correctly specified model, with residual mean of zero and symmetrical variance

The sixth assumption was addressed by basing the hypothesized structural equation model on past research and theory.

Basing one's model upon past research and theory, however, does not guarantee a correctly specified model. There may be several ways of framing a model, based on theory or past research. Each way of framing the model may be equally valid. Moreover, models may not necessarily be correctly specified in order to explain the data (Arbuckle, 2010). Thus, the structural equation model will almost certainly need to be respecified.

Examination of critical ratios (along with their accompanying level of significance) for parameter estimates indicate which existing pathways belong in the model. Similarly, examination of residual matrices and modification indices highlight pathways or associations that, if included, would improve model fit to the data (Arbuckle, 2010). More specifically, the modification indices show which pathways or associations, if included into the model, would improve model fit statistics such that the decline in the chi squared statistics would be greater than the accompanying decline in degrees of freedom associated with that chi squared statistic (Arbuckle, 2010). Thus, the larger the modification index would have the greatest impact on model fit. In using modification indices, therefore, the researcher should consider the pathway or association with the greatest modification indices first and only incorporate them if those proposed pathways or associations make theoretical sense (Arbuckle, 2010). Residual matrices would approach a null matrix (with values approaching zero in each cell of the matrix) when all additional pathways or associations have been incorporated in the model. If there are large residual values remaining in the residual matrix (above 1.96), then those figures highlight a potential pathway or association between the two variables that contribute to that high value.

However, where there is missing data, neither modification indices nor residual matrices are available through **A**nalysis of **Mo**ment **S**tructures (AMOS) Graphics. Instead, AMOS Graphics uses full information maximum likelihood estimation (FIML) and estimates both means and intercepts (Arbuckle, 2010). It was therefore decided to fit the hypothesized model using a sample of 427 cases. The structural equation model was then tested progressively. The sample size was stepped downwards in order to explore sections of the model whilst retaining complete data for the component of the model being explored. In this way, model respecification could make full use of the residual matrices and modification indices.

Stepping the sample size, *n,* progressively down enabled the model to be fitted on the maximum number of cases at each stage of model respecification. In so doing, means and intercepts need not be estimated (Arbuckle, 2010), and hence, fewer parameters are fitted for the same model. Consequently, the *n:p* ratio is maximized through each step of model-testing. It was hoped that the hypothesized model represented errors of commission (if any) rather than errors of omission. If so, the number of parameters to be estimated would reduce as the sample was progressively stepped down. In this way, it was expected that the reducing sample size at each step of model testing would still meet the *n:p* minimum ratio.

Note that when a variable's predicted pathways turned out to be non-significant in the earlier steps, the variable was retained in the model with its associations to other variables in the model. The variable was thus retained until the final step. If no significant (but unhypothesized) pathways were found between that variable and remaining variables in the model that made theoretical sense, it was deleted as part of the final step. In this way, it could be assessed whether the variable was indeed useful in directly, or indirectly, explaining investor behavior, even if the variable was initially 'mis-placed' in the model.

Six of the seven scales were imputed, and thus had complete data. The count of "don't know" (as a marker of underconfidence) also had complete data. These variables thus entered the model first with a sample size, *n* of 427 cases. The second group to enter the model consisted of three demographic variables (age, financial education and years of investor experience). With the introduction of the demographic variables into the model, sample size, *n,* was stepped down to 377 cases.

The third group to enter the model consisted of the three variables measuring investment practices (hours spent on investments, number of companies followed and number of companies in portfolio). Doing so stepped the sample size, *n,* down to 329 cases.

Had the four types of investment strategies been entered into the model next, sample size would have reduced to 314 cases. Similarly, entering overconfidence (without imputation) into the model next would have meant working with a sample in the order of 217 cases. See Table 11.

It was therefore decided to fit the remaining variables using FIML using the full sample, *n*, of 427 cases. Overconfidence (without imputation) was introduced into the model, followed by the four types of shares in turn.

Table 11 *Entry of Variables into the Structural Equation Model*

	n	missing
Group 1 (*n* = 427)		
Overreaction Imputed	427	0
Square root of count of don't know	427	0
July Effect Imputed	427	0
Appetite for Financial Risk Imputed	427	0
Information Sources Imputed	427	0
Anxiety Imputed	427	0
Lack of Attention Imputed	427	0
Lack of Planning Imputed	427	0
Motor Activity Imputed	427	0
Group 2 (*n* = 377 listwise)		
D1: age	416	11
Years of Investor Experience	390	37
D7: financial education	420	7
Group 3 (n = 327 listwise)		
C4: Hours spent on investments	412	15
C18: Companies followed	389	38
C19: Companies in portfolio	397	30
Group 4 (*n* = 217 listwise)		
4_Overconfidence	273	154
Group 5 (*n* = 314 listwise)		
Natural log of Defensive Shares	386	41
C21: Growth shares	385	42
Natural log of Cyclical Shares	384	43
Natural Log of Asset/turnarounds	385	42

In the first three steps of model testing, modification indices and residual matrices were examined to determine parameters to include in the model. Critical ratios were examined to determine parameters to remove from the model. Modification indices and residual matrices were unavailable in the final two steps of model testing. Thus, only critical ratios were used to determine which parameters may be removed from the model at the final step of model testing.

As recommended by Ullman (2014), parameters were added or removed one parameter at a time such that all additional pathways were included before any pathways were removed. In each case, model changes were guided by theory (Arbuckle, 2010). *Ceteris paribus*, the most parsimonious solution was preferred (Kline, 2011). When no further pathways could be added or removed on theoretical grounds, the model could be considered the best fit to the data. Model fit was assessed using chi squared, CFI, TLI and RMSEA. As with the confirmatory factor analyses (see section 4.7.2), model fit was considered good when chi squared test was not significant, CFI and TLI exceeded 0.90, and RMSEA was less than 0.08. The final model has been reported in Chapter 9. For the ease of interpretability, standardized solutions were reported throughout.

4.13.5 Measuring manifest variables on at least interval scale

With the exception of education and financial education, all remaining variables were measured on at least an interval scale. Analyses using ordinal variables with at least four levels have been considered fairly robust, especially when the covariance matrix is entered into AMOS. (See discussion in Byrne, 2010). Both education and financial education were measured with more than four levels. The seventh assumption has therefore been met.

4.13.6 Random sampling

The final assumption was met by drawing the random sample described in section 4.3.

4.14 Statistical tools

All analyses were performed using SPSS (2010b, 2010c), Version 19 and AMOS Graphics, (Arbuckle, 2010) Version 19. Both statistical packages are licensed statistical software packages available through IBM.

4.15 Conclusion

This chapter introduced the research philosophy underlying this research. This chapter also described the sample, survey questionnaire and method used in this thesis. In order to address the five research questions, scales will need to be developed. The reliability and validity of those scales will also need to be assessed. The next chapter, therefore, describes the factor structure and reliability of the scales used in this research.

Chapter 5 Scale Development

5.1 Introduction

This chapter describes the factor structure, reliability analysis and discriminant validity of the scales developed or adapted for use in this survey. In so doing, it answers the first objective of this thesis. As the researcher developed questions or adapted scales used in this survey, the factor analyses were undertaken in two stages. Initially, exploratory factor analyses were used with the training sample (260 cases). Confirmatory factor analyses were then used with the validation sample (261 cases). As described in section 4.6, respondents with odd-numbered identification numbers formed part of the training sample while respondents with even-numbered identification numbers formed part of the validation sample.

5.2 Development of factors

5.2.1 Overreaction, January effect, July effect, psychological biases and social herding

The factor structure of overreaction, January effect, July effect, psychological biases and social herding, were obtained using principal axis factoring and varimax rotation on the training sample (n = 260). See sections 4.5.1 (overreaction), 4.5.3 (January effect), 4.5.4 (July effect), 4.5.7 (psychological biases) and 4.5.8 (social herding) for a description of each of these scales. Tables 1, 3, 4, 7 and 8 provide a list their respective questions.

An initial principal axis factoring with varimax rotation was obtained for the combined set of questions measuring overreaction, January effect, July effect, psychological biases and social herding. Six factors had eigenvalues greater than 1. Together, they explained 46.4 percent of the variance in the data. The Kaiser-Meyer-Olkin measure of sampling adequacy was .83. Bartlett's test for sphericity was 1,888.4 (df = 351, p < .001).

Communalities ranged from .07 to .77. Two questions (B2 and B27) did not have a salient loading on any factor, while several other questions had salient loadings on two factors. Thus, the six-factor solution did not demonstrate simple structure.

Principal axis factoring with varimax rotation was therefore repeated, extracting progressively fewer factors in turn. The three- and the four-factor solutions best approached simple structure. However, questions B12 to B16, which were designed to help flesh out some of the reasons investors might be subject to the January and/or the July effect loaded on a separate factor, while the three questions measuring the January effect loaded on the same factor as the three questions measuring the July effect. The same two questions (i.e., B2 and B27) still did not have salient loadings on any factor solution. Several questions continued to have salient loadings on more than one factor.

It was therefore decided to remove questions B12 to B16, along with questions that did not have a salient loading on any factor. It was also decided to remove the questions that had salient loadings on more than one factor. Finally, from Table 12, it can be seen that the three questions intended to measure the January effect fit on the same factor as those intended to measure the July effect. While the January and July effects seem to be separate effects in the literature (see section 2.6.3), they appear to form part of the same latent variable. It is possible that they represent a combined seasonal factor. See Table 12.

As the primary aim of this research was to test an empirically developed model of investor behavior, it was decided to fit the latent variable with one of these two constructs. Moreover, as the taxation year falls on the 30^{th} June in Australia, it was decided to retain the three questions measuring the July effect. It is also recognized that in countries where the financial year aligns with the calendar year, the questions on this scale may be couched in the form so as to address a January effect. Table 13 provides the factor structure for the July effect seasonal, along with a combined social herding/psychological biases scale and an overreaction scale. Once again, questions are ordered in size of salient loading on their respective factors.

Table 12 *Factor Structure of Seasonal Effect, Social Herding/Psychological Biases and Overreaction*

	Seasonal effect	Social herding/ Psychologi-cal biases	Over-reaction
B8: Towards the end of June each year, I sell shares for more than I had paid for them.	.83		
B9: At the beginning of July each year, I buy more shares.	.81		
B7: Towards the end of June each year, I sell shares for less than I had paid for them.	.74		
B10: I use the tax time of year to sell shares at a capital loss.	.64		
B5: At the end of each year, I sell shares for more than I had paid for them.	.59		
B6: At the beginning of each year, I buy more shares.	.58		
B4: At the end of each year, I sell shares for less than I had paid for them.	.52		
B22: I prefer to hold on to losing stocks in the hope that they will eventually make a capital gain.		.73	
B23: I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income.		.66	
B1: The best way to protect one's wealth is to do as others do in the share market.		.42	
B3: It is important to look at the same information that fellow investors look at.		.36	
B24: I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares.		.36	
B25: When a company's share price performance has done badly, I sell out, no matter how little I get for selling them.			.84
B26: When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them.			.60
B18: I keep separate accounts (e.g., car, home, income, investment, savings, and 'windfalls') for different kinds of activities.			.30

The final model explains 44.3 percent of the variance in the data. The Kaiser-Meyer-Olkin measure of sampling adequacy was .75. Bartlett's test for sphericity was 779.8 ($df = 66$, $p < .001$). Communalities ranged from .11 to .75.

Table 13 *Factor Structure of July Effect Seasonal, Social Herding/Psychological Biases and Overreaction*

	July effect seasonal	Social herding / Psycho-logical biases	Over-reaction
B7: Towards the end of June each year, I sell shares for less than I had paid for them.	.80		
B8: Towards the end of June each year, I sell shares for more than I had paid for them.	.80		
B9: At the beginning of July each year, I buy more shares.	.75		
B10: I use the tax time of year to sell shares at a capital loss.	.70		
B22: I prefer to hold on to losing stocks in the hope that they will eventually make a capital gain.		.72	
B23: I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income.		.66	
B1: The best way to protect one's wealth is to do as others do in the share market.		.40	
B24: I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares.		.38	
B3: It is important to look at the same information that fellow investors look at.		.37	
B25: When a company's share price performance has done badly, I sell out, no matter how little I get for selling them.			.83
B26: When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them.			.62
B18: I keep separate accounts (e.g.., car, home, income, investment, savings, and 'windfalls') for different kinds of activities.			.32

As can be seen from Table 13, the first factor includes all three questions developed to measure the July effect, including B10: I use the tax time of year to sell shares at a capital loss. This factor can thus be referred to as the July effect seasonal, or simply the July effect.

The second factor includes the two questions measuring social herding (B1 and B3), as well as three questions measuring psychological biases. This factor can thus be described as a composite of social herding and psychological biases.

The final factor includes the two questions measuring overreaction and appears to be defined by this construct. This factor can thus be defined as overreaction. See Table 13.

A confirmatory factor analysis was undertaken. As the training sample was used to explore the factor structure for overreaction, January effect, July effect, psychological biases and social herding, the validation sample (n = 261) was used to confirm their factor structure. The variances for latent variables were fixed to '1'. Initially, each of the questions was used to fit the model. Not surprisingly, the initial model was a poor fit to the data (*CFI* = .63; *TLI* = .57; *RMSEA* = .10). Separating out the January seasonal from that of the July effect, and allowing latent variables to correlate, negligibly improved model fit (*CFI* = .67; *TLI* = .61; *RMSEA* = .09). However, doing so highlighted an almost perfect correlation between both latent variables (r = .95; p < .001). This finding is consistent to that of the exploratory factor analytic solution for the July effect seasonal. Once again, questions intending to measure the January effect appear to tap into the same seasonal construct as those intending to measure the July effect.

As this is an Australian study, it makes more theoretical sense to make use of a July seasonal (over that of a January seasonal). Thus, the questions originally intended to measure the January effect will not be considered any further in this research. The first confirmatory factor analytic model will thus only draw upon the questions intending to measure social herding, psychological biases, overreaction and the July effect seasonal.

Examination of the social herding/psychological biases component of the model revealed that the three questions intended to measure social herding had the lowest weights and the lowest squared multiple correlations. Moreover, three of the six questions measuring psychological biases had low factor loadings. The same three questions, along with one other question intending to measure psychological biases, also had squared multiple correlations that were lower than .3. Model fit was improved by removing the three questions measuring social herding (*CFI* = .69; *TLI* = .63; *RMSEA* = .10). In so doing, the combined social herding/psychological biases latent variable was now effectively a psychological biases latent variable. This latent variable was further improved by removing three questions from psychological biases with the lowest factor loadings (*CFI* = .72; *TLI* = .65; *RMSEA* = .11). However, the squared multiple correlation for the fourth question became even lower. Removing this question from the factor would result in a two-question factor. It was therefore decided to completely remove this latent variable from the model. It would appear that neither the questions measuring social herding, nor the ones measuring psychological biases were able to form a single or combined latent variable.

Examination of the overreaction component of the model showed that three of the four questions for overreaction had moderate squared multiple correlations while the fourth one (B18) had a squared multiple correlation of .10. It was therefore removed from the model (*CFI* = .72; *TLI* = .63; *RMSEA* = .13).

The questions initially intended to measure the July seasonal included three questions measuring the July effect, (B7 to B9) along with eight questions (B10 to B17) measuring a range of potential reasons for the July effect. Examination of the July effect seasonal component of the model revealed that questions B7 to B9, along with the first two explanatory questions had the highest squared multiple correlations and beta weights. As B10 (selling shares for capital gain) and B11 (selling shares for capital loss) were highly correlated, only B10 was retained. A further five questions with the lowest squared multiple correlations were also removed from the July effect seasonal component of the model. The resultant model was a good fit to the data (*Chi squared* = 49.44; *df* = 19; $p < .001$; *normed chi squared* = 2.33; *CFI* = .95; *TLI* = .90; *RMSEA* = .08). See Figure 4.

With modification, overreaction and the July effect seasonal demonstrated good factor structure. The constructs of psychological biases and social herding were unable to demonstrate good factor structure. Both constructs have not been considered any further in this research.

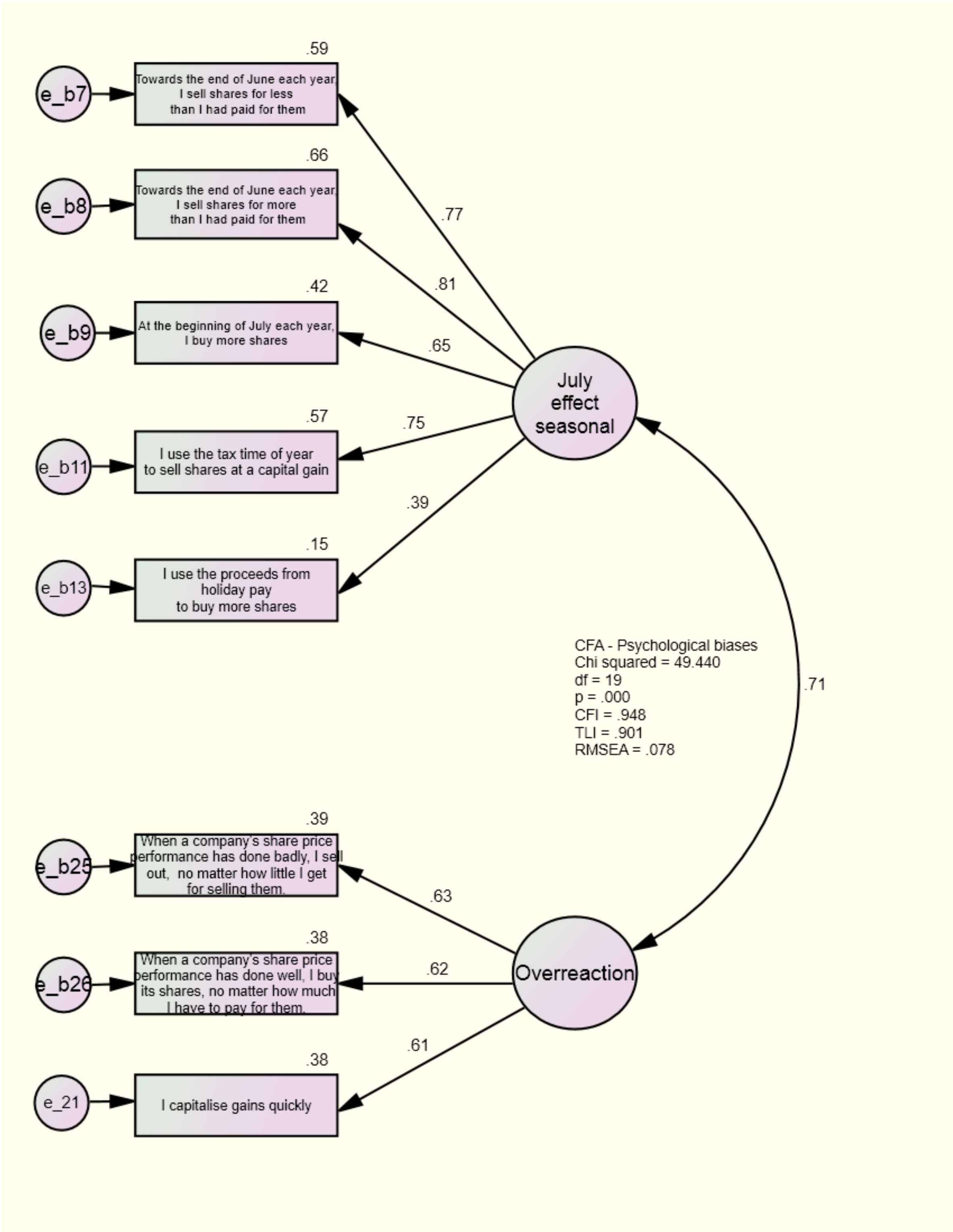

Figure 4 Final Model for July effect and Overreaction with R-Squared Values and Standardized Weights.

Tables 14 and 15 show the questions used in the exploratory and confirmatory factor analyses for these five constructs. Both Tables also show the factor loadings for the questions retained in the final model.

Table 14 *Questions Retained for Social Herding, January Effect and July Effect and Factor Loadings*

Questions	Description	PFA	CFA
	Social Herding:		
B1	The best way to protect one's wealth is to do as others do in the share market	.40	dropped
B2	Most of my friends are also investors	dropped	dropped
B3	It is important to look at the same information that fellow investors look at	.37	dropped
	January Effect:		
B4	At the end of each year, I sell shares for less than I had paid for them	dropped	dropped
B5	At the end of each year, I sell shares for more than I had paid for them	dropped	dropped
B6	At the beginning of each year, I buy more shares	dropped	dropped
	July Effect:		
B7	Towards the end of June each year, I sell shares for less than I had paid for them	.80	.77
B8	Towards the end of June each year, I sell shares for more than I had paid for them	.80	.81
B9	At the beginning of July each year, I buy more shares	.75	.65
B10	I use the tax time of year to sell shares at a capital loss	.70	dropped
B11	I use the tax time of year to sell shares at a capital gain	dropped	.75
B12	I use the proceeds from share sales to buy more shares	dropped	dropped
B13	I use the proceeds from holidays pay to buy more shares	dropped	.39
B14	I use the proceeds from annual bonuses to buy more shares	dropped	dropped
B15	I use the proceeds from dividend income to buy more shares	dropped	dropped
B16	I use the proceeds from tax refunds to buy more shares	dropped	dropped
B17	I use reporting seasons as an opportunity to sell my high risk shares and purchase more conservative, 'blue chip' shares	dropped	dropped

Table 15 *Questions Retained for Psychological Biases and Overreaction and Factor Loadings*

Questions	Description	PFA	CFA
	Psychological Biases:		
B18	I keep separate accounts (mental accounting)	.32	dropped
B19	A company's profit performance has the same prospects as that of its share price performance (representative bias)	dropped	dropped
B20	When I buy or sell shares, I consider the original purchase price of those shares I already have (anchoring)	dropped	dropped
B21	I prefer to capitalize gains quickly (disposition effect)	dropped	.56-.61
B22	I prefer to hold on to losing stocks in the hope that they will eventually make a gain (disposition effect)	.72	dropped
B23	I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income (status quo bias)	.66	dropped
B24	I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares (endowment effect)	.38	dropped
B27	Of the different companies in your portfolio, what proportion are listed on the Australian stock exchange … and what proportion are listed on other stock exchanges (reverse-scored) (familiarity bias)	dropped	dropped
	Overreaction:		
B25	When a company's share price performance has done badly, I sell out, no matter how little I get for selling them	.83	.63
B26	When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them	.62	.62-.68

5.2.2 Overconfidence

The factor structure of overconfidence was obtained using principal axis factoring with varimax rotation on the training sample (n = 260). See section 4.5.2 and Table 2 for a description of this scale, along with each of its questions. Two factors had eigenvalues greater than 1. Both factors explained 63.1 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .76. Bartlett's test of sphericity was 586.2 (df = 1, p < .001). Communalities range from .3 to .7.

The factor model demonstrated simple structure. Three questions had salient loadings on the first factor. These questions sampled investor knowledge about investing overall and in relation to other investors. The first factor may therefore be defined as investor knowledge.

Four questions had salient loadings on the second factor. These questions probed expectations about portfolio performance overall and in relation to those of other investors. The second factor may therefore be defined as investor portfolio expectations. See Table 16. Note that the questions have been ordered on the basis of size of salient loadings on their respective factors.

Table 16 *Factor Structure of Overconfidence*

	Investor Knowledge	Investor Expectation about Portfolio Performance
A19: In comparison to other investors, how more or less knowledgeable do you consider yourself to be about investing?	.89	
A18: How knowledgeable do you consider yourself to be about investing?	.88	
A20: How knowledgeable do you consider yourself to be about share price indices (e.g., All Ordinaries, ASX200, S&P 200, etc.)?	.83	
A22:By the end of 2010, do you expect the All Ordinaries Index to (decrease by 10%-or-more to increase by 10%-or-more)		.78
A21: By the end of 2010, do you expect the portfolio you own or manage to (decrease by 10%-or-more to increase by 10%-or-more)		.77
A23: What percent return do you expect your portfolio to earn by the end of the year (i.e., the income and/or capital gains as a percent of your share investments)?		.72
A24: What percent return do you believe other investors, on average, will earn on their portfolios by the end of the year (i.e., the income and/or capital gains as a percent of share investment)		.57

A confirmatory factor analysis was undertaken. As the training sample was used to generate the exploratory factor structure of overconfidence, the validation sample (n = 261) was used to confirm the two-factor structure for this construct. The variances for the latent variables (i.e., investor knowledge and investor portfolio expectations) were fixed to '1'. In the first instance, the confirmatory factor analysis was fitted treating both factors as uncorrelated. Model fit was poor (CFI = .84; TLI = .67; $RMSEA$ = .19).

One might expect an association between investor knowledge and investor portfolio expectations as two dimensions of an underlying construct of overconfidence. The model was therefore refitted, allowing both factors to be correlated. The model remained a poor fit to the data (*CFI* = .89; *TLI* = .75; *RMSEA* = .16). With the removal of one question on investor portfolio expectations, this model became a good fit to the data (*CFI* = 1.0; *TLI* = 1.0; *RMSEA* = .01). As the association between both factors was moderate (r = 46; $p < .001$), a higher order factor was also fitted. Whilst it made no difference to model fit (*Chi squared* = 8.25; *df* = 8; p = .41; *CFI* = 1.0; *TLI* = 1.0; *RMSEA* = .01), it was favored on theoretical grounds. See Figure 5. With the removal of one question, overconfidence and both its subscales demonstrated good factor structure. Table 17 shows the questions used in the factor analyses for overconfidence. It also shows the factor loadings for those questions that were retained in the final model.

Table 17 *Questions Retained for Overconfidence, and their Factor Loadings*

Questions	Description	PFA	CFA
	Investor Knowledge:		
A18	How knowledgeable do you consider yourself to be about investing?	.88	.93
A19	In comparison to other investors, how more or less knowledgeable do you consider yourself to be about investing?	.89	.85
A20	How knowledgeable do you consider yourself to be about share price indices	.83	.79
	Investor Expectation About Portfolio Performance		
A21	By the end of 2010, do you expect your portfolio you own or manage to decrease by 10% or more … to increase by 10% or more	.77	.97
A22	By the end of 2010, do you expect the All Ordinaries Index to decrease by 10% or more … to increase by 10% or more	.78	.71
A23	What percent return do you expect your portfolio to earn by the end of the year?	.72	dropped
A24	What percent return do you believe other investors to earn on their portfolios by the end of the year?	.57	.34

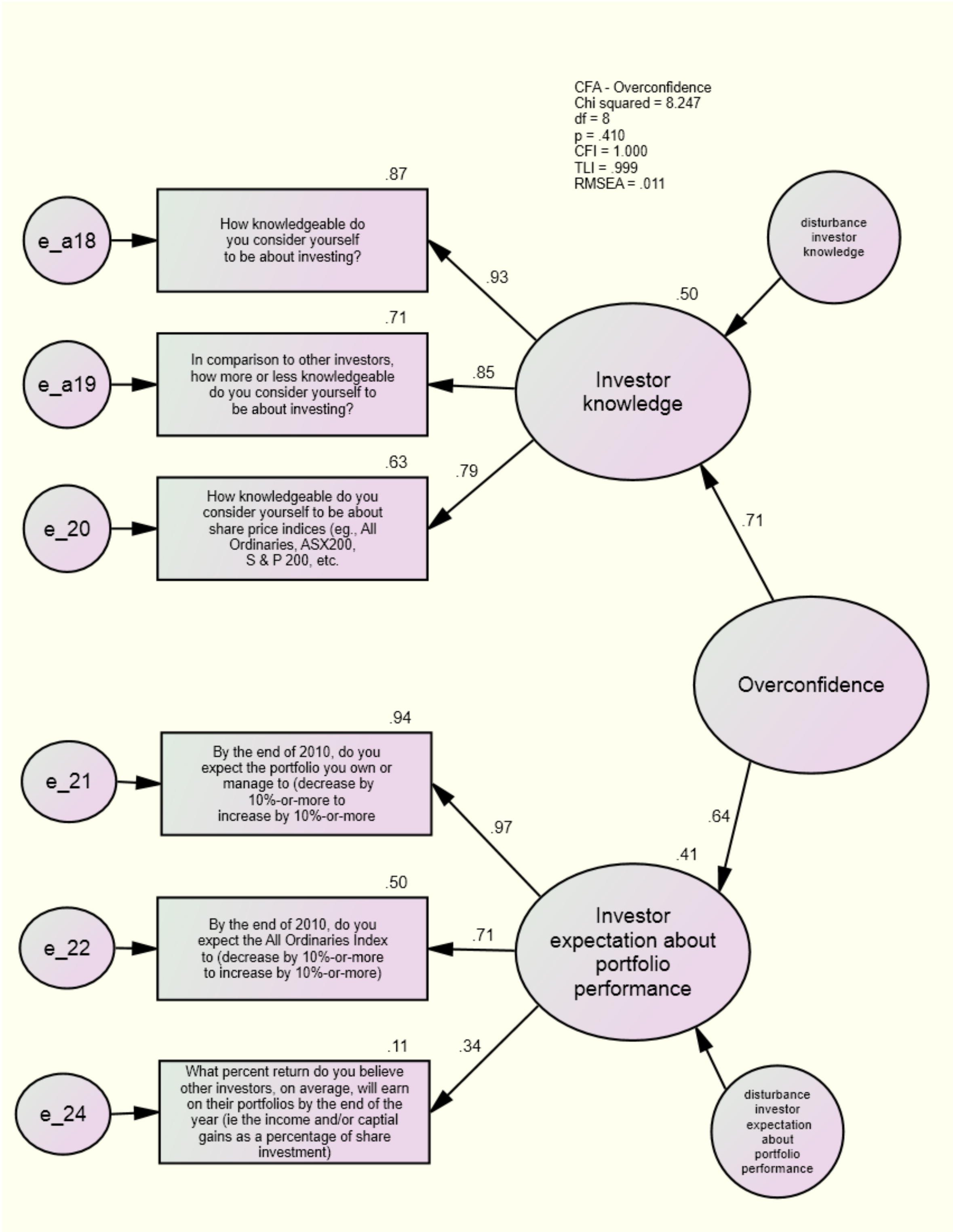

Figure 5. Final Model for Overconfidence with R-Squared Values and Standardized Weights.

5.2.3 Appetite for financial risk

The factor structure for appetite for financial risk was obtained using principal axis factoring with varimax rotation on the training sample (n = 260). Questions measuring appetite for financial risk included A3: investing safely; A13: margin lending; and C74: During the recent Global Financial Crisis, I used margin lending. Where appropriate, questions have been reverse-scored so that higher scores reflect a greater appetite for financial risk. See section 4.5.5 and Table 5 for a description of this scale, along with each of its questions.

Six factors had eigenvalues greater than 1. They explained 57 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .75. Bartlett's test of sphericity was 1,464.3 (df = 136, p < .001). Communalities ranged from .12 to .96. However, three factors had only two salient loadings, and several questions had salient loadings on two factors. This solution did not demonstrate simple structure.

Principal axis factoring with varimax rotation was therefore repeated progressively extracting fewer factors in turn. Of these solutions, the one-, two- and three-factor solutions represented the best fit to the data. However, none of these solutions demonstrated simple structure. In the first instance, questions that did not have any salient loadings were removed from the model and the analyses rerun. In so doing, the one- and two-factor solutions best approached simple structure.

Examination of the two factor solution showed questions such as A14: options trading; A16: derivatives; and A15: warrants loading on the first factor, while A4: share price growth; A8R: knowing the companies in your investment package, reverse-scored; and A6R: spreading investments across share market sectors, reverse-scored, loaded on the second. The first factor appears to represent the theoretical construct of financial risk taking while the second factor appears to represent a more balanced approach to risk taking.

It was therefore decided to remove questions loading on the second factor (of the two factor solution) and extract a single-factor solution. Doing so would result in a solution that better represented the type of risk appetite described by the literature. With the removal of C74 (which asked about investor use of margin lending during the GFC) and C75 (which asked about investor use of options, warrants, derivatives and other financial products during the GFC), the single-factor solution demonstrated simple structure. Kaiser-Meyer-Olkin Measure of Sampling Adequacy was .82. Bartlett's test of sphericity was 859.3 ($df = 21$, $p < .001$). Communalities ranged from .31 to .74.

Questions on this factor included A11: automatic stop loss orders, A13*:* margin lending and A16: derivatives. This factor can be referred to as appetite for financial risk. See Table 18. Once again, questions have been ordered in order of size of salient loading on this factor.

Table 18 *Factor Structure of Appetite for Financial Risk*

	Appetite for Financial Risk
A14: Options trading (i.e., financial contract that gives the right to buy or sell shares at a set price by a given date, but not the obligation to do so)	.86
A15: Warrants (i.e., financial contracts that give you the right to buy shares at a set price by a given date -- usually longer time frame than a buy option)	.80
A16: Derivatives (i.e., simple or complex financial products that may involve options, forward contracts, swaps or future contracts)	.79
A12: Automatic 'buy' orders (i.e., an order to buy shares if their price falls below a predetermined price)	.69
A13: Margin lending (i.e., purchasing shares on stockbroker loans)	.65
A11: Automatic 'stop loss' or 'sell' orders (i.e., an order to sell shares if their price falls below a predetermined price)	.64
A17: Bank loans or home mortgage redraw facilities to buy shares	.56

A confirmatory factor analysis was undertaken. As the training sample was used to generate the exploratory factor structure of appetite for financial risk, the validation sample (n = 261) was used to confirm its factor structure. The variance for appetite for financial risk was fixed to '1'. The initial model was a poor fit to the data (CFI = .85; TLI = .66; RMSEA = .21). With the removal of three questions (A17: Bank loans or home mortgage redraw facilities to buy shares; A12: Automatic ‘buy’ orders and A11: Automatic ‘stop loss’ or ‘sell’ orders), the model demonstrated a good fit to the data (*Chi squared* = 5.36; *df* = 2; *p* = .07; *CFI* = .99; *TLI* = .96; *RMSEA* = .08). See Figure 6.

Table 19 shows the questions used in the exploratory and confirmatory factor analyses. This Table also shows the factor loadings for the questions retained in the final model.

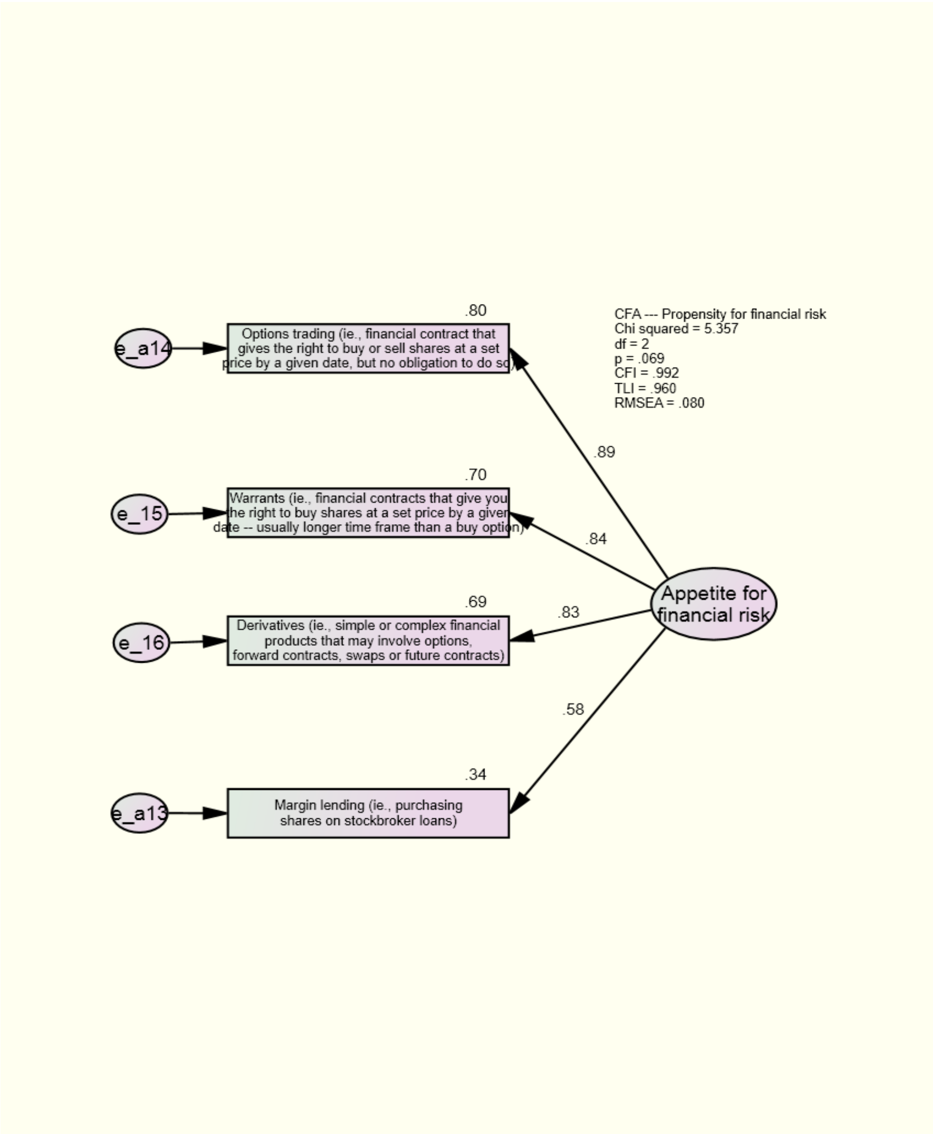

Figure 6. Final Model for Appetite for financial risk with R-Squared Values and Standardized Weights.

Table 19 *Questions Retained for Appetite for Financial Risk, and their Factor Loadings*

Questions	Description	PFA	CFA
A3R	Investing safely (reverse-scored)	dropped	dropped
A4	Share price growth	dropped	dropped
A5	Taking risks to earn good returns	dropped	dropped
A6R	Spreading investments across share market sectors (reverse-scored)	dropped	dropped
A7R	Spreading investments across asset classes (reverse-scored)	dropped	dropped
A11	Automatic 'stop loss' or 'sell' orders	.64	dropped
A12	Automatic 'buy' orders	.69	dropped
A13	Margin lending	.65	.58
A14	Options trading	.86	.89
A15	Warrants	.80	.84
A16	Derivatives	.79	.83
A17	Bank loans or home mortgage redraw facilities to buy shares	.56	dropped
C74	During the GFC, I used margin lending	dropped	dropped
C75	During the GFC, I used options, warrants, derivatives or other financial products	dropped	dropped
C76	During the GFC, I used bank loans or redraw facilities on my home loan to buy shares	dropped	dropped

5.2.4 Information sources

The factor structure of information sources was obtained using principal axis factoring with a varimax rotation on the training sample (n = 260). See section 4.5.6 and Table 6 for a description of this scale, along with each of its questions. Six factors had eigenvalues greater than 1. Together, the six factors explained 53.0 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .74. Bartlett's test of sphericity was 967.9 (df = 210, p < .001). Communalities ranged from .20 to .90.

While each question had a salient loading, several questions had salient loadings on more than one factor, while one factor had only two salient loadings. The six-factor solution, therefore, did not demonstrate simple structure.

Principal axis factoring with varimax rotation was repeated extracting progressively fewer factors. Of these solutions, a two- or three- factor solution best approached simple structure. However, there were still questions loading on more than one factor. There were also questions that no longer had salient loadings on any factor. It was therefore decided to remove those questions in turn. Five questions were removed, resulting in a two-factor solution that was conceptually meaningful. As this solution only explained 41.8 percent of the variance in the data, a further five questions with the lowest salient loadings were removed from the first factor. The final solution explained 51 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .82. Bartlett's test of sphericity was 981.6 (*df* = 55; *p* < .001). See Table 20.

Table 20 *Factor Structure of Information Sources*

	Investor Research	Social Network
C53: Financial magazines	.81	
C54: Financial trade journals	.77	
C47: Company websites	.71	
C46: Company annual reports	.70	
C50: Business newspapers, and/or business supplements	.66	
C45: IPO prospectus	.59	
C60: A work friend or colleague		.80
C58: A friend (outside work)		.78
C57: Your neighbour		.70
C59: A family member		.64
C56: Your experience as an employee of the company		.48

In order of size of salient loadings, questions loading on the first factor were (a) C53: financial magazines; (d) C54: financial trade journals; (c) C47: company websites; (d) C46: company annual reports; (e) C50: business newspapers and/or supplements and (f) C45: IPO prospectus. This factor can be defined as investor research.

In order of size of salient loadings, questions loading on the second factor were (a) C60: a work friend or colleague; (b) C58: a friend (outside work); (c) C57: neighbour; (d) C59: a family member; and (e) C56: experience as an employee of the company. This factor may therefore be defined as social network.

A confirmatory factor analysis was undertaken. As the training sample was used to generate the exploratory factor structure of information sources, the validation sample (n = 261) was used to confirm the factor structure for this construct. The variances for both latent variables (i.e., investor research and social networking) were fixed to '1'.

Fitting six questions to investor research and five questions to social network resulted in a poor fit to the data (CFI = .82; TLI = .74; $RMSEA$ = .12). One might expect different forms of information sources to be associated with other forms of information sources. The model was therefore refitted allowing both factors to be correlated. The association between both factors was significant. However the model remained a poor fit to the data (CFI = .85; TLI = .78; $RMSEA$ = .11). It was therefore decided to remove four questions from the model (three from the first factor, and one from the second), producing good model fit (CFI = 1.0; TLI = 1.0; $RMSEA$ = 0.0). The correlation between both factors was significant (r = .31; p < .001). However, a higher order factor was favored on theoretical grounds. This model also demonstrated good fit to the data (*Chi squared* = 20.32; df = 14; p = .12; CFI = .99; TLI = .98; $RMSEA$ = .04). See Figure 7. Thus, with modification, information sources and both its subscales demonstrated good factor structure. Table 21 shows the questions included in the exploratory and confirmatory factor analyses. This Table also shows the questions retained in the final model, along with their respective factor loadings.

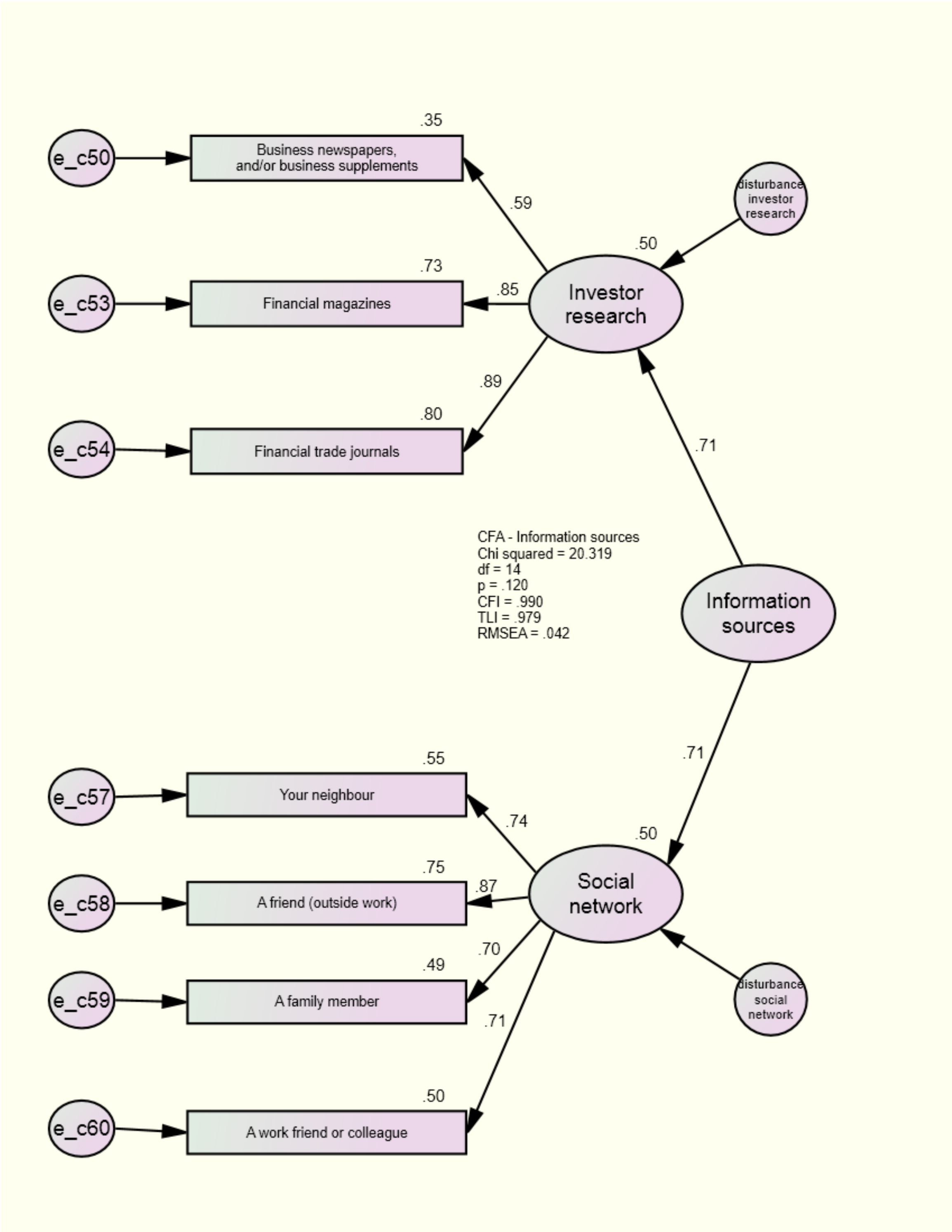

Figure 7. Final Model for Information sources with R-Squared Values and Standardized Weights.

Table 21 *Questions Retained for Information Sources, and their Factor Loadings*

Question	Description	PFA	CFA
	Investor Research		
C40	Your accountant	dropped	dropped
C41	Your financial advisor	dropped	dropped
C42	Internet brokers	dropped	dropped
C43	Full service brokers	dropped	dropped
C44	The Australian Stock Exchange (ASX) website	dropped	dropped
C45	IPO prospectus	.59	dropped
C46	Company annual reports	.70	dropped
C47	Company websites	.71	dropped
C48	Other websites	dropped	dropped
C49	Newspapers in general	dropped	dropped
C50	Business newspapers and/or business supplements	.66	.59
C51	Television	dropped	dropped
C52	Radio	dropped	dropped
C53	Financial magazines	.81	.85
C54	Financial trade journals	.77	.89
	Social network:		
C55	Your experience as a customer of the company	dropped	dropped
C56	Your experience as an employee of the company	.48	dropped
C57	Your neighbor	.70	.74
C58	A friend (outside work)	.78	.87
C59	A family member	.64	.70
C60	A work friend or colleague	.80	.71

5.2.5 Anxiety

The factor structure for the ten IPIP questions measuring anxiety was obtained using principal axis factoring with varimax rotation on the training sample (n = 260). See section 4.5.9 and Table 9 for a description of anxiety and the questions adapted to measure it. Two factors had eigenvalues greater than 1 and explained 44.9 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .81. Bartlett's test of sphericity was 786.7 (df = 45, p < .001). Communalities ranged from .13 to .64.

Examination of the rotated solution showed evidence of simple structure. Six of the ten questions had salient loadings on the first factor. Three questions had salient loadings on the second factor. All three questions loading on the second factor were reverse-scored while only one of the six questions loading on the first factor was reverse-scored. One question did not load on either factor and was therefore removed from the model.

The final solution explained 48.9 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .82. Bartlett's test of sphericity was 746.6 (df = 36, p < 001). Communalities ranged from .18 to .66. Table 22 provides the factor structure for anxiety. Questions have been ordered by size of loadings on their respective factors.

Table 22 *Factor Structure of Anxiety*

	Anxiety Positively worded	Anxiety Negatively worded
B31: I get stressed easily.	.81	
B32: I get caught up in my problems.	.79	
B30: I fear for the worst.	.75	
B29: I worry about things happening.	.73	
B28R: I am relaxed most of the time (reverse-scored)	.58	
B34: I am afraid of many things.	.54	
B36R: I don't worry about things that have already happened (reverse-scored)		.78
B35R: I am not easily disturbed by events (reverse-scored)		.73
B33R: I am not easily bothered by things (reverse-scored)		.33

With the exception of one question, the first factor had questions framed in the positive direction. All three questions loading on the second factor had questions framed in the negative direction. Consequently, these three items have been reverse-scored so that when summated, the higher the score, the greater the anxiety.

Both factors tapped into the domain of anxiety. Apart from the direction of wording, there does not seem to be any real distinguishing feature through which to discriminate the first and second factors. One is left to conclude that there may be a method effect coming through the second factor. This method effect may be an artifact of the direction of wording for each question.

A confirmatory factor analysis was undertaken. As the training sample was used to generate the exploratory factor structure of anxiety, the validation sample (n = 261) was used to confirm the two-factor structure. The variance for the latent variables, anxiety positively worded and anxiety negatively worded, were fixed to '1'. This model approached a good fit to the data with the original ten questions (*CFI* = .93; *TLI* = .88; *RMSEA* = .08). There was a moderate correlation between the latent variables (r = .18; p = .02). However, introducing an association between the latent variables had little impact on model fit (*CFI* = .93; *TLI* = .89; *RMSEA* = .08).

Two questions on the second factor had low square multiple loadings. Removal of any one question on the second factor did not provide a stable solution. Moreover, fitting associations between error terms as Brown (2006) suggested confirmed suspicions of a method effect in operation based on the direction of wording for each question. As per the first Marsh (1996) recommendation, it was decided to remove the three negatively-worded questions on the second factor and thereby fit the first factor only. With the removal of two questions on the first factor, the model demonstrated a good fit to the data (*Chi squared* = 2.6; *df* = 2; p = .27; *CFI* = 1.0; *TLI* = .99; *RMSEA* = .03). The resultant latent variable has four questions that tap into the construct of anxiety. See Figure 8.

Table 23 shows the questions included in the exploratory and confirmatory factor analyses, as well as the questions that form part of the final model. Table 23 also shows the factor loadings for each question that formed part of the final model.

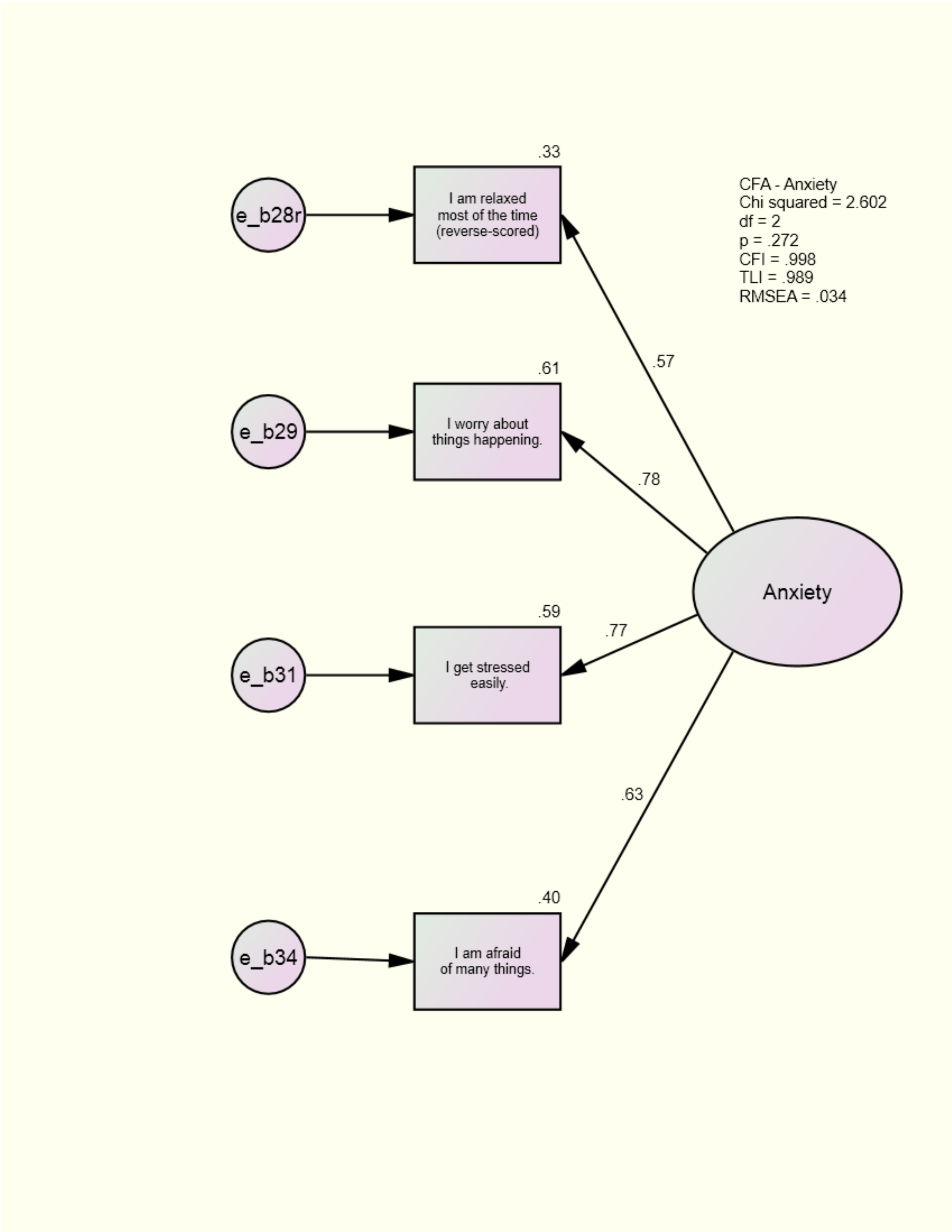

Figure 8. Final Model for Anxiety with R-Squared Values and Standardized Weights.

Table 23 *Questions Retained for Anxiety and their Factor Loadings*

Question	Description	PFA	CFA
B28R	I am relaxed most of the time (reverse-scored)	.58	.57
B29	I worry about things happening	.73	.78
B30	I fear for the worst	.75	dropped
B31	I get stressed easily	.81	.77
B32	I get caught up in my problems	.79	dropped
B33R	I am not easily bothered by things (reverse-scored)	.33	dropped
B34	I am afraid of many things	.54	.63
B35R	I am not easily disturbed by events (reverse-scored)	.73	dropped
B36R	I don't worry about things that have already happened (reverse-scored)	.78	dropped
B37R	I adapt easily to new situations (reverse-scored)	dropped	dropped

5.2.6 Impulsivity

The factor structure of impulsivity was obtained using principal axis factoring with a varimax rotation on the training sample (n = 260). Questions B38 and B43 to B47 were reverse-scored so that higher scores indicate greater impulsivity for each item. Section 4.5.10 and Table 10 describe impulsivity and the questions adapted to measure it.

Four factors had eigenvalues greater than 1 and explained 51.5 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .77. Bartlett's test of sphericity was 1301.2 (df = 105, p < .001). Communalities ranged from .25 to .77. With three variables loading on two factors, the four-factor solution did not demonstrate simple structure.

Spinella (2007) has shown impulsivity to contain three subscales: lack of attention, lack of planning and motor activity. A three-factor solution was therefore obtained using principal axis factoring and varimax rotation. One question (B38R) loaded on two-factors and was removed from the analysis. The final solution demonstrated simple structure and was theoretically meaningful. This solution explained 47.7 percent of the variance in the data. Kaiser-Meyer-Olkin measure of sampling adequacy was .75.

Bartlett's test of sphericity was 1215.1 ($df = 91$, $p < .001$). Communalities ranged from .21 to .68.

Five questions loaded on the first factor including B48: I act on impulse; B49: I act on the spur of the moment; and B52: I buy things on impulse. This factor represents the motor activity subscale of impulsivity. Five questions loaded on the second factor including B43: I plan for job security; B44: I plan for the future; and B45: I save regularly. When reverse-scored, these questions contribute to the lack of planning subscale of impulsivity.

Finally, four questions loaded on the third factor including B39: I am restless at lectures or talks; and B41: I don't pay attention. This factor represents the lack of attention subscale of impulsivity. See Table 24. Once again, questions have been ordered by size of salient loading on their respective factors.

Table 24 *Factor Structure of Impulsivity*

	Motor Activity	Lack of Planning	Lack of Attention
B49: I act on the spur of the moment.	.79		
B50: I do things without thinking.	.78		
B51: I say things without thinking.	.70		
B48: I act on impulse.	.68		
B52: I buy things on impulse.	.62		
B47R: I am a careful thinker (reverse-scored)		.75	
B44R: I plan for the future (reverse-scored)		.73	
B46R: I plan tasks carefully (reverse-scored)		.65	
B45R: I save regularly (reverse-scored)		.53	
B43R: I plan for job security (reverse-scored)		.45	
B40: I squirm at plays or lectures.			.80
B41: I don't pay attention.			.67
B42: I get easily bored when solving problems.			.62
B39: I am restless at lectures or talks.			.52

A confirmatory factor analysis was undertaken. As the training sample was used to generate the exploratory factor structure of impulsivity, the validation sample (n = 261) was used to confirm the three-factor structure for this construct. The variances for the three latent variables of impulsivity (i.e., lack of attention, lack of planning and motor activity) were fixed to '1'. The solution was initially fitted with uncorrelated latent variables. However, this solution demonstrated poor fit. (*CFI* = .79; *TLI* = .72; *RMSEA* = .11).

B38R, the reverse-scored question, I concentrate easily loaded on two factors in the exploratory factor analysis. This variable was therefore removed from the model. As one might expect the three factors to be associated, the model was rerun allowing the three latent variables to be correlated. Both modifications resulted in improved model fit. However, it was still not a good fit to the data (*CFI* = .86; *TLI* = .80; *RMSEA* = .10). Moreover, one of the three associations (between lack of attention and lack of planning) was not significant.

Question B43R: I plan for job security might not be expected to play an important role to investors. Spinella (2007) previously found that question B51: I say things without thinking loaded on the motor activity subscale in the BIS15, whereas it loaded on the lack of planning subscale on the full scale. It was therefore decided to remove both questions and refit the model. It was also decided to remove the non-significant association. The final model was thus a good fit to the data (*Chi squared* = 118.06; *df* = 52; $p < .001$; *normed chi squared* = 2.27; *CFI* = .94; *TLI* = .91; *RMSEA* = .07). See Figure 9.

With the removal of three questions (one from each factor), the three factors of impulsivity were confirmed. However, as only two of the three factors demonstrated significant associations ($r_{13} = .39$; $p < .001$; $r_{23} = .16$; $p = .02$) the three factors were treated as measuring independent constructs. However, it is recognized that past research (described in 3.2.3 and 4.5.10) treated impulsivity as a higher order of a three-factor construct. For the sake of consistency with past research this thesis refers to (a) lack of attention; (b) lack of planning; and (c) motor activity as the three dimensions of impulsivity.

Table 25 shows the questions included in the factor analyses for the three dimensions of impulsivity. It also shows the questions retained, along with their respective factor loadings.

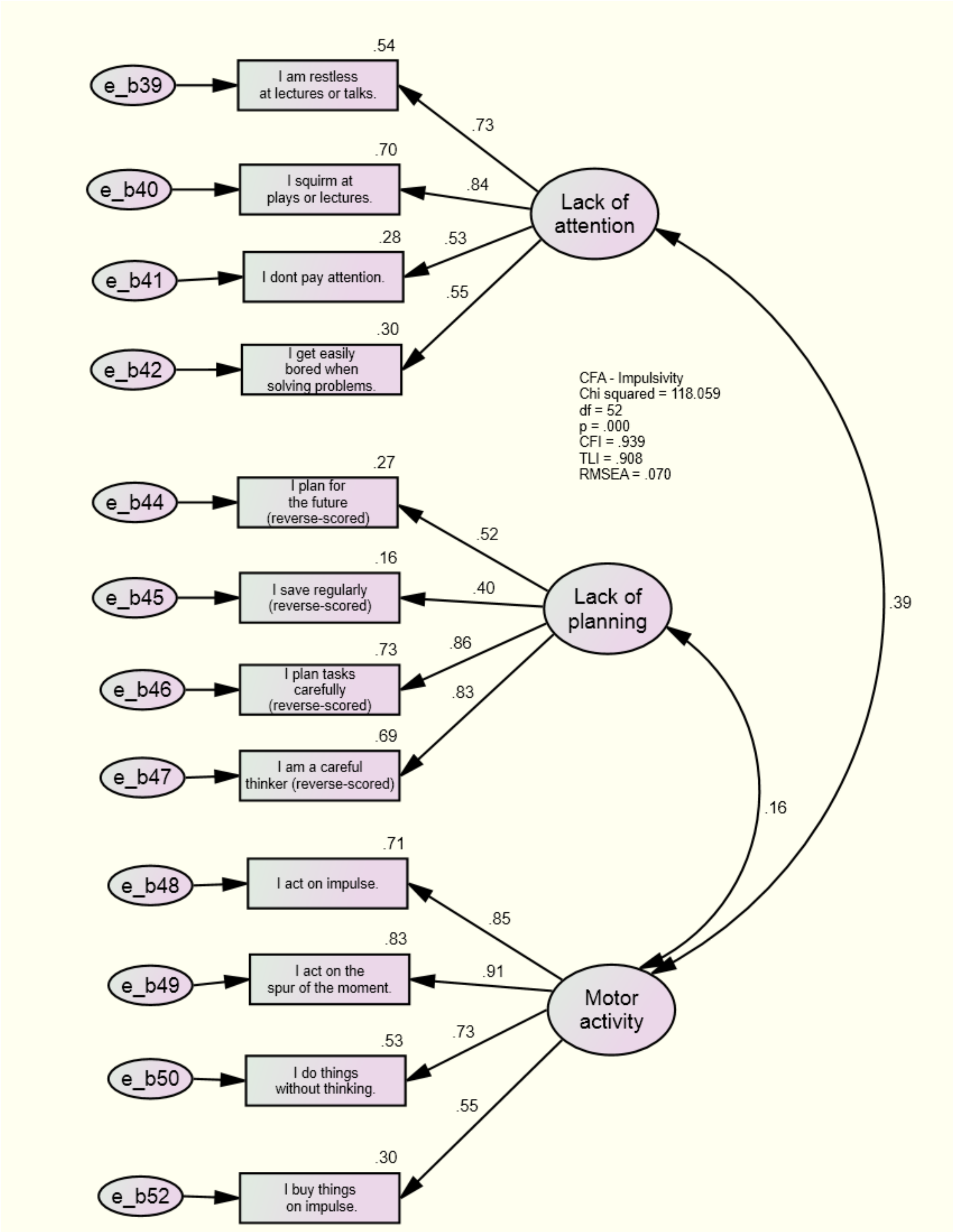

Figure 9. Three Dimensions of Impulsivity, R-Squared Values and Standardized Weights.

Table 25 *Questions Retained for Three Dimensions of Impulsivity, and their Factor Loadings*

Questions	Description	PFA	CFA
	Lack of Attention:		
B38R	I concentrate easily (reverse-scored)	dropped	dropped
B39	I am restless at lectures or talks	.52	.73
B40	I squirm at plays or lectures	.80	.84
B41	I don't pay attention	.67	.53
B42	I get easily bored when solving problems	.62	.55
	Lack of Planning:		
B43R	I plan for job security (reverse-scored)	.45	dropped
B44R	I plan for the future (reverse-scored)	.73	.52
B45R	I save regularly (reverse-scored)	.53	.40
B46R	I plan tasks carefully (reverse-scored)	.65	.86
B47R	I am a careful thinker (reverse-scored)	.75	.83
	Motor Activity:		
B48	I act on impulse	.68	.85
B49	I act on the spur of the moment	.79	.91
B50	I do things without thinking	.78	.73
B51	I say things without thinking	.70	dropped
B52	I buy things on impulse	.62	.55

With modification, seven of the ten scales demonstrated good factor structure. Section 10.2.1 discusses the factor structure of the seven scales. The next section describes their reliability and discriminant validity.

5.3 Reliability analysis

As discussed in section 4.7.3, scale scores were obtained by summating responses to each question forming part of the final model. All seven scales demonstrated good psychometric properties.

As shown in Table 26, Cronbach's alpha ranged from .64 (overreaction) to .86 (appetite for financial risk). Both subscales on overconfidence and information sources demonstrated good reliability. Cronbach's alpha for the subscales on overconfidence were .73 (investor expectation about portfolio performance) and .89 (investor knowledge). Cronbach's alpha for the subscales on information sources were .83 (investor research) and .81 (social network).

Model reliability coefficients for each scale were also calculated based on model statistics using the method described by Fornell and Larcker (1981). Whilst Cronbach's alpha may over- or under- estimate a scale's true reliability (Brown, 2006), it is pleasing to note that on the whole, Cronbach alpha coefficients yielded similar reliability coefficients to those obtained using model statistics. Indeed, the decision to retain the seven scales remains unchanged, irrespective of the set of coefficients used. See final column in Table 26. Section 10.2.2 discusses the reliability analysis.

Table 26 *Scale and Subscale Reliability*

Scale	Scale Name	No. of questions	No. of cases	Cronbach's alpha[1]	Cronbach's Alpha[2]	Model Reliability
1	Overreaction	3	472	.64	.64	.67
2	Overconfidence	6	335	.76	.79	.92
	Investor knowledge	*3*	*490*	*.89*	*.89*	*.87*
	Investor expectation about portfolio performance	*3*	*339*	*.73*	*.75*	*.82*
3	July effect	5	458	.82	.81	.86
4	Appetite for financial risk	4	430	.86	.88	.83
5	Information sources	7	448	.78	.79	.88
	Investor research	*3*	*464*	*.83*	*.84*	*.76*
	Social network	*4*	*462*	*.81*	*.82*	*.82*
6	Anxiety	4	501	.76	.76	.77
7a	Lack of attention	4	491	.75	.76	.73
7b	Lack of planning	4	487	.75	.76	.78
7c	Motor activity	4	505	.83	.84	.84

1. Listwise deletion of missing data for each scale
2. Imputed values for each scale

5.4 Discriminant validity of the seven scales

The average variance extracted has been calculated for each of the questions loading on their respective scales using the method described in Fornell and Larcker (1981). The results have been provided in Table 27. The highest squared correlation coefficient between each scale and remaining ten scales (or subscales) has also been reported in Table 27. Discriminant validity is said to exist when the average variance extracted for every pair of scales is greater than their highest squared correlation coefficient (Fornell & Larcker, 1981).

Table 27 shows that all seven scales demonstrate discriminant validity. Section 10.2.3 discusses the discriminant validity of the seven scales. The remainder of this chapter discusses the missing data analysis, imputation method, as well as descriptive statistics for both the variables used in this thesis.

Table 27 *Scale Discriminant Validity*

Scale	Scale Name	No. of cases	Variance extracted	Highest squared correlation	Variable with whom highest correlation
1	Overreaction	472	.38	.27	July effect
2	Overconfidence	335	.63	.07	July effect
	Investor knowledge	490	.74	.11	investor expectation
	Investor expectation	339	.52	.05	investor knowledge
3	July effect	458	.48	.27	Overreaction
4	Appetite for financial risk	430	.63	.17	July effect
5	Information sources	448	.59	.07	July effect
	Investor research	464	.62	.11	investor knowledge
	Social network	462	.57	.07	investor research
6	Anxiety:	501	.48	.07	Motor activity
7a	Lack of attention	491	.46	.12	Motor activity
7b	Lack of planning	487	.46	.04	Motor activity
7c	Motor activity	505	.60	.12	Lack of Attention

Listwise deletion of missing data for each scale

5.5 Missing data analyses and imputing scale values

Missing data analyses were also performed. *Little's MCAR Chi square* = 7223.4; *df* = 6388; *normed chi squared* = 1.13; $p > .05$. As the normed chi square of 1.13 was not significant, the data may be considered missing completely at random (MCAR). As described in section 4.8.1, imputed values were obtained for missing data on the eight scales and the subscales using the E.M. algorithm. This algorithm is suitable for data that is MCAR (SPSS Inc., 2010a). The second last column of Table 26 reports the Cronbach's alpha for the seven scales and subscales using imputed values. As might be expected when the data is MCAR, Cronbach's alpha coefficients using imputed values are little changed from those obtained using listwise deletion of missing data. (See Table 26).

Table 28 reports the number of missing cases for each scale. Motor activity has the lowest missing data with 16 cases (3.07 percent). Overconfidence has the highest missing data with 186 cases (35.7 percent). With the exception of overconfidence and one of its subscales, remaining scales had less than 15 percent missing data.

Table 29 reports the number of missing cases for remaining variables used in this thesis. Gender, marital status, and their interaction, along with education each had ten cases with missing data (1.91 percent). Three-year wealth change had the highest number of missing data with 233 cases (44.72 percent). With the exception of three-year wealth change, remaining variables had less than 15 percent missing data.

Table 28 *Missing Data Profile for Seven Scales and Subscales*

Scale	Scale Name	No. of questions	No. of Valid Cases	No of Missing Cases	Percent Missing Cases
1	Overreaction	3	472	49	9.40%
2	Overconfidence	6	335	186	35.70%
	Investor knowledge	3	490	31	5.95%
	Investor expectation	3	339	182	34.93%
3	July effect	5	458	63	12.09%
4	Appetite for financial risk	4	430	91	17.47%
5	Information sources	7	448	73	14.01%
	Investor research	3	464	57	10.94%
	Social network	4	462	59	11.32%
6	Anxiety	4	501	20	3.84%
7a	Lack of attention	4	491	30	5.76%
7b	Lack of planning	4	487	34	6.53%
7c	Motor activity	4	505	16	3.07%

n = 521

Table 29 *Missing Data Profile for Remaining Variables Used in Thesis*

Question	Variable name	No. of Valid Cases	No. of Missing Cases	Percent Missing Cases
C4	Hours spent on investments	492	29	5.57%
C18	Companies followed	463	58	11.13%
C19	Companies in portfolio	474	47	9.02%
C20	Defensive shares	452	69	13.24%
C21	Growth shares	452	69	13.24%
C22	Cyclical shares	450	71	13.62%
C23	Asset/turnarounds	451	70	13.44%
D1	Age	503	18	3.45%
D2	Gender	511	10	1.91%
D3	Marital status	511	10	1.91%
C1	Years experience	468	53	10.17%
D6	Education	511	10	1.91%
D7	Financial Education	508	13	2.50%
	Marital status x gender	511	10	1.91%
	Count of "don't know"	521	0	0%
	Count of missing data	521	0	0%
	Count of "don't know" and missing data	521	0	0%
	Three-year wealth change	288	233	44.72%

n = 521

Thirty-four respondents left more than 20 percent of the questionnaire blank. These cases were removed from the datafile. Doing so led to a sample size *n* of 487 cases.

Tables 30 and 31 provide the missing data profile for the scales and remaining variables following the removal of the thirty-four respondents from the datafile. Once again, overconfidence, along with one of its subscales, and three-year wealth changes had more than 20 percent missing data. Both variables represent key variables in this thesis. Consequently, they were used with caution. For this reason, the full scale for overconfidence, with missing data, was used in remaining analyses. The imputed form of this variable was not be used.

Table 30 *Missing Data Profile for Seven Scales and Subscales*

Scale	Scale Name	No. of questions	No. of Valid Cases	No of Missing Cases	Percent Missing Cases
1	Overreaction	3	452	35	7.19%
2	Overconfidence	6	323	164	33.68%
	Investor knowledge	3	465	22	4.52%
	Investor expectation	3	326	161	33.06%
3	July effect	5	442	45	9.24%
4	Appetite for financial risk	4	411	76	15.61%
5	Information sources	7	441	46	9.45%
	Investor research	3	456	31	6.37%
	Social network	4	455	32	6.57%
6	Anxiety	4	476	11	2.26%
7a	Lack of attention	4	469	18	3.70%
7b	Lack of planning	4	465	22	4.52%
7c	Motor activity	4	481	6	1.23%

n = 487

Table 31 *Missing Data Profile for Remaining Variables Used in Thesis*

Question	Variable name	No. of Valid Cases	No. of Missing Cases	Percent Missing Cases
C4	Hours spent on investments	469	18	3.70%
C18	Companies followed	445	42	8.62%
C19	Companies in portfolio	454	33	6.78%
C20	Defensive shares	437	50	10.27%
C21	Growth shares	436	51	10.47%
C22	Cyclical shares	435	52	10.68%
C23	Asset/turnarounds	436	51	10.47%
D1	Age	475	12	2.46%
D2	Gender	481	6	1.23%
D3	Marital status	481	6	1.23%
C1	Years experience	446	41	8.42%
D6	Education	481	6	1.23%
D7	Financial Education	480	7	1.44%
	Marital status x gender	481	6	1.23%
	Count of “don’t know”	487	0	0%
	Count of missing data	487	0	0%
	Count of “don’t know” and missing data	487	0	0%
	Three-year wealth change	278	209	42.92%

n = 487

5.6 Associations amongst factors

Tables 32 and 33 report the Pearson's correlation matrices for the scales and subscales. Reliability coefficients have been reported down the leading diagonal.

Table 32 *Pearson's Correlation Coefficients for Seven Scales*[#]

	Anxiety Imp	Lack of Atten-tion Imp	Lack of Plan-ning Imp	Motor Activi-ty Imp	Informa-tion Sources Imp	Over-confi-dence	Appetite for Financial Risk Imp	July Effect Imp	Over-reac-tion Imp
Anxiety	***.77***								
Lack of Attention	.28***	***.76***							
Lack of Planning	.06	.13**	***.76***						
Motor Activity	.27***	.34***	.20***	***.84***					
Information Sources	.19***	.15**	-.09	.21***	***.78***				
Overconfidence	-.08	-.08	-.08	-.02	.12**	***.76***			
Appetite for Financial Risk	.13**	.12**	.01	.22***	.21***	.07	***.86***		
July Effect	.14**	.18***	.01	.13**	.26***	.30***	.36***	***.82***	
Overreaction	.11*	.23***	.01	.18***	.27***	.23***	.27***	.53***	***.64***

*** correlation is significant at .001 level (2 tail)
** correlation is significant at .01 level (2 tail)
* correlation is significant at .05 level (2 tail)
[#] Cronbach's alpha using imputed values reported in bold italics down leading diagonals
n = 487 for 7 of 8 scales (overconfidence *n* = 323)

There were many low/moderate associations amongst the seven scales. The associations amongst the subscales were also low/moderate. See Tables 30 and 31.

Table 33 *Pearson's Correlation for Subscales on Information Sources and Overconfidence*#

	Investor Research Imp	Social Network Imp	Investor Knowledge Imp	Investor Expectation About Portfolio Performance
Investor Research	***.83***			
Social Network	.26***	***.81***		
Investor Knowledge	.33***	-.07	***.89***	
Investor Expectation About Portfolio Performance	.11	.01	.22***	***.73***

*** correlation is significant at .001 level (2 tail)
** correlation is significant at .01 level (2 tail)
* correlation is significant at .05 level (2 tail)
# Cronbach's alpha using imputed values reported in bold italics down leading diagonals
n = 487 for 3 of 4 subscales (Investor expectation about portfolio performance *n* = 326)

5.7 Descriptive statistics

Table 34 provides descriptive statistics for the seven scales and subscales. With the exception of overconfidence and one of its subscales, descriptive statistics have been reported using imputed values. Overconfidence, and one of its subscales, has in excess of 20 percent missing values. Descriptive statistics were thus reported on the original variable and without the benefit of imputation of missing data for these variables. Note, descriptive statistics have been reported following the removal of thirty-four cases with more than 20 percent missing items. Sample size, *n*, has thus become 487 cases.

Table 34 *Descriptive Statistics for Seven Scales and Subscales with Imputed Values*

	N	Min	Max	Mean	SD	Skewness	Kurtosis
Overreaction	487	3.00	12.00	5.87	2.20	0.44	-0.55
Overconfidence**	323	10.00	30.00	21.71	3.64	-0.23	-0.09
Investor Knowledge	487	3.00	15.00	9.31	2.99	-0.27	-0.41
Investor Expectation about Portfolio Performance**	326	3.00	15.00	11.62	1.95	-1.09	2.70
July Effect	487	5.00	20.00	7.81	3.31	1.09	0.34
Appetite for Financial Risk	487	4.00	19.00	7.49	3.77	0.99	0.13
Information Sources	487	7.00	34.00	14.32	5.01	0.62	0.21
Investor Research	487	3.00	15.00	7.51	3.09	0.16	-0.88
Social Network	487	4.00	20.00	6.82	3.22	1.32	1.95
Anxiety	487	4.00	20.00	9.28	3.27	0.49	0.09
Lack of Attention	487	4.00	18.00	9.27	3.26	0.29	-0.47
Lack of Planning	487	4.00	17.00	7.99	2.70	0.45	-0.17
Motor Activity	487	4.00	20.00	8.73	3.22	0.56	0.16

** Note: with the exception of Overconfidence, and Investor Expectation about Portfolio Performance, descriptive statistics are based on scales using imputed missing data

Table 35 provides descriptive statistics for other variables used in this thesis. It also reports the number of missing cases for each variable. Where transformations have been considered, these have been provided immediately after the variable's original scale statistics. Note that where log transformations have been used, a constant has been added to the raw score prior to undertaking the log transformation.

Table 35 *Descriptive Statistics for Remaining Variables*

	N	Missing	Min	Max	Mean	SD	Skew	Kurtosis
C4: How many hours per week do you typically spend thinking, reading, researching or discussing investments?	469	18	0.00	80.00	7.08	13.54	2.91	8.68
Natural Log of C4: Hours spent on investments	469	18	0.00	4.39	1.30	1.13	0.92	0.04
C18: How many different companies do you follow, research or analyze?	445	42	0.00	9000.00	40.89	428.28	20.72	434.14
Natural Log of C18: Companies Followed	445	42	0.00	9.11	2.10	1.40	0.49	0.92
C19: How many different company's shares do you currently have in the share portfolio that you own and/or manage?	454	33	0.00	12000.00	47.83	575.49	20.04	413.92
Natural log of C19: Companies in portfolio	454	33	0.00	9.39	2.21	1.09	1.36	5.70
C20: Defensive shares	437	50	0.00	160.00	34.96	35.74	0.75	-0.60
Natural log of C20: Defensive shares	437	50	0.00	5.08	2.49	1.89	-0.42	-1.58
C21: Growth shares	436	51	0.00	100.00	37.80	35.94	0.61	-0.95
C22: Cyclical shares	435	52	0.00	111.10	20.50	31.08	1.65	1.59
Natural log of C22: Cyclical shares	435	52	0.00	4.72	1.67	1.84	0.34	-1.64
C23: Asset/turnarounds	436	51	0.00	100.00	6.50	13.67	2.96	11.79
Natural Log of C23: Asset/turnarounds	436	51	0.00	4.62	0.82	1.39	1.20	-0.33
D1: age	475	12	22.00	92.00	59.26	12.63	0.13	-0.30
D6: education	481	6	0.00	8.00	4.09	1.84	-0.35	-0.05
D7: financial education	480	7	0.00	10.00	2.80	3.06	0.55	-1.20
Count of “don’t know”	487	0	0.00	115.00	7.37	13.20	3.31	15.27
Square root of count of don’t know	487	0	1.00	10.77	2.34	1.70	1.60	2.58
Count of missing data	487	0	0.00	32.00	6.94	6.30	1.45	2.05
Square root of count of missing data	487	0	1.00	5.74	2.62	1.05	0.61	-0.07
Combined Count	487	0	0.00	126.00	14.31	15.28	2.69	10.75
Square root of combined Count	487	0	1.00	11.27	3.55	1.64	1.13	1.76
Years of Investor Experience	446	41	0.00	65.00	23.47	12.33	0.84	0.32
One-year wealth change	298	189	-100.00	1233.33	25.29	109.49	8.60	87.23
Natural log of one-year wealth change	298	189	2.30	7.20	4.80	0.40	0.38	16.02
Two-year wealth change	275	212	-100.00	12627.27	77.91	777.76	15.51	249.93
Natural log of two-year wealth change	275	212	2.30	9.45	4.77	0.60	2.42	17.47
Three-year wealth change	278	209	-100.00	13233.33	78.32	821.54	15.06	239.80
Natural log of three-year wealth change	278	209	4.61	9.51	5.34	0.45	4.93	35.31

5.8 Conclusion

This chapter described the factor structure, reliability, and discriminant validity of the scales used in the remainder of this thesis. This chapter showed that seven scales demonstrated good factor structure. All seven scales demonstrated good reliability and discriminant validity.

Scale development will be discussed in section 10.2. The next chapter addresses the first two research questions: Overconfidence and underconfidence.

Chapter 6 Overconfidence and Underconfidence

6.1 Introduction

This chapter addresses research questions one and two. In so doing, it also answers part of the third objective, along with the second objective, of this thesis. More specifically, through research question one, this chapter considers whether the level of overconfidence follows the same gender by marital status sequence that was found by Barber and Odean (2001). Exploration of this research question will help unpack the factors that underlie overconfidence. In so doing, it may help unpack investor behavior in the share market.

Through research question two, this chapter also considers whether (a) the count of “don’t know”; (b) the count of missing data; and (c) the combined count of “don’t know” and missing data can act as markers of underconfidence. If the count of “don’t know” and/or the count of missing data can act as markers of underconfidence, then this research, and indeed, future research, has a readily available variable that can act as a marker of underconfidence. Moreover, having access to a marker of underconfidence provides a second handle on the construct of overconfidence, albeit expressed in the inverse direction to overconfidence.

6.2 Research question 1: The influence of gender and marital status on overconfidence

A one way analysis of variance was performed using gender by marital status as the grouping variable. It was of interest to know whether scores on overconfidence depended on the group to which the respondent belonged. Based on the findings of Barber and Odean (2001), it was hypothesized that single women would demonstrate the least overconfidence, followed by partnered women and partnered men in turn. It was also hypothesized that single men would demonstrate the greatest levels of overconfidence. If the findings prove to be as hypothesized, it would provide further evidence for the findings of Barber and Odean (2001). Moreover, it would suggest that overconfidence can be predicted knowing both the investor's gender and marital status. Analyses were based on the original scale with missing values. For this analysis, sample size, *n,* was 313 cases.

Table 36 summarizes the findings of the one way analysis of variance for overconfidence without imputed values. The first column of Table 36 provides Levine's test for homogeneity. The next four columns provide the means, standard deviations and sample sizes for single women, partnered women, partnered men and single men in turn. The final column provides the F-value and significance level.

Table 36 *The Relationship Between Gender, Marital Status and Overconfidence*

	Levine Test	Single Women Mean *(SD)*	Partnered Women Mean *(SD)*	Partnered Men Mean *(SD)*	Single Men Mean *(SD)*	F statistic*
Overconfidence	0.36 $^{n.s.}$	19.72 (3.00) n = 36	20.77 (3.74) n = 48	22.19 (3.44) n = 202	22.85 (3.660 n = *27*	7.41***

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

Levine's test for homogeneity of variances for overconfidence (n = 313) was not significant. Thus, the analysis of variance assumption of homogeneity of variances has been met. See Table 36.

The one way analysis of variance showed that there was a significant difference in overconfidence across the four groups ($F_{3,322}$ = 7.41, $p < .001$). See Table 36. Figure 10 plots the means at each combination of gender and marital status. From Figure 10, it would appear that the sequence of group means were consistent with those previously shown by Barber and Odean (2001).

To assess whether the data follows the sequence previously shown by Barber and Odean (2001), a Bonferroni's post hoc test was performed. The results of this test can be found in Table 37. The Bonferroni test provides all possible paired comparisons and adjusts their significance level to ensure that Type I error remains at an alpha of .05 (Francis, 2013). Examination of the mean differences of each of the four groups showed single women to have significantly different means from those of partnered men and single men. The mean differences were -2.47 and -3.13 respectively. While both comparisons showed a level of significance of .001 and .003 respectively, both comparisons are considered to have a significance of .05. Remaining possible comparisons were not significant. See Table 37.

The null hypothesis for the first research question can be partially rejected. It would appear that single women experience less overconfidence than either partnered men or single men. There is insufficient evidence, however, to show that partnered women were significantly different on overconfidence from the remaining three groups or that single men were significantly different in overconfidence from partnered men.

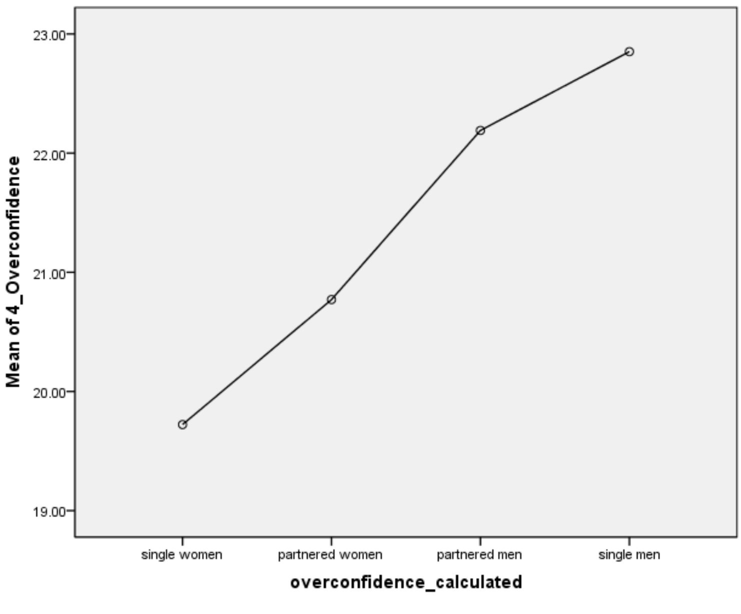

Figure 10. Overconfidence at different levels of gender X marital status.

Table 37 *Bonferroni Post Hoc Tests at Different Levels of Overconfidence*

Overconfidence (I)	Overconfidence (J)	Mean Difference (I-J)	Sig.
single women	partnered women	-1.05	1.000
	partnered men	-2.47*	.001
	single men	-3.13*	.003
partnered women	single women	1.05	1.000
	partnered men	-1.42	.066
	single men	-2.08	.077
partnered men	single women	2.47*	.001
	partnered women	1.42	.066
	single men	-0.66	1.000
single men	single women	3.13*	.003
	partnered women	2.08	.077
	partnered men	0.66	1.000

* The mean difference is significant at the .05 level.

6.3 Research question 2: Markers of underconfidence

The count of "don't know" per respondent represented a tally of all the questions to which a respondent endorsed "don't know" in the survey questionnaire. Similarly, the count of missing data per respondent represented the tally of all the questions a respondent left blank in the survey questionnaire. Finally, the combined count of "don't know and missing data per respondent represented tally of all the questions a respondent left blank as well as those questions to which the respondent endorsed "don't know".

Sections 6.3.1 to 6.3.3 consider whether each of these variables could be utilized as markers of investor underconfidence. In this regard, multiple regression analyses were performed. To meet the statistical assumptions of this test, separate analyses were conducted using the square root transformation of (a) the count of "don't know"; (b) the count of missing data; and (c) the combined count of "don't know" and missing data per respondent. In each analysis, overconfidence (without imputation) and financial education were used as independent (predictor) variables. It has been hypothesized that the predictor variables would have significant, negative beta weights with each dependent variable. If this proves to be the case, the dependent variables could act as markers of underconfidence.

6.3.1 The count of "don't know" per respondent as a marker of underconfidence

Multiple regression with pairwise deletion of missing data was performed using a square root transformation of the count of "don't know" as the dependent variable. Overconfidence (without imputed values) and financial education were treated as independent variables in this analysis.

The multiple regression R^2 adjusted of .17 was significant ($F_{2,\ 308} = 32.11$; $p < .001$). The standardized beta weight for overconfidence was -.24 ($p < .001$). The standardized beta weight for financial education was -.25 ($p < .001$).

Both variables were significantly able to predict the count of "don't know" and the direction of their beta weights was negative. The null hypothesis can thus be rejected. The greater the financial education and level of overconfidence, the less likely the investor was to endorse "don't know". The square root count of "don't know" per respondent may thus be considered a marker of underconfidence.

Whilst the regression equation was significant, the order of magnitude in the multiple regression coefficient suggests that there is still much unexplained variance in the dependent variable. It was therefore decided to repeat this analysis using financial education plus both subscales of overconfidence as predictor variables.

Using investor knowledge, investor expectation about portfolio performance (without imputation) and financial education as independent (predictor) variables, with pairwise deletion of missing data, a multiple regression R^2 adjusted of .13 was found and shown to be significant ($F_{2,470} = 95.44$; $p < .001$). The standardized beta weights for investor knowledge, investor expectation about portfolio performance and financial education were -0.23 ($p < .001$), -0.11 ($p = .05$) and -0.17 ($p = .006$) respectively. Of these three variables, it would appear that investor knowledge and financial education played greater roles in the prediction of the square root count of “don’t know” than did investor expectation about portfolio performance (without imputation).

The analysis was therefore repeated using only investor knowledge and financial education as independent (predictor) variables. Once again, pairwise deletion of missing data was used. The multiple regression R^2 adjusted of .29 was significant ($F_{2,470} = 95.44$; $p < .001$). The standardized beta weights for investor knowledge and financial education were -0.47 ($p < .001$) and -0.11 ($p = .02$) respectively. The null hypothesis can be rejected. It would appear that the greater the investor knowledge and the greater the financial education, the less likely the respondent was to endorse “don’t know”. Thus, the square root count of “don’t know” may indeed act as a marker of underconfidence and this marker of underconfidence may tap into the knowledge aspects of underconfidence; more so than it does the expectations aspects of underconfidence.

6.3.2 The count of missing data per respondent as a marker of underconfidence

Multiple regression with pairwise deletion of missing data was performed using a square root transformation of the count of missing data as the dependent variable. Once again, overconfidence (without imputed values) and financial education were used as independent variables for this analysis.

The multiple regression R^2 adjusted of .000 was not significant ($p > .05$). As might be expected, both variables had non-significant beta weights ($p > .05$). Thus, there is insufficient evidence to reject the null hypothesis for this variable.

It would appear that, on its own, the count of missing data cannot act as a marker of underconfidence. It is also possible that the presence of missing data may reflect other factors instead of, or in addition to, underconfidence. Other factors may include carelessness, refusal to complete a question, and/or a belief that a particular question does not apply to the respondent. If the count of missing data indeed reflects other factors only, then this measure cannot act as a marker of underconfidence. If other factors have indeed combined with underconfidence, these other factors may have masked the count of missing data's ability to act as a marker of underconfidence.

6.3.3 The combined count of "don't know" and missing data as marker of underconfidence

Multiple regression using pairwise deletion of missing data was performed using a square root transformation of the combined count of "don't know" and missing data as the dependent variable. Overconfidence (without imputed values) and financial education were once again used as independent (predictor) variables.

The multiple regression R^2 adjusted of .08 was significant (p < .00l). The standardized beta weight for overconfidence was -.13 (p = .036). The standardized beta weight for financial education was -.22 (p < .001).

Once again, the null hypothesis can be rejected. It would appear that the greater the overconfidence and the greater the financial education, the fewer items left blank or endorsed with "don't know". The combined count of "don't know" and missing data may thus act as a marker of underconfidence.

Once again, the order of magnitude in the multiple regression coefficient was low and suggests that there is still much unexplained variance in the dependent variable. It was therefore decided to repeat this analysis using both subscales of overconfidence. Initially, investor knowledge and financial education were used as independent variables. However, the beta weight for financial education was not significant. The regression model was therefore repeated using investor knowledge alone. The multiple regression R^2 adjusted of 0.19 was significant (p < .00l). The standardized beta weight for investor knowledge was -0.44 (p < .001). The null hypothesis can be rejected. It would appear that the greater the investor knowledge, the less likely the respondent was to endorse either "don't know" or leave an item blank. The combined count of "don't know" and missing data (with square root transformation) may thus act as a marker of underconfidence. Once again, this form of underconfidence is more akin to the knowledge aspects of underconfidence.

6.4 Conclusion

This chapter provided partial support for the research of Barber and Odean (2001). There was a significant difference between mean scores on overconfidence, based on the interaction between gender and marital status. Based on the results of the Bonferroni test, only single women had statistically significant (and lower) levels of overconfidence than partnered men or single men.

This chapter also showed that the count of "don't know" and the combined count of "don't know" and missing data per respondent may both act as markers of underconfidence. Both markers of underconfidence may be more akin to informational aspects of underconfidence than they might to investor expectations about portfolio performance.

The count of missing data per respondent does not appear to be a marker of underconfidence. This variable may be measuring other factors such as carelessness, refusal to complete a question, and/or respondent belief that a question does not apply to them. As the count of "don't know" and missing data is a composite of the count of "don't know" and the count of missing data, this variable may also be subject to factors other than underconfidence, albeit to a lesser extent than the count of missing data alone. It is possible that the inclusion of the count of missing data may weaken the precision of this variable's ability to act as a marker of underconfidence. Indeed, the R^2 adjusted is lower for the combined count of "don't know" and missing data than it is for the count of "don't know". For this reason, the count of "don't know" only was used as a marker of underconfidence for the remainder of this thesis. Section 10.3.2 discusses the markers of underconfidence. Sections 10.3 and 10.4 discuss the findings of the first two research questions respectively. The next chapter examines the dimensions upon which retail investors can be distinguished from institutional investors.

Chapter 7 Demographic Profiles of Retail and Institutional Investors

7.1 Introduction

Chapter 7 addresses the third research question. In so doing, it answers part of the third objective of this thesis. This chapter explores the dimensions upon which retail investors can be distinguished from institutional investors. Understanding the differences between both groups of investors can help flesh out key drivers of investor behavior in the share market. Moreover, examination of subgroup differences may provide a more nuanced understanding of investor behavior.

7.2 Investor profile

The third research question asks whether retail investors can be discriminated from institutional investors, and if so, on what dimensions can they be discriminated. Tables 38 to 44 provide the means and standard deviations for retail and institutional investors on seven sets of variables. Each Table also reported Wilk's lambda coefficient and effect size for each variable. In each case, discriminant analyses were performed to determine whether retail investors could be discriminated from institutional investors based on their (a) demographic profile; (b) investment practices; (c) investment strategies; (d) emotional presentation; (e) personality variables; (f) behavioral practices; and (g) changes in portfolio wealth over the GFC.

Variables selected for the first two discriminant analyses were selected on practical grounds. If these variables are able to discriminate retail investors from their institutional counterparts, they represent easily obtained data to help determine whether one is working with a retail or institutional investor.

Variables selected for the remaining discriminant analyses were selected on theoretical grounds. Variables chosen for the third and final discriminant analysis have direct bearing on share market behavior. As retail and institutional investors represent the major two groups of investors, it is plausible that they may differ in their preferences and skill in each of these areas. If this indeed proves to be the case, one might also expect both groups of investors to differ in meaningful ways on the variables used in the fourth, fifth and/or sixth discriminant analyses.

Discriminant analysis is a multivariate technique, and hence, reduces the risk of a Type I error that would have occurred had univariate tests been used. Discriminant analysis is similar to multivariate analysis of variance, but takes a different perspective. Multivariate analysis of variance tests mean differences across groups. It effectively tests whether group membership can predict scores on a set of variables. By contrast, discriminant analysis tests whether a set of variables can distinguish members of one group from those of the other(s). In other words, group membership is predicted from a set of variables (Tabachnick & Fidell, 2014).

Discriminant analysis also provides a classification table to assess how effectively a set of variables can distinguish members of one group from those of the other(s) (Tabachnick & Fidell, 2014).

As discussed in section 4.11, discriminant analysis makes a number of assumptions. These assumptions had been checked and addressed prior to testing the first research question. See section 4.8.3. Of concern was whether or not the requirement for homogeneity of the variance – covariance matrix had not been met. As will be seen from sections 7.3 to 7.9, the Box's M statistic was significant in three of the seven discriminant analyses. As part of the discussion in section 4.11, this potential violation was checked and the results of this section were considered valid. The only analysis that appeared to have unequal variances (in section 7.4) showed that the classification procedure favored the group with the smaller dispersal of scores (i.e., retail investors), not the group with the larger dispersal of scores (i.e., the institutional investors). Consequently, the findings of this analysis may also be considered valid.

Finally, it was decided to use equal probability of classifying cases into one group or the other, based on the profile of scores alone in each discriminant function. It is recognized that use of the ratio of retail investors to institutional investors in the present sample may aid the classification procedure. However, it was of greater interest in the present research to see how the combination of each of the predictor variables performed in distinguishing members of one group from those of the other.

Forty-nine investors did not indicate whether they were institutional and/or retail investors. Hence, the institutional sample (n = 53) and the retail sample (n = 378) were a subset of the full sample (n = 480) for which this information was known. Discriminant analysis uses listwise deletion. The sample size for both groups has therefore been reported for each analysis.

7.3 Research question 3(a): Demographic profile

The first discriminant analysis was performed using age, education, financial education, and years of investor experience as discriminating variables. This analysis had an overall Box's M of 31.62 (p = .001). As retail and institutional investors were classified into two groups, only one discriminant function could be obtained. It was found to be significant. (*Wilk's lambda* = .77; *chi squared* = 99.93; p < .001). The discriminant function had an eigenvalue of .30.

The effect size, eta squared, of the discriminant function is obtained by squaring the canonical correlation coefficient for that function (Tabachnick & Fidell, 2014). Effect size is considered small when they are less than .06. Effect sizes are considered moderate when they range between .06 and .14. Large effect sizes are in excess of .14 (Tabachnick & Fidell, 2014). The canonical correlation between the four variables and the discriminant function was .48. Thus, the effect size for this discriminant function was .23; a large effect size.

All four variables made a significant contribution to the discriminant function: Age (*Wilk's lambda* = .94; *p* < .001); education (*Wilk's lambda* = .96; *p* < .001); financial education (*Wilk's lambda* = .83; *p* < .001); and years of investor experience (*Wilk's lambda* = .98; *p* = .011). See Table 38.

The effect size for each variable's contribution to the discriminant function can be obtained by squaring its loading (correlation) on that discriminant function. These coefficients can be found in the structure matrix (Tabachnick & Fidell, 2014). The structure matrix highlights the importance of financial education in discriminating between both groups, followed by age (inverse relationship), education, and lastly, by years of investor experience. Their respective effect sizes were .67, .23, .14 and .06. See Table 38.

Table 38 *Demographic Profile of Retail and Institutional Investors*

	Mean *(SD)* Retail Investor (*n* = 338)	Mean *(SD)* Institutional Investor (*n* = 50)	Wilk's Lambda	Effect size (eta squared)
D1: age	60.01 (12.43)	50.44 (11.19)	.94***	.23
D6: education	4.04 (1.80)	5.12 (1.44)	.96***	.14
D7: financial education	2.59 (2.88)	6.34 (2.40)	.83***	.67
Years of Investor Experience	23.28 (12.68)	28.14 (11.49)	.98*	.06

*** *p* < .001 ** p < .01 * p < .05 n.s. not significant

In summary from Table 38, it would appear that retail investors are less educated and less financially educated than their institutional peers. Retail investors are also older, but less experienced than their institutional counterparts. Of these four variables, financial education makes the largest contribution in distinguishing retail from institutional investors. Financial education has a very large effect size of .67. In turn, age, education and years of investor experience make the next contribution to the first discriminant function.

The mean score on the first discriminant function for retail investors and institutional investors were -0.21 and 1.41 respectively. Figures 11 and 12 show the distribution of scores for retail and institutional investors on the first discriminant function. The distributions of scores on a discriminant function are akin to factor scores in a factor analysis with a difference: The weights for variables loading on a discriminant function are constructed so as to maximally distinguish members of one group from those of another.

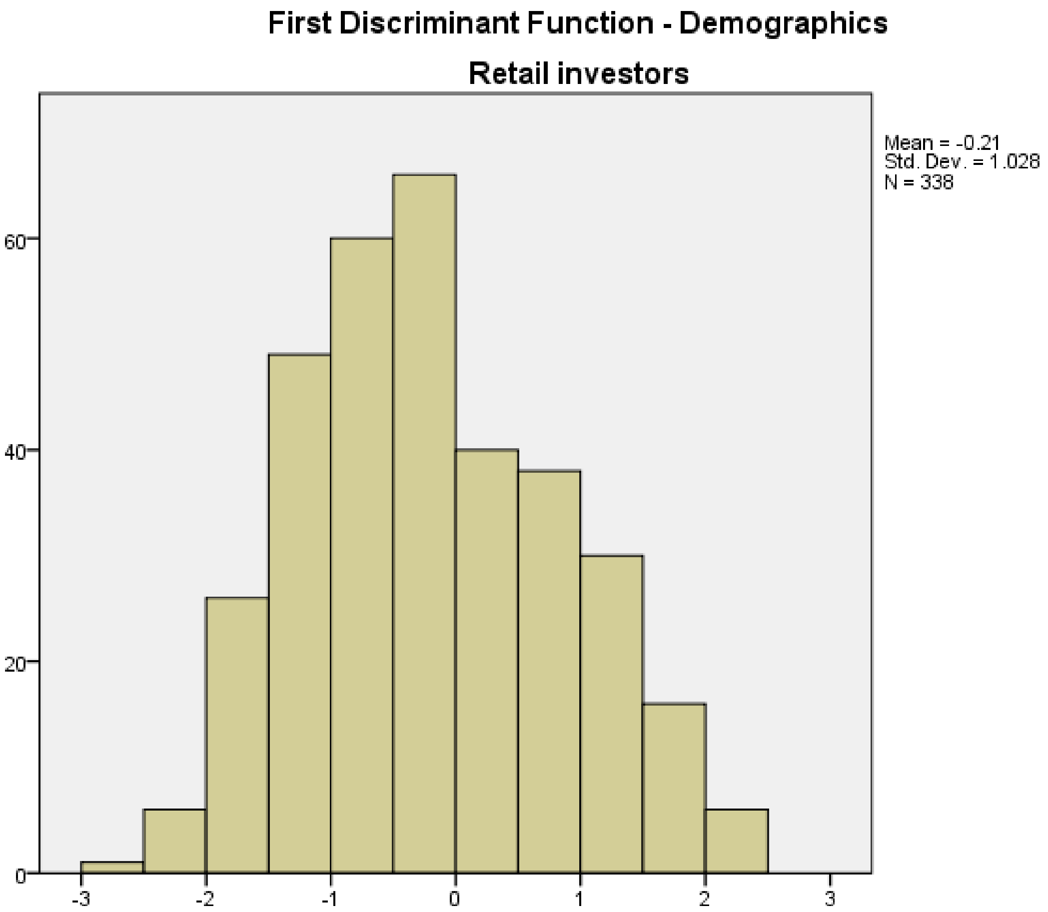

Figure 11. Retail investor scores on first discriminant function (demographics).

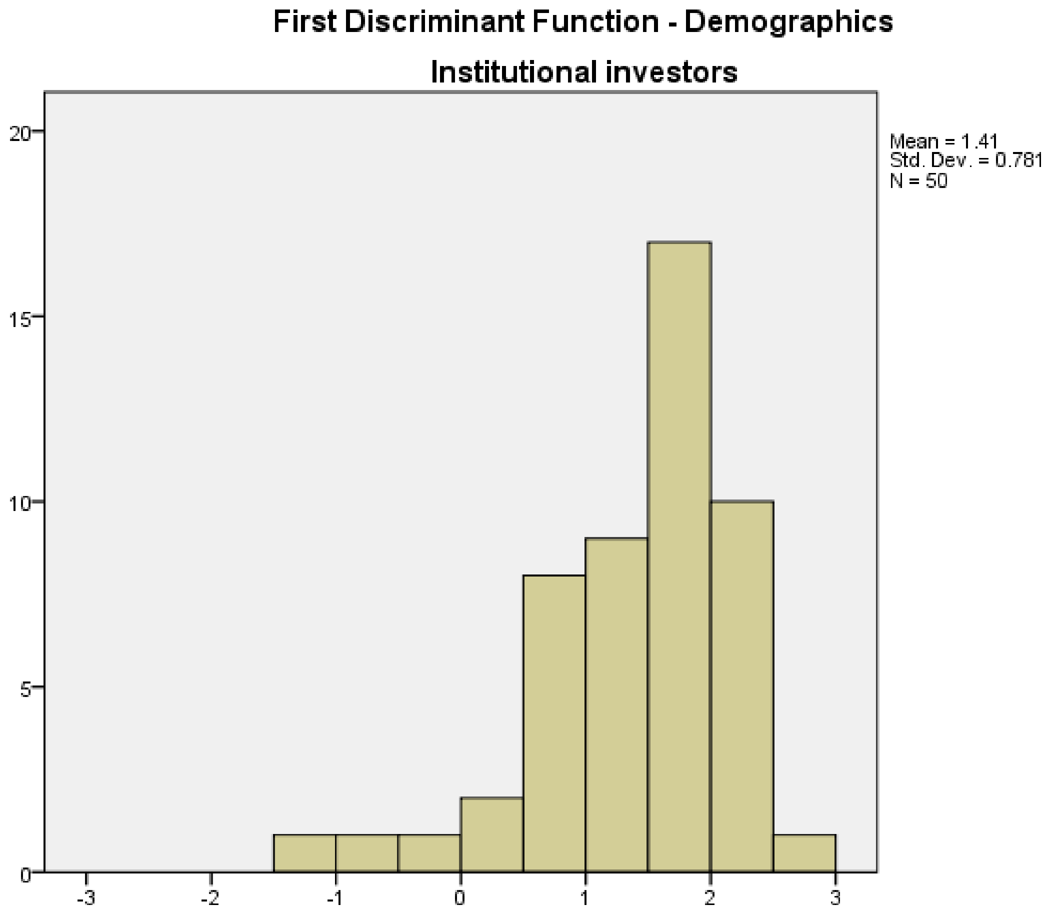

Figure 12. Institutional investor scores on first discriminant function (demographics).

Figure 13 shows the distribution of scores for investors who had not reported whether they were retail or institutional investors (that is, ungrouped respondents). In some instances, ungrouped respondents had left the question blank. In other cases, ungrouped respondents indicated that they did not know to which group they belonged. It is interesting to note that the distribution of scores for ungrouped respondents more closely matches those of retail investors.

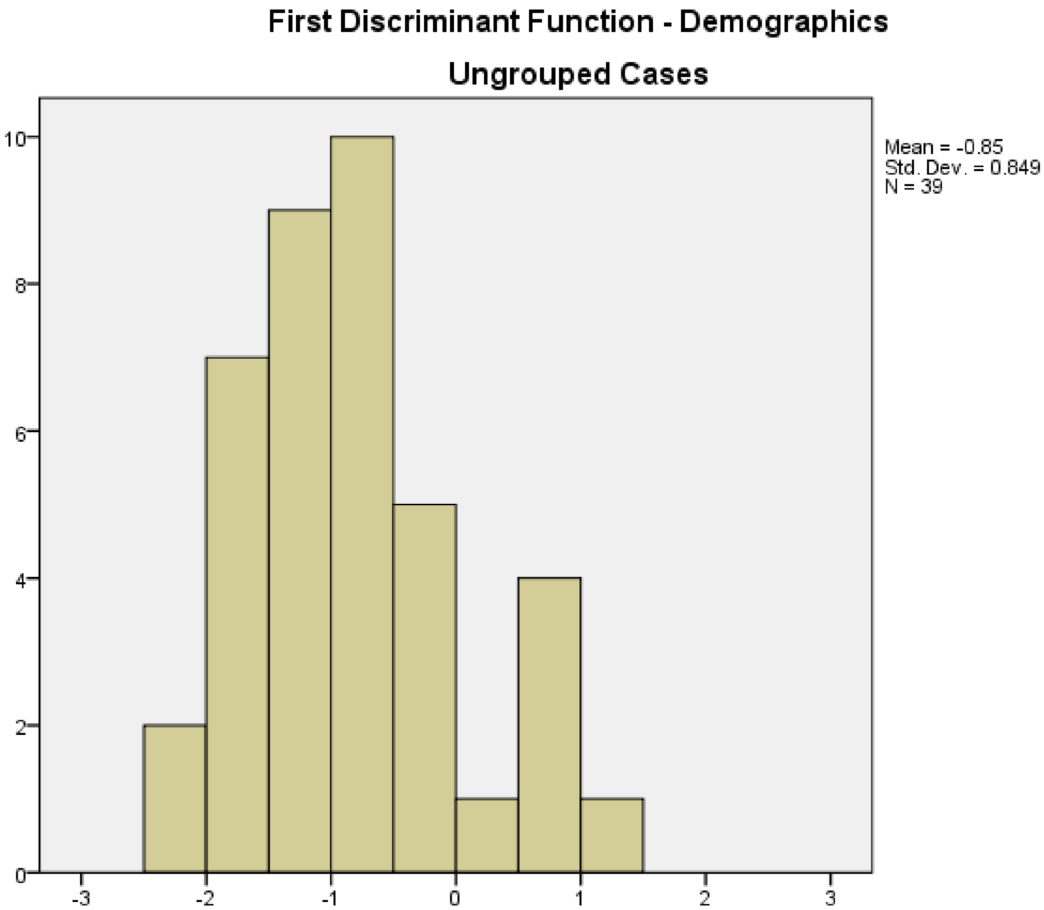

Figure 13. Ungrouped investor scores on first discriminant function (demographics).

The discriminant function could correctly classify 78.1 percent of respondents.

The third null hypothesis can be rejected for the first discriminant function. It would appear that one can distinguish between retail and institutional investors on the basis of (a) financial education; (b) age; (c) education; and (d) years of investor experience. To the extent that investors are less financially educated, older, less educated or less experienced, they are more likely to be retail investors than if the reverse was true.

7.4 Research Question 3(b): Investment practices

The second discriminant analysis used (a) Natural log of C4: Hours spent on investments; (b) Natural log of C18: Companies followed; and (c) Natural log of C19: Companies in portfolio. This analysis had an overall Box's M of 6.27 (p = .409). Once again, only one discriminant function could be obtained. It was found to be significant. (*Wilk's lambda* = .61; *chi squared* = 189.3; p < .001). This function had an eigenvalue of .65.

A canonical correlation between the three variables and the discriminant function was .63. The effect size of this discriminant function was thus .39; a large effect size.

All three variables made significant contributions to this function: Natural log of C4: Hours spent on investments (*Wilk's lambda* = .61; p < .001); Natural log of C18: Companies followed (*Wilk's lambda* = .80; p < .001); Natural log of C19: Companies in portfolio (*Wilk's lambda* = .85; p < .001). See Table 39.

The structure matrix highlighted the importance of Natural log of C4: Hours spent on investments in discriminating between both groups, followed by Natural log of C18: Companies followed and lastly by Natural log of C19: Companies in portfolio. Their respective effect sizes were .97 .39 and .27. See Table 39.

Table 39 *Investor Practices*

	Mean *(SD)* Retail Investor (*n* = 332)	*Mean (SD)* Institutional Investor (*n* = 49)	Wilk's Lambda	Effect size (eta squared)
Natural log of C4: Hours spent on investments	1.15 (0.86)	3.23 (1.03)	.61***	.97
Natural log of C18: Companies followed	2.00 (1.14)	3.76 (1.34)	.80***	.39
Natural log of C19: Companies in portfolio	2.10 (0.96)	3.32 (1.10)	.85***	.27

*** p < .001 ** p < .01 * p < .05 n.s. not significant

In summary, Table 39 shows hours spent on investments was the most important variable in discriminating retail from institutional investors. Indeed, with an effect size of .97, this variable almost defined the second discriminant function. With an effect size of .39, companies followed was the next most important variable in discriminating between the two groups. Number of companies in portfolio made the least important to the discriminant function. Table 39 also shows that retail investors spend fewer hours on their investments, monitor fewer companies and invest in fewer companies than do their institutional counterparts.

The mean score for retail and institutional investors on the second discriminant function were -0.31 and 2.09 respectively.

Figures 14 and 15 show the distribution of scores for retail and institutional investors on the second discriminant function.

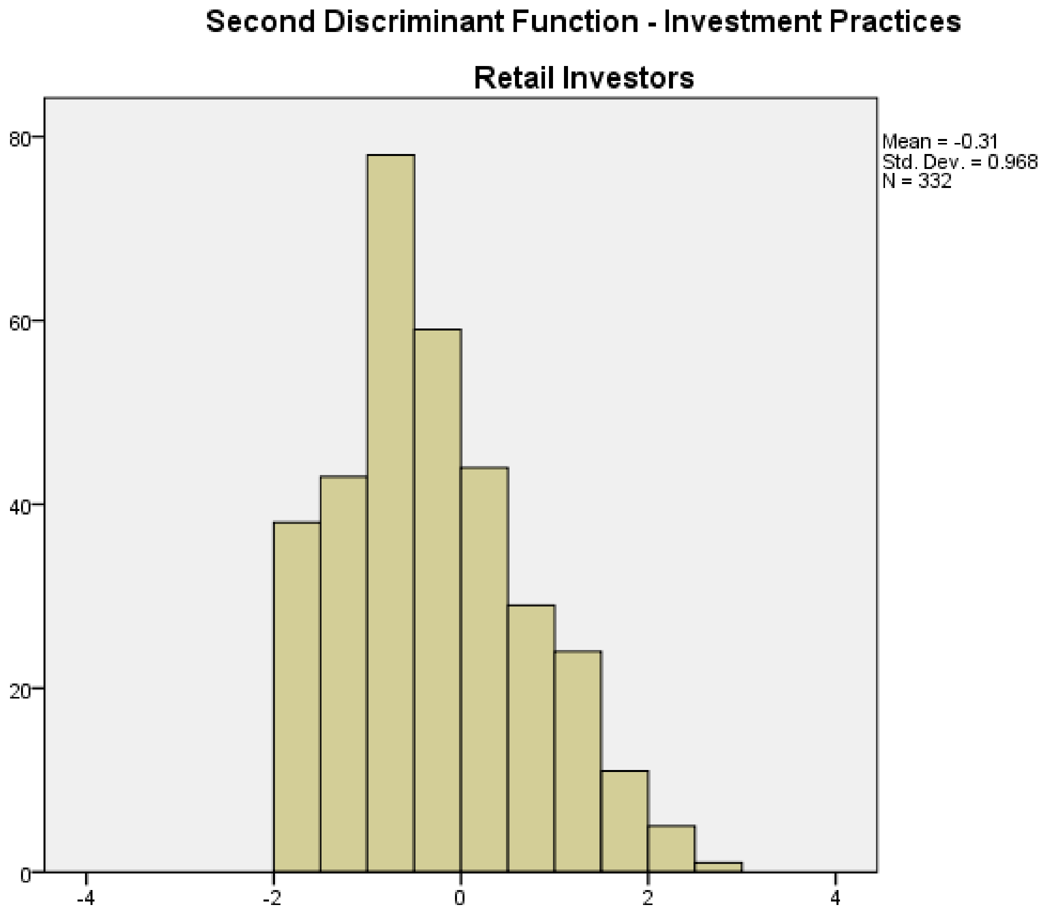

Figure 14 Retail investor scores on second discriminant function (investment practices).

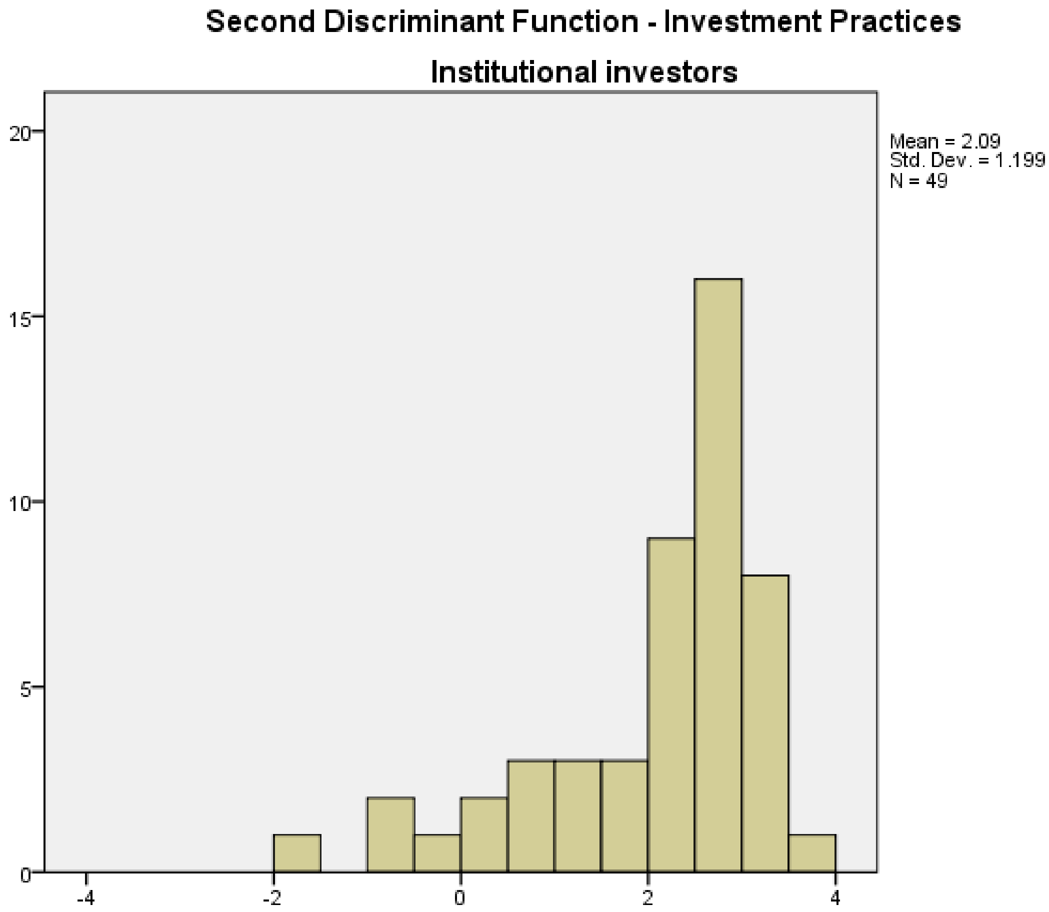

Figure 15. Institutional investor scores on 2nd discriminant function (investment practices).

Figure 16 shows the distribution of scores for ungrouped investors on the second discriminant function. As mentioned in section 7.3, ungrouped investors are those investors who did not indicate whether they were retail or institutional investors. Once again, ungrouped investors appeared to more closely resemble retail investors on the second discriminant function.

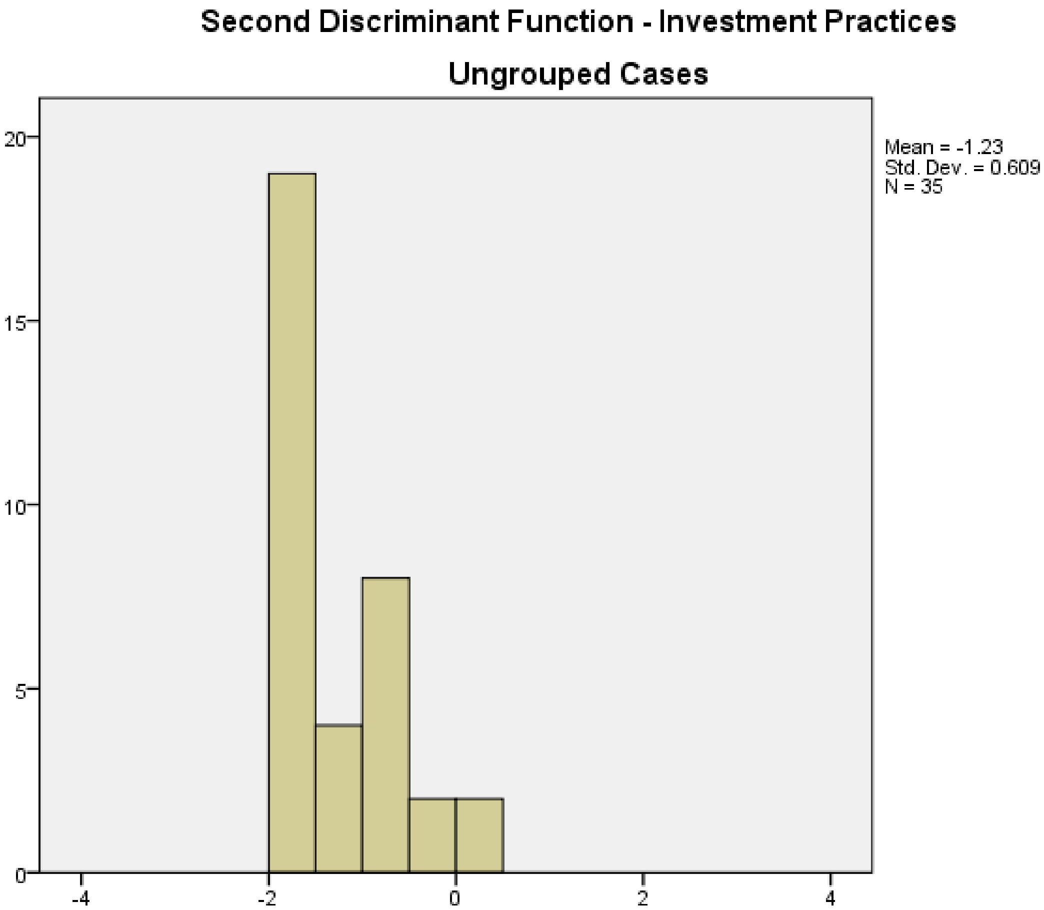

Figure 16. Ungrouped investor scores on 2nd discriminant function (investment practices).

The discriminant function could correctly classify 85.6 percent of respondents. It is interesting to note that all ungrouped respondents were classified as retail investors.

The third null hypothesis can be rejected for the second discriminant function. It would appear that one can discriminate retail from institutional investors on the basis of (a) hours spent on investments; (b) companies followed; and (c) number of companies in portfolio. More specifically, the retail investor is more likely to spend fewer hours per week on their investments, as well as monitor, and invest, in fewer companies than their institutional counterparts.

7.5 Research question 3(c): Investment strategies

The third discriminant analysis used (a) Natural log of C20: Defensive shares; (b) C21: Growth shares; (c) Natural log of C22: Cyclical shares; and (d) Natural log of C23: Asset/turnarounds as discriminating variables. The overall Box's *M* was 14.95 ($p = .15$). Once again, only one discriminant function could be obtained. It was found to be significant. (*Wilk's lambda* = .94; *chi squared* = 22.95; $p < .001$). This function had an eigenvalue of .06.

A canonical correlation between the four variables and the third discriminant function was .24. Thus the effect size of this discriminant function was .06; a small effect size.

Two of the four variables made a significant contribution to the third discriminant function. Natural log of C22: Cyclical shares and the Natural log of C23: Asset/turnarounds both had a *Wilk's lambda* of .98 ($p = .006$). *Wilk's lambda* for Natural log of C20: Defensive shares and C21: Growth shares were .997 ($p = .29$) and 1.0 ($p = .99$) respectively. Examination of the structure matrix shows the Natural log of C22: Cyclical shares and Natural log of C23: Asset/turnarounds had the greatest importance on the third discriminant function. Natural log of C20: Defensive and C21: Growth shares had the least importance on this function. Their respective effect sizes were .33, .32, .05 and .00004. See Table 40.

Table 40 *Investment Strategies*

	Mean *(SD)* Retail Investor ($n = 350$)	Mean *(SD)* Institutional Investor ($n = 46$)	Wilk's Lambda	Effect size (eta squared)
Natural log of C20: Defensive shares	2.53 (1.89)	2.84 (1.50)	.99 n.s.	.05
C21: Growth shares	37.64 (35.98)	37.70 (26.42)	1.00 n.s.	.00004
Natural log of C22: Cyclical shares	1.62 (1.84)	2.41 (1.54)	.98**	.33
Natural log of C23: Asset/turnarounds	0.82 (1.40)	1.43 (1.51)	.98**	.32

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

In summary, from Table 40, it would appear that retail investors allocate less of their portfolios to cyclical shares and asset/turnarounds. However, there appears to be little difference between the two groups on how much of their portfolio they allocate to defensive and growth shares.

Mean score on the third discriminant function for retail and institutional investors were -.09 and 0.68 respectively.

The distribution of scores for retail, institutional and ungrouped investors on the third discriminant function can be found in Figures 17 to 19 respectively. Recall, from section 7.3, that ungrouped investors are those investors who did not indicate whether they were retail or institutional investors.

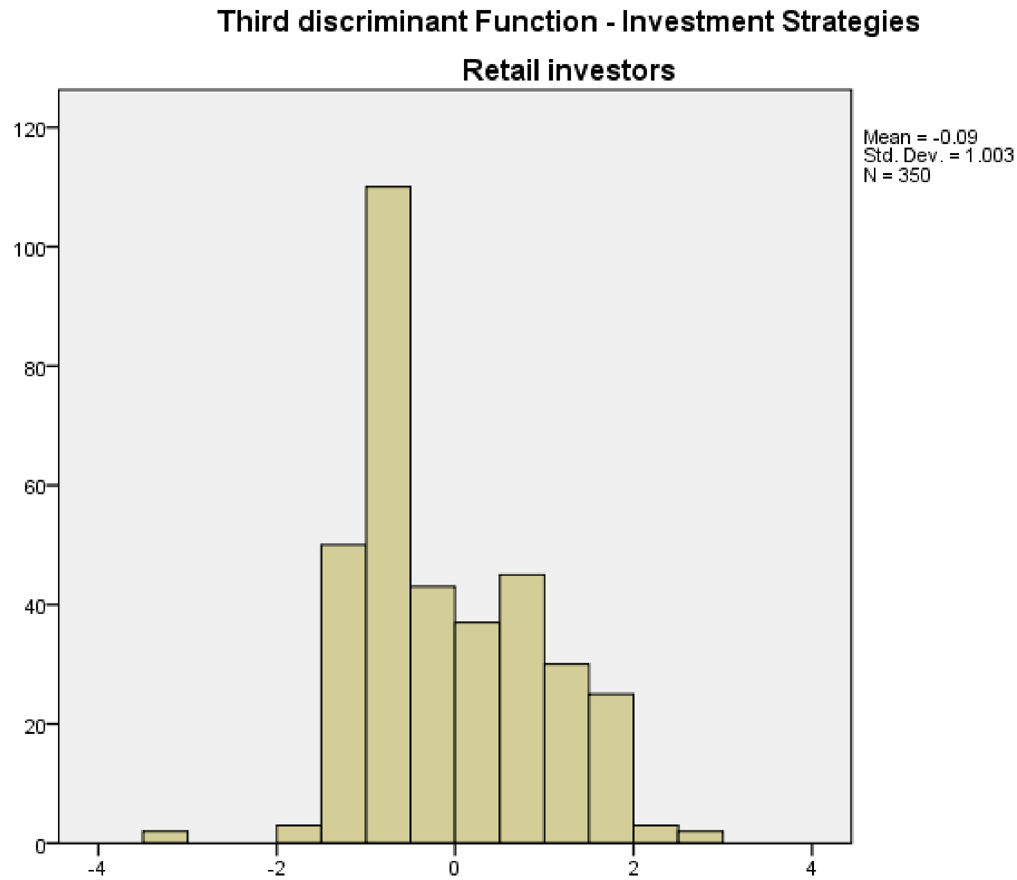

Figure 17. Retail investor scores on third discriminant function (investment strategies).

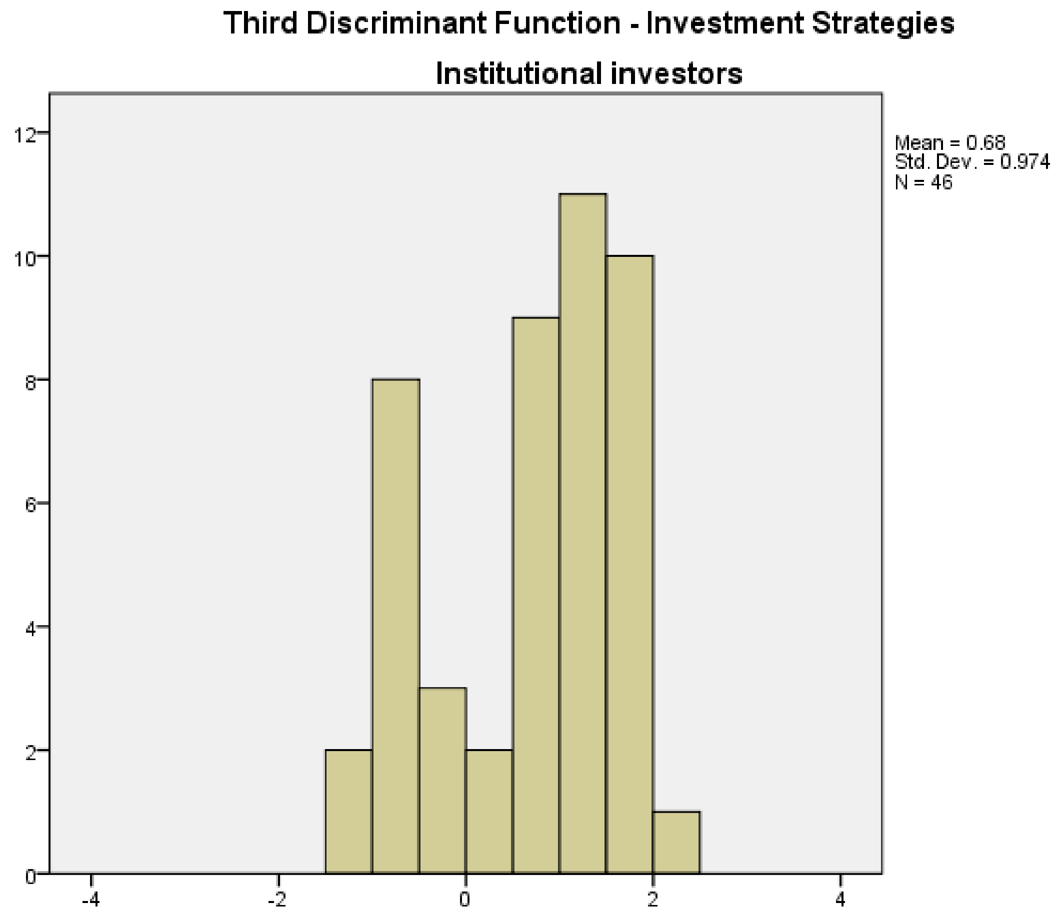

Figure 18. Institutional investor scores on 3rd discriminant function (investment strategies).

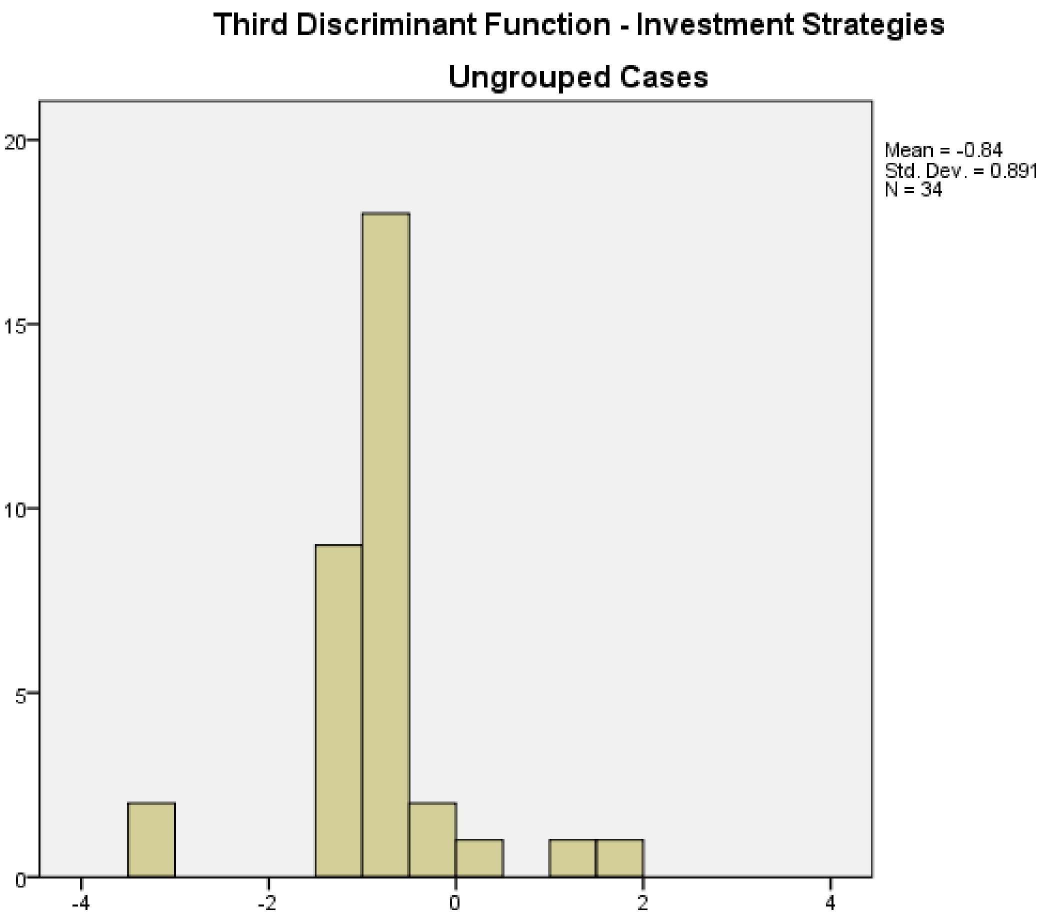

Figure 19. Ungrouped investor scores on 3rd discriminant function (investment strategies).

The third discriminant function was able to correctly classify 63.4 percent of respondents.

Whilst the third discriminant function is significant, there only was a small effect size. Moreover, only two of the four variables made a significant contribution to this function. Consequently, only 63.4 percent of cases could be correctly classified. The third discriminant function thus can partially contribute to the rejection of the third null hypothesis.

7.6 Research question 3(d): Emotional presentation

The fourth discriminant analysis used (a) overreaction; (b) overconfidence (without imputation); and (c) the count of "don't know", as a marker of underconfidence. Note a square root transformation of the count of "don't know" was used. Note also that the subscales of overconfidence were not included in this analysis so as to avoid the problem of singularity. The overall Box's M was 25.43 ($p < .001$). Once again, only one discriminant function could be obtained and was found to be significant. (*Wilk's lambda* = .83; *chi squared* = 55.9; $p < .001$). This function had an eigenvalue of .21.

A canonical correlation between the three variables and the fourth discriminant function was .42. The effect size for the discriminant function was thus .17; a large effect size.

All three variables made a significant contribution to the fourth discriminant function: overreaction (*Wilk's lambda* = .98; $p = .02$); overconfidence (*Wilk's lambda* = .83; $p < .001$); and count of "don't know", as a marker of underconfidence (*Wilk's lambda* = .99; $p = .04$). See Table 41.

Examination of the structural matrix highlighted the importance overconfidence on the fourth discriminant function. Overreaction, followed by the count of "don't know" made less of a contribution to this function. Their respective effect sizes were .97, .09 and .07. See Table 41.

Table 41 *Emotional Presentation*

	Mean *(SD)* Retail Investor (n = 254	Mean *(SD)* Institutional Investor (n = 43)	Wilk's Lambda	Effect size(eta squared)
Overreaction	6.12 (2.15)	6.95 (2.37)	.98*	.09
Overconfidence (without imputation)	21.28 (3.33)	25.42 (2.63)	.83***	.97
Count of "don't know" (with square root transformation)	1.73 (1.11)	1.36 (0.64)	.99*	.07

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

In summary, Table 41 shows that overconfidence made the most contribution to the discrimination of retail investors from their institutional peers. With an effect size of .97, overconfidence appears to have defined the fourth discriminant function. Moreover, Table 41 shows that retail investors reported less overconfidence (and more underconfidence) and less overreaction than did institutional investors.

The mean scores on the fourth discriminant function for retail and institutional investors were -0.19 and 1.11 respectively.

The distribution of scores for retail, institutional and ungrouped respondents on the fourth discriminant function can be found in Figures 20 to 22 respectively. As mentioned in section 7.3, ungrouped investors represent the group of investors who did not endorse whether they were retail or institutional investors. In some instances, the question was left blank. In other instances, ungrouped investors endorsed the "don't know" alternative.

Examination of Figures 20 to 22 places ungrouped respondents at the lowest end of the discriminant function and institutional investors on the highest end on the same discriminant function. If retail investors show less confidence than do institutional investors, then ungrouped investors demonstrate even less confidence than do retail investors. This finding is consistent with the classification procedure of the second discriminant function, which classified all ungrouped respondents into retail investors. Moreover, if ungrouped investors do indeed demonstrate less overconfidence than do retail investors, they may even lack the confidence to determine whether or not they are indeed retail investors.

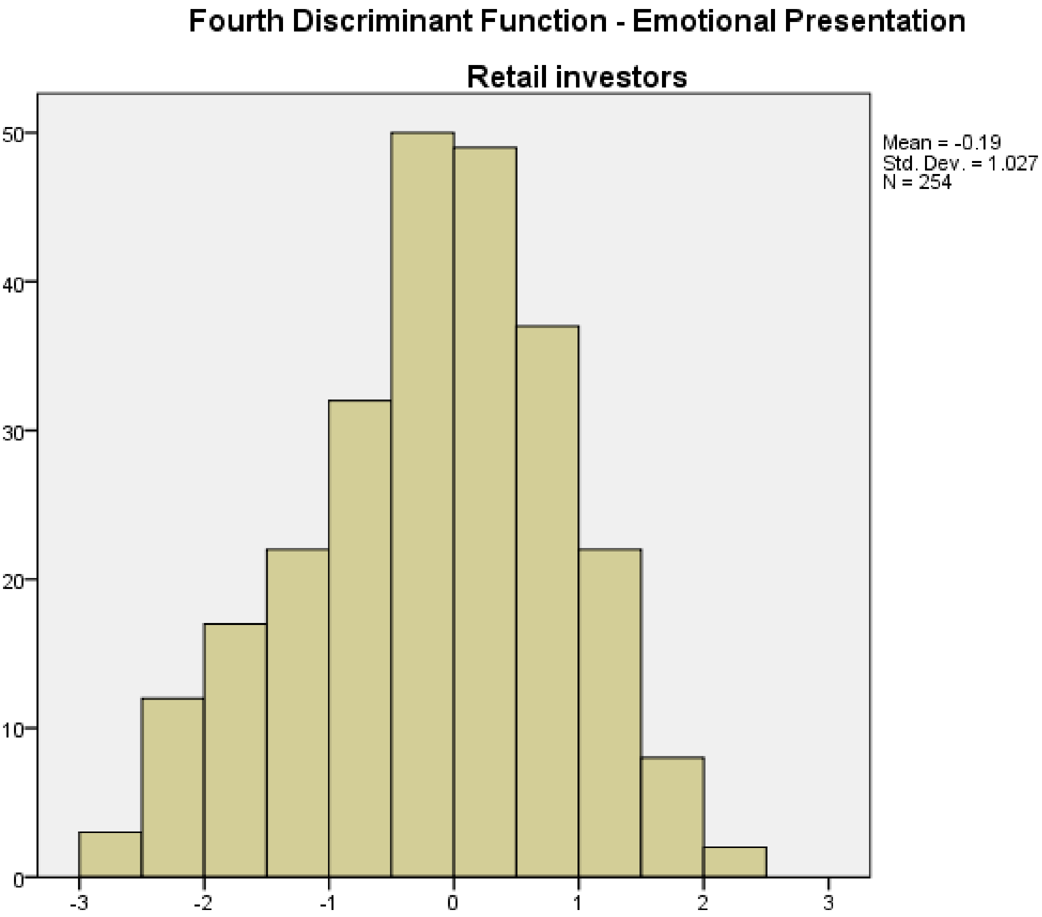

Figure 20. Distribution of scores for retail investors on 4th discriminant function.

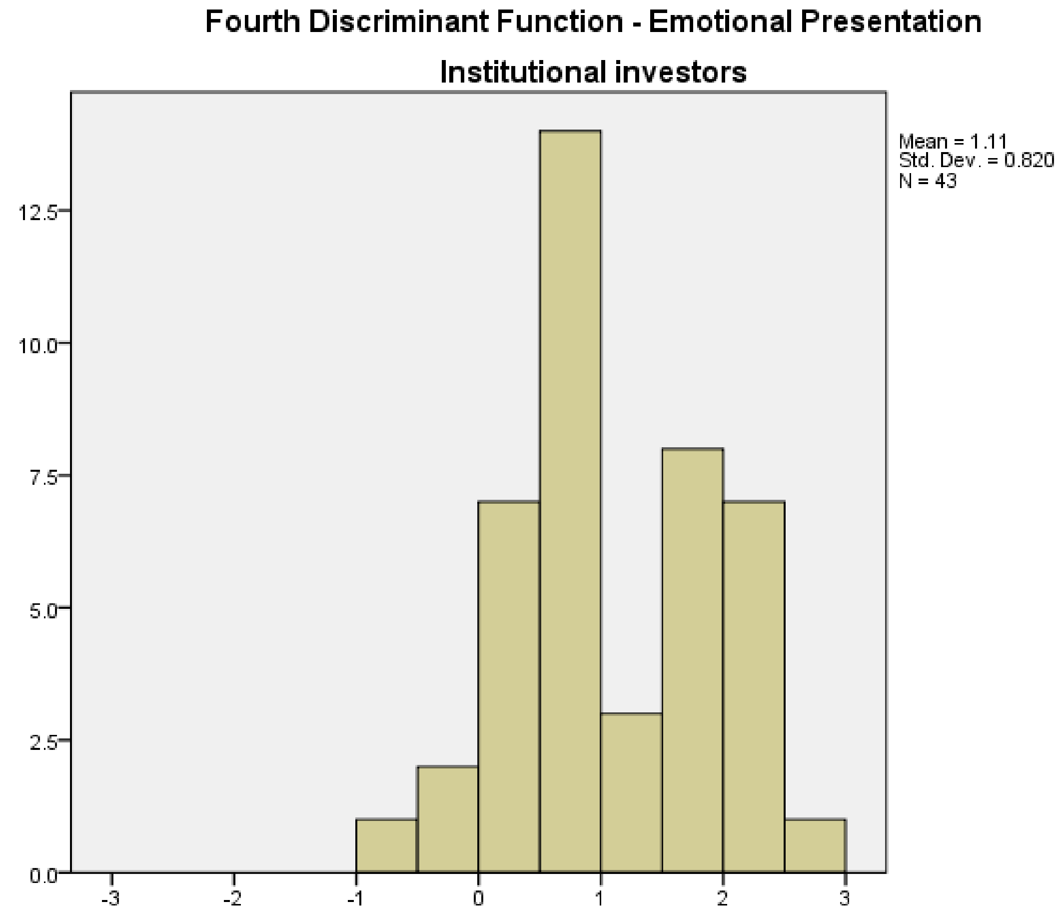

Figure 21. Distribution of scores for institutional investors on 4th discriminant function.

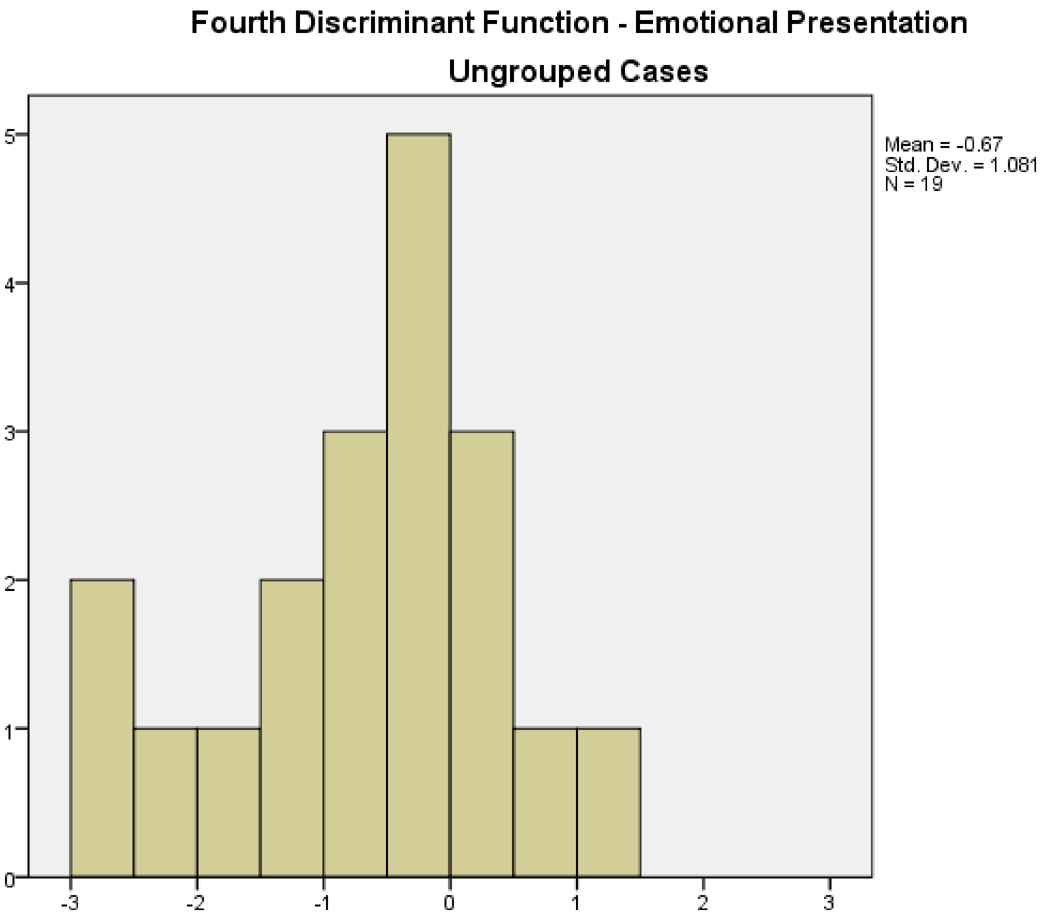

Figure 22. Distribution of scores for ungrouped investors on 4th discriminant function.

The fourth discriminant function was able to correctly classify 73.1 percent of respondents.

The third null hypothesis can be rejected for the fourth discriminant function. It would appear that one can distinguish retail from institutional investors based on the investors' reported level of overconfidence (and its converse, the count of "don't know"), as well as the degree of overreaction. Retail investors demonstrate less overconfidence (and more underconfidence) as well as less overreaction than do their institutional counterparts.

7.7 Research question 3(e) Personality variables

The fifth discriminant analysis used (a) anxiety; and the three dimensions of impulsivity (i.e., (b) lack of attention; (c) lack of planning; and (d) motor activity) as discriminating variables. The overall Box's *M* was 11.3, which was not significant (p = .36). Once again, only one discriminant function could be obtained. It was also not significant. (*Wilk's lambda* = .1.0; *chi squared* = 1.58; p = .81*)*. This function had an eigenvalue of .004.

A canonical correlation between the four variables and the discriminant function was .06. Thus, the effect size for the discriminant function was .0036; which was a negligible effect size.

Not surprisingly, none of the variables were able to make a significant contribution to the discriminant function. See Table 42.

Table 42 *Personality Variables*

	Mean *(SD)* Retail Investor (n = 378)	Mean *(SD)* Institutional Investor (n = 53)	Wilk's Lambda	Effect size(eta squared)
Anxiety	9.27 (3.29)	9.45 (3.24)	1.00 n.s.	.09
Lack of attention	9.13 (3.23)	9.54 (2.86)	.99 n.s.	.49
Lack of planning	7.92 (2.65)	8.25 (2.65)	.99 n.s.	.46
Motor activity	8.75 (3.23)	8.77 (3.10)	1.00 n.s.	.002

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

The mean scores on the fifth discriminant function for retail and institutional investors were -0.02 and 0.16 respectively.

The single discriminant function was able to correctly classify investors in only 54.1 percent of cases, which is little better than chance.

There is insufficient evidence to reject the third null hypothesis on the basis of the fifth discriminant analysis. It would appear that measures of anxiety and the three dimensions of impulsivity (i.e., lack of attention, lack of planning and motor activity) are unable to distinguish between retail and institutional investors beyond what one might expect by chance.

7.8 Research question 3(f): Behavioral practices

The sixth discriminant analysis used (a) July effect; (b) appetite for financial risk; and (c) information sources. Both subscales of information sources were not used in this analysis so as to prevent the problem of singularity. The overall Box's M was 11.60 (p = .08). Once again, only one discriminant function could be obtained. However, it was not significant. (*Wilk's lambda* = .99; *chi squared* = 3.76; p = .29). This function had an eigenvalue of .009.

A canonical correlation between the three variables and the discriminant function was .09, yielding an effect size of .009; a negligible effect size. Not surprisingly, none of the three variables made significant contributions to the sixth discriminant function: July effect (*Wilk's lambda* = .99; p = .06); information sources (*Wilk's lambda* = 1.0; p = .45); and appetite for financial risk (*Wilk's lambda* = 1.0; p = .80). See Table 43.

Examination of the structure matrix showed that July effect was the most important variable on the sixth discriminant function, followed by information sources. Appetite for financial risk had the least contribution on this function. Their respective effect sizes were .92, .15 and .02. See Table 43.

Table 43 *Behavioral Practices*

	Mean *(SD)* Retail Investor (*n* = 378)	Mean *(SD)* Institutional Investor (*n* = 53)	Wilk's Lambda	Effect size (eta squared)
July effect	7.92 (3.38)	8.84 (3.37)	.99 n.s	.97
Appetite for financial risk	7.54 (3.91)	7.68 (3.14)	1.0 n.s.	.02
Information Sources	14.37 (4.88)	14.91 (4.63)	1.0 n.s.	.15

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

In summary, from Table 43, it would appear that the sixth discriminant function was not able to discriminate retail investors from institutional investors. Not surprisingly, none of the three variables were able to make a significant contribution to the sixth discriminant function. See Table 43.

The group means for retail and institutional investors on the sixth discriminant function were -0.04 and 0.25 respectively. The discriminant function was correctly able to classify 59.4 percent of respondents.

There is insufficient evidence to reject the third null hypothesis based on the results of the sixth discriminant analysis. It would appear that retail investors cannot be distinguished from institutional investors based on their tendency towards the July effect, use of information sources or appetite for financial risk.

7.9 Research question 3(g): Wealth changes

The final discriminant analysis used (a) twelve month changes in portfolio wealth (b) two year changes in portfolio wealth; and (c) three year changes in portfolio wealth as discriminating variables. In each case, a natural log transformation was used. The overall Box's *M* was 21.44 ($p = .002$). Once again, only one discriminant function could be obtained. However, it was not significant (*Wilk's lambda* = .98; *chi squared* = 4.45; $p = .22$). This function had an eigenvalue of .02.

A canonical correlation between the three variables and the final discriminant function was .14. Thus, the effect size for the discriminant function was .02; a negligible effect size.

Not surprisingly, none of the three variables were able to make a significant contribution to the final discriminant function. See Table 44.

Table 44 *One, Two and Three Year Wealth Changes*

	Mean *(SD)* Retail Investor (n = 214)	Mean *(SD)* Institutional Investor (n = 33)	Wilk's Lambda	Effect size (eta squared)
Natural log of one-year wealth change	4.76 (0.38)	4.88 (0.27)	.99 n.s.	.66
Natural log of two-year wealth change	4.75 (0.57)	4.83 (0.48)	1.00 n.s.	.12
Natural log of three-year wealth change	5.32 (0.35)	5.30 (0.25)	1.00 n.s.	.03

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant

Mean scores on the seventh discriminant function were -0.05 (retail investors) and 0.34 (institutional investors).

The final discriminant function correctly classified 63.2 percent of respondents. However, with a non-significant discriminant function, negligible effect size and non-significant discriminating variables, it would appear that the third null hypothesis cannot be rejected on the basis of the final discriminant function. It would appear that one cannot significantly discriminate between retail and institutional investors based on changes in portfolio wealth over time. Section 10.5 discusses these findings.

7.10 Conclusions

This chapter explored the dimensions upon which retail and institutional investors differ. The third research question asked whether retail investors could be discriminated from institutional investors. Three of the seven discriminant analyses did find points of differentiation between both groups of investors.

From the first, second and fourth discriminant analyses, it can be seen that retail investors can be distinguished from institutional investors on the basis of (a) demographic profile; (b) investment practices; and (c) emotional presentation. Demographically, in relation to institutional investors, retail investors reported being older, less educated, less financially educated and reported less investment experience. In terms of institutional investment practices, retail investors reported spending fewer hours on their investments, following fewer companies and investing in fewer companies. Finally, in terms of emotional presentation, retail investors reported less overreaction, less overconfidence and more underconfidence than did their institutional counterparts.

Retail investors could not be distinguished from their institutional counterparts based on (a) investment strategies; (b) personality variables; (d) behavioral practices; or (e) changes in portfolio wealth over time.

The fourth research question asked whether the key variables that distinguished both groups of investors could themselves be predicted. As the points of differentiation on the first and second discriminant analyses may come as no surprise, closer examination was given to the three variables measuring emotional presentation.

Retail investors were shown to differ from institutional investors on key variables. To coin a common phrase, institutional investors invest "other people's money", whereas retail investors invest their own money. For this reason alone, one might therefore expect the needs and motivations of both groups to differ. These needs and motivations could be best served by analyzing each group separately. It would be more apt, therefore, to consider retail investors separately from institutional investors. However, this sample contained only 53 institutional cases. It was further decided to pursue this research question on retail investors alone. It is left to future research to drill further into the profile of institutional investors. The fourth and final research questions will focus on retail investors alone. Moreover, on the strength of the second and fourth discriminant analyses, investors who did not report whether they were retail or institutional investors were grouped with retail investors. It would appear from both discriminant analyses that ungrouped investors are indeed retail investors.

The findings of the third research questions are discussed in section 10.5. The next chapter addresses the fourth research question. More specifically, hierarchical regressions are performed with (a) overreaction; (b) overconfidence; and (c) count of “don’t know” as a marker of underconfidence.

Chapter 8 Overreaction, Overconfidence and Underconfidence

This chapter addresses the fourth research question. In so doing, it answers the balance of the third objective. More specifically, this chapter considers the variables that predict the presence of overreaction, overconfidence and the count of "don't know" (as a marker of underconfidence). Understanding what may predict each of these variables may help flesh out what drives investor behavior.

For the reasons discussed at the end of the last chapter, the findings of this chapter, along with that of the next chapter are limited to the sample of 427 retail (and previously ungrouped) investors. The findings for this research question have been repeated using the smaller sample (i.e., of 378 retail investors). The repeated analyses can be found in appendix A6.

8.1 Investor overreaction

A hierarchical regression was undertaken with overreaction as the dependent variable. Block one consisted of demographic variables (age; gender; marital status; education; financial education; and years of investor experience). The second block consisted of three variables measuring investment practices (i.e., Natural log of C4: Hours spent on investments; Natural log of C18: Companies followed; and Natural log of C19: Companies in portfolio). The third block consisted of personality variables (i.e., anxiety; along with the three dimensions of impulsivity [i.e., lack of attention; lack of planning; and motor activity]). The final block consisted of July effect, appetite for financial risk, and information sources). Note that gender and marital status were introduced to the model as 'dummy variables'.

Tables 45 and 46 provide the standardized beta weights and change statistics for each block entered into the model. The model intercept has not been shown.

The results shown in Tables 45 and 46 are based on a sample of 427 retail (and previously ungrouped) investors. Based on the findings of the second and fourth discriminant analyses, it would appear that these investors are also retail investors. For comparison purposes, appendix A6 provides the same findings using the sample of 378 retail investors alone.

Table 45 *Standardized Beta Weights for Overreaction*

Variables	**Block 1**	**Block 2**	**Block 3**	**Block 4**
Block 1: Demographic variables:				
Age	-.07	-.02	.01	.06
Gender	-.18**	-.06	-.04	-.01
Marital status	.09	.06	.04	.07
Education	-.00	.02	.06	.06
Financial education	.02	-.06	-.05	-.07
Years of investor experience	.01	-.03	-.03	-.03
Block 2:				
Natural log of C4: Hours spent on investments		.21**	.22***	.10
Natural log of C18: Companies followed		.15*	.13	.09
Natural log of C19: Companies in portfolio		-.00	.01	-.04
Block 3: Personality variables:				
Anxiety			.04	-.01
Lack of attention			.17**	.09
Lack of planning			-.08	-.03
Motor activity			.08	.02
Block 4: Behavioral practices:				
July effect				.40***
Information sources				.07
Appetite for financial risk				.11*

*** $p < .001$ ** $p < .01$ * $p < .05$

Research hypothesis 4(a) has partial support. This model showed that (a) age; (b) hours spent on investments; (c) number of companies followed; and (d) lack of attention (the first dimension of impulsivity) could contribute to the prediction of retail investor overreaction. However, none of these variables remained in the model in the final block. Indeed, each block progressively replaced those variables that had entered the model in the preceding block. See Table 45. Each block made a significant contribution to the prediction of overreaction. See Table 46. The final model was significant (R^2 *adjusted* = .31, $F_{16,295}$ = 9.65, p < 001).

Two of the three variables, entering the model in the final block, made a significant (and overriding) contribution to the prediction of retail investor overreaction. Retail investor overreaction can be predicted by (a) July effect; and (b) appetite for financial risk. More specifically, retail investor overreaction is more prevalent the greater the tendency towards the July effect and the greater the appetite for financial risk.

Note that the smaller sample (of 378 respondents) shows a similar pattern to that shown in the larger sample (of 427 respondents). Only one variable showed a significant coefficient in block three that was not significant in the larger sample. Moreover, appetite for financial risk was no longer significant in the smaller sample. (See Table 70 in appendix A6).

Table 46 *Hierarchical Regression Fit Statistics for Overreaction*

					Change Statistics				
Model	R	R^2	Adj R^2	SE	R^2 Change	F Change	df_1	df_2	Sig. F Change
Block 1	.23	.05	.03	2.05	.05	2.70	6	305	.014
Block 2	.35	.12	.10	1.97	.07	8.35	3	302	.000
Block 3	.41	.17	.14	1.93	.05	4.32	4	298	.002
Block 4	.59	.34	.31	1.73	.17	25.81	3	295	.000

Variables entered in block 1: (a) age; (b) gender; (c) marital status; (d) education; and (e) financial education.
Variables added in block 2: (a) C4: Hours spent on investments; (b) C18: companies followed; and (c) C19: companies in portfolio.
Variables added in block 3: (a) Anxiety; (b) lack of attention; (c) lack of planning; and (d) motor activity.
Variables added in block 4: (a) July effect; (b) information sources; and (c) appetite for financial risk.
Dependent Variable: Overreaction

8.2 Investor overconfidence

A hierarchical regression was undertaken with overconfidence as the dependent variable. Once again, demographic variables (age; gender; marital status; education; financial education; and years of investor experience) were entered first. The second block consisted of three variables measuring investment practices (i.e., Natural log of C4: Hours spent on investments; Natural log of C18: Companies followed; and Natural log of C19: Companies in portfolio). The third block included personality variables (i.e., anxiety; along with the three dimensions of impulsivity [i.e., lack of attention; lack of planning; and motor activity]). The final block included July effect, appetite for financial risk, and information sources). Note that, once again, both gender and marital status were introduced to the model as 'dummy variables'.

The change statistics and standardized beta weights for each block of variables as they were entered into the model have been provided in Tables 47 and 48 respectively. For the sake of simplicity, the intercept has not been shown.

The results shown in Tables 47 and 48 are based on a sample of 427 retail investors. Once again, this sample includes the 49 investors who did not originally indicate to which group they belonged. However, based on the findings of the second and fourth discriminant analyses, it would appear that these investors are also retail investors. For comparison purposes, appendix A6 provides the same findings based on a sample of 378 retail investors alone.

Once again, partial support has been found for research question 4(b). Five of the six variables made a significant contribution in the first block. Only three of the variables continued to make a contribution in the second and third and final blocks. None of the variables in the final block made a significant contribution to the prediction of overconfidence. See Table 47.

The first three blocks all made significant contributions to the prediction of overconfidence. The final block did not make a significant contribution to the model. See Table 48. The final model was significant (R^2 *adjusted* = .33; $F_{16,\ 207}$ = 7.71; $p < .001$).

Table 47 *Standardized Beta Weights for Overconfidence*

Variables	**Block 1**	**Block 2**	**Block 3**	**Block 4**
Block 1: Demographic variables:				
Age	-.24**	-.17*	-.17*	-.17*
Gender	-.17*	-.06	-.08	-.08
Marital status	.04	.01	.02	.02
Education	-.17*	-.14*	-.16**	-.16*
Financial education	.31***	.23***	.23***	.22***
Years of investor experience	.19**	.09	.09	.08
Block 2:				
Natural log of C4: Hours spent on investments		.14*	.15*	.13
Natural log of C18: Companies followed		.23**	.21**	.20**
Natural log of C19: Companies in portfolio		.15*	.15*	.14*
Block 3: Personality variables:				
Anxiety			-.14*	-.15*
Lack of attention			-.14*	-.15*
Lack of planning			-.05	-.04
Motor activity			.11	.10
Block 4: Behavioral practices:				
July effect				.05
Information sources				.02
Appetite for financial risk				.03

*** $p < .001$ ** $p < .01$ * $p < .05$

Table 48 *Hierarchical Regression Fit Statistics for Overconfidence*

					Change Statistics				
Model	R	R^2	Adj R^2	SE	R^2 Change	F Change	df_1	df_2	Sig. F Change
Block 1	.45	.20	.18	2.97	.20	8.94	6	217	.000
Block 2	.57	.33	.30	2.74	.13	13.68	3	214	.000
Block 3	.61	.37	.33	2.68	.04	3.56	4	210	.008
Block 4	.61	.37	.33	2.69	.01	0.39	3	207	.760

Variables entered in block 1: (a) age; (b) gender; (c) marital status; (d) education; and (e) financial education.
Variables added in block 2: (a) C4: Hours spent on investments; (b) C18: Companies followed; and (c) C19: Companies in portfolio.
Variables added in block 3: (a) Anxiety; (b) lack of attention; (c) lack of planning; and (d) motor activity.
Variables added in block 4: (a) July effect; (b) information sources; and (c) appetite for financial risk.
Dependent Variable: Overconfidence (without imputation)

Overconfidence in retail investors can thus be predicted on the basis of (a) age; (b) education; (c) financial education; (d) number of companies followed; (e) number of companies in the investment portfolio; (f) anxiety; and (g) lack of attention (the first dimension of impulsivity). More specifically, overconfidence is more prevalent in younger retail investors, with less overall education but greater financial education. Overconfident retail investors are also more likely to follow a greater the number of companies as well as be invested in a greater number of companies. Overconfidence is also more prevalent in the less anxious and the more attentive retail investor.

Note that the smaller sample (of 378 respondents) shows a similar pattern to that shown in the larger sample (of 427 respondents). General education was not significant in the smaller sample in any of the blocks. Anxiety was not significant in the final block for the smaller sample while lack of attention was not significant in the final two blocks for the smaller sample. In their place, hours spent on investments became significant in the final block. (See Table 71 in appendix A6).

8.3 Count of "don't know" (as a marker of underconfidence)

A hierarchical regression was undertaken with count of "don't know" as the dependent variable. Demographic variables (age; gender; marital status; education; financial education; and years of investor experience) were entered first. The second block consisted of three variables measuring investment practices (i.e., Natural log of C4: Hours spent on investments; Natural log of C18: Companies followed; and Natural log of C19: Companies in portfolio). The third block included personality variables (i.e., anxiety; along with the three dimensions of impulsivity [i.e., lack of attention; lack of planning; and motor activity]). The final block included July effect, appetite for financial risk, and information sources). Note that, once again, gender and marital status were introduced to the model as 'dummy variables'.

The standardized beta weights and change statistics can be found in Tables 49 and 50 respectively. Once again, intercept statistics have not been reported.

The results shown in Tables 49 and 50 are based on a sample of 427 retail (and previously ungrouped) investors. Based on the findings of the second and fourth discriminant analyses, it would appear that these investors are also retail investors. For comparison purposes, appendix A6 provides the same findings using the sample of 378 retail investors alone.

Once again, research hypothesis 4(c) has been partially supported. Three of the six variables in the first block made a significant contribution to the prediction of count of "don't know". However, only one of those variables remained when the three variables of the second block were introduced into the model. Financial education and natural log of companies followed made a significant contribution from the second block through to the final block. None of the four variables in the third block made a significant contribution to the model. Only appetite for financial risk made a significant contribution to the contribution of count of "don't know" in the final block. The first two blocks made significant contributions to the prediction of the count of "don't know". However, the remaining two blocks did not. See Table 50. The final model was significant (R^2 *adjusted* = .26; $F_{16,\ 312}$ = 8.11; p < .001). Count of "don't know" (as a marker of underconfidence) could be predicted by (a) financial education; (b) natural log of companies followed; and (c) appetite for financial risk. See Table 49. More specifically, retail investor underconfidence was more likely to the extent that they had lesser financial education, monitored fewer companies but had an appetite for financial risk.

Note that, once again, the smaller sample (of 378 respondents) shows a similar pattern to that shown in the larger sample (of 427 respondents). The only difference between the smaller and larger samples was that of marital status, which was not significant in the first block for the smaller sample. (See Table 72 in appendix A6).

Table 49 *Standardized Beta Weights for the Square Root Count of "Don't Know"*

Variables	**Block 1**	**Block 2**	**Block 3**	**Block 4**
Block 1: Demographic variables:				
Age	.00	-.05	-.06	-.04
Gender	.13*	-.01	-.01	-.03
Marital status	-.11*	-.08	-.07	-.07
Education	.06	.03	.03	.04
Financial education	-.29***	-.20***	-.20***	-.20***
Years of investor experience	-.08	-.01	-.01	-.01
Block 2:				
Natural log of C4: Hours spent on investments		-11	-.11	-.11
Natural log of C18: Companies followed		-.32***	-.32***	-.32***
Natural log of C19: Companies in portfolio		-.01	-.01	-.00
Block 3: Personality variables:				
Anxiety			.09	.09
Lack of attention			.06	.06
Lack of planning			-.05	-.05
Motor activity			-.08	-.10
Block 4: Behavioral practices:				
July effect				-.08
Information sources				.03
Appetite for financial risk				0.12*

*** $p < .001$ ** $p < .01$ * $p < .05$

Table 50 *Hierarchical Regression Fit Statistics for Count of "Don't Know"*

					Change Statistics				
Model	R	R^2	Adj R^2	SE	R^2 Change	F Change	df_1	df_2	Sig. F Change
Block 1	.39	.15	.14	1.38	.15	9.74	6	322	.000
Block 2	.52	.27	.25	1.29	.11	16.20	3	319	.000
Block 3	.53	.28	.25	1.28	.02	1.67	4	315	.157
Block 4	.54	.29	.26	1.28	.01	1.92	3	312	.127

Variables entered in block 1: (a) age; (b) gender; (c) marital status; (d) education; and (e) financial education.
Variables added in block 2: (a) C4: Hours spent on investments; (b) C18: Companies followed; and (c) C19: Companies in portfolio.
Variables added in block 3: (a) Anxiety; (b) lack of attention; (c) lack of planning; and (d) motor activity.
Variables added in block 4: (a) July effect; (b) information sources; and (c) appetite for financial risk.
Dependent Variable: Square root of count of "don't know" as a marker of underconfidence

8.4 Conclusion

Table 51 provides a summary of the variables that predict level of overreaction, overconfidence and underconfidence. Table 51 shows that level of overreaction in retail investors can be jointly predicted by tendency towards the July effect as well as appetite for financial risk.

As can be seen from Table 51, overconfidence can be predicted by (a) age; (b) education; (c) financial education; (d) number of companies followed; (e) number of companies in the investment portfolio; (f) anxiety; (g) lack of attention (the first dimension of impulsivity); and (h) the July effect. More specifically, retail investor overconfidence is more prevalent the younger and less educated the investor. Overconfidence, in retail investors, is also more prevalent the less anxious and the more focused the investor. Overconfidence in retail investors is also more prevalent when investors has greater levels of financial education, follows more companies and is invested in more companies. Finally, overconfidence in retail investors is also more prevalent when investors also engage in practices commonly associated with the July effect.

Table 51 also shows that count of "don't know" (as a marker of underconfidence) can be predicted by financial education, number of companies followed and appetite for financial risk. The first two variables also contribute to the prediction of overconfidence. Not surprisingly, the greater the financial education, the more likely the retail investor was to be overconfident and the less likely they were to be underconfident. Similarly, the greater the number of companies followed, the more likely the retail investor was to be overconfident and the less likely the investor was to be underconfident. Surprisingly, the greater the appetite for financial risk, the more likely the investor was to be underconfident.

The findings of the fourth research questions are discussed in sections 10.6. The next chapter provides the structural equation models for defensive shares, growth shares; cyclical shares and asset/turnarounds. The models are, once again, based on the sample of retail investors only.

Table 51 *Hierarchical Regression Equations for Overreaction, Overconfidence and Count of "Don't Know" (using Standardized Beta Weights)*

	Over-reaction	Over-confidence	Count of "Don't Know
Age	.06	-0.17*	-.04
Gender	-.01	-.08	-.03
Marital status	.07	.02	-.07
Education	.06	-0.16*	.04
Financial education	-.07	0.22***	-.20***
Years of investor experience	-.03	.08	-.01
Natural log of C4: Hours spent on investments	.10	.13	-.11
Natural log of C18: Companies followed	.09	0.20**	-0.32***
Natural log of C19: Companies in portfolio	-.04	0.14*	-.00
Anxiety	-.01	-0.15*	.09
Lack of attention	.09	-0.15*	.06
Lack of planning	-.03	-.04	-.05
Motor activity	.02	.10	-.10
July effect	0.40***	.05	-.08
Information sources	.07	.02	.03
Appetite for financial risk	0.11*	.03	0.12*
R^2	0.34	0.37	0.29
R^2 Adjusted	0.31	0.33	0.26

*** $p < .001$ ** $p < .01$ * $p < .05$

Chapter 9 Modeling Retail Investor Behavior in the Share Market

9.1 Introduction

This chapter reports the results of the structural equation modeling of investor behavior in the share market. In so doing, this chapter answers the final objective of this thesis. The structural equation model uses the retail (and ungrouped) investor sample alone, that is, a sample of 427 cases.

9.2 Hypothesized model fit for retail investor behavior in the share market

Structural equation modeling was performed through AMOS Graphics. The hypothesized model of retail investor behavior had a chi squared value of 933.6 (df = 127, $p < .001$). This suggests that the hypothesized model demonstrated poor fit in relation to the data. Additional fit statistics confirmed the poor fit (CFI = .55; TLI = .25; $RMSEA$ = .12). See Figure 23, (reproduced from Figure 3).

One hundred and three parameters were fitted by the model. When fitting a separate model for defensive shares, growth shares, cyclical shares and asset/turnarounds, each model would fit eighty-five parameters. As AMOS uses full information maximum likelihood (FIML) estimation when there is missing data, the number of parameters estimated included those of means and intercepts.

When using FIML estimation in AMOS, modification indices and residual matrices become unavailable. It was therefore decided to introduce segments of the model in turn, starting with variables that contained complete data and progressively stepping down the sample size as other variables are entered into the model. Table 11, provided towards the end of chapter 4, shows the order in which variables were introduced into the model. This process was continued for the first three steps of model testing. (See Figures 24 to 27). The final two steps of the model-testing used FIML.

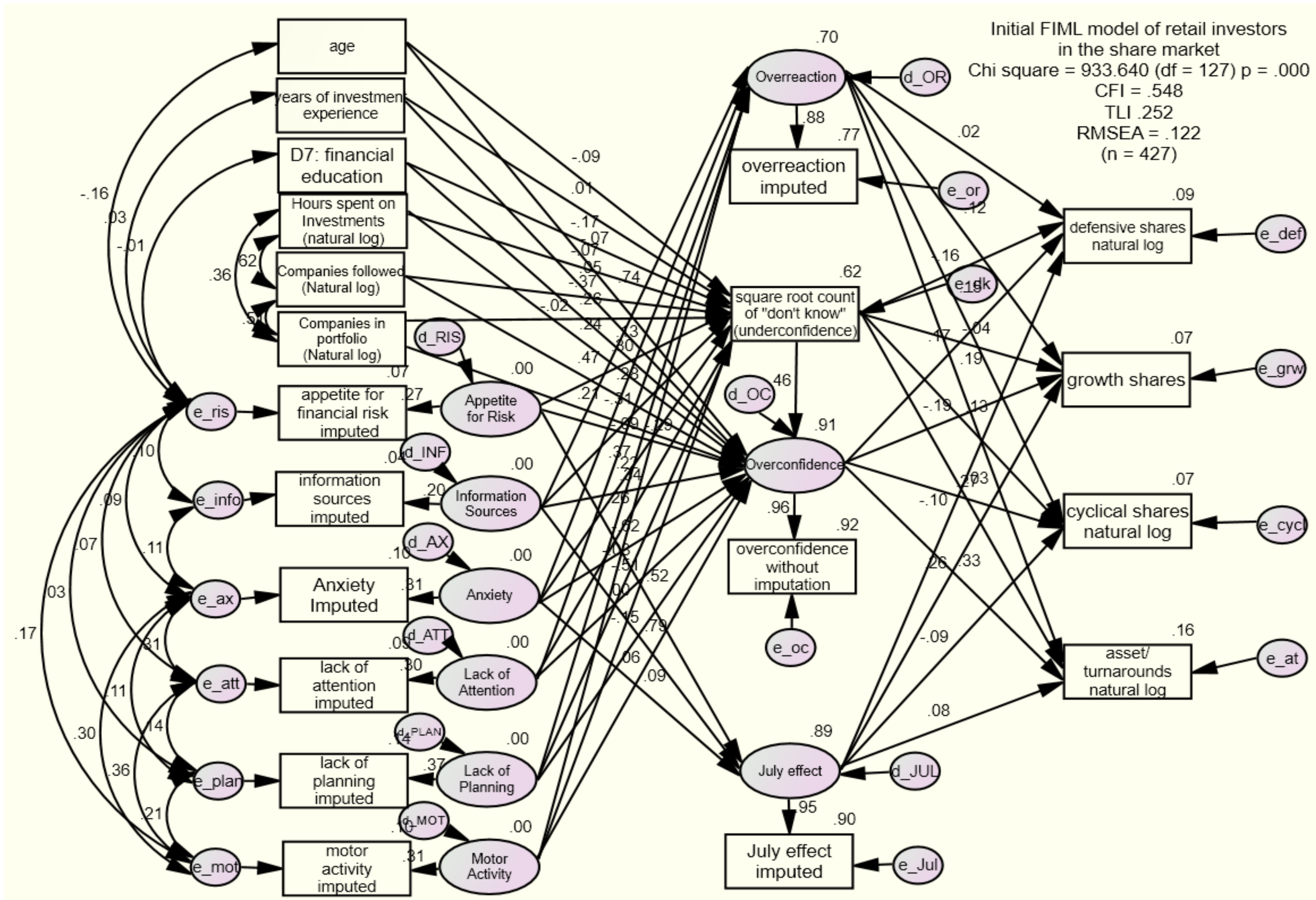

Figure 23. The hypothesized structural equation model of retail investor behavior in the share market.

(n = 427).

9.3 First model fit --- Six scales and underconfidence

The first model fit was fitted using the six scales with imputed data, along with the count of "don't know" as a marker of underconfidence; that is, (a) overreaction; (b) count of "don't know", as a marker of underconfidence; (c) July effect; (d) appetite for financial risk; (e) information sources; (f) anxiety; and (g) the three dimensions of impulsivity (i.e., (a) lack of attention; (b) lack of planning; and (c) motor activity). Note that overconfidence (without imputation) was not included in the model at this stage of model testing. It will be considered as part of the fourth and final steps of model testing, when full information maximum likelihood (FIML) estimation will be used. This component of the model thus drew on those variables that contained complete data and was based on a sample of 427 cases. Note that a square root transformation of count of "don't know" had been performed prior to structural equation modeling.

For this component of the model, it was hypothesized that overreaction could be predicted by (a) information sources; (b) anxiety; and (c) the three dimensions of impulsivity. All three variables were expected to have positive beta weights for overreaction. See hypothesis 5_a.

This component of the model, also hypothesized that the count of "don't know" as a marker of underconfidence could be predicted by (a) appetite for financial risk; (b) information sources; (c) anxiety; and (d) the three dimensions of impulsivity. Appetite for financial risk, information sources and the three dimensions of impulsivity were expected to have negative beta weights with the count of "don't know" as a marker of underconfidence. It was also expected that anxiety would have a positive beta weight with the count of "don't know" as a marker of underconfidence. See hypothesis 5_c.

It was further hypothesized that the July effect could be predicted by (a) appetite for financial risk; (b) information sources; and (c) anxiety. All three variables were expected to have positive beta weights with the July effect. See hypothesis 5_d.

This component of the model initially had a poor fit to the data. (*Chi squared* = 85.88; *df* = 13; $p < .001$). Fit statistics were poor (*CFI* = .84; *TLI* = .56; *RMSEA* = .12).

Examination of the standardized residual matrix highlighted twelve standardized residuals in excess of 1.96. The non-zero residual values were associated with overreaction, July effect, appetite for financial risk; information sources, anxiety, along with the first and third dimension of impulsivity (i.e., lack of attention and motor activity). With residual values approaching zero for count of "don't know" as a marker of underconfidence and lack of planning (the second dimension of impulsivity), it might be assumed that both variables were well explained by the model.

Examination of the modification indices suggested a number of pathways and covariances that could be introduced to the model. Table 52 shows the suggested pathways and covariances, along with their modification indices and/or standardized residual values. Standardized residual values less than 1.96 were not reported in Table 52. They were left blank.

It is interesting to note that the modification indices provide suggestions for both latent variables and manifest variables. The residual matrices consider the manifest variables alone. So, it is possible for pairs of latent variables to already be fitted by the model while the modification indices and/or the residual values highlight potential pathways or covariances between their manifest counterparts. For the sake of simplicity, and as doing so would not make theoretical (or indeed logical) sense, these recommendations have not been included in Table 52.

One might expect appetite for financial risk to predict overreaction. Indeed, having an appetite for financial risk, by its very nature, may lead investors to invest in more volatile share investments. If those same investments were to perform poorly later on, investors could conceivably overreact over that poor performance. One might also expect that those who are inclined to engage in the July effect may demonstrate a lack of attention to their investments throughout the financial year. One might also expect information sources to be related to the three dimensions of impulsivity (i.e., (a) lack of attention; (b) lack of planning; and (c) motor activity). Thus, two pathways and three associations were included in the model. They have been highlighted in italics. See Table 52.

Table 52 *Parameter Modifications to Six Scales and Underconfidence Section of Model*

Recommended pathways		**Modification indices**	**Standardized residual values**
Appetite for financial risk	*Overreaction**	*13.37*	*5.90*
Lack of attention	*July effect*	*6.91*	*3.79*
Motor activity	July effect		2.23
Lack of attention	Appetite for financial risk	4.44	
Recommended Associations			
Appetite for financial risk	Overreaction	10.59	5.90
Information sources	*Lack of attention*	*7.96*	*2.94*
Information sources	*Lack of planning*	*7.04*	
Information sources	*Motor activity*	*11.53*	*3.83*

* italicized pathways and associations were introduced into model (n = 427)

Examination of the residual matrix revealed the presence of seven remaining coefficients in excess of 1.96. Six of the seven coefficients relate to existing pathways in the model. They have consequentially not been considered. Examination of the modification indices showed a number of further potential pathways and associations. Once again, when the modification indices and/or residual values highlight potential pathways or associations between pairs of manifest variables (and a pathway has already been fitted between the accompanying pairs of latent variables), they were not considered. Table 53 highlights potential pathways and associations not yet included in the model.

As can be seen from Table 53, the modification indices highlighted potential pathways to both appetite for financial risk, and information sources. A potential pathway from motor activity (the third dimension of impulsivity) to the July effect was also highlighted. In a model of investor behavior, it would be of more interest to predict appetite for financial risk than it would to predict information sources. It also makes theoretical sense for anxiety and the three dimensions of impulsivity to predict appetite for financial risk. Moreover, the demographic variables entered into the model during the second step of model testing, might also be expected to influence appetite for financial risk. It was thus decided to refit the model, placing appetite for financial risk alongside overreaction, count of “don’t know” (and ultimately overconfidence) and the July effect. Thus, five pathways to appetite for financial risk were included in the model. The five pathways included the three highlighted in Table 53 (i.e., from information sources, anxiety and lack of attention). Recall that lack of attention is the first dimension of impulsivity. The remaining two dimensions of impulsivity (i.e., lack of planning and motor activity) were also included in the model.

Table 53 *Additional Parameter Modifications in First Step of Model Testing*

Recommended pathways		**Modification indices**	**Standardized residual values**
Motor activity	July Effect		2.22
Information sources	*Appetite for financial risk**	*4.02*	
Anxiety	*Appetite for financial risk*	*4.88*	
Lack of attention	*Appetite for financial risk*	*8.81*	
Appetite for financial risk	Information sources	7.97	
Anxiety	Information sources	4.84	
Lack of attention	Information sources	6.32	
Recommended Associations			
Nil			

* italicized pathways and associations were introduced into model (n = 427)

No further parameters could be estimated. Thus, the next step in model testing was to consider whether each of the parameters in the model were significant. Examination of the critical ratios showed that seven of the pathways were not significant. All covariances were significant. Thus the seven non-significant pathways were removed from the model. With modification, this step of the model provided a reasonable fit to the data. (*Chi squared* = 37.8; df = 18; p = .004; *CFI* = .96; *TLI* = .92; *RMSEA* = .05).

The initial component of the model estimated 27 parameters. Seventy percent of the variance in overreaction was explained by the model. Sixty-five percent of the variance in the count of "don't know" was explained by the model. Ninety percent of the variance in the July effect was explained by the model and eighty-six percent of the variance in appetite for financial risk was explained by the model. See Figure 24.

It was originally hypothesized that overreaction could be predicted by information sources, anxiety and the three dimensions of impulsivity (i.e., (a) lack of attention; (b) lack of planning; and (c) motor activity). It was also predicted that they would have a positive beta weight with overreaction. See hypothesis 5_a. As can be seen from Figure 24, information sources along with the first and third dimensions of impulsivity (i.e., lack of attention and motor activity) contributed to the prediction of overreaction in the expected direction. Anxiety and lack of planning (the second dimension of impulsivity) were unable to significantly contribute to the prediction of overreaction.

It was also hypothesized that the count of "don't know" could be predicted by (a) appetite for financial risk; (b) information sources; (c) anxiety; and (d) the three dimensions of impulsivity. Three of the hypothesized variables were expected to show negative beta weights (appetite for financial risk, information sources, and the three dimensions of impulsivity) while the fourth (anxiety) was expected to show a positive beta weight with this variable. See hypothesis 5_c. Only two of the four predicted pathways were shown to be significant (i.e., information sources and anxiety). They were both in the expected direction. Note that before appetite for financial risk was repositioned in the model, it did show a significant pathway to count of "don't know" albeit not in the predicted direction.

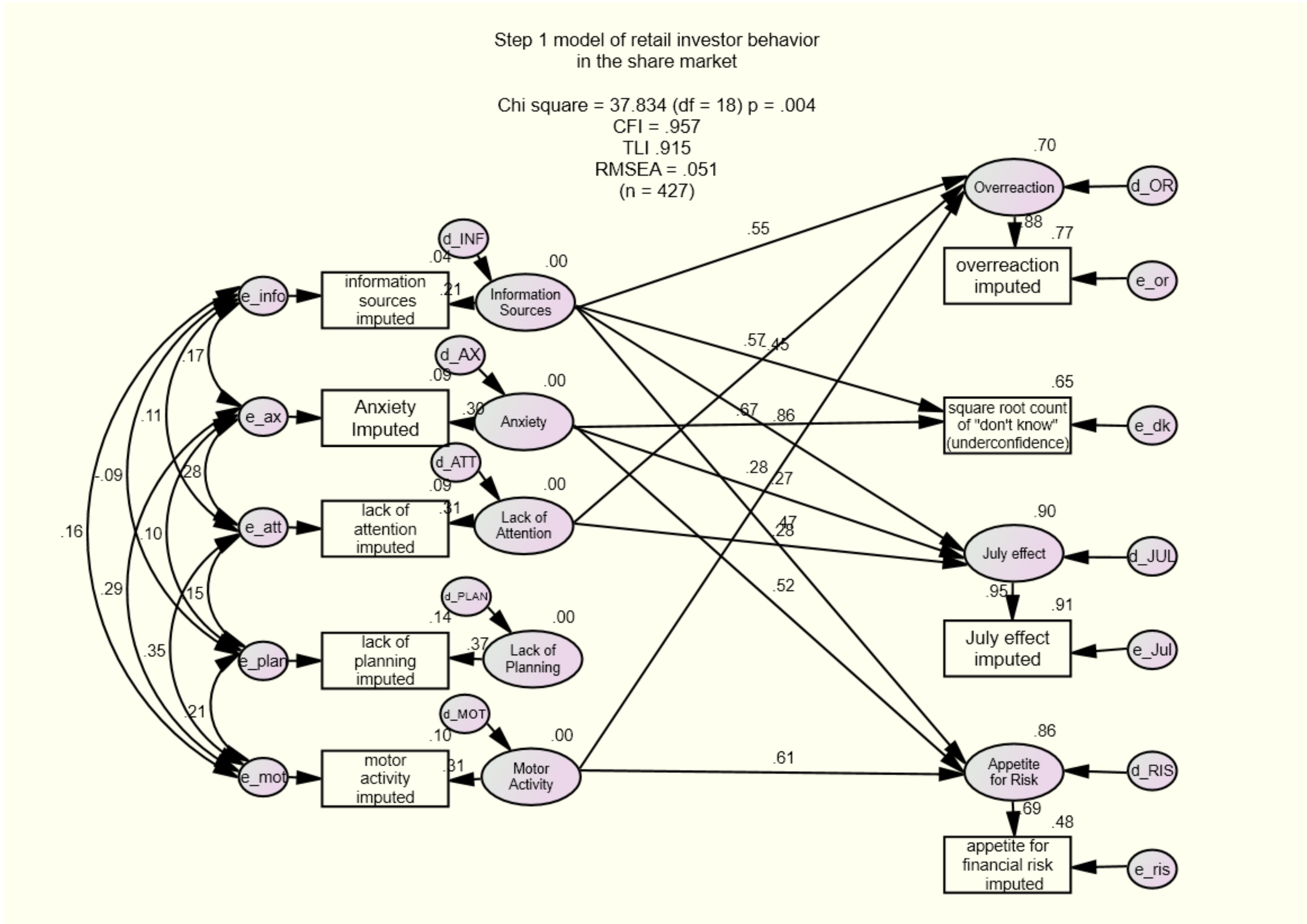

Figure 24. Step 1: Introducing variables with complete data into model of retail investor behavior in the share market. (n = 427).

It was hypothesized that July effect could be predicted by (a) appetite for financial risk; (b) information sources; and (c) anxiety. All three were expected to show positive beta weights with the July effect. See hypothesis 5_d. Two of the three hypothesized pathways (i.e., information sources and anxiety) were significant and in the expected direction. Moreover, before appetite for financial risk was repositioned in the model, it showed a significant pathway to the July effect and in the expected direction. In addition to the hypothesized pathways, lack of attention (the first dimension of impulsivity) was also shown to significantly contribute to the prediction of the July effect. The direction of its beta weight with the July effect was positive.

Finally, no hypotheses were formulated regarding appetite for financial risk. However, as this variable had been repositioned in the model as part of this step of model testing, it is interesting to note that information sources, anxiety and the third dimension of impulsivity (i.e., motor activity) contributed to the prediction of appetite for financial risk. Their beta weights were all positive.

9.4 Second model fit --- Introducing three demographic variables into model

Figure 24 was then extended to include three demographic variables (age, years of investment experience and financial education). In order to retain access to the modification indices and residual matrices, a smaller sample (n = 377) was used.

No hypotheses were formulated regarding these three variables with either overreaction, the July effect or appetite for financial risk.

It was hypothesized that age, financial education and years of investor experience could contribute to the prediction of the count of “don’t know” as a marker of underconfidence. Moreover, it was hypothesized that age would show a positive beta weight with the count of “don’t know” as a marker of underconfidence, while the latter two variables would show a negative beta weight. See hypothesis 5_c.

Thus, the model was initially fitted with those retained from the previous step, along with the hypothesized pathways for the three demographic variables. Moreover, prior to appetite for financial risk being repositioned in the model as part of step 1, it was fitted with associations to the three demographic variables. Consequently, the model was initially fitted by translating those associations into pathways to appetite for financial risk. Initial fit statistics indicated that this portion of the model was not a good fit to the data. (*Chi squared* = 236.7; *df* = 43; $p < .001$; *CFI* = .69; *TLI* = .53; *RMSEA* = .11).

Examination of the standardized residual matrix highlighted the presence of sixteen standardized residual values in excess of 1.96. Examination of the modification indices highlighted many potential pathways and covariances. Once again, modification indices and/or residual values that highlighted potential pathways or associations between pairs of manifest variables (when a pathway had already been fitted between the accompanying pairs of latent variables), were not reported in Table 54. The modification indices identified eleven potential pathways. Of them, it only made theoretical sense for financial education to contribute to the prediction of July effect. This pathway was therefore introduced into the model. See Table 54.

The modification indices also recommended nine covariances. Five of the recommended covariances were also recommended as potential pathways. While it was of no theoretical interest to make predictions about these variables, it did make theoretical sense that the nine pairs of variables might be associated. The nine covariances were therefore included into the model. The introduced pathway and nine covariances have been highlighted in Table 54.

Table 54 *Parameter Modifications with Three Demographic Variables Included in Model*

Recommended pathways		**Modification indices**	**Standardized residual values**
Financial education	Overreaction		2.04
Anxiety	Overreaction		2.20
Financial education	*July effect**	*6.02*	*3.72*
Lack of attention	Risk		2.28
Age	Information sources	5.49	-3.20
Financial education	Information sources	15.08	3.33
Age	Anxiety	10.27	-4.22
Years experience	Anxiety	7.20	-2.90
Years experience	Lack of attention	5.00	
Age	Motor activity	6.20	-3.56
Years experience	Motor activity	6.23	-2.71
Recommended associations			
Age	*Years experience*	*87.92*	*9.38*
Age	*Financial education*	*9.54*	*-3.09*
Age	*Information sources*	*5.49*	*-3.20*
Financial education	*Information sources*	*9.67*	*3.33*
Age	*Anxiety*	*10.27*	*-4.22*
Years experience	*Anxiety*	*7.20*	*-2.90*
Years experience	*Lack of attention*	*5.00*	
Age	*Motor activity*	*6.20*	*-3.56*
Years experience	*Motor activity*	*6.23*	*-2.71*

* italicized pathways and associations were introduced into (n = 377)

No further parameters could be fitted. Examination of the critical ratios identified three non-significant pathways. These were removed from the model. With modification, step 2 of the model was a reasonable fit to the data. (C*hi squared* = .57.6; *df* = 36; *p* = .013; *CFI* = .97; *TLI* = .94; *RMSEA* = .04).

This component of the model was estimated with 42 parameters. Sixty-eight percent of the variance in overreaction was explained by the model. Sixty-one percent of the variance in the count of "don't know" was explained by the model. Eighty-nine percent of the variance in the July effect was explained by the model. Eighty-seven percent of the variance in appetite for financial risk was explained by the model. See Figure 25.

No hypotheses were originally formulated regarding age, financial education and years of investor experience on overreaction. The model did not fit a pathway from either of these variables to overreaction.

It was originally hypothesized that age, financial education and years of investor experience would have significant pathways to count of “don’t know” as a marker of underconfidence. Moreover, it was expected that age would show a positive beta weight, while the remaining two variables would show negative beta weights with this variable. See hypothesis 5_c. Age did not have a significant beta weight to count of “don’t know” as a marker of underconfidence, but the remaining two variables did have significant pathways to the count of “don’t know”. Those pathways were in the expected direction.

No hypotheses were originally formulated regarding age, financial education and years of investor experience on the July effect. However, financial education proved to have a significant pathway to the July effect. The direction of the pathway was positive.

No hypotheses were originally formulated regarding appetite for financial risk. With this variable’s repositioning in the model, it would be of interest to note whether there were significant pathways for these variables to appetite for financial risk. Age proved to have a significant negative pathway to appetite for financial risk.

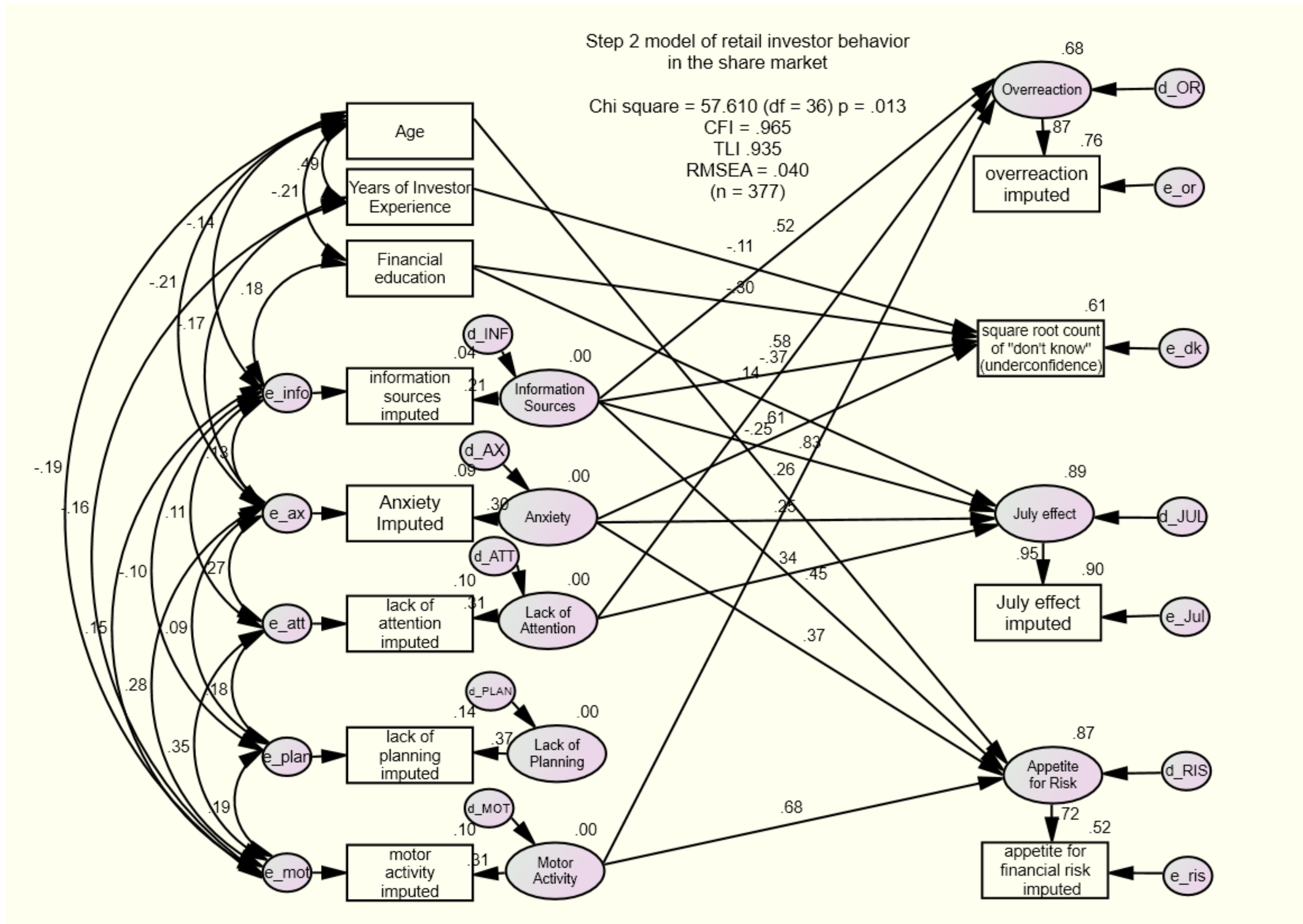

Figure 25. Step 2: Introducing three demographic variables into model of retail investor behavior in the share market. (n = 377)

9.5 Third model fit – Three further variables

Figure 25 was extended by introducing hours spent on investments, companies followed and number of companies in the investment portfolio. Once again, the sample size was reduced (n = 329) in order to retain access to the modification indices and residual matrices.

No hypotheses were formulated regarding overreaction, the July effect or appetite for financial risk for this component of the model. It was, however, hypothesized that all three variables would show significant negative beta weights with the count of "don't know" as a marker of underconfidence. See hypothesis 5_c.

Initial fit statistics were poor. (*Chi squared* = 217.98; *df* = 69; $p < .001$; *CFI* = .84; *TLI* = .76; *RMSEA* = .08).

Examination of the residual matrix highlighted the presence of 24 residual values in excess of 1.96. Seven of the 24 residual values were related to pathways already fitted in the model. They were therefore not reported in Table 55. A number of potential pathways and covariances were also identified. Five of the potential pathways were of theoretical interest. One might expect the greater number of companies monitored and/or invested in, along with the greater the amount of time spent on one's investments, the greater the likelihood that the investor might overreact or engage in the July effect when investments do not perform the way the investor might hope. The five pathways italicized in Table 55 were therefore introduced into the model. Finally, one might expect hours spent, companies followed and companies in portfolio to be related to years of investment experience and financial education. It is also conceivable that the number of hours spent and companies followed might be related to lack of attention. One might also expect that as one ages, one might have accrued increasingly more investments in the portfolio. Thus, the ten italicized associations shown in Table 55 were also introduced into the model. See Table 55.

Table 55 *Parameter Modifications with Inclusion of Three Further Variables in Model*

Recommended pathways		**Modifica-tion indices**	**Standardized residual values**
Hours spent	*Overreaction**	*9.15*	*5.96*
Companies followed	*Overreaction*	*8.41*	*5.62*
Companies in portfolio	Overreaction		2.52
Hours spent	*July effect*	*11.90*	*7.16*
Companies followed	*July effect*	*10.84*	*6.54*
Companies in portfolio	*July effect*	*10.80*	*4.54*
Hours spent	Appetite for financial risk		2.14
Lack of attention	Appetite for financial risk		2.01
Hours spent	Information sources	45.91	4.86
Companies followed	Information sources	37.97	5.06
Companies in portfolio	Information sources	18.83	
Hours spent	Lack of attention	24.11	
Companies followed	Lack of attention	23.96	
Recommended associations			
Years investment experience	July effect	4.11	
Hours spent	*Years investment experience*		*2.38*
Companies followed	*Years investment experience*		*4.01*
Companies in portfolio	*Years investment experience*	*5.55*	*4.89*
Hours spent	*Financial education*	*10.18*	*6.16*
Companies followed	*Financial education*		*5.53*
Companies in portfolio	*Financial education*		*2.50*
Hours spent	*Information sources*	*14.06*	*4.86*
Companies followed	*Information sources*		*5.06*
Hours spent	*Lack of attention*	*6.13*	
Companies followed	*Lack of attention*	*5.84*	
Companies in portfolio	Age		2.62

* italicized pathways and associations were introduced into (n = 329)

No further parameters could be fitted. Examination of the critical ratios identified three non-significant pathways and three non-significant associations. They were removed from the model. With modification, step 3 of the model was a reasonable fit to the data. (*Chi squared* = 61.85; *df* = 58; *p* = .34; *CFI* = 1.0; *TLI* = .99; *RMSEA* = .01).

This component of the model was fitted with 62 parameters. Sixty-seven percent of the variance in overreaction was explained by the model. Fifty-four percent of variance in underconfidence was explained by the model. Eighty-nine percent of the variance in the July effect was explained by the model. Eighty-four percent of the variance in appetite for financial risk was explained by the model. See Figure 26.

No hypotheses were initially formulated for overreaction regarding hours spent, companies followed or companies in portfolio. However, both hours spent and companies followed proved to have significant positive betas weights with overreaction.

It was hypothesized that all three variables would show significant negative beta weights with the count of "don't know" as a marker of underconfidence. See hypothesis 5_c. Two of the three hypothesized pathways had significant beta weights and they were in the expected direction. Companies in portfolio did not have a significant beta weight with the count of "don't know" as a marker of underconfidence.

No hypotheses were initially formulated on the July effect regarding hours spent, companies followed or companies in portfolio. However, all three showed significant positive beta weights with the July effect. Hypotheses were also not formulated regarding these three variables on appetite for financial risk. No pathways between any of these variables were introduced into the model.

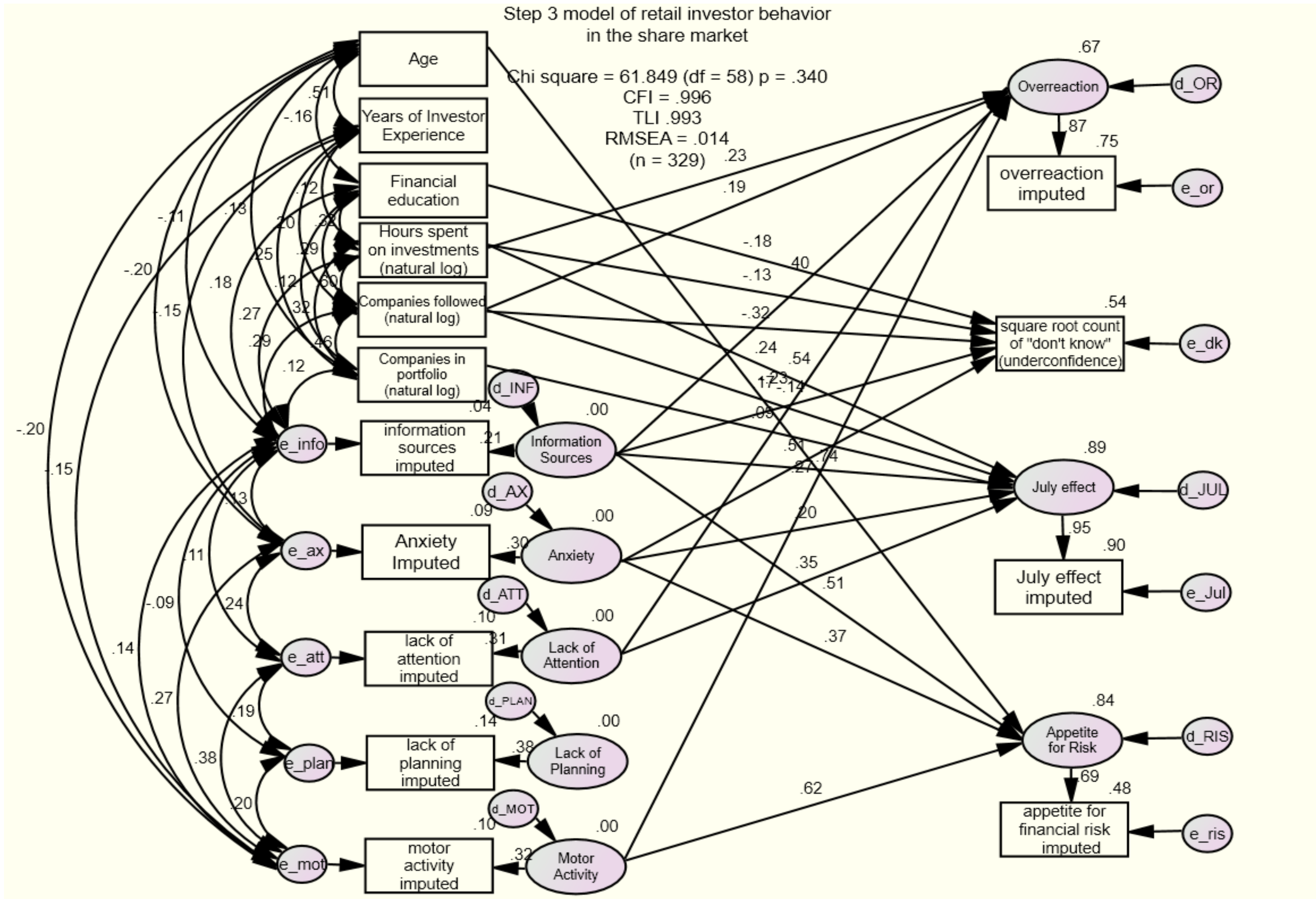

Figure 26. Step 3: Introducing three further variables into model of retail investor behavior in the share market. (*n* = 329)

9.6 Fourth model fit --- Including overconfidence without imputation into model

Figure 26 was extended to include overconfidence. Due to the extent of missing data, it was decided to use this variable in its original form, that is, without the benefit of imputation. As there would now be missing data, the model was fitted using full information maximum likelihood estimation (FIML). Consequently, information normally available through the modification indices and residual matrices were no longer available for this or the final step of model testing.

It was hypothesized that ten predictors would contribute to the prediction of overconfidence. More specifically, it was expected that (a) financial education, (b) years of investor experience; (c) hours spent on investments; (d) companies followed; (e) companies in portfolio; (f) appetite for financial risk; (g) information sources; and (h) the three dimensions of impulsivity (i.e., lack of attention; lack of planning and motor activity) would have positive beta weights with overconfidence. It was also expected that (a) age; and (b) anxiety would have negative beta weights with overconfidence. See hypothesis 5_b.

Initial fit statistics showed the model to be a good fit to the data. (*Chi squared* = 106.3; *df* = 64; *p* = .001; *CFI* = .97; *TLI* = .93; *RMSEA* = .04). Examination of the critical ratios identified seven non-significant pathways and one non-significant covariance. They were removed from the model. The model remained a good fit to the data (*Chi squared* = 134.4; *df* = 72; *p* < .001; *CFI* = .95; *TLI* = .91; *RMSEA* = .05).

This component of the model was fitted with 80 parameters. Seventy percent of the variance in overreaction was explained by the model. Ninety-two percent of the variance in overconfidence was explained by the model. Sixty-five percent of variance in underconfidence was explained by the model. Eighty-nine percent of the variance in the July effect was explained by the model. Ninety-three percent of the variance in appetite for financial risk was explained by the model. See Figure 27.

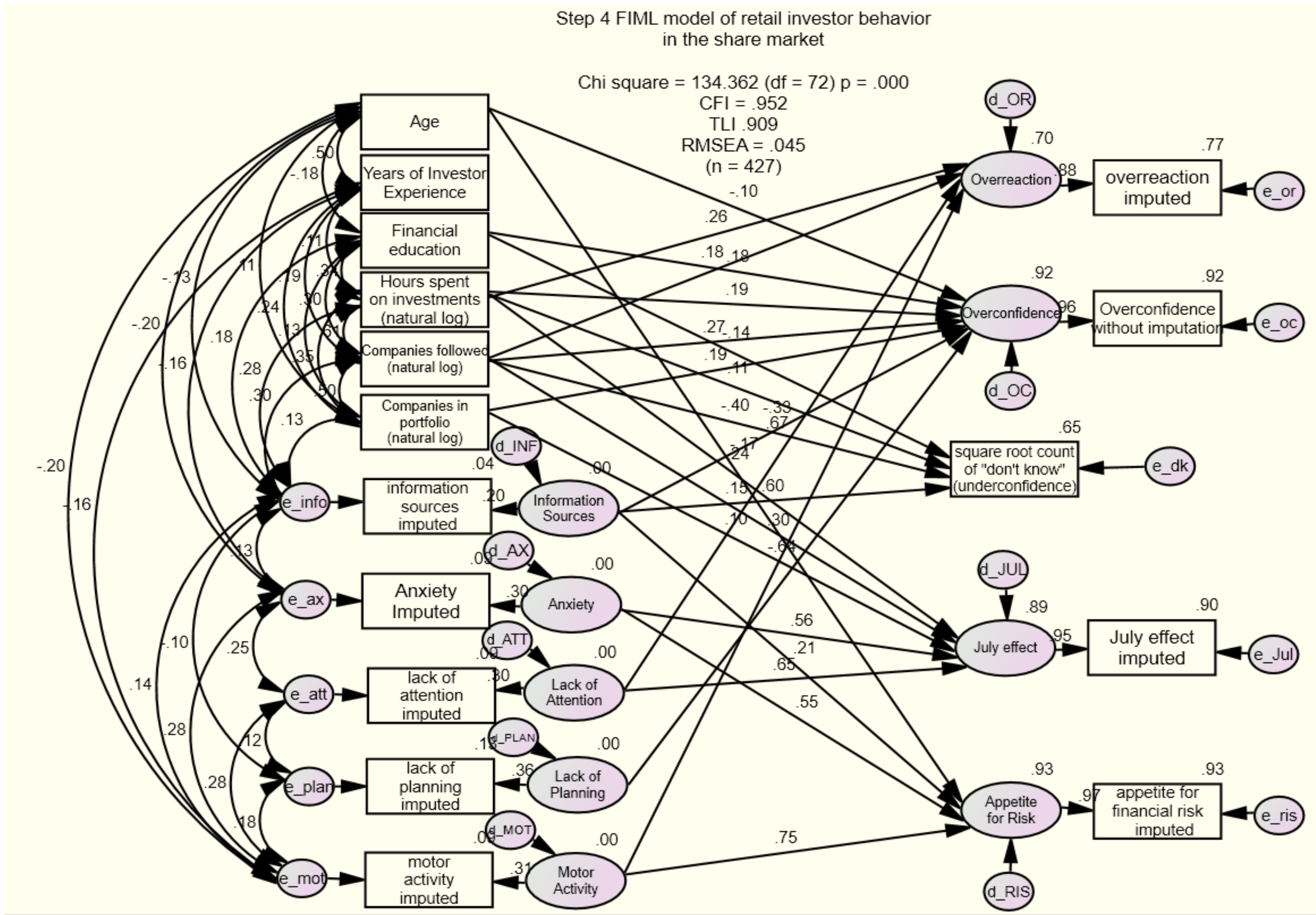

Figure 27. Introducing overconfidence (without imputation) into model of retail investor behavior in the share market. (n = 427)

It was hypothesized that ten variables would contribute to the prediction of overconfidence. More specifically, it was expected that (a) financial education; (b) years of investor experience; (c) C4: hours spent on investments; (d) C18: companies followed; (e) companies in portfolio; (f) appetite for financial risk; (g) information sources; and (h) the three dimensions of impulsivity (i.e., lack of attention, lack of planning and motor activity) would have positive beta weights with overconfidence. It was also hypothesized that (a) age; and (b) anxiety would have negative beta weights with overconfidence. See hypothesis 5_b.

Years of investment experience, anxiety, along with the first and third dimensions of impulsivity (i.e., lack of attention and motor activity) did not have significant pathways to overconfidence. Moreover, with the repositioning of appetite for financial risk in the model, this variable could no longer be fitted against that of overconfidence.

Of the remaining variables, five variables had significant pathways in the expected direction. As expected, age had a negative pathway to overconfidence. Also as expected, financial education, hours spent on investments, companies followed and companies in the portfolio had positive pathways to overconfidence. Information sources had a significant pathway to overconfidence. However, the direction of the pathway was not as predicted. Perhaps the more overconfident the investor becomes, the less they rely on information sources regarding their investments. Finally, lack of planning (the third dimension of impulsivity) had a significant pathway to overconfidence. However, the negative direction of the pathway was opposite to that expected. It would appear that the more overconfident the investor, the more they plan their investments.

It is interesting to note that with the inclusion of overconfidence in the model, three previously predicted pathways were now non-significant (i.e., information sources to overreaction, information sources to July effect and anxiety to count of “don’t know” as a marker of underconfidence).

It is interesting to note that four of the seven pathways to overconfidence also contributed to the prediction of the count of “don’t know” as a marker of underconfidence. As one might expect for two variables that demonstrate an inverse relationship to each other, the direction of the pathways to overconfidence were opposite to the direction of the pathways to the count of “don’t know” as a marker of underconfidence. Thus, financial education had a positive pathway to overconfidence and a negative pathway to the count of “don’t know” as a marker of underconfidence. Hours spent on investments and companies followed both had positive pathways to overconfidence and negative pathways to the count of “don’t know” as a marker of underconfidence. Finally, information sources had a negative pathway to overconfidence and a positive pathway to the count of “don’t know” as a marker of underconfidence.

9.7 Introducing model of investor behavior with defensive shares

Figure 27 was extended to predict investments in defensive shares. It was initially hypothesized that overreaction, overconfidence and July effect would all have negative pathways to defensive shares, while the count of “don’t know” as a marker of underconfidence would have a positive pathway to defensive shares. No hypothesis was formulated regarding appetite for financial risk on defensive shares. See hypothesis 5_e.

As hypothesized, the model was initially fitted showing pathways from overreaction, overconfidence, the count of “don’t know” as a marker of underconfidence and the July effect. While the initial model was not a good fit to the data (*chi squared* = 545.8; *df* = 85; $p < .001$; *CFI* = .66; *TLI* = .38; *RMSEA* = .11), 69 percent of the variance in defensive shares was explained by the model.

Three of the four hypothesized predictors had significant beta weights with defensive shares. However, only the direction of pathway from the July effect to defensive shares was in the expected direction. The pathway from the count of “don’t know” as a marker of underconfidence was not significant. It would appear that there are other variables that may help explain the variance in defensive shares.

As appetite for financial risk was repositioned in the model as part of step 1 of model testing, it was of interest to assess whether this variable can contribute to the prediction of defensive shares. One might expect investors with a preference for defensive shares to have more investment experience and to have built up a number of companies in their investment portfolio. One might also expect investors with a preference for defensive shares to research their investments, pay attention to their investments and plan their investments. It was therefore of interest to assess whether years of investor experience, companies in portfolio, information sources, the first two dimensions of impulsivity (i.e., lack of attention; and lack of planning) could contribute to the prediction of defensive shares. Fitting pathways from each of these variables to defensive shares led to improved model fit, albeit still not a good fit to the data. (*Chi squared* = 249.8; *df* = 79; *p* < .001; *CFI* = .87; *TLI* = .75; *RMSEA* = .07).

Examination of the critical ratios revealed that four variables did not have significant beta weights. Their pathways were therefore removed from the model. In so doing, the model became a good fit to the data. (*Chi squared* = 144.1; *df* = 83; *p* < .001; *CFI* = .96; *TLI* = .92; *RMSEA* = .04). One of the non-significant pathways removed from the model pertained to years of investor experience. As this variable no longer had any pathways emanating from it, this variable was also removed from the model. The model remained a good fit to the data. (*Chi squared* = 133.8; *df* = 73; *p* < .001; *CFI* = .95; *TLI* = .91; *RMSEA* = .04). See Figure 28.

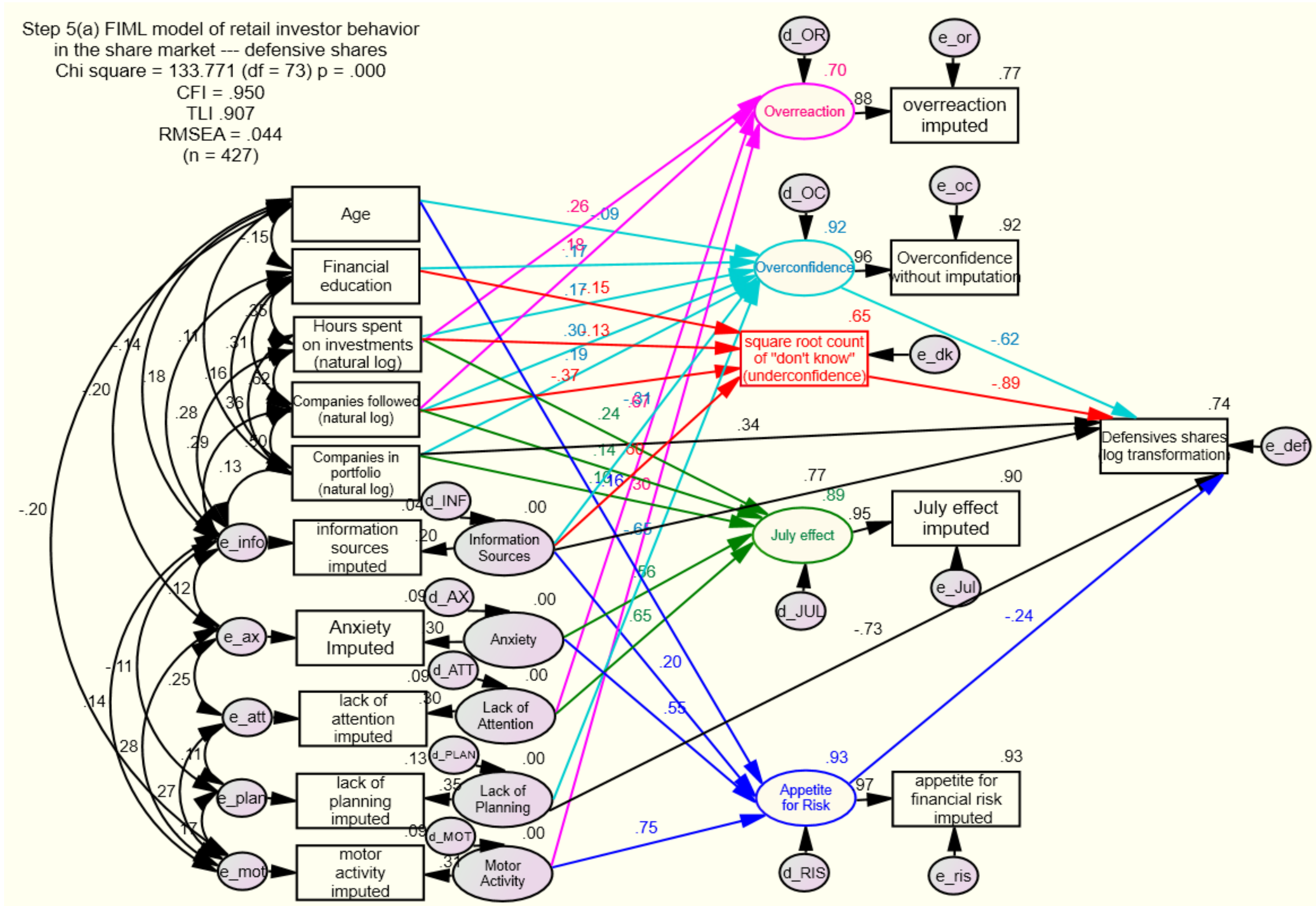

Figure 28. Model of retail investor behavior for defensive shares in the share market: standardized coefficients shown. (n = 427)

The Human Investor: The Profile of Retail and Institutional Investors, and a Structural Equation Model of Investor Behavior in the Share Market. A Thesis in Behavioral Finance (also known as economic psychology).

The model for defensive shares was fitted with 79 parameters. Seventy-four percent of the variance in defensive shares was explained by the model. It was originally hypothesized that overreaction, overconfidence, the count of "don't know" as a marker of underconfidence and the July effect would have significant pathways to defensive shares. It was also hypothesized that overreaction, overconfidence and the July effect would have negative pathways while the count of "don't know" as a marker of underconfidence would have a positive pathway to defensive shares. See hypothesis 5_e.

Of the four hypothesized pathways to defensive shares, only those for overconfidence and count of "don't know" were significant. Both predictors had negative pathways to defensive shares. The direction of the pathways was as hypothesized for overconfidence, but in the opposite direction to that predicted for the count of "don't know" as a marker of underconfidence. Overreaction and the July effect did not have significant pathways to defensive shares.

There were four further significant pathways to defensive shares: (a) companies in portfolio; (b) information sources; (c) lack of planning (the second dimension of impulsivity); and d) appetite for financial risk. The former two had positive pathways, while the latter two had negative pathways.

The six significant pathways to defensive shares reflect direct effects in the model. However, as can be seen in Figure 28, three of the variables that have direct pathways to defensive shares also have direct pathways leading to them (i.e., overconfidence, the count of "don't know" as a marker of underconfidence and appetite for financial risk). These three variables are both dependent and independent variables in the model for defensive shares. This gives rise to the possibility that there may be both direct and indirect effects in the model and the potential for these three variables to act as mediators in the model. Table 56 thus reports the direct, indirect and total effects for defensive shares. The significance levels of direct pathways reported in Table 56 has been provided. Figure 28 has been color coded so as to visually highlight the direct and indirect pathways to defensive shares.

Table 56 *Standardized Direct, Indirect and Total Effects for Defensive Shares*

	Direct effects	Indirect effects	Total effects
Age	.00	.10	.10
Financial education	.00	.03	.03
Years investment experience	.00	.00	.00
Hours spent	.00	.01	.01
Companies followed	.00	.14	.14
Companies in portfolio	.34***	-.12	.22
Overreaction	.00	.00	.00
Overconfidence	-.62***	.00	-.62
Count of "don't know" as a marker of underconfidence	-.89***	.00	-.89
July effect	.00	.00	.00
Appetite for financial risk	-.24***	.00	-.24
Information sources	.77***	-.39	.38
Anxiety	.00	-.13	-.13
Lack of attention	.00	.00	.00
Lack of planning	-.73***	.40	-.32
Motor activity	.00	-.18	-.18

*** $p < .001$ ** $p < .01$ * $p < .05$

As can be seen from Table 56, and as already known from Figure 28, there are negative direct effects from both count of "don't know" as a marker of underconfidence and overconfidence. As both variables are inversely related to defensive shares, one might conclude that investors who prefer defensive shares are neither particularly overconfident or underconfident. They may simply be confident investors. There were no direct effects (or indeed any effects) emanating from overreaction or the July effect on defensive shares.

As already known from Figure 28, companies in portfolio, appetite for financial risk, information sources and lack of planning (the second dimension of impulsivity) also have negative direct effects on defensive shares. See Table 56.

Information sources, lack of planning (the second dimension of impulsivity) and companies in portfolio have both direct and indirect effects on defensive shares. In each case, their pathways through overconfidence, the count of “don’t know” and/or appetite for financial risk temper their total effect on defensive shares. Finally, age, companies followed, anxiety and motor activity (the third dimension of impulsivity) have indirect effects on defensive shares, while financial education and hours spent on investments have negligible indirect effects on defensive shares. Years of investment experience did not have any effect on defensive shares. See Table 56.

Based on the direct effects shown in Table 56 and Figure 28, it would appear that investors who prefer defensive shares are neither overconfident nor underconfident. Nor do they have an appetite for financial risk. They seek information about, and plan, their many investments. In short, investors with a preference for defensive shares may be best described as ‘confident, conservative, informed and planful’.

9.8 Introducing model of retail investor behavior with growth shares

Figure 27 was extended to predict investments in growth shares. It was originally hypothesized that overreaction, overconfidence, the count of “don’t know” as a marker of underconfidence and the July effect would have significant pathways to growth shares. More specifically, it was hypothesized that both overconfidence and overreaction would have negative pathways to growth shares while the count of “don’t know” as a marker of underconfidence and the July effect would both have positive pathways to growth shares. No hypotheses were formulated regarding appetite for financial risk on growth shares. See hypothesis 5_f.

Pathways were therefore fitted from overreaction, overconfidence, the count of “don’t know” as a marker of underconfidence and the July effect to growth shares. The initial model fit to the data was poor. (*Chi squared* = 464.89; *df* = 85; $p < .001$; *CFI* = .71; *TLI* = .49; *RMSEA* = .10). The initial model for growth shares explained 65 percent of the variance in growth shares. Three of the four hypothesized predictors had significant pathways to growth shares. Two pathways were in the expected direction (overreaction and the July effect). However, the pathway emanating from overconfidence was in the opposite direction to that expected. The pathway from the count of "don't know" as a marker of underconfidence was not significant.

Once again, there may be other variables that may make a contribution to the prediction of growth shares. Moreover, as appetite for financial risk was repositioned in the model as part of the first step of model testing, it would be of interest to assess whether this variable can make a contribution to the prediction of growth shares. One might also expect an inverse relationship between financial education and growth shares, with those having increasingly greater financial education making use of their financial education by investing in riskier types of shares (cyclical shares and asset/turnarounds). Similarly, one might expect those with less financial education to be more timid in their investment activities, as well as making up for their lack of financial education in other ways. Thus, one might expect investors with a preference for growth shares to seek out more information, be more planful with their investments, be more anxious and have less desire to be physically active with their portfolio. One might also expect that if lack of attention plays a role, it might do so through an appetite for financial risk pathway.

These pathways were therefore fitted to the model. Doing so led to a good fit to the data. (*Chi squared* = 140.16; *df* = 78; $p < .001$; *CFI* = .95; *TLI* = .91; *RMSEA* = .04). Examination of the critical ratios revealed the presence of three non-significant pathways. They were removed from the model. As years of investor experience had no pathways emanating from it, this variable was removed from the model. Final model fit remained a good fit to the data . (*Chi squared* = 133.81; *df* = 71; $p < .001$; *CFI* = .95; *TLI* = .90; *RMSEA* = .05). See Figure 29.

The final model for growth shares was fitted with 81 parameters. This model explained 72 percent of the variance in growth shares. It was originally hypothesized that overreaction, overconfidence, the count of “don’t know” as a marker of underconfidence and the July effect would have significant pathways to growth shares. It was also expected that overreaction and overconfidence would show negative pathways to growth shares, while the count of “don’t know” as a marker of underconfidence and the July effect would show positive pathways. See hypothesis 5_f.

All four hypothesized variables were significant. Moreover, three of the four variables had pathways in the expected direction. As expected, overreaction had a negative pathway to growth shares. Also as expected, the count of “don’t know” as a marker of underconfidence and the July effect had positive pathways to growth shares. However, with a positive beta weight from overconfidence to growth shares, this pathway proved to be in the opposite direction to that expected.

Moreover, five other variables proved to have significant pathways to growth shares: Information sources, anxiety and motor activity (the third dimension of impulsivity) had negative pathways to growth shares. Moreover, lack of planning (the second dimension of impulsivity) and appetite for financial risk had positive pathways to growth shares.

Five of the nine variables with significant pathways to growth shares also had pathways leading to them. Table 57 thus reports the direct, indirect and total effects for growth shares. Once again, the significance levels for direct effects have been provided in Table 57. As with defensive shares, Figure 29 has been color coded so as to facilitate tracing the direct and indirect pathways to growth shares.

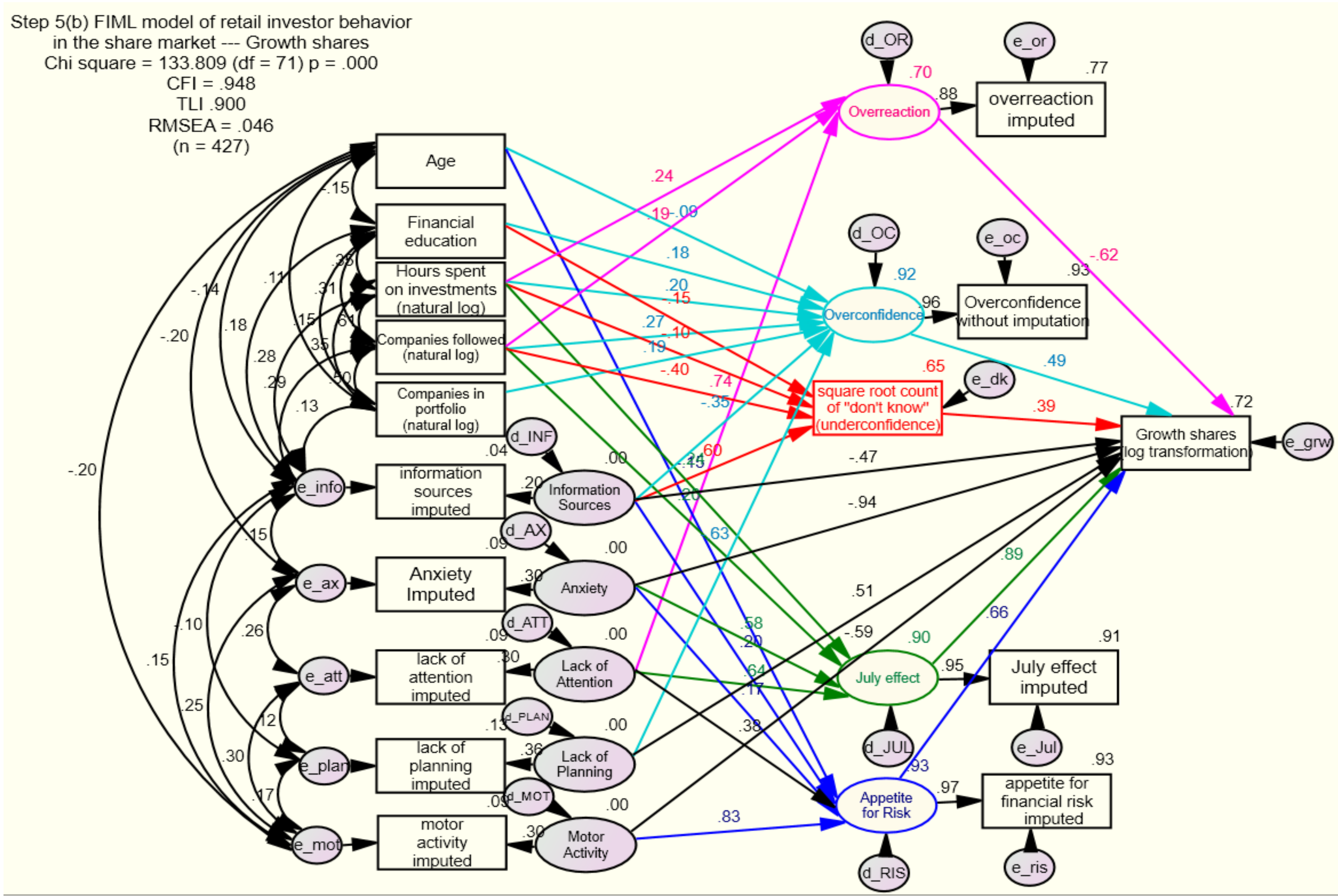

Figure 29. Model of retail investor behavior for growth shares in the share market: standardized coefficients shown.

(n = 427)

Table 57 *Standardized Direct, Indirect and Total Effects for Growth Shares*

	Direct effects	Indirect effects	Total effects
Age	.00	-.14	-.14
Financial education	.00	.03	.03
Years investment experience	.00	.00	.00
Hours spent	.00	.12	.12
Companies followed	.00	.04	.04
Companies in portfolio	.00	.09	.09
Overreaction	-.62***	.00	-.62
Overconfidence	.49**	.00	.49
Count of "don't know" as a marker of underconfidence	.39*	.00	.39
July effect	.89***	.00	.89
Appetite for financial risk	.66*	.00	.66
Information sources	-.47***	.19	-.28
Anxiety	-.94***	.63	-.31
Lack of attention	.00	.37	.37
Lack of planning	.51***	-.31	.20
Motor activity	-.59*	.55	-.04

*** $p < .001$ ** $p < .01$ * $p < .05$

As can be seen from Table 57, and as already known from Figure 29, there are direct positive effects from both overconfidence and the count of "don't know" as a marker of underconfidence. This finding is similar to that found for defensive shares. However, the direction of the pathways differed between both models. A comparison of Table 56 against that of Table 57 (or Figure 28 against that of Figure 29) reveals that both variables had negative signs leading towards defensive shares and positive signs leading towards growth shares. The direction of their pathways may therefore indicate that investors with a preference for defensive shares may be neither overconfident nor underconfident. In the case of growth shares, the direction of those positive pathways (or direct effects) to growth shares may indicate that investors with a preference for growth shares may oscillate between periods of overconfidence and underconfidence.

As already known from Figure 29, there are also direct effects from overreaction and the July effect. There were also direct effects emanating from appetite for financial risk, information sources, anxiety, along with the second and third dimensions of impulsivity (i.e., lack of planning and motor activity) on growth shares. See Table 57.

Information sources, anxiety, lack of planning and motor activity have both direct and indirect effects on growth shares. In each case, their direct effects through overreaction, overconfidence, the count of “don’t know” as a marker of underconfidence, the July effect and/or appetite for financial risk temper their total effect on growth shares. Indeed, the total effect of motor activity on growth shares becomes almost negligible. See Table 57.

Age, hours spent on investments, companies in portfolio and lack of attention have indirect effects on growth shares. Moreover, financial education and companies followed have negligible indirect effects on growth shares. Years of investor experience does not have a direct or indirect effect on growth shares. See Table 57.

Based on the direct effects reported in Table 57, and as can be seen in Figure 29, it would appear that investors with a preference for growth shares neither overreact, nor get anxious. They do, however, appear to oscillate between periods of overconfidence and underconfidence. They have an appetite for financial risk and engage in the July effect. They do not seek information about their investments. They do not plan their investments nor do they want to be physically active with their portfolio. In short, investors with a preference for growth shares may be best described as ‘unfazed investors with an appetite for financial risk who oscillate between periods of overconfidence and underconfidence’.

9.9 Introducing model of retail investor behavior with cyclical shares

Figure 27 was extended to predict investments in cyclical shares. It was hypothesized that overreaction, overconfidence and July effect would have significant positive pathways to cyclical shares. It was also hypothesized that the count of “don’t know” as a marker of underconfidence would have a negative pathway to cyclical shares. No hypothesis was formulated about appetite for financial risk. See hypothesis 5_g.

Pathways were therefore included from overreaction, overconfidence, the count of "don't know" as a marker of underconfidence and the July effect to that of cyclical shares. Initial model fit was poor. (*Chi squared* = 448.39; *df* = 85; *p* < .001; *CFI* = .72; *TLI* = .50; *RMSEA* = .10). The initial model explained 64 percent of the variance in cyclical shares. All four hypothesized predictors had significant beta weights, two of which (overreaction and overconfidence) were in the expected direction.

Once again, it would appear that other variables in the model may be playing a role in contributing to the explanation of cyclical shares. As appetite for financial risk was repositioned in the model, it would be of interest to assess whether this variable can aid in the prediction of cyclical shares. It is conceivable that those with a greater appetite for financial risk might have a greater appetite for cyclical shares. It is also conceivable that anxiety, information sources and years of investment experience may have an inverse relationship with cyclical shares. As one might expect to be more actively involved with a cyclical share portfolio, one might expect motor activity (the third dimension of impulsivity) to play a role in cyclical shares. Finally, we might expect that lack of attention and lack of planning (the first two dimensions of impulsivity) to play a role in appetite for financial risk. Similarly, motor activity might be expected to be inversely related to the count of "don't know".

A pathway from each of these variables to cyclical shares was therefore introduced into the model. While model fit was improved, it was not yet a good fit to the data. *(Chi squared* = 186.0; *df* = 77; *p* < .001; *CFI* = .92; *TLI* = .84; *RMSEA* = .06). Examination of the critical ratios revealed that there were three non-significant pathways leading to cyclical shares. These pathways were therefore removed from the model. Doing so led to a good fit to the data. *(Chi squared* = 145.7; *df* = 80; *p* < .001; *CFI* = .95; *TLI* = .91; *RMSEA* = .04). One of the non-significant pathways emanated from years of investor experience. Consequently, this variable had no significant pathways emanating from it. It was therefore removed from the model. The model remained a good fit to the data *(Chi squared* = 131.1; *df* = 70; $p < .001$; *CFI* = .95; *TLI* = .90; *RMSEA* = .05). See Figure 30.

The final model for cyclical shares was fitted with 82 parameters. It explained 71 percent of the variance in cyclical shares.

It was originally hypothesized that overreaction, overconfidence, the count of "don't know" as a marker of underconfidence, and the July effect would have significant pathways to cyclical shares. Moreover, it was expected that overreaction, overconfidence and the July effect would have positive pathways to cyclical shares, while the count of "don't know" as a marker of underconfidence would have a negative pathway to cyclical shares. See hypothesis 5_g.

Three of the four hypothesized pathways were significant. Overconfidence and July effect showed pathways in the expected direction. The pathway for overreaction was in the opposite direction to that expected. The count of "don't know" as a marker of underconfidence did not have a significant pathway to cyclical shares.

Three other variables had significant pathways to cyclical shares: (a) anxiety; (b) information sources; and (c) motor activity (the third dimension of impulsivity). Anxiety had a negative pathway to cyclical shares while information sources and motor activity had positive pathways to cyclical shares.

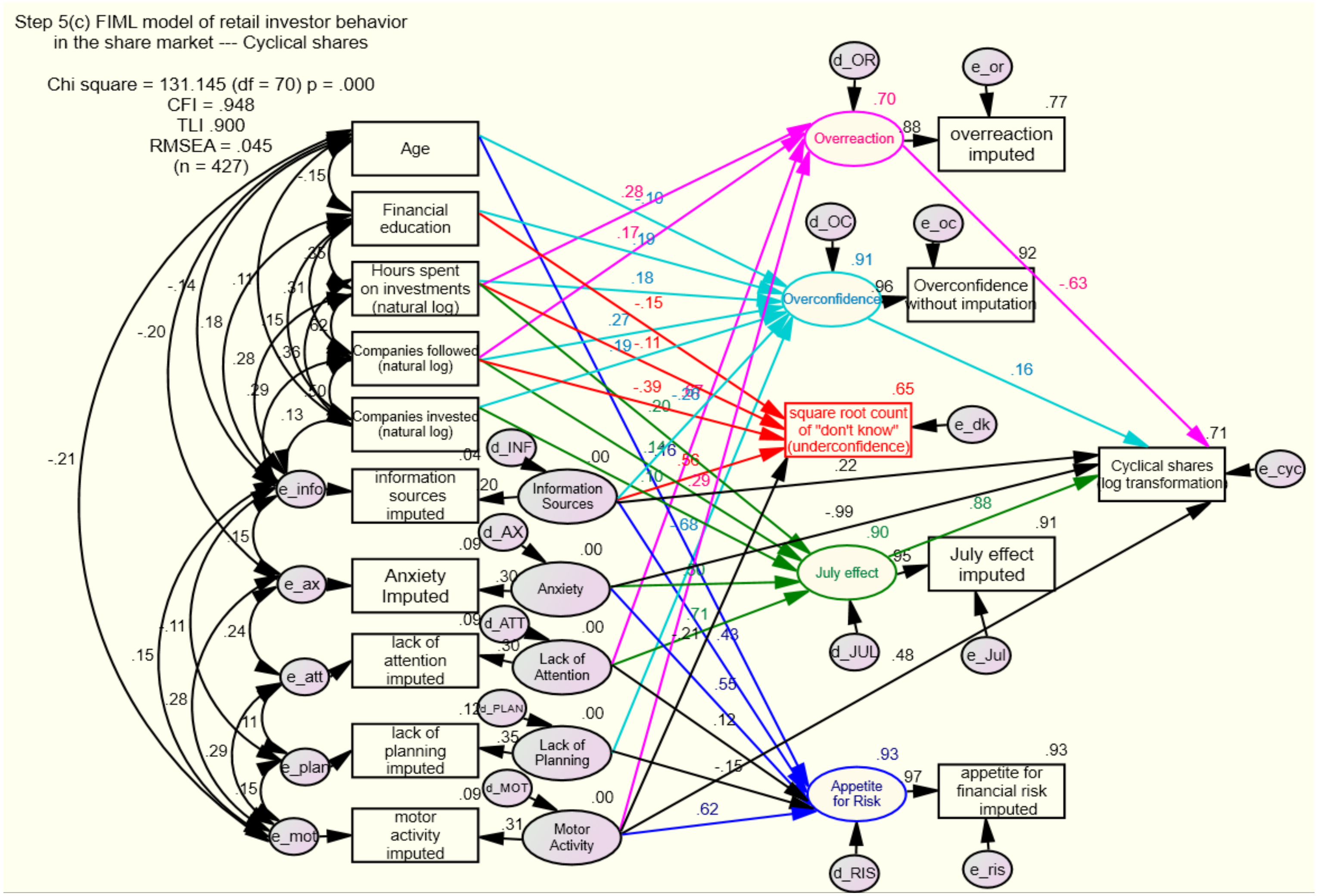

Figure 30. Model of retail investor behavior for cyclical shares in the share market: standardized coefficients shown.

(n = 427)

Three of the seven variables that had significant pathways to cyclical shares also had significant pathways leading to them (i.e., overreaction, overconfidence and the July effect). Table 58 thus reports the standardized direct, indirect and total effects. The significance levels for direct effects have also been reported in Table 58. Once again, pathways have been color coded so as to facilitate tracing direct and indirect pathways to cyclical shares.

Table 58 *Standardized Direct, Indirect and Total Effects for Cyclical Shares*

	Direct effects	Indirect effects	Total effects
Age	.00	-.02	-.02
Financial education	.00	.03	.03
Years investment experience	.00	.00	.00
Hours spent	.00	.03	.03
Companies followed	.00	.06	.06
Companies in portfolio	.00	.12	.12
Overreaction	-.63***	.00	-.63
Overconfidence	.16*	.00	.16
Count of "don't know" as a marker of underconfidence	.00	.00	.00
July effect	.88***	.00	.88
Appetite for financial risk	.00	.00	.00
Information sources	.22**	-.04	.17
Anxiety	-.99***	.44	-.56
Lack of attention	.00	.20	.20
Lack of planning	.00	-.11	-.11
Motor activity	.48***	-.19	.29

*** $p < .001$ ** $p < .01$ * $p < .05$

As can be seen in Table 58, and as already known from Figure 30, overreaction, overconfidence and the July effect have significant direct effects on cyclical shares. Overreaction has a negative direct effect on cyclical shares while both overconfidence and the July effect have positive direct effects. There were no direct effects (or indeed, any effects) from the count of "don't know" as a marker of underconfidence, appetite for financial risk or years of investment experience on cyclical shares.

As can be seen from Table 58, anxiety, information sources and motor activity (the third dimension of impulsivity) have both direct and indirect effects on cyclical shares. In each case, their total effects on cyclical shares have been tempered by their indirect effects through overreaction, overconfidence or the July effect.

Seven variables had indirect effects on cyclical shares. Companies followed, companies in portfolio, lack of attention and lack of planning (the first and second dimensions of impulsivity) have indirect effects on cyclical shares. Age, financial education and hours spent on investments have negligible indirect effects on cyclical shares. See Table 58.

Based on the direct effects shown in Table 58 and Figure 30, it would appear that investors with a preference for cyclical shares tend to be overconfident. They do not overreact or get anxious. They engage in the July effect. They tend to seek information about their investments and like being physically active with their investments. In summary, investors with a preference for cyclical shares may be best described as 'overconfident, unfazed and active'.

9.10 Introducing model of retail investor behavior with asset/turnarounds

Figure 27 was extended to predict investments in asset/turnarounds. It was hypothesized that overreaction, overconfidence, the count of "don't know" as a marker of underconfidence and July effect would all contribute to the prediction of asset/turnarounds. It was further hypothesized that overreaction, overconfidence and the July effect would have positive pathways to asset/turnarounds while the pathway from the count of "don't know" as a marker of underconfidence would be negative. No hypothesis was formulated about appetite for financial risk. See hypothesis 5_h. Pathways were therefore included from overreaction, overconfidence, the count of "don't know" as a marker of underconfidence and the July effect to asset/turnarounds. The initial model was not a good fit to the data. *(Chi squared* = 220.5; *df* = 85; *p* < .001; *CFI* = .90;

TLI = .83; *RMSEA* = .06). This model explained 30 percent of the variance in asset/turnarounds.

Two of the four hypothesized predictors had significant pathways (overreaction and overconfidence). Both significant pathways were in the expected direction. It would appear that there are other variables that may also help explain the variance in asset/turnarounds.

As appetite for financial risk was repositioned in the model as part of the first step of model testing, it would be of interest to assess whether this variable can contribute to the explanation of asset/turnarounds. It is conceivable that information sources, anxiety and the three dimensions of impulsivity (i.e., lack of attention, lack of planning and motor activity) might have both direct and indirect pathways to asset/turnarounds. Moreover, one might expect both years of investor experience and financial education to directly play a role in asset/turnarounds. These variables were therefore fitted to the model. Doing so, led to a good model fit to the data. *(Chi squared* = 139.5; *df* = 77; $p < .001$; *CFI* = .96; *TLI* = .91; *RMSEA* = .04).

Examination of the critical ratios revealed four non-significant pathways. They were removed from the model. Years of investor experience was one of those four variables. Consequently, this variable had no pathways emanating from it in the model and was removed from the model. The final model for asset/turnarounds remained a good fit to the data. *(Chi squared* = 132.7; *df* = 71; $p < .001$; *CFI* = .95; *TLI* = .91; *RMSEA* = .05). See Figure 31.

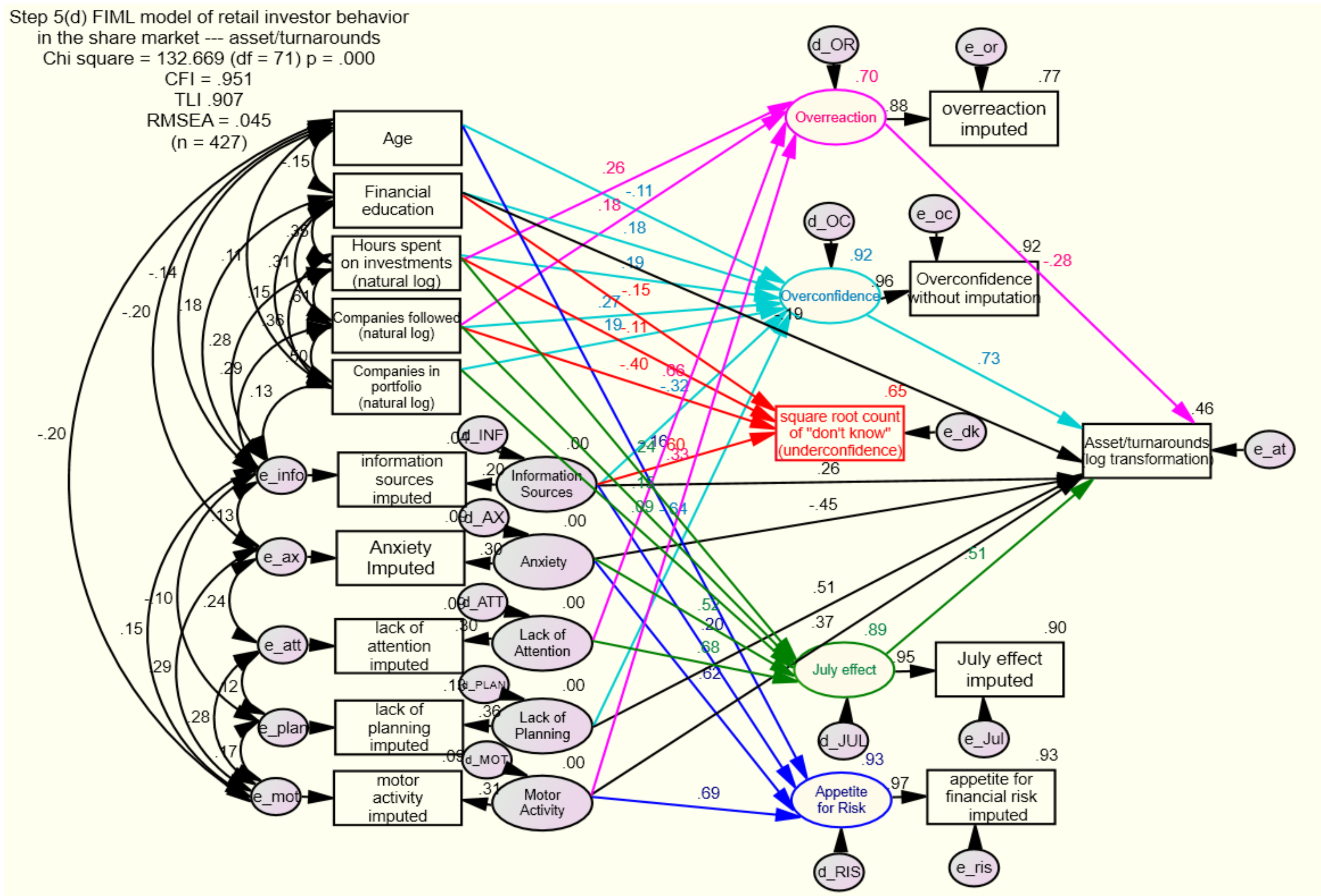

Figure 31. Model of retail investor behavior for asset/turnarounds in the share market: standardized coefficients shown. (n = 427)

The final model for asset/turnarounds was fitted with 81 parameters and explained 46 percent of the variance in asset/turnarounds. It was originally hypothesized that overreaction, overconfidence, the count of "don't know" as a marker of underconfidence and the July effect would have significant pathways to asset/turnarounds. It was further hypothesized that the direction of pathways emanating from overreaction, overconfidence and July effect would be positive, while the direction of pathway emanating from the count of "don't know" as a marker of underconfidence would be negative. See hypothesis 5_h.

As hypothesized, overreaction, overconfidence and the July effect contributed to the prediction of asset/turnarounds. The count of "don't know" as a marker of underconfidence did not have a significant pathway to asset/turnarounds. The direction of pathways from overconfidence and the July effect were as expected. However, the direction of pathway from overreaction to asset/turnarounds was in the opposite direction to that expected.

In addition, information sources, along with the second and third dimensions of impulsivity (i.e., lack of planning and motor activity), had positive pathways to asset/turnarounds. Anxiety and financial education had negative pathways to asset/turnarounds.

Three of the eight variables with significant pathways to asset/turnarounds, also had significant pathways leading to them. Thus, Table 59 provides the direct, indirect and total effects for asset/turnarounds. The significance levels for direct effects have also been reported in Table 59. Once again, Figure 31 has been color coded so as to facilitate visually tracing the direct and indirect pathways to asset/turnarounds.

Table 59 *Standardized Direct, Indirect and Total Effects for Asset/Turnarounds*

	Direct effects	Indirect effects	Total effects
Age	.00	-.08	-.08
Financial education	-.19**	.13	-.06
Years of investment experience	.00	.00	.00
Hours spent	.00	.19	.19
Companies followed	.00	.22	.22
Companies in portfolio	.00	.19	.19
Overreaction	-.28**	.00	-.28
Overconfidence	.73***	.00	.73
Count of "don't know" as a marker of underconfidence	.00	.00	.00
July effect	.51***	.00	.51
Appetite for financial risk	.00	.00	.00
Information sources	.26**	-.24	.02
Anxiety	-.45***	.27	-.18
Lack of attention	.00	.17	.17
Lack of planning	.51***	-.47	.04
Motor activity	.37***	-.09	.28

*** $p < .001$ ** $p < .01$ * $p < .05$

As can be seen from Table 59, and as previously known from Figure 31, there is a negative direct effect from overreaction to asset/turnarounds. There are also direct positive effects from overconfidence and the July effect to asset/turnarounds. There are no direct (or indeed any effects) from the count of "don't know" as a marker of underconfidence or appetite for financial risk to asset/turnarounds.

There were also direct effects from financial education, information sources, anxiety, along with the second and third dimensions of impulsivity (i.e., lack of planning and motor activity) on asset/turnarounds. See Table 59.

There are both direct and indirect effects from financial education, information sources, anxiety, lack of planning and motor activity. In each case, their total effects on asset/turnarounds have been tempered by their direct effects on overreaction, overconfidence or July effect. Finally, age, hours spent on investments, companies followed, companies in portfolio and lack of attention have indirect effects on asset/turnarounds. Years of investor experience does not have any effect on asset/turnarounds. See Table 59.

Based on the direct effects reported in Table 59 (or shown in Figure 31), it would appear that investors with a preference for asset/turnarounds are overconfident investors with little financial education and who engage in the July effect. Moreover, they neither overreact, nor get anxious. They seek information about their investments, but do not really plan their investments. Finally, they like to be physically active with their portfolios. See Table 59 and Figure 31. In short, this group of investors could be best described as 'overconfident, unfazed, unplanned and active'.

9.11 Summary of hypothesized, added and trimmed pathways

Tables 60 to 67 summarize the predicted pathways, along with the added or trimmed pathways fitted at each step of model testing. As can be seen from Table 60, fourteen pathways were predicted, a further seven were added to the model, while seven pathways were trimmed from the model. Note that pathways emanating from appetite for financial risk became redundant when this variable was repositioned in the model. For this reason, 11 pathways were included during the first step of model testing.

Table 60 *Predicted, Added or Trimmed Pathways for Step 1 of Model Testing*

Dependent Variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Overreaction	Information sources		
Overreaction	Anxiety		Anxiety
Overreaction	Lack of attention		
Overreaction	Lack of planning		Lack of planning
Overreaction	Motor activity		
Overreaction		Appetite for financial risk	
Count of "don't know"	Appetite for financial risk		
Count of "don't know"	Information sources		
Count of "don't know"	Anxiety		
Count of "don't know"	Lack of attention		Lack of attention
Count of "don't know"	Lack of planning		Lack of planning
Count of "don't know"	Motor activity		Motor activity
July effect	Appetite for financial risk		
July effect	Information sources		
July effect	Anxiety		
July effect		Lack of attention	
Appetite for financial risk		Information sources	
Appetite for financial risk		Anxiety	
Appetite for financial risk		Lack of attention	Lack of attention
Appetite for financial risk		Lack of planning	Lack of planning
Appetite for financial risk		Motor activity	
Total predicted, added or trimmed pathways	14	7	7

A further six pathways were predicted in the second step of model testing. One further pathway was introduced to the model while three further variables were trimmed from the model. Note that with the repositioning of appetite for financial risk in the model, covariances with appetite for financial risk and the three demographic variables model were translated into pathways at this step of the model. Consequently, fifteen parameters were included by the end of the second step of model testing. See Table 61.

Table 61 *Predicted, Added or Trimmed Pathways for Step 2 of Model Testing*

Dependent Variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Overreaction			
Count of “don’t know”	Age		Age
Count of “don’t know”	Years of investor experience		
Count of “don’t know”	Financial education		
July effect		Financial education	
Appetite for financial risk	Age		
Appetite for financial risk	Years of investor experience		Years of investor experience
Appetite for financial risk	Financial education		Financial education
Total predicted, added or trimmed pathways	6	1	3

As can be seen from Table 62, three further hypothesized pathways were introduced into the model at step 3. Five pathways were added to the model while three were trimmed from the model. Thus, twenty pathways were included in the third step of model testing.

Table 62 *Predicted, Added or Trimmed Pathways for Step 3 of Model Testing*

Dependent Variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Count of "don't know"	Hours spent on investments		
Count of "don't know"	Companies followed		
Count of "don't know"	Companies in portfolio		Companies in portfolio
Count of "don't know"			Years of investor experience
Overreaction		Hours spent on investments	
Overreaction		Companies followed	
July effect		Hours spent on investments	
July effect		Companies followed	
July effect		Companies in portfolio	
July effect			Financial education
Total predicted, added or trimmed pathways	3	5	3

As can be seen from Table 63, a further eleven pathways were hypothesized for the fourth step of model testing. No pathways were added to the model. However, seven pathways were removed from the model. This step of model testing was fitted with full information maximum likelihood (FIML) estimation. Thus while there were only 24 pathways of interest, means and intercepts were also obtained by the model.

Table 63 *Predicted, Added or Trimmed Pathways for Step 4 of Model Testing*

Independent Variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Overconfidence	Age		
Overconfidence	Years of investor experience		Years of investor experience
Overconfidence	Financial education		
Overconfidence	Hours spent on investments		
Overconfidence	Companies followed		
Overconfidence	Companies in portfolio		
Overconfidence	Information sources		
Overconfidence	Anxiety		Anxiety
Overconfidence	Lack of attention		Lack of attention
Overconfidence	Lack of planning		
Overconfidence	Motor activity		Motor activity
Overreaction			Information sources
Count of "don't know"			Anxiety
July effect			Information sources
Total predicted, added or trimmed pathways	11	0	7

As can be seen from Table 64, the model for defensive shares fitted four hypothesized pathways, added a further five pathways and trimmed four non-significant pathways from the model. Two of the trimmed pathways were initially hypothesized pathways. The model for defensive shares includes 30 pathways. Note that one of those trimmed pathways was that of years of investor experience. This variable was subsequently removed from the model. Once again, this model uses FIML, so means and intercepts were also obtained by the model.

Table 64 *Predicted, Added or Trimmed Pathway for Defensive Shares*

Independent variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Defensive shares	Overreaction		Overreaction
Defensive shares	Overconfidence		
Defensive shares	Count of "don't know"		
Defensive shares	July effect		July effect
Defensive shares		Appetite for financial risk	
Defensive shares		Years of investor experience	Years of investor experience
Defensive shares		Companies in portfolio	
Defensive shares		Information sources	
Defensive shares		Lack of attention	Lack of attention
Defensive shares		Lack of planning	
Total predicted, added or trimmed pathways	4	6	4

As can be seen from Table 65, the model for growth shares included the four hypothesized pathways, added a further six pathways and trimmed three non-significant pathways. This model thus included 32 pathways. This model was also fitted with FIML, so once again, the model obtained means and intercepts.

Table 65 *Predicted, Added or Trimmed Pathways for Growth Shares*

Independent variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Growth shares	Overreaction		
Growth shares	Overconfidence		
Growth shares	Count of "don't know"		
Growth shares	July effect		
Growth shares		Appetite for financial risk	
Growth shares		Financial education	Financial education
Growth shares		Information sources	
Growth shares		Anxiety	
Growth shares		Lack of planning	
Growth shares		Motor activity	
Appetite for financial risk		Lack of attention	
Overreaction			Motor activity
July effect			Companies in portfolio
Total predicted, added or trimmed pathways	4	7	3

As can be seen from Table 66, the model for cyclical shares included the four hypothesized pathways, added a further eight pathways and trimmed three non-significant pathways. As years of investment experience did not have any significant pathways emanating from it, this variable was also excluded from the model. This model thus included 33 pathways. Once again, this model was fitted with FIML, and hence the model also obtained means and intercepts.

Table 66 *Predicted, Added or Trimmed Pathways for Cyclical Shares*

Independent variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Cyclical shares	Overreaction		
Cyclical shares	Overconfidence		
Cyclical shares	Count of "don't know"		Count of "don't know"
Cyclical shares	July effect		
Cyclical shares		Appetite for financial risk	Appetite for financial risk
Cyclical shares		Anxiety	
Cyclical shares		Information sources	
Cyclical shares		Motor activity	
Cyclical shares		Years of investment experience	Years of investment experience
Appetite for financial risk		Lack of attention	
Appetite for financial risk		Lack of planning	
Count of "don't know"		Motor activity	
Total predicted, added or trimmed pathways	4	8	3

As can be seen from Table 67, the model for asset/turnarounds included the four hypothesized pathways, added a further eight pathways and removed four non-significant pathways. This model thus included 32 pathways. Note that one of the trimmed pathways was that of years of investor experience. As this variable did not have any remaining pathways emanating from it, this variable was also removed from the model. Once again, this model was fitted using FIML, and hence, the model also included means and intercepts.

Table 67 *Predicted, Added or Trimmed Pathways for Asset/Turnarounds*

Independent variable	Predicted Pathways	Added Pathways	Trimmed Pathways
Asset/turnarounds	Overreaction		
Asset/turnarounds	Overconfidence		
Asset/turnarounds	Count of "don't know"		Count of "don't know"
Asset/turnarounds	July effect		
Asset/turnarounds		Years of investor experience	Years of investor experience
Asset/turnarounds		Financial education	
Asset/turnarounds		Appetite for financial risk	Appetite for financial risk
Asset/turnarounds		Information sources	
Asset/turnarounds		Anxiety	
Asset/turnarounds		Lack of attention	Lack of attention
Asset/turnarounds		Lack of planning	
Asset/turnarounds		Motor activity	
Total predicted, added or trimmed pathways	4	8	4

9.12 Description of the models

Four structural equation models have been found; one for each of the four types of share investments (i.e., defensive shares, growth shares, cyclical shares and asset/turnarounds). See Figures 28 to 31. Table 68 summarizes the pathways leading to each of the four different share types.

Table 68 *Summary of Standardized Pathways and Fit Statistics for the Four Models*

	Defensive Shares	Growth Shares	Cyclical Shares	Asset/ Turnarounds
Age				
Financial Education				-.19
Years of Investor Experience				
Hours spent on investments				
Companies followed				
Companies in portfolio	.34			
Overreaction		-.62	-63	-.28
Overconfidence	-.62	.49	.16	.73
Count of "don't know" as a marker of underconfidence	-.89	.39		
July effect		.89	.88	.51
Appetite for financial risk	-.24	.66		
Information sources	.77	-.47	.22	.26
Anxiety		-.94	-.99	-.45
Lack of attention				
Lack of planning	-.73	.51		.51
Motor activity		-.59	.48	.37
Chi squared	133.8	133.8	131.1	132.7
df	73	71	70	71
Level of significance	P < .001	P < .001	P < .001	P < .001
CFI	.95	.95	.95	.95
TLI	.91	.90	.90	.91
RMSEA	.04	.05	.05	.05
Parameters in model	79	81	82	81
Variance explained in dependent variable	.74	.72	.71	.46
Description of investors with preference for this type of share:	Confident	Oscillating confidence	Overconfident	Overconfident
	Conservative	Unfazed Risk appetite	Unfazed	Unfazed
	Informed Planful	Unplanned Inactive	Active	Unplanned Active

Examining each variable's contribution across models highlights the differential contribution each variable makes to the prediction of each the four different types of shares. See Table 68.

For instance, overreaction had significant negative pathways for growth shares, cyclical shares and asset/turnarounds. This pattern of results suggests that while the literature believes investors overreact (see section 2.6.1), investors may not share that belief. These same investors also report a lack of anxiety and that they engage in the July effect. Moreover, each model shows a positive pathway from anxiety to the July effect. Assuming that the models have well represented actual share market behavior, it is possible that the experience of anxiety triggers behaviors associated with the July effect. It is also possible that investors do indeed overreact, and get anxious, but that they are not aware of their overreaction (or anxieties) because these emotions are masked by their engagement in activities associated with the July effect.

Examination of the pattern of overconfidence, in conjunction with that of the count of "don't know" as a marker of underconfidence may elucidate further understandings of investor behavior. Both variables have negative pathways in the model for defensive shares. As discussed in section 9.7, investors with a preference for defensive shares may be neither particularly overconfident, nor underconfident. Both overconfidence and the count of "don't know" as a marker of underconfidence have positive pathways in the model for growth shares. As discussed in section 9.8, investors with a preference for growth shares may experience oscillating periods of overconfidence and underconfidence. Only overconfidence has significant pathways leading to cyclical shares and asset/turnarounds and those pathways are both positive. Thus, there appears to be a trend where investors become increasingly more overconfident as they move away from defensive shares and into asset/turnarounds.

It is also interesting to note that investors have little desire to be physically active in the share market in the case of growth shares, but do in the case of cyclical shares and asset/turnarounds. The preference to be physically active with one's investment portfolio may thus be associated with increasing levels of overconfidence to a point where investors who no longer oscillate between periods of overconfidence and underconfidence may prefer to actively engage with their investments and thus prefer to allocate more of their portfolios to cyclical shares and asset/turnarounds.

9.13 Conclusion

This chapter developed a structural equation model for each of four different types of share investments (i.e., defensive shares, growth shares, cyclical shares and asset/turnarounds).

Investors with a preference for defensive shares do not appear to be either overconfident or underconfident, nor do they have an appetite for financial risk. They tend to seek information about their investments and plan their investment portfolios. They also have invested in many companies. Investors with a preference for growth shares appear to oscillate between periods of overconfidence and underconfidence. They do not appear to overreact, or get anxious. However, they do engage in the July effect. They do not want to actively engage with their investment portfolio.

Investors with a preference for cyclical shares or asset/turnarounds do not appear to overreact or get anxious. They do appear to be overconfident and engage in the July effect. Moreover, they also want to actively engage with their investment portfolio.

In examining similarities and differences across the four models, it would appear that investors with a preference for growth shares, cyclical shares and asset/turnarounds do not get anxious, nor do they overreact. In all three cases, however, they engage in the July effect; a variable for which anxiety is a significant predictor.

It would also appear that investors with a preference for defensive shares are neither particularly overconfident or underconfident. Those with a preference for growth shares appear to oscillate between periods of overconfidence and underconfidence while those with a preference for cyclical shares or asset/turnarounds are overconfident. In the case of cyclical shares and asset/turnarounds, investors also have a preference to be physically active with their investment portfolios.

The next chapter discusses the research findings from chapters 5 to 9. Chapter 11 draws conclusions, notes the limitations of this research and makes recommendations for future research.

Chapter 10 Discussion

10.1 Introduction

Table 69 locates the research findings from chapters 5 to 9 by the five research questions, as well as by variable considered. The numbers reported within the Table refer to the section in which each research finding has been reported.

Table 69 *Location of Findings by Research Question, Research Objective and Variables*

Research Question	Scale Develop-ment	RQ1 (overcon-fidence)	RQ2 (undercon-fidence)	RQ3 (retail vs institutional)	RQ4 (hierarchical regressions)	RQ5 (SEM)
Research Objective	1st	3rd	2nd	3rd	3rd	4th
Age				7.3		9.4
Gender		6.2				
Marital status		6.2				
Education				7.3		
Financial education				7.3		9.4
Years of investor experience				7.3		9.4
Hours spent				7.4		9.5
Companies followed				7.4		9.5
Companies in portfolio				7.4		9.5
Overreaction	5.2.1, 5.3-5.4			7.6	8.1	9.3
Overconfidence	5.2.2, 5.3-5.4	6.2		7.6	8.2	9.6
Underconfidence			6.3	7.6	8.3	9.3
The July effect	5.2.1, 5.3-5.4			7.8		9.3
Appetite for financial risk	5.2.3, 5.3-5.4			7.8		9.3
Information sources	5.2.4, 5.3-5.4			7.8		9.3
Anxiety	5.2.5, 5.3-5.4			7.7		9.3
Lack of attention	5.2.6, 5.3-5.4			7.7		9.3
Lack of planning	5.2.6, 5.3-5.4			7.7		9.3
Motor activity	5.2.6, 5.3-5.4			7.7		9.3
The January effect	5.2.1					
Social herding	5.2.1					
Psychological biases	5.2.1					
Defensive shares				7.5		9.7
Growth shares				7.5		9.8
Cyclical shares				7.5		9.9
Asset/turnarounds				7.5		9.10
Wealth change				7.9		

As can be seen from Table 69, scale development answered the first objective of this thesis while research questions 1, 3 and 4 answered the third objective of this thesis. Research question 2 answered the second objective of this thesis while the fifth research question answered the final objective of this thesis. As can be seen from the fifth and final columns in Table 69, much of the research in this thesis has been given to an exploration of the differences between retail and institutional investors (RQ3) as well as testing a structural equation model (RQ5). Examination across variables shows that this thesis has given the most attention to overconfidence and its inverse, followed by overreaction.

Sections 10.2 to 10.7 consider the findings of this thesis in relation to scale development and the five research questions in turn. Section 10.8 distills the findings of this thesis on overreaction across the five research questions, while section 10.9 distills the findings on overconfidence and its inverse.

10.2 Scale development

Much of previous research used portfolio simulation or experimental research. (See, for instance, Carosa, 2005; Chua et al., 1987; Griffin & Tversky, 1992). Before the five research questions could be addressed, a set of psychometrically sound scales would need to be developed. Seven (of ten) scales developed or adapted for use in this survey demonstrated good factor structure, reliability and discriminant validity. The seven scales were (a) overreaction; (b) overconfidence; (c) July effect; (d) appetite for financial risk; (e) information sources; (f) anxiety; and (g) the three dimensions of impulsivity (i.e., lack of attention, lack of planning and motor activity). Both the subscales for overconfidence and information sources also demonstrated good psychometric properties. See sections 5.2.1 to 5.2.6. Social herding and psychological biases did not demonstrate good factor structure. Moreover, the January effect was found to be part of the same seasonal effect as that of the July effect. See section 5.2.1.

Section 10.2.1 discusses the factor structure of each of the scales developed or adapted in the present study for use with investors. Section 10.2.2 discusses the reliability of the seven scales that demonstrated good factor structure while section 10.2.3 discusses their discriminant validity.

10.2.1 Factor structure

Tables 14 and 15 provided a list of questions developed to measure the January effect, the July effect, overreaction, psychological biases and social herding, along with the loadings on their respective factors. With modification, both the July effect seasonal and overreaction demonstrated good factor structure. Questions intended to measure the January effect were found to tap into the same seasonal construct as those intending to measure the July effect. See section 5.2.1. As the Australian taxation year ends on the 30th June, it made theoretical sense to make use of a July effect in this research. It is recognized that when research is undertaken in countries whose financial year aligns with the calendar year, it may make more sense to couch the seasonal construct in the form of a January effect seasonal. For the sake of simplicity, and consistency with the literature described in section 2.6.3, this scale has been referred to as the July effect. Overreaction and the July effect were developed by the author. No prior research is available on their factor structure. Moreover, no prior scales for overreaction or the July seasonal effect exist in the literature. This thesis thus contributes to the literature by providing scales for overreaction and the July effect that demonstrate good factor structure.

Social herding and psychological biases both demonstrated poor factor structure in this thesis. Questions intending to measure social herding and psychological biases were also developed by the author. However, they did not result in psychometrically sound scales. This thesis was thus unable to provide scales on social herding or psychological biases. Prior research, however, had made attempts to measure both constructs: Asif (2016) made use of a three question measure of social herding, along with a three question measure of anchoring (one type of psychological biases). Asif (2016) did not report the factor structure for the measure of social herding or anchoring. Ates et al. (2016) developed scales to measure psychological biases in conjunction with overconfidence. Moreover, Lee et al. (2013) made use of the Pompian (2012) measure of psychological biases. However, the factor structure for Ates et al. (2016) and Pompian (2012) measures of psychological biases were not provided.

Table 17 provided the list of questions and their factor loadings on overconfidence. With modification, overconfidence demonstrated good factor structure. See section 5.2.2. Once, again, however, this scale was developed by the researcher. Thus, no prior research is available on the factor structure for this construct. The factor structure for the Ates et al. (2016) and Iqbal et al. (2014) measures of overconfidence were not provided. The factor structure was also not provided for the overconfidence measures used by Asif (2016) or Lee et al. (2013). This thesis thus extends their work by providing a scale for overconfidence that demonstrates good factor structure. Finally, Kafayat (2014) also provided an overconfidence scale that demonstrated good factor structure. This thesis provides an alternate scale to that provided by Kafayat (2014).

Table 19 provides the list of questions developed to measure appetite for financial risk. It also provides their factor loadings on this factor. With modification, appetite for financial risk demonstrated good factor structure. See section 5.2.3. As the questions developed to measure appetite for financial risk were developed by the researcher, no prior research is available on the factor structure for appetite for financial risk. This thesis extends the work of Iqbal et al. (2014) by providing an appetite for financial risk scale that demonstrates good factor structure. This thesis also provides an alternate scale to that of Rajagopalan and Gurusamy (2014). This thesis also provides a scale that complements that of Chin et al. (2016) so that future research can consider a more generic approach to risk-taking as well as a more focused appetite for financial risk.

Table 21 provides the list of questions developed to measure information sources. It also provides their factor loadings. Once again, with modification, information sources demonstrated good factor structure. See section 5.2.4. As the questions were developed by the researcher, no prior research is available on the factor structure for information sources. There is no prior research available on alternative scales measuring information sources. Thus this thesis contributes to the literature by providing an information sources scale that demonstrates good factor structure.

Table 23 provides the list of questions adapted to measure anxiety with share investors. Table 23 also provides their factor loadings on anxiety. These questions have been adapted from the original IPIP (2010) anxiety scale. Once again, with modification, this construct demonstrated good factor structure. See section 5.2.5. Anxiety had previously been shown to be a subscale of the personality trait of neuroticism (Costa & McCrae, 1992). Neuroticism is often measured using the NEO Personality Inventory (Revised) along with introversion/extroversion, openness, agreeability and conscientiousness. (See Costa & McCrae, 1992). The IPIP scale had been previously shown to have a correlation of .75 with the NEO Personality Inventory (Revised) subscale of anxiety (IPIP, 2010). This thesis extends the IPIP (2010) work by demonstrating that the scale has good factor structure when adapted for use with share investors.

Table 25 provided the list of questions measuring three dimensions of impulsivity (i.e., (a) lack of attention; (b) lack of planning; (c) and motor activity) adapted for use with share investors. Table 25 also provided the factor loadings for each question. With modification, the construct of impulsivity demonstrated good factor structure. See section 5.2.6. The three dimensions of impulsivity found in this thesis were consistent with the three factor varimax solution found by Spinella (2007) . The three independent factors of impulsivity found in this thesis were also consistent with the findings of Cootlee et al. (2014). This thesis thus extends the work of Spinella (2007) by demonstrating that this scale, when adapted for use with share investors, demonstrates good factor structure.

10.2.2 Reliability analysis

The seven scales that demonstrated good factor structure (i.e., (a) overreaction; (b) overconfidence; (c) the July effect; (d) appetite for financial risk; (e) information sources; (f) anxiety; and (g) the three dimensions of impulsivity), also demonstrated good reliability. Both subscales of overconfidence and information sources demonstrated good reliability.

Five of the seven scales were developed by the researcher (i.e., (a) overreaction; (b) overconfidence; (c) July effect; (d) appetite for financial risk; and (e) information sources). Consequently, no prior research is available on their reliability. No alternate scales have been put forward in the literature for three of the seven scales (i.e., overreaction, July effect and information sources). Thus, this thesis contributes to the literature by providing an overreaction, July effect and information sources scale that demonstrates both good factor structure and internal reliability.

Previous research provided alternate overconfidence scales (Ates et al., 2016; Iqbal et al., 2014; Kafayat, 2014) as well as scales measuring appetite for financial risk (Iqbal et al., 2014; Rajagopalan & Gurusamy, 2014). Moreover, Chin et al. (2016) provided a scale measuring generic risk-taking. Asif (2016) made use of a 9 item measure of overconfidence, a three item measure of social herding and a three item measure of anchoring (a type of psychological bias) while Lee et al. (2013) made use of a combined measure of overconfidence and psychological biases. With the exception of Asif (2016), Chin et al. (2016) and Kafayat (2014), these studies did not provide the Cronbach's alpha coefficients for their respective scales. This thesis thus extends the work of Iqbal et al. (2014), Ates et al. (2016), Lee et al. (2013) and Asif (2016) by providing an overconfidence scale that demonstrates both good factor structure and reliability. This thesis also provides an alternate overconfidence scale to that of Kafayat (2014). This thesis also extends the Rajagopalan and Gurusamy (2014) and Iqbal et al. (2014) by providing an appetite for financial risk scale that, not only demonstrates both good factor structure but also good internal reliability. While the Chin et al. (2016) scale measures more generic risk-taking, the appetite for financial risk scale provided in the current thesis measures a more focused risk-taking behavior in share markets. This thesis thus also provides a complementary scale to that of Chin et al. (2016). Finally, this thesis was unable to extend the work of Asif (2016) for social herding or anchoring.

Anxiety and the three dimensions of impulsivity were both adapted for use with share investors. Cronbach's alpha for anxiety was .76 in the present study. This finding is consistent with past research which found the anxiety subscale on the NEO Personality Inventory (Revised) to range between .78 and .82 (Costa & McCrae, 1992). The International Personality Item Pool (IPIP) version of anxiety had a reported Cronbach's alpha of .83 (IPIP, 2010). This thesis also extends the work of IPIP (2010) by providing an anxiety scale for use with investors that not only demonstrates good factor structure but also good reliability.

Cronbach's alpha for the three dimensions of impulsivity (i.e., lack of attention, lack of planning and motor activity) were .75, .75 and .83 respectively. The three dimensions of impulsivity were an adaptation of the three subscales of the Spinella (2007) Barratt Impulsivity Scale, short form (BIS15). The Cronbach's alphas reported in the present study were consistent with, and superior to, past research. Spinella (2007) did not report Cronbach's alpha for the three subscales on the BIS15. However, the BIS15 was previously shown to have a Cronbach's alpha of .79 (Spinella, 2007). The three subscales of the full Barratt Impulsivity Scale (BIS30) were previously shown to have a Cronbach's alpha ranging from .45 to .74 (Haden & Shiva, 2008; Johnson & Jones, 2009; Stanford et al., 2009). This thesis thus extends the literature by showing that the BIS15 scale, when adapted for use with share investors, demonstrates good factor structure and internal reliability.

10.2.3 Discriminant validity

The seven scales demonstrating good factor structure and reliability (i.e., (a) overreaction; (b) overconfidence; (c) the July effect; (d) appetite for financial risk; (e) information sources; (f) anxiety; and (g) the three dimensions of impulsivity) were assessed for discriminant validity.

The average variance extracted for each of the questions loading on a particular scale was compared to the squared correlation between the scale and remaining ten scales. In each case, the average variance extracted exceeded the highest of the squared correlations with remaining scales. Moreover, perusal of the correlation matrix showed that the associations between each scale and those of the remaining ten scales were much lower than their respective Cronbach's alpha coefficients. It would appear that the seven scales also demonstrated discriminant validity.

It is noted that while the literature in section 2.6.3 refers to both a January effect and July effect as separate phenomenon, they both appear to form part of the same seasonal effect. Indeed, as part of the testing of model fit, it was found that the three questions measuring the January effect were correlated with their counterparts measuring the July effect in the order of .95. Both constructs thus appear to be measuring part of the same latent variable. While this research has simplified the latent variable to measure a July effect seasonal, it is recognized that this scale may be couched in a form that best aligns with the country in which the research is undertaken.

No prior research on the discriminant validity was available for the five scales developed by the researcher (i.e., (a) overreaction; (b) overconfidence; (c) July effect; (d) appetite for financial risk; and (e) information sources). Moreover, no alternate scales were provided by the literature for overreaction, July effect or information sources. This thesis thus contributes to the literature by providing scales for overreaction, July effect and information sources that demonstrate good factor structure, internal reliability and discriminant validity.

Once again, this work extends the work of Iqbal et al. (2014), Ates et al. (2016), Lee et al. (2013), Asif (2016) and Kafayat (2014) by providing an overconfidence scale that not only demonstrates good factor structure and reliability, but also demonstrated discriminant validity. This thesis also extends the work of Iqbal et al. (2014) and Rajagopalan and Gurusamy (2014) by providing an appetite for financial risk scale that not only demonstrates good factor structure and reliability, but also good discriminant validity. This thesis also provides a complementary scale to that of Chin et al. (2016) by providing a more focused measure of appetite for financial risk.

Costa and McCrae (1992) reported a series of studies that demonstrate evidence of discriminant validity for each of the big five scales (including the neuroticism scale to which anxiety belongs) along with each of the subscales. The NEO Personality Inventory (Revised) subscale of anxiety thus has good discriminant validity. While discriminant analyses were not available for the IPIP version of anxiety, it was shown to have a correlation of .75 with the NEO Personality Inventory (Revised) anxiety subscale (IPIP, 2010). This thesis thus extended the work of IPIP (2010) by showing that, when adapted for use with share investors, it demonstrates good factor structure, reliability and discriminant validity.

While reliability data and factor structure is available for the BIS15 (Spinella, 2007), and indeed the BIS30 (e.g., Haden & Shiva, 2008; Myrseth, Pallesen, Molde, Johnsen, & Lorvik, 2009; Patton et al., 1995; Skitch & Hodgins, 2004; Stanford et al., 2009), there does not appear to be any prior discriminant validity data available for the three dimensions of impulsivity. This study thus adds to previous research by showing that the BIS15, when adapted for use with share investors, not only demonstrates good factor structure and internal reliability, but also good discriminant validity.

10.3 Research question 1 - Overconfidence

Based on the findings of Barber and Odean (2001), the first research question hypothesized that single women would demonstrate the least overconfidence, followed by partnered women and partnered men in turn. Single men were expected to demonstrate the greatest overconfidence.

Using a one way analysis of variance, with Bonferroni post hoc tests, overconfidence was shown to differ at different combinations of gender and marital status such that single women were shown to demonstrate less overconfidence than men in general. The findings of the current research thus provided partial support for this hypothesis.

That this finding does not fully support the findings of Barber and Odean (2001) suggests that knowledge of a person's gender, but not marital status, may be important to the prediction of overconfidence. It is also possible that other (demographic) variables may aid prediction of overconfidence. The answer to the question of "what else" may come from the findings reported in section 10.6.2.

10.4 Research question 2 --- Underconfidence

As discussed in Cohen and Cohen (1983), missing data may prove to be valuable data in a survey. While the count of "don't know" is not missing data *per se*, it is often treated as same. The second research question therefore asked whether the count of "don't know" per respondent and/or the count of missing data per respondent could act as markers of underconfidence. It may be recalled that the count of "don't know" represents a tally of the number of questions a respondent endorsed as "don't know" across the questionnaire. The count of missing data represents an equivalent tally of all the questions a respondent left blank in the questionnaire. The count of "don't know" and the count of missing data per respondent thus represents the combined tally of the number of questions a respondent either left blank or endorsed with "don't know".

One might therefore expect the count of "don't know" and/or the count of missing data to act as markers of underconfidence. Indeed, the count of "don't know" per respondent, along with the count of "don't know" and count of missing data per respondent were shown to be markers of underconfidence. As was expected, scores on financial education and overconfidence had significant negative beta weights with both markers of underconfidence. When this analysis was repeated using the subscales of overconfidence, it was clear that the form of overconfidence was informationally related, rather than based on expectations. This finding is therefore consistent with the Griffin and Tversky (1992) finding that underconfidence is related to poor availability of information.

The count of missing data per respondent, however, was not shown to be a marker of underconfidence. The count of missing data may be measuring other factors such as carelessness, refusal-to-complete a question and the belief that the question does not apply to the respondent's circumstances. As the count of "don't know" and missing data incorporates the count of missing data, the factors affecting the count of missing data may also affect the count of "don't know" and count of missing data. Consequently, the count of "don't know" may act as a cleaner, more precise, measure of underconfidence than might the count of "don't know" and count of missing data. That is, the count of "don't know and count of missing data may contain greater error variance than might the count of "don't know" alone. For this reason, the count of "don't know" was used in remaining analyses. The count of "don't know" as a marker of underconfidence may prove to be a useful addition to future investor surveys.

10.5 Research question 3 --- Discriminating between retail and institutional investors

The third research question asked whether retail investors could be distinguished from their institutional peers. Seven discriminant analyses were performed to explore the dimensions upon which retail investors could be distinguished from institutional investors.

The variables used in the first two discriminant analyses were chosen for practical reasons. If these variables proved to be able to discriminate members of one group from those of the other, then it would be easy for future researchers to obtain scores on these variables to determine investor group membership. Variables used in the third and subsequent discriminant analyses were all selected on theoretical reasons. Each variable was intended to tap into important aspects of investor personality, behavior or share market activity. It was anticipated that any differences found between both groups of investors may help elucidate key differences in investor thinking and behavior.

The first discriminant analysis showed that retail investors could be distinguished from their institutional counterparts. In order of importance, both groups could be distinguished based on (a) financial education; (b) age; (c) education; and (d) years of investor experience. More specifically, retail investors were more likely to be older, less (financially) educated and less experienced than their institutional counterparts.

Previous research has reported retail investors to be at least 45 years of age and tertiary educated, but have not reported the level of financial education retail investors have obtained (ASX Ltd, 2015; Cohn et al., 1975; Lease et al., 1974). In a study that considered both retail and institutional investors, respondents were reported to be aged 25 to 45 years old and tertiary educated (Lai et al., 2013).

The second discriminant analysis showed that retail investors could be distinguished from their institutional counterparts. Once again, in order of importance, retail investors could be distinguished from institutional investors based on (a) hours spent on investments; (b) companies followed; and (c) number of companies in portfolio. More specifically, retail investors were more likely to spend fewer hours on their share investments. They were also more likely to monitor and invest in fewer companies than their institutional counterparts. Not surprisingly, this discriminant analysis demonstrated that retail investors could successfully be distinguished from their institutional counterparts in 93.5 percent of cases. As all ungrouped respondents were classified as retail investors by the second discriminant function, they were reclassified as retail investors for the fourth and final research questions. While this finding may appear self-evident, it also provides a simple way of distinguishing members of one investor group from those of the other.

The finding of the second discriminant analysis is consistent with past research. Lease et al (1974) found that retail investors spent five hours or less on their investments per week. These authors also found that retail investors held the shares of six or more different companies (Lease et al., 1974). Past research had not surveyed institutional investors in this regard.

The third discriminant analysis was also able to distinguish retail from institutional investors. However, investors differed on only two of the four share types. In relation to institutional investors, retail investors were shown to allocate a smaller proportion of their portfolio to cyclical shares and asset/turnarounds. This analysis had a small effect size. Moreover, only 63.4 percent of respondents could be correctly classified into their respective investment groups based on responses to these four variables.

While previous research had not considered the kinds of shares retail and institutional investors choose to invest in, previous research has found that retail investors were willing to make use of margin lending and warrants (Lease et al., 1974). As both these products represent an element of risk, however, it would appear that the retail investors in the Lease et al. (1974) sample were willing to take on financial risk. If this is indeed the case, it may be that these retail investors were prepared to invest aggressively to a certain degree. As Lease et al. (1974) had not surveyed institutional investors, it remains to be seen whether retail investors were willing to invest more, less or equally aggressively as their institutional counterparts. Given that this discriminant analysis showed institutional investors to have a greater preference for cyclical shares and asset/turnarounds, one might expect retail investors to invest less aggressively than their institutional counterparts.

The fourth discriminant analysis showed that retail and institutional investors could be discriminated from each other based on their level of overreaction, overconfidence and underconfidence. More specifically, retail investors reported less overreaction, less overconfidence and more underconfidence than their institutional counterparts. It was interesting to note that ungrouped respondents endorsed even greater levels of underconfidence than did retail investors. It is possible that the level of underconfidence ungrouped respondents experienced was so great that they could not determine to which group of investors they belonged.

Past research found male retail investors to be more overconfident than female retail investors. (See, for example, Barber & Odean, 2001; Pompian & Longo, 2004) and that increased overconfidence resulted in increased trading with poorer portfolio returns for having traded Barber and Odean (2000, 2001). Past research has not shown whether this relationship holds with institutional investors. This research extends past research to show that there are subgroup differences in level of overreaction, overconfidence (and its inverse).

The remaining three discriminant analyses could not distinguish retail from institutional investors. It is no surprise that one could not distinguish retail from institutional investors based on degree of anxiety or on the three dimensions of impulsivity (fifth discriminant function). However, it was of surprise that appetite for financial risk could not contribute to the discrimination between both groups of investors. It was also of surprise that wealth change over time could not be used to discriminate members from one group from those of the other (seventh discriminant function). It would appear that both groups of investors have portfolios that perform equally well (or poorly) over time.

In summary, the results of the seven discriminant analyses showed that retail investors were older; less (financially) educated; and less experienced than their institutional counterparts. Retail investors were also shown to spend fewer hours per week on their investments. They were also shown to follow, and invest in, fewer companies than their institutional counterparts. Retail investors reported less overreaction, less overconfidence and more underconfidence than their institutional peers. Retail investors were also shown to allocate less of their portfolio to either cyclical shares or asset/turnarounds than were institutional investors. It is possible that level of overconfidence (underconfidence) goes hand in hand with degree of aggressive (or conservative) investment practices. Retail investors could not be distinguished from their institutional counterparts based on measures of July effect, appetite for financial risk, information sources, anxiety, the three dimensions of impulsivity or changes in wealth over time.

10.6 Research question 4 – Overreaction, overconfidence and underconfidence

10.6.1 Prediction of Overreaction

Research question 4(a) asked what variables could predict overreaction from four sets of variables. Using hierarchical regression, overreaction was shown to be predicted by the July effect and appetite for financial risk. More specifically, the greater the investor's tendency was towards either variable, the greater investor tendency to overreact. Moreover, if knowledge of either of these variables are unavailable, gender (being male), hours spent on investments, companies followed and/or lack of attention (the first dimension of impulsivity) may also help explain factors affecting an investor's tendency to overreact.

Past research on overreaction has been based on portfolio simulation (see section 2.6.1). One might expect, however, that investors who follow a larger number of companies may be less likely to fully attend (lack of attention) to each company in their portfolio, leaving rise to overreaction when their investments do not perform the way they would like them to. This finding is therefore consistent with the finding that those who are impulsive are, by the very nature of their impulsivity, unable to avoid situations that may evoke impulsive behaviors (See Gray, 1987).

10.6.2 Prediction of Overconfidence

Research question 4(b) similarly asked which variables out of four sets of variables could contribute to the prediction of overconfidence. Using hierarchical regression, overconfidence was shown to be predicted by (a) age; (b) education; (c) financial education; (d) companies followed; (e) companies in portfolio; (f) anxiety*;* and (g) lack of attention. Recall that lack of attention is the first dimension of impulsivity.

More specifically, overconfidence was shown to be related with younger, less educated, (but greater financial education), who monitored (and invested in) a greater number of companies. Moreover, overconfidence was associated with lower levels of anxiety and being more attentive.

It was interesting to note that whilst gender and marital status were included as potential predictors of overconfidence, gender was only a significant predictor in the first block. Neither variable assumed any importance in the prediction of overconfidence when other variables were available to help predict overconfidence. This finding is consistent with the finding of the first research question. (See section 10.2). Moreover, it expands on the findings of the first research question to highlight variables that may assume greater importance in the explanation of overconfidence. For this reason, this finding adds to the understanding of investor overconfidence.

This finding confirms some of the findings of Ates et al. (2016). Like the Ates et al. (2016) study, financial education and gender appear to predict overconfidence. However, this thesis also found age (inverse relationship) and education (inverse relationship) to predict overconfidence, but not marital status. This thesis also found that the number of companies followed, the number of companies invested in, anxiety (inverse relationship) and lack of attention (inverse relationship) also contributed to the prediction of overconfidence. As not all the variables selected in this thesis were included in the study of Ates et al. (2016) and vice versa, it is possible that the difference between the findings of this thesis and that of Ates et al. (2016) may be due to random differences in sampling, differences between both overconfidence scales and/or the set of predictor variables chosen.

10.6.3 Prediction of Underconfidence

Finally, research question 4(c) asked which variables out of four sets of variables could contribute to the prediction of count of "don't know" as a marker of underconfidence. Count of "don't know" as a marker of underconfidence could be predicted by financial education, companies followed and appetite for financial risk. More specifically, investor underconfidence was shown to be related to having lower levels of financial education, monitoring fewer companies, but having an appetite for financial risk.

The presence of an appetite for financial risk in underconfident investors is an intriguing one. Perhaps underconfident investors express their appetite for financial risk by delving into the share market, in spite of the lack of financial knowledge they believe they have.

Previous research has found that the tendency towards overconfidence or underconfidence is reflected primarily on the strength of information gleaned. If the strength of information was strong, the investor would demonstrate overconfidence. If the strength of information was weak, the investor would demonstrate underconfidence (Griffin & Tversky, 1992). Remaining research on overconfidence considered only gender differences in overconfidence and consequent outcomes on portfolio performance (see section 2.4.4). The present research adds to the understanding of overconfidence by identifying the variables that can predict level of overconfidence and its inverse.

10.7 Research question 5 --- Structural equation model

Research question 5 asked whether the structural equation model put forward in Figure 3 (with, or without modification) fits the sample of retail investors. Four separate structural equation models were fitted to the data, representing each of the four types of share investments (i.e., (a) defensive shares; (b) growth shares; (c) cyclical shares; and (d) asset/turnarounds).

The structural equation model for defensive shares showed that investors who allocated more of their portfolio to defensive shares reported (a) being neither particularly overconfident nor underconfident; (b) not having an appetite for financial risk; as well as (c) seeking information about their investments and planning their many investments. Investors who allocate more of their portfolio to defensive shares may be best described as confident, conservative, informed and planful.

The structural equation model for growth shares showed that investors who allocated more of their portfolio to growth shares reported (a) oscillation between periods of overconfidence and underconfidence; (b) less overreaction or anxiety; (c) engagement with the July effect; (d) having an appetite for financial risk; (e) not seeking information about their investments nor planning their investments and (f) not wanting to actively engage with their portfolio. Investors who allocate more of their portfolio to growth shares may be best described as unfazed, oscillating between periods of overconfidence and underconfidence and who have a risk appetite.

The structural equation model for cyclical shares showed that investors who allocated more of their portfolio to cyclical shares reported (a) more overconfidence; (b) less overreaction or anxiety; (c) engagement with the July effect; (d) seeking information about their investments; and (e) a preference for being physically active with their investment portfolio. Investors who allocate more of their portfolio to cyclical shares may be best described as overconfident, unfazed and active investors.

The structural equation model for asset/turnarounds showed that investors who allocated more of their portfolio to asset/turnarounds reported (a) more overconfidence; (b) less overreaction or anxiety; (c) engagement with the July effect; (d) little financial education; (e) seeking information about their investments but did not really planning their investments; and (f) a preference for being physically active with their investment portfolios. Investors who allocated more of their portfolio to asset/turnarounds could be best described as overconfident, unfazed, unplanned and active investors.

Of interest, it would appear that investors who allocated more of their portfolios to growth shares, cyclical shares or asset/turnarounds did not believe they overreacted or got anxious. This same group of investors engaged in the July effect. Moreover, one of the pathways leading to the July effect was that of anxiety. The direction of that pathway was positive. It is possible that investors might engage in the July effect to allay any anxieties they may feel and, in so doing, may not recognize any anxieties they may be feeling. Figure 32 shows the relationship between overreaction, anxiety and the July effect on the four different types of share investments.

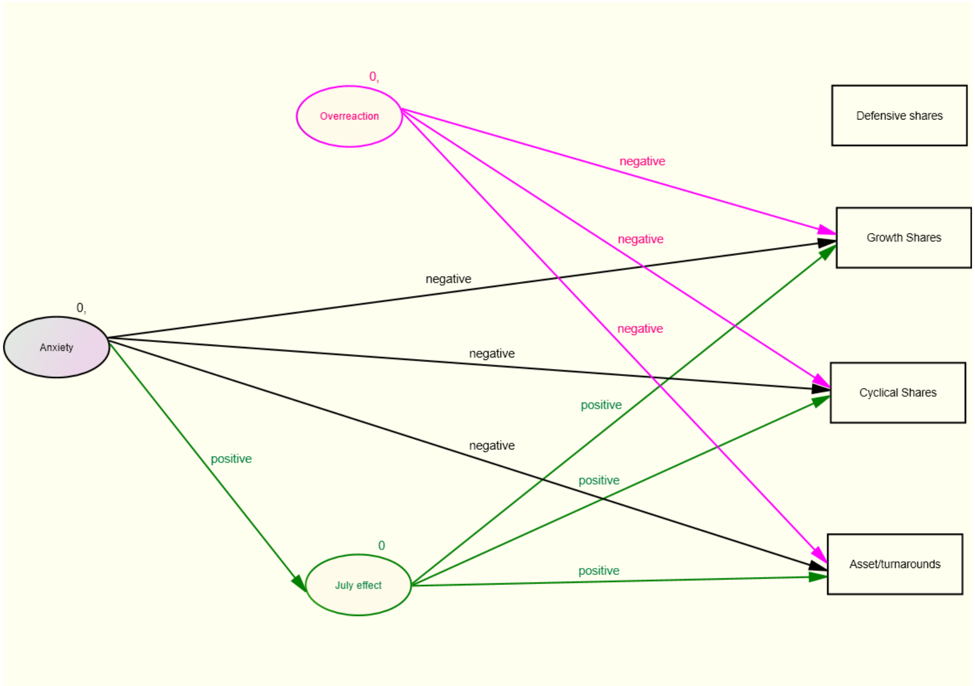

Figure 32. Relationship between overreaction, anxiety and July effect on the four types of share investments.

This set of findings may help shed light on the presence of a July effect, or indeed, the January effect, along with the presence of positive and negative returns in other months of the year. (See, for example, Bentzen, 2009; Ogieva et al., 2013). Moreover, this pattern of findings may also be explained by fight/flight behavior, and more specifically, the Gray (1987, 1990) behavioral inhibition and behavioral activation systems. The behavioral activation system may be responsible for share investors seeking higher investment returns through growth shares, cyclical shares and asset/turnarounds. The behavioral activation system may be expressed through the desire for being physically active with their portfolios (the third dimension of impulsivity) at the very least. If the share investments chosen later appear to be of poor choice, the behavioral inhibition system may become activated, leading to feelings of anxiety and the consequent decision to sell out of those same investments. As Gray (1987) suggested, those who are prone to impulsivity may be unable to prevent placing themselves into future situations where they may act impulsively. At an aggregate level, investors may appear to overreact with bull and bear runs and share price volatility becomes evident.

Examination of the four models suggests that there may be a continuum of overconfidence. At one end of the continuum, those who prefer to invest in defensive shares report neither overconfidence nor underconfidence. Those with a preference in growth shares report oscillating periods of overconfidence and underconfidence, while those with a preference for cyclical shares or asset/turnarounds report overconfidence. Moreover, those with a preference for cyclical shares and asset/turnarounds also report a desire to be actively involved with their investments. Figure 33 shows the relationship between overconfidence (and its inverse) on the four different types of share investments. This figure also shows the contribution of motor activity (the third dimension of impulsivity) on the four different types of share investments.

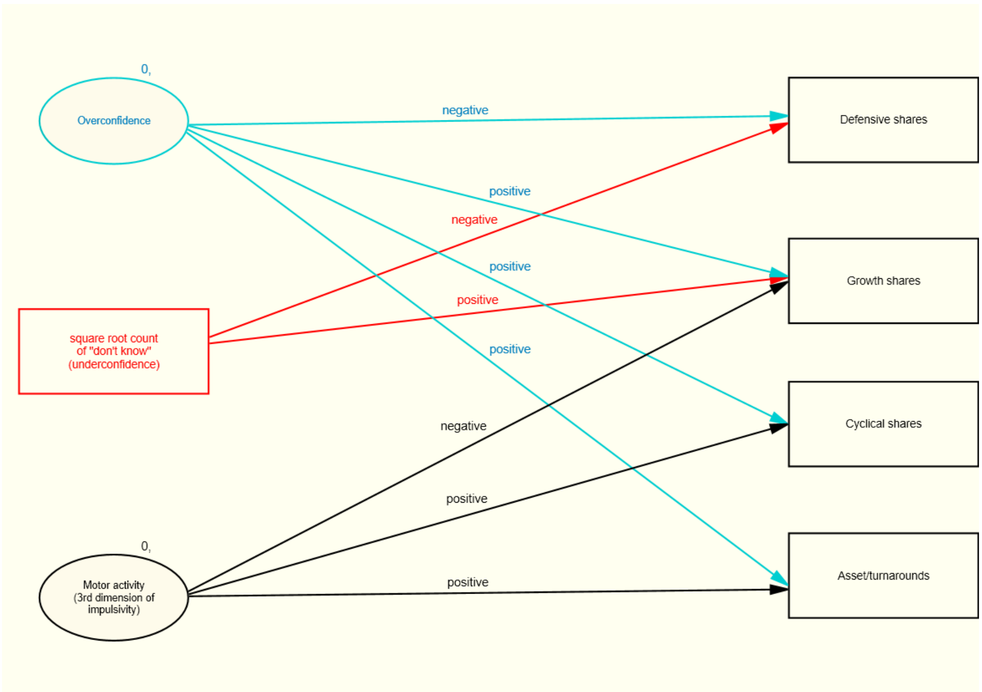

Figure 33. Relationship between overconfidence, underconfidence and motor activity (the third dimension of impulsivity) on the four types of share investments.

Past research has shown that overconfidence has a negative impact on portfolio wealth due to poor financial decisions (Asaad, 2015; Koellinger & Treffers, 2015), and ultimately, increased trading activity (Barber & Odean, 1999, 2000, 2001; Glaser &

Weber, 2003; Grinblatt & Keloharju, 2009; Lin, 2005). This research extends past research by showing that increasing levels of overconfidence may influence the types of shares an investor chooses to invest in. It also extends past research by showing that overconfidence is coupled with a greater desire to be physically active with one's portfolio when investing in cyclical shares and asset/turnarounds. The desire for greater physical involvement with one's portfolio in cyclical shares and asset/turnarounds may help explain the increased trading activity previously seen with overconfident investors. Section 11.2.6 draws conclusions regarding the final research question.

10.8 Distilling the findings of this thesis on overreaction

The third research question has shown that retail investors report less overreaction than do institutional investors. The fourth research question showed that overreaction could be predicted by appetite for financial risk and the July effect. If these variables were not available, then overreaction could be predicted by gender, hours spent on investments, companies followed and/or lack of attention (the first dimension of impulsivity).

The final research question confirmed that hours spent on investments, companies followed and lack of attention contributed to the prediction of overreaction. In addition, motor activity was also found to contribute to the prediction of overreaction. Note that the structural equation model did not test whether appetite for financial risk or the July effect could contribute to the prediction of overreaction. In turn, overreaction was shown to contribute to the prediction of growth shares, cyclical shares and asset/turnarounds, but not defensive shares. In each case, the direction of the pathway was negative.

As discussed above, overreaction, anxiety and the July effect had the same pattern of relationships with growth shares, cyclical shares and asset/turnarounds such that both overreaction and anxiety negatively contributed to the prediction of the three types of share investments, while the July effect positively contributed to the same three types of investments. Moreover, anxiety had a positive contribution to the prediction of the July effect. When considered together, one might conclude that investors think they do not overreact or get anxious, but perhaps express any anxieties they may be feeling by engaging in the July effect. In engaging in the July effect, the evidence of the share market may conclude otherwise about investor tendency towards overreaction. As discussed in the previous section, this pattern of findings may explain the presence of a July effect (or indeed, the January effect) along with other months demonstrating positive or negative returns. This pattern of findings may also be explained by the Gray (1987, 1990) behavioral activation and behavioral inhibition systems.

In summary, it would appear that investors who overreact are more likely to (a) be male; (b) spend many hours on their investments; (c) follow many companies; (d) not fully attend to their investments; (e) be physically active with their portfolios; (f) have an appetite for financial risk; and (g) engage in the July effect. Institutional investors may be more prone to overreaction than might their retail counterparts. This latter finding may be an artifact of the greater number of hours spent on investments and number of companies followed by institutional investors. If Gray (1987) is correct, institutional investors may have created an environment where they cannot fully attend to as many companies as they follow and ultimately overreact to their investments. Finally, investors may not recognize their own tendency towards anxiety or overreaction, but this tendency may be masked by their tendency towards the July effect.

10.9 Distilling the findings on overconfidence and its inverse

The first research question showed that single women demonstrated less overconfidence than did men in general. The second research question showed that the count of “don’t know” could act as a marker of underconfidence and that this marker was more closely (and inversely) related to the informational aspect of overconfidence than it was expectations. The third research question showed that retail investors showed less overconfidence, and more underconfidence (as measured by the count of “don’t know”), than did their institutional counterparts.

The fourth and final research questions showed that overconfidence could be predicted by (a) gender; (b) age; (c) education; (d) financial education; (e) hours spent on investments; (f) companies followed; (g) companies in portfolio; (h) information sources; (i) anxiety; (j) lack of attention; as well as (k) lack of planning (the first and second dimensions of impulsivity). The fourth and final research questions also showed that the count of “don’t know” as a marker of underconfidence could be predicted by (a) education; (b) financial education; (c) hours spent on investments; (d) companies followed; (e) information sources; and (f) appetite for financial risk.

Moreover, the final research question showed that overconfidence can contribute to the prediction of all four types of share investments, while the count of “don’t know” as a marker of underconfidence contributed to the prediction of both defensive shares and growth shares. Overconfidence was inversely related to defensive shares and positively related to the remaining three types of share investments. The count of “don’t know” as a marker of underconfidence was also negatively related to defensive shares and positively related to growth shares.

As discussed in section 10.7, it would appear that level of overconfidence, and its inverse, may influence the choice of shares that an investor will choose. When investors are neither particularly overconfident or underconfident, they will allocate more of their portfolio to defensive shares. When investors oscillate between overconfidence and defensive shares, they may choose growth shares. However, those who are purely overconfident will prefer to allocate more of their portfolios to cyclical shares or asset/turnarounds. One might wonder whether investor may have an increasingly greater appetite for financial risk as one moves away from defensive shares and towards cyclical shares and asset/turnarounds. However, appetite for financial risk only played a role in allocation of the portfolio to defensive shares (negative) or growth shares (positive), but not cyclical shares or asset/turnarounds. Thus, this appetite may not be a recognized (or acknowledged) one. At the very least, and as discussed in section 10.7, level of overconfidence may influence the kinds of shares investors choose for their portfolios. When coupled with the desire to be physically active with their portfolios, it may become clearer why overconfidence leads to more active trading with deleterious consequences for portfolio performance that has been seen in past research.

In summary, overconfident investors are more likely to be financially educated, younger men, who spend more time on their investments, as well as follow (and invest in) more companies. Overconfident investors do not appear to get anxious, they attend and plan their investments. It is interesting to note that the more overconfident the investor, the less they rely on information sources. Not surprisingly, institutional investors report greater levels of overconfidence than do their retail counterparts.

Overconfidence appears to have implications for the kinds of shares investors choose to invest in. Those who are neither overconfident nor underconfident allocate more of their portfolio to defensive shares while those who are purely overconfident allocate more of their portfolio to cyclical shares and asset/turnarounds.

10.10 Conclusion

This chapter discussed the research from chapters 5 to 9. The next chapter draws conclusions, discusses limitations of this research and provides direction for future research.

Chapter 11 Conclusions

11.1 Introduction

This chapter summarizes the research findings, considers the implications and limitations of this research as well as considers directions for future research.

11.2 Summary and implications of this research

11.2.1 Scale development

Seven of ten scales, including both subscales on overconfidence and information sources demonstrated good factor structure. All seven scales (and both sets of subscales) demonstrated good reliability and discriminant validity. Five of the seven scales were developed by the researcher (i.e., (a) overreaction; (b) overconfidence; (c) information sources; (d) the July effect; and (e) appetite for financial risk). The remaining two scales (i.e., anxiety and the three dimensions of impulsivity) were adapted for use with investor populations.

Previous research developed scales for overconfidence and appetite for financial risk (e.g., Ates et al., 2016; Iqbal et al., 2014; Kafayat, 2014; Rajagopalan & Gurusamy, 2014). However, their full psychometric properties have not been reported. Moreover, the full psychometric properties have not been reported for the anxiety scale developed by IPIP (2010) or the BIS 15 developed by Spinella (2007). Previous research has not developed scales for overreaction, the July effect seasonal or information sources.

Thus, the development and validation of seven (of the original ten) scales with good psychometric properties will go a long way to further research in investor behavior. Indeed, the use of these scales in multivariate surveys will enable investor behavior to be explored in depth. Moreover, researchers will be able to drill down and examine subgroup differences between retail and institutional investors, as well as those based on age, gender and marital status.

It is of concern, however, that this thesis was unable to provide a psychological biases or social herding scale that would demonstrate good psychometric properties. Based on prior research on psychological biases (e.g., Caparrelli et al., 2004; Kahneman & Tversky, 1972; Lehenkari & Perttunen, 2004), one might expect both constructs to play an important role in the understanding of investor behavior. Previous research has made a start in developing scales to measure psychological biases (e.g., Ates et al., 2016) and for social herding (Asif, 2016). With the impact of media on trading behavior (e.g., Engelberg & Parsons, 2011; Peress, 2014; Tetlock, 2007, 2011; Tetlock et al., 2008), it is possible that social herding is little more than an artifact of the methods used by share investors to seek information about their investments.

11.2.2 Research question 1 --- Overconfidence

Single women were shown to be less overconfident than men generally. This finding shows that gender was more important than marital status in determining the level of overconfidence an investor might experience. Simply knowing that an investor is male or female, then, one knows whether the investor is likely to be over- or under- confident. As past research has shown that level of overconfidence has implications on investor trading and subsequent portfolio performance (Barber & Odean, 1999, 2000, 2001), level of overconfidence can be expected to play an important role in investor portfolio performance. Further implications of overconfidence on investor portfolio performance will be discussed under sections 11.2.4 to 11.2.6 below.

11.2.3 Research question 2 –Underconfidence

The count of "don't know" on its own, or in conjunction with the count of missing data, was shown to be a marker of underconfidence, but not the count of missing data alone.

For this reason, the count of "don't know" is a cleaner measure of underconfidence than is the combined count of "don't know" and missing data.

The count of "don't know" as a marker of underconfidence could thus be used as an additional measure when surveying investors. This measure would not require adding any additional questions to an investor survey in order to collect this data. Moreover, doing so may turn data that might otherwise have been treated as missing into valuable data. Indeed, if it becomes unfeasible to directly measure overconfidence with investors, or when the researcher would like to make use of multiple measures of overconfidence, this measure may prove to be a welcome addition in investor research.

11.2.4 Research question 3 – Discriminating between retail and institutional investors

Based on the findings of seven discriminant analyses, retail investors reported (a) being older; (b) having less (financial) education; (c) less experience; (d) spending fewer hours on their investments; (e) monitoring (and investing in) fewer companies; (f) allocating less of their portfolio to cyclical shares and asset/turnarounds; (g) less overreaction; (h) less overconfidence and more underconfidence than their institutional counterparts. Retail investors could not be distinguished from institutional investors based on the July effect, appetite for financial risk, information sources, anxiety, the three dimensions of impulsivity, or changes to portfolio wealth over time.

As portfolio management may be expected to be a full time vocation for institutional investors, but not for retail investors, it may come as no surprise that both groups of investors can be distinguished from each other on the basis of financial education, hours spent on investments, as well as the number of companies monitored and invested in. As this data is easily obtained, future researchers may find the inclusion of one or more of these variables useful in distinguishing between retail and institutional investors. In this regard, hours spent on investments may be the most able variable in distinguishing between both groups of investors.

It is interesting to note that retail investors reported less overconfidence (more underconfidence) than their institutional peers, and with it, allocating less of their portfolio to cyclical shares and asset/turnarounds. The combination of both findings is consistent with those of the four structural equation models where overconfident investors were more likely to allocate more of their portfolio to cyclical shares and asset/turnarounds. One might expect that those who invest in cyclical shares and asset/turnarounds may also be engaging in more frequent trading activities than those who invest in defensive and growth shares. If this proves to be the case, it may be no surprise that Barber and Odean (1999, 2000, 2001) found that overconfident investors traded more with deleterious effects on their long-term portfolio wealth.

11.2.5 Research question 4 – Overreaction, overconfidence and underconfidence

The hierarchical regression analysis for overreaction showed that it could be predicted by the July effect and appetite for financial risk. Moreover, if these variables were unavailable, gender, hours spent on investments, companies followed and lack of attention (a dimension of impulsivity) may help predict investor tendency towards overreaction. It makes sense that lack of attention (a dimension of impulsivity) can contribute to the prediction of investor overreaction. If lack of attention to one's investments is combined with a great many companies in one's portfolio, there is an increased risk that one of the investments may perform poorly. In so doing, it invites investor overreaction.

The hierarchical regression analysis for overconfidence showed that it could be predicted by age, (financial) education, companies followed and in portfolio, anxiety and lack of attention. When considered with age and (financial) education, gender made a significant contribution to the prediction of overconfidence. However, when remaining variables were included in the regression model, gender could not make a unique contribution to the prediction of overconfidence. Thus, while knowledge of an investor's gender may help determine their level of overconfidence, other variables are better able to determine an investor's level of overconfidence.

The hierarchical regression analysis for count of "don't know" as a marker of underconfidence showed that it could be predicted by financial education, companies followed and appetite for financial risk. It is interesting to note that while higher levels of financial education contributed to the prediction of overconfidence, its inverse contributed to the prediction of underconfidence. Similarly, higher numbers of companies followed contributed to the prediction of overconfidence, while its inverse contributed to the prediction of underconfidence. Whilst fewer variables contributed to the prediction of underconfidence than were able to predict overconfidence, it is clear that those that predict both show different directions. That variables that predicted overconfidence and the count of "don't know" had opposite signs was consistent with the hypothesis that the count of "don't know" is indeed a marker of underconfidence. As discussed in sections 10.2.3 and 11.2.3, the count of "don't know" may prove to be an invaluable tool in tapping into the domain of overconfidence, either when formal measures of overconfidence are not available or when multiple markers of overconfidence are required.

11.2.6 Research question 5 – Structural equation model

Four structural equation models were put forward. Investors who allocated more of their portfolio to defensive shares could be best described as confident, conservative, informed and planful investors. Those who allocated more of their portfolio to growth shares could be best described as those with oscillating levels of confidence, an appetite for financial risk, unfazed, unplanned and inactive investors. Those who allocated more of their portfolio to cyclical shares could be best described as overconfident, unfazed and active investors. Finally, those who allocated more of their portfolio to asset/turnarounds, could be best described as overconfident, unfazed, unplanned and active investors.

It was interesting to note that investors with a preference for growth shares, cyclical shares or asset/turnarounds reported not overreacting or getting anxious. They did, however, report engaging in the July effect. As anxiety proved to be a predictor of the July effect, it may be possible that investors may engage in the July effect to soothe any feelings of anxiety that they may had. If this proves to be the case, then anxiety may play an important (albeit currently unrecognized) role in investor behavior.

Also of interest, the structural equation models for defensive shares, growth shares, cyclical shares and asset/turnarounds showed that investors differed in levels of overconfidence across the four types of share investments. Indeed, investors who reported neither overconfidence nor underconfidence, allocated more of their portfolio to defensive shares. Investors who reported oscillation between periods of overconfidence and underconfidence allocated more of their portfolio to growth shares. Investors who reported overconfidence allocated more of their portfolios to either cyclical shares or asset/turnarounds. Moreover, those who allocated more of their portfolios to either cyclical shares or asset/turnarounds reported a preference of being physically active with their investment portfolios. It would thus appear that as investor overconfidence increases, investors increasingly turn to more risky types of shares investments and simultaneously become more willing to actively engage with their investment portfolios.

Overconfidence may thus represent a driver of appetite for financial risk. All else being equal, this information may inform financial advisors when guiding investors into suitable financial products based on their risk profile. However, it may be more apt to advise those same investors about the negative impact of overconfidence on portfolio wealth. (See, for example, Asaad, 2015; Barber & Odean, 1999, 2000, 2001; Glaser & Weber, 2003; Koellinger & Treffers, 2015).

11.3 Limitations

Several general limitations of this research have been identified. Firstly, the response rate was only 14.03 percent. While care was taken to analyze the data carefully, the low response rate may mean that the findings of this research may not adequately represent the population from which investors were drawn.

Second, it is also recognized that retrospective, self-report data has its own flaws. Self-report data may be subject to respondent desire for positive self-presentation. It may also reflect what respondents think they might do in particular circumstances, rather than what might actually do if and when they find themselves in those same circumstances. When self-report data includes retrospective self-reports, that data may also be subject to respondent memory.

Third, it is recognized that this survey was cross sectional and no intervention had been undertaken as part of this research. Consequently, the findings of this research can only provide correlational evidence. It does not provide evidence of any causal links.

Fourth, respondents in the present survey primarily endorsed buy and hold investing or contrarian investing as their preferred investment strategy. Few investors endorsed dollar cost averaging, index investing, or momentum investing as their preferred investment method. Consequently, this variable had been excluded from any of the analyses in the present study. However, it is recognized that preferred investment method *per se,* and their combination with the types of shares invested, may play a significant role in changes to portfolio wealth over time. It is left to future research to explore differences in portfolio performance based on the interaction between investment strategy and types of share investments.

With respect to scale development, it is recognized that insufficient items had been written for some of the constructs (including social herding, psychological biases, overreaction, and July effect. In two instances, this led to an inability to construct a scale that demonstrated good psychometric properties.

Finally, structural equation modeling was limited to 427 retail investors. With only 56 institutional investors, it was not possible to compare the SEM model across both groups of investors. Nor was it possible to consider any model differences based on gender differences. Given the sample size, it was also not possible to randomly split the sample in two in order to test the model in the first sample and validate the model in the second. It is left to future research to undertake such validations.

11.4 Suggestions for future research

There are a number of avenues for future research arising from this research. Firstly, it may prove worthwhile validating the seven scales (and both sets of subscales) with future samples of share investors. As part of this work, it may prove worthwhile exploring whether the seven scales demonstrate invariance (or variability) across investor subgroups. It may also prove worthwhile developing further questions to tap into the domains of psychological biases and social herding. In so doing, future research may be able to develop two further psychometrically sound scales for use with share investors. As part of this work, it may prove worthwhile fleshing out the construct of social herding in relation to that of information sources with a view to clarifying whether they are indeed independent constructs or whether social herding is an artifact of the social networking subscale of information sources.

Secondly, future research might also consider exploring the relationship between the four types of share investments (i.e., defensive shares to asset/turnaround) and the five methods of share investing (i.e., (a) buy and hold investing; (b) contrarian investing; (c) dollar cost averaging; (d) index investing; and (e) momentum trading). If this line of research could be combined with finding an optimal level of overconfidence, financial advisers may be better placed to advise their clients on the kinds of financial products that may best meet their financial goals.

Thirdly, it may be worthwhile for future research to replicate the findings of the four structural equation models with other samples of investors. If such samples are sufficiently large, a test for invariance across gender and investor sub-groups could also be considered. With a large enough sample, future research may be able to extend the four models to include the five major types of investment strategies and wealth changes over time. In so doing, future research may be able to test for invariance across share investments, along with testing for the most effective combination of share investments and investment strategies.

Fourthly, future research may find it worthwhile exploring the relationship between overreaction, anxiety and the July effect with future samples of investors, along with a test for invariance across investor subgroups. As part of this work, it may prove worthwhile considering the Gray (1987, 1990) behavioral inhibition and behavioral activation systems, and ultimately, the underlying concept of fight/flight behavior.

Finally, future research may find it worthwhile to explore the relationship between overconfidence and the preference for increasingly riskier share investments (i.e., from defensive shares to asset/turnarounds). As part of this analysis, it may prove worthwhile to explore the relationship between overconfidence and appetite for financial risk, along with a test for invariance across investor subgroups. Moreover, the inclusion of the count of "don't know" may enable future research to extend the range of confidence considered (i.e., from underconfidence to confidence to overconfidence).

11.5 Conclusion

Seven of the ten scales put forward in this thesis demonstrated good psychometric properties. Both subscales of overconfidence and information sources also demonstrated good psychometric properties. Five of these scales were developed for use with share investors. The remaining two scales were adapted for use with share investors. At the time of writing, this research was the first to develop or adapt seven scales that demonstrated good factor structure, reliability and discriminant validity for use with share investors. The introduction of the scales can, therefore, open up a new avenue of research with future samples of share investors.

This thesis added to the knowledge by showing single women demonstrated lower levels of overconfidence than do men generally.

This thesis also added to the knowledge of missing data by showing that missing data can make a meaningful contribution to the understanding of the subject under investigation. More specifically, this thesis showed that the count of "don't know" (normally treated as missing data), as well as the count of "don't know" and count of missing data per respondent can contribute to the understanding of investor behavior as easily obtained markers of underconfidence. Not only does using data in this way make a meaningful contribution to the subject under investigation, but it also does so without extending the length of the questionnaire (and hence, the time required for respondents to complete the questionnaire).

This thesis also added to the knowledge of investor subgroups by showing that retail and institutional investors could be discriminated based on (a) age; (b) education; (c) financial education; (d) years of investor experience; (e) hours spent on investments; (f) number of companies followed; (g) number of companies in portfolio; (h) allocation of portfolio to cyclical shares; (i) allocation of portfolio to asset/turnarounds; (j) overreaction; (k) overconfidence; and (l) underconfidence. More specifically, in relation to institutional investors, retail investors were older, less (financially) educated and less experienced. Retail investors spent fewer hours on their investments, monitored (and invested in) fewer companies. Retail investors also allocated less of their portfolio to cyclical shares and asset/turnarounds. Finally, retail investors were less prone to overreaction or overconfidence. Instead, they demonstrated greater levels of underconfidence than their institutional counterparts. Interestingly, retail and institutional investors did not differ in their propensity for the July effect, appetite for financial risk or use of information sources.

Moreover, this thesis showed that overreaction, overconfidence and underconfidence could also be predicted. Overreaction was shown to be predicted by appetite for financial risk and the July effect. Overconfidence was shown to be predicted by (a) age; (b) education; (c) financial education; (d) companies followed; (e) companies in portfolio; (f) anxiety; and (g) lack of attention (the first dimension of impulsivity). More specifically, those inclined towards overconfidence were more likely to be younger, less educated (but greater financial education) and following (and investing in) more companies. Those more inclined towards overconfidence were also less likely to be anxious and more likely to be attentive to their investments. Underconfidence was shown to be predicted by financial education, companies followed and appetite for financial risk. More specifically, those more prone to underconfidence were more likely to have lower levels of financial education, monitor fewer companies but still have an appetite for financial risk. Consistent with what one might expect for two variables that represent the inverse of one another, both financial education and companies followed contributed to the prediction of both overconfidence and underconfidence. Only the direction of their prediction was reversed. Thus, higher levels of financial education contributed to the prediction of overconfidence, while its inverse contributed to the prediction of underconfidence. Similarly, greater numbers of companies followed contributed to the prediction of overconfidence, while fewer companies followed contributed to the prediction of underconfidence.

Finally, this thesis put forward four structural equation models. By examining the four models, it could be seen that investors primarily differed in levels of overconfidence. While those with a preference for growth shares, cyclical shares or asset/turnarounds reported not overreacting or getting anxious, they reported engaging in the July effect.

As anxiety was a significant predictor of the tendency towards the July effect, this thesis suggests that anxiety may play a previously unrecognized role in investor behavior.

While this thesis had a number of limitations, it has also opened up several lines of future research. It is hoped that, ultimately, the findings from this line of research can help investors make more financially sound investment decisions, and ultimately, maximize their portfolio wealth over time.

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Appendices

A1 Ethics clearance and final report to Swinburne Research Ethics Committee (Project 2010/111)

From: "RES Ethics" <resethics@swin.edu.au>>
To: "Bruce Findlay" <bfindlay@swin.edu.au>, "Abramson, Rachel" <RAbramson@groupwise.swin.edu.au>, "rachela@ozemail.com.au" <rachela@ozemail.com.au>
Cc: "Anne Cain" <ancain@swin.edu.au>, "s.rahman@cqu.edu.au" <s.rahman@cqu.edu.au>
Sent: Mon, 16 Aug 2010 05:16:49 +0000
Subject: SUHREC Project 2010/111 Ethics Clearance for Modified Protocol (1)

To: Dr Bruce Findlay, FLSS/Ms Rachel Abramson

Dear Bruce and Rachel

SUHREC Project 2010/111 The Rational and Human Investor: A Financial and Behavioural Model of Wealth Changes in the Share Market
Dr Bruce Findlay, FLSS/FBE; Ms Rachel Abramson, Prof Sheikh Rahman (CQU)
Approved Duration: 02/07/2010 To 14/09/10 [Modification August 2010]

I refer to your request for ethics clearance for significant modification to the above project protocol in light of queries recently put to you. Your request was as per the email of 5 pm 11 August 2010 with attachments. The request documentation was put to a delegate of the relevant SUHREC Subcommittee (SHESC2) for consideration.

I am pleased to advise that the modified protocol, as submitted to date, has approval to proceed in line with on-going ethics clearance conditions previously communicated and reprinted below. In given approval, the SHESC2 delegate expressed thanks for the detailed submission and further clarification. Please also note that approval has been given on the understanding that agreements with external parties cover legally available material used for mail-outs.

Please contact the Research Ethics Office if you have any queries regarding the ethical review undertaken or you require a signed ethics clearance certificate, citing the SUHREC project number. Copies of clearance emails should be retained as part of project record-keeping.

Best wishes for the project.

Yours sincerely

Keith Wilkins for
Kaye Goldenberg
Secretary, SHESC2
****
Kaye Goldenberg
Administrative Officer (Research Ethics)
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From: "Rachel Abramson" <rachela@ozemail.com.au>>
To: "RES Ethics" <resethics@swin.edu.au>, "rachela@ozemail.com.au" <rachela@ozemail.com.au>
Cc: "Bruce Findlay" <bfindlay@swin.edu.au>, "Anne Cain" <ancain@swin.edu.au>, "s.rahman@cqu.edu.au" <s.rahman@cqu.edu.au>
Sent: Thu, 4 Nov 2010 01:38:04 +0000
Subject: Re: SUHREC Project 2010/111 Ethics Clearance for Modified Protocol (1)

Dear Research Ethics Committee,

The Swinburne research project No. 2010/111 received 519 responses. This represents a 14.68% response rate (when factoring in returns). Ohe hundred and thirty investors asked to receive a copy of the summary results.

Bruce and I received a few calls, emails and snailmail notes. These interactions were quite positive. It would seem that investors were genuinely interested in this research.

There were two unusual interactions where shareholders had sent information to me intended for a third party. In one instance, I sent the correspondence back to the shareholder concerned. In the second instance, I forwarded the correspondencer onto the intended party. One shareholder asked if I could help her track down some investments held in trust for her children. I suggested that she make contact with the company in which she believed these shares to be held. An institutional investor had an extended chat with me about my research.

A number of investors added comments on the questionnaires. While this project had not intended to analyse any qualitative data, investor commentary adds an extra element of understanding to this study and I may end up including some of this commentary in my thesis.

The FBE will ultimately receive a copy of my thesis and I will continue to work with my two supervisors to bring the thesis to a standard primae facie ready for examination. However, if there is any further information you may require regarding this project, please do not hesitate to contact me.

Best wishes,

R

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Rachel Abramson & Associates
P O Box 300
Caulfield South, Vic., 3162
0418 149 506
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Skype: rachel.abramson.and.associates
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http://www.centreforcareerdevelopmentandericksonianhypnosis.com.au

A2 Cover Letter to Potential Investors

This research project has been approved by the Swinburne University Human Research Ethics Committee in line with the National Standard on Ethical Conduct in Human Research. If you have any concerns, or complaints about the conduct of this project, you can contact the Research Ethics Officer, Swinburne Research (H68), Swinburne University of Technology, P O Box 218, Hawthorn, Vic, 3122, 03 9214 5218 or resethics@swin.edu.au.

The Rational and Human Investor:
Opinions, Perceptions and Practices of Retail and Institutional Shareholders.

Dear Shareholder, 13th August 2010

My name is Rachel Abramson. I am currently completing a PhD at Swinburne University's Faculty of Business and Enterprise. My supervisors are Professor Sheikh Rahman and Dr. Bruce Findlay.

I am writing to you because you are a retail or institutional shareholder. I am seeking your opinions, perceptions and practices as a shareholder. As such, I invite you to take part in the attached survey. Results from this survey may be used to help investors make more informed decisions, and ultimately, may have a positive impact on portfolio wealth.

Participation in this survey is purely voluntary and completely anonymous. No identifying information is being sought in the attached questionnaire. *Your consent to participate in the study is assumed by returning your completed questionnaire in the envelope provided*.

Every effort is undertaken to ensure your privacy. We obtained your address details from a list provider solely for the purpose of two mail-outs for this research project and in accordance with its requirements. No contact details have been retained by the researchers. The use of reply paid envelopes ensures a secure, anonymous contact point for receipt of your completed survey. To ensure confidentiality and integrity of results, access to questionnaire data will be restricted to my supervisors and me. Questionnaire data will be stored for seven years in accordance with University regulations. Only unidentifiable group results will be reported in my thesis, and any other publications that may arise from it.

Ultimately, the results of this survey can only be as useful as those who take part in it. I therefore encourage you to complete the attached questionnaire and post it in the reply-paid envelope provided. You can also post it to Reply Paid 300, Caulfield South, Vic., 3162. This questionnaire will take between 20 and 30 minutes to complete. As it is anonymous, feel free to complete it as openly and as honestly as you can.

For your information, a summary of the overall, unidentifiable results will be available approximately three months from the date of this letter. To receive a copy of the overall results, please print your name and address on the attached form and send under separate cover to: Reply Paid 300, Caulfield South 3162. Please be assured that contact details used to post overall project results to you will not be retained beyond this purpose.

If you require any further information, please do not hesitate to contact Dr. Findlay (03 9214 8093), Professor Rahman (03 8662 0810) or myself (0418 149 506).

Thank you and best wishes,

Rachel Abramson

Rachel Abramson, PhD Student
Swinburne University
Faculty of Business and Enterprise
Reply Paid 300
Caulfield South, Vic., 3162.
0418 149 506

I would like to receive a copy of the overall results. I understand that it will available in mid-November.

In this regard, I print my name and address details as follows:

NAME: ____

ADDRESS: ____

SUBURB: ______________________________ POSTCODE: ______________

Please post this form, under separate cover, to:

REPLY PAID 300
CAULFIELD SOUTH, VIC, 3162.

A3 Sample (blank) questionnaire

ID: [ ][ ][ ][ ]

Office Use Only

Instructions for share investors:

This survey asks about your opinions, perceptions and practices regarding shares that you directly hold and/or manage. This survey also asks about your background. Most of the questions in this survey will ask you to tick [\/] or circle the alternative that best reflects your position. Other questions will ask you to place a numerical value in the space provided. For each question, please report the alternative that best reflects your opinions, perception, and practices. If you change your mind about an answer, feel free to cross out the incorrect alternative and then indicate your preferred alternative. You can use the space on the back page for any additional comments you would like to make. Thank you.

A] Your Opinions	**Completely Unimportant**	………………			**Completely Important**	**Don't Know**
How important is each of the following for you as an investor?						
1. Dividend (i.e., how much you receive per share)	1	2	3	4	5	9
2. Franking tax credits (i.e., attached to dividend income and ensures that tax is not paid twice on that same income)	1	2	3	4	5	9
3. Investing safely	1	2	3	4	5	9
4. Share price growth	1	2	3	4	5	9
5. Taking risks to earn good returns	1	2	3	4	5	9
6. Spreading investments across share market sectors (e.g., energy, financial, media, mining and retail, etc.).	1	2	3	4	5	9
7. Spreading investments across asset classes (e.g., shares, property, gold, art and antiques, etc.).	1	2	3	4	5	9
8. Knowing the companies in your investment package	1	2	3	4	5	9
9. Knowing a company's share price history	1	2	3	4	5	9
10. Taking profits through selling your shares	1	2	3	4	5	9
11. Automatic 'stop loss' or 'sell' orders (i.e., an order to sell shares if their price falls below a predetermined price)	1	2	3	4	5	9
12. Automatic 'buy' orders (i.e., an order to buy shares if their price falls below a predetermined price)	1	2	3	4	5	9
13. Margin lending (i.e., purchasing shares on stockbroker loans)	1	2	3	4	5	9
14. Options trading (i.e., financial contract that gives the right to buy or sell shares at a set price by a given date, but not the obligation to do so)	1	2	3	4	5	9
15. Warrants (i.e., financial contracts that give you the right to buy shares at a set price by a given date – usually longer time frame than a buy option)	1	2	3	4	5	9
16. Derivatives (i.e., simple or complex financial products that may involve options, forward contracts, swaps or future contracts)	1	2	3	4	5	9
17. Bank loans or home mortgage redraw facilities to buy shares	1	2	3	4	5	9

	Completely Unknowledgeable …				Completely Knowledgeable	Don't Know
18. How knowledgeable do you consider yourself to be about investing?	1	2	3	4	5	9
19. In comparison to other investors, how more or less knowledgeable do you consider yourself to be about investing?	1	2	3	4	5	9
20. How knowledgeable do you consider yourself to be about share price indices (e.g., All ordinaries, ASX 200, S & P 200, etc.)?	1	2	3	4	5	9

	Decrease 10% or more	Decrease 2-5%	Stay the same	Increase 2-5%	Increase 10% or more	Don't Know
21. By the end of 2010, do you expect the portfolio you Own or manage to:	1	2	3	4	5	9
22. By the end of 2010, do you expect the All Ordinaries Index to:	1	2	3	4	5	9

	-10% or less	-2 to -5%	0%	2 to 5%	+10% or more	Don't Know
23. What percent return do you expect your portfolio to earn by the end of the year (i.e., the income and/or capital gains as a percent of your share investments)?	1	2	3	4	5	9
24. What percent return do you believe other investors, on average, will earn on their portfolios by the end of the year (i.e., the income and/or capital gains as a percent of share Investments?	1	2	3	4	5	9

B] Your Perceptions

The following statements relate to your general perceptions on investment.

	Strongly Disagree ……				Strongly Agree	Don't Know
1. The best way to protect one's wealth is to do as others do in the share market.	1	2	3	4	5	9
2. Most of my friends are also investors.	1	2	3	4	5	9
3. It is important to look at the same information that fellow investors look at.	1	2	3	4	5	9
4. At the end of each year, I sell shares for less than I had paid for them.	1	2	3	4	5	9
5. At the end of each year, I sell shares for more than I had paid for them.	1	2	3	4	5	9
6. At the beginning of each year, I buy more shares.	1	2	3	4	5	9
7. Towards the end of June each year, I sell shares for less than I had paid for them.	1	2	3	4	5	9
8. Towards the end of June each year, I sell shares for more than I had paid for them.	1	2	3	4	5	9
9. At the beginning of July each year, I buy more shares.	1	2	3	4	5	9
10. I use the tax time of year to sell shares at a capital loss.	1	2	3	4	5	9

	Never	Rarely	Half the time	Mostly	Always	Don't Know
11. I use the tax time of year to sell shares at a capital gain.	1	2	3	4	5	9
12. I use the proceeds from share sales to buy more shares.	1	2	3	4	5	9
13. I use the proceeds from holiday pay to buy more shares	1	2	3	4	5	9
14. I use the proceeds from annual bonuses to buy more shares.	1	2	3	4	5	9
15. I use the proceeds from dividend income to buy more shares.	1	2	3	4	5	9
16. I use the proceeds from tax refunds to buy more shares.	1	2	3	4	5	9
17. I use reporting seasons as an opportunity to sell my high risk shares and purchase more conservative, 'blue chip' shares.	1	2	3	4	5	9

	Strongly Disagree				Strongly Agree	Don't Know
18. I keep separate accounts (e.g., car, home, income, investment, savings, 'windfalls') for different kinds of activities.	1	2	3	4	5	9
19. A company's profit performance has the same prospects as that of its share price performance.	1	2	3	4	5	9
20. When I buy or sell shares, I consider the original purchase price of those shares I already have.	1	2	3	4	5	9
21. I prefer to capitalize gains quickly.	1	2	3	4	5	9
22. I prefer to hold on to losing stocks in the hope that they will eventually make a capital gain.	1	2	3	4	5	9
23. I prefer to keep my existing shares rather than selling them to buy other shares that might generate more income.	1	2	3	4	5	9
24. I expect to receive more for my shares than I would be prepared to pay if I were to buy those same shares.	1	2	3	4	5	9
25. When a company's share price performance has done badly, I sell out, no matter how little I get for selling them.	1	2	3	4	5	9
26. When a company's share price performance has done well, I buy its shares, no matter how much I have to pay for them.	1	2	3	4	5	9

27. Of the different company shares in your portfolio, what proportion are listed on the Australian Stock Exchange, (including those jointly listed on the ASX and another exchange), and what proportion are listed on other stock exchanges: [tick one only]

a) all listed on the Australian Stock Exchange only [________]1
b) dually listed on the Australian Stock Exchange and other stock exchanges [________]2
c) approximately 70% listed/dual-listed on the ASX, 30% on other stock exchanges [________]3
d) approximately 50% listed/dual-listed on the ASX, 50% on other stock exchanges [________]4
e) approximately 30% listed/dual-listed on the ASX, 70% on other stock exchanges [________]5
f) all listed on other stock exchanges only [________]6
g) Don't know [________]9

The following statements relate to your personal style.	**Strongly Disagree** ……				**Strongly Agree**	**Don't Know**
28. I am relaxed most of the time.	1	2	3	4	5	9
29. I worry about things happening.	1	2	3	4	5	9
30. I fear for the worst.	1	2	3	4	5	9
31. I get stressed easily.	1	2	3	4	5	9
32. I get caught up in my problems.	1	2	3	4	5	9
33. I am not easily bothered by things.	1	2	3	4	5	9
34. I am afraid of many things.	1	2	3	4	5	9
35. I am not easily disturbed by events.	1	2	3	4	5	9
36. I don't worry about things that have already happened.	1	2	3	4	5	9
37. I adapt easily to new situations.	1	2	3	4	5	9
38. I concentrate easily.	1	2	3	4	5	9
39. I am restless at lectures or talks.	1	2	3	4	5	9
40. I squirm at plays or lectures.	1	2	3	4	5	9
41. I don't pay attention.	1	2	3	4	5	9
42. I get easily bored when solving problems.	1	2	3	4	5	9
43. I plan for job security.	1	2	3	4	5	9
44. I plan for the future.	1	2	3	4	5	9
45. I save regularly.	1	2	3	4	5	9
46. I plan tasks carefully.	1	2	3	4	5	9
47. I am a careful thinker.	1	2	3	4	5	9
48. I act on impulse.	1	2	3	4	5	9
49. I act on the spur of the moment.	1	2	3	4	5	9
50. I do things without thinking.	1	2	3	4	5	9
51. I say things without thinking.	1	2	3	4	5	9
52. I buy things on impulse.	1	2	3	4	5	9

C] Your Practices

1. In what year did you place your first share investment? ________________________

2. Do you:

[tick one only]

a) directly own and manage your own investment portfolio, irrespective of whether or not you receive investment advice on your portfolio, and irrespective of whether your portfolio is held in your name, 'in trust' for you or held through a self-managed superannuation fund (that is, are you considered to be a retail investor)? [________]0

b) manage other people's investment funds (that is, are you considered to be a fund manager/institutional investor)? [________]1

c) both own your own investment portfolio, and manage other people's investment funds (that is, are you both a retail and institutional investor)? [________]2

d) Don't know. [________]9

3. *Do you use*: [tick one only]

a) Fundamental analysis (i.e., analysis of a company's financial position, perhaps drawing on its annual reports, company briefings, or your own research on the company)? [________]0
b) Technical analysis (i.e., analysis of a company's share price history, perhaps looking for trends or patterns in a plot of the company's share prices over time)? [________]1
c) Both fundamental and technical analysis? [________]2
d) Neither. [________]3
e) Other (please state): ______________________________ [________]4
f) Don't know. [________]9

4. How many hours per week do you typically spend thinking, reading, researching or discussing investments? ________________ Hours

5. Do you monitor the movements of a share price index: Daily Weekly Monthly Annually Never

Do you trade shares listed in the following countries (and exchanges)?	**Not at all**	**……………**	**……………**	**……………**	**Every Transaction**	**Don't Know**
6. Australia (Australian Stock Exchange)	1	2	3	4	5	9
7. Canada (Toronto Stock Exchange)	1	2	3	4	5	9
8. China (Shenzhen Stock Exchange)	1	2	3	4	5	9
9. Hong Kong (Stock Exchange of Hong Kong)	1	2	3	4	5	9
10. India (National Stock Exchange of India)	1	2	3	4	5	9
11. Japan (Tokyo Stock Exchange)	1	2	3	4	5	9
12. Singapore (Stock Exchange of Singapore)	1	2	3	4	5	9
13. UK (London Stock Exchange)	1	2	3	4	5	9
14. USA (Nasdaq Stock Exchange)	1	2	3	4	5	9
15. USA (New York Stock Exchange)	1	2	3	4	5	9
16. Other countries (and exchanges) ____________ (please state)	1	2	3	4	5	9

17. Would you describe your **primary** investment strategy as: [tick one only]

a) Buying shares with the intention of holding them (i.e., buy and hold)? [________]0
b) Buying shares when they are priced cheaply, selling them when they are priced more highly (i.e., contrarian)? [________]1
c) Regularly buying a set number of shares in a specified company (i.e., dollar-cost averaging)? [________]2
d) Buying shares for a portfolio so that they mirror that of a particular index [e.g., ASX100, ASX 200 or ASX500] such that shares in the portfolio would make up the same percentage in the portfolio as they do in the index (i.e., index investing)? [________]3
e) Buying shares that are rising in price, selling shares that are falling in price (i.e., momentum investing)? [________]4
f) Other (Please state): ______________________________ [________]5
g) Don't know. [________]9

18. How many different companies do you follow, research or analyze? ________________

19. How many different company's shares do you currently have in the share portfolio that you own and/or manage? ________________

Of the different company's shares you own or manage, how many are:

20. Defensive shares (i.e., shares with prices that tend to remain relatively unchanged over time and have high dividends)? ____________________
21. Growth shares (i.e., shares with prices that tend to grow over time and have low dividends)? ____________________
22. Cyclical shares (i.e., shares with prices that tend to rise or fall over time in line with industry business cycles)? ____________________
23. Asset/turnarounds (i.e., shares in companies that are trading very cheaply, and have potential for significant share price gains)? ____________________

Which of the following company ratios do you use in share buy decisions?	**Never**	**Rarely**	**Half the time**	**Mostly**	**Always**	**Don't Know**
24. Return on investment (i.e., how much a company earned, in relation to its assets)	1	2	3	4	5	9
25. Company gearing (i.e., how much a company owes, in relation to how much it owns)	1	2	3	4	5	9
26. Earnings per share (i.e., how much company has earned, on a per share basis)	1	2	3	4	5	9
27. Dividends per share (i.e., how much income is earned on a per share basis)	1	2	3	4	5	9
28. Price/earnings ratio (i.e., a company's share price divided by what it earned per share)	1	2	3	4	5	9
29. Dividend yield (i.e., how much income received per share, expressed as a percentage of share price)	1	2	3	4	5	9
30. Net assets per share (i.e., what a company owns less what a company owes, on a per share basis)	1	2	3	4	5	9
31. Other ____________________ (please state)	1	2	3	4	5	9

Which of the following company ratios do you use in share sale decisions?	**Never**	**Rarely**	**Half the time**	**Mostly**	**Always**	**Don't Know**
32. Return on investment	1	2	3	4	5	9
33. Company gearing	1	2	3	4	5	9
34. Earnings per share	1	2	3	4	5	9
35. Dividends per share	1	2	3	4	5	9
36. Price/earnings ratio	1	2	3	4	5	9
37. Dividend yield	1	2	3	4	5	9
38. Net assets per share	1	2	3	4	5	9
39. Other ____________________ (please state)	1	2	3	4	5	9

How important is each of the following information sources on your investment decisions?	**Completely Unimportant**	…………………			**Completely Important**	**Don't Know**
40. Your accountant	1	2	3	4	5	9
41. Your financial advisor	1	2	3	4	5	9
42. Internet brokers	1	2	3	4	5	9
43. Full service brokers (i.e., ones who provide advice, make recommendations as well as conduct trades)	1	2	3	4	5	9
44. The Australian Stock Exchange (ASX) website	1	2	3	4	5	9
45. IPO prospectus	1	2	3	4	5	9

	Completely Unimportant ………………..				Completely Important	Don't Know
46. Company annual reports	1	2	3	4	5	9
47. Company websites	1	2	3	4	5	9
48. Other websites _______________ (please state)	1	2	3	4	5	9
49. Newspapers in general	1	2	3	4	5	9
50. Business newspapers, and/or business supplements	1	2	3	4	5	9
51. Television	1	2	3	4	5	9
52. Radio	1	2	3	4	5	9
53. Financial magazines	1	2	3	4	5	9
54. Financial trade journals	1	2	3	4	5	9
55. Your experience as a customer of the company	1	2	3	4	5	9
56. Your experience as an employee of the company	1	2	3	4	5	9
57. Your neighbour	1	2	3	4	5	9
58. A friend (outside work)	1	2	3	4	5	9
59. A family member	1	2	3	4	5	9
60. A work friend or colleague	1	2	3	4	5	9

61. What was the approximate value of the share portfolio that you own and/or manage as at:

a) 30th June 2010? $______________ In Australian Dollars

b) 30th June 2009? $______________ in Australian Dollars

c) 30th June 2008? $______________ in Australian Dollars

d) 30th June 2007? $______________ in Australian Dollars

The following statements relate to your investment activities during the global financial crisis (GFC) (approximately November 2007 to September 2009).	Not at all ………………….……….				Every Transaction	Don't Know
62. During the recent GFC, I bought shares for less than those I already owned.	1	2	3	4	5	9
63. During the recent GFC, I bought shares for the same price as those I already owned.	1	2	3	4	5	9
64. During the recent GFC, I bought shares for more than than those I already owned.	1	2	3	4	5	9
65. During the recent GFC, I sold shares for less than I Had paid for them.	1	2	3	4	5	9
66. During the recent GFC, I sold shares for the same price I had paid for them.	1	2	3	4	5	9
67. During the recent GFC, I sold shares for more than I had originally paid for them.	1	2	3	4	5	9
68. During the recent GFC, I bought bonds, gold or term deposits.	1	2	3	4	5	9
69. During the recent GFC, I sold bonds, gold or term deposits.	1	2	3	4	5	9
70. During the GFC, I increased my cash holdings.	1	2	3	4	5	9

	Not .... at all				Every Transaction	Don't Know
71. During the GFC, I decreased my cash holdings.	1	2	3	4	5	9
72. During the recent GFC, I used automatic 'stop loss' or 'sell' orders.	1	2	3	4	5	9
73. During the recent GFC, I used automatic 'buy' orders.	1	2	3	4	5	9
74. During the recent GFC, I used margin lending.	1	2	3	4	5	9
75. During the recent GFC, I used options, warrants, derivatives or other financial products.	1	2	3	4	5	9
76. During the recent GFC, I used bank loans or redraw facilities on my home loan to buy shares.	1	2	3	4	5	9

D] Your Background

1. Your age: ______________________________ (years)

2. Your gender:
[________]0 Male
[________]1 Female

3. Your marital status:
[________]0 Single
[________]1 De facto relationship
[________]2 Married
[________]3 Divorced
[________]4 Widowed

4. Your country of residence:
[________]0 Australia
[________]1 Canada
[________]2 China
[________]3 Hong Kong
[________]4 India
[________]5 Japan
[________]6 Singapore
[________]7 UK
[________]8 US
[________]9 Other (please state) ________

5. Do you live in a:
[________]0 Rural region
[________]1 Semi-rural region
[________]2 Urban region

6. Your highest level of completed education:
[________]0 Year 9 or equivalent
[________]1 Year 10 or equivalent
[________]2 Year 11 or equivalent
[________]3 Year 12 or equivalent
[________]4 Diploma or equivalent
[________]5 Degree, or double degree
[________]6 Honours degree or equiv.
[________]7 Masters degree
[________]8 Doctorate or PhD
[________]9 Other (please state) ________

7. Your highest training in finance, accounting or share investing:

[________]0 Nil
[________]1 Year 10 or quivalent
[________]2 Year 11 or equivalent
[________]3 Year 12 or equivalent
[________]5 ASX short course(s) (please state) _________
[________]4 other short course(s) (please state) _______
[________]6 Diploma or equivalent
[________]7 Degree
[________]8 Honours degree or postgraduate training
[________]9 Masters degree
[________]10 Doctorate or PhD
[________]11 Other (please state)____________________

8. Your **main** occupation:

[________]0 Portfolio management
[________]1 Trade/Technical (e.g., electrician, engineer, gardener, mechanic, plumber)
[________]2 Scientific (e.g., biologist, mathematician, physicist, researcher)
[________]3 Creative (e.g., artist, musician, creative writer, design)
[________]4 Helping (e.g., counselor, nurse, social worker, teacher)
[________]5 Enterprising (e.g., lawyer, leader, manager, sales)
[________]6 Administrative (e.g., accountant, clerk, personal assistant)
[________]7 Student
[________]8 Retired/Semi-retired
[________]9 Unemployed
[________]10 Other (please state)____________________

9. Your annual salary earned through your main occupation:

[________]0 $10,000 or less
[________]1 $10,001 - $20,000
[________]2 $20,001 - $30,000
[________]3 $30,001 - $40,000
[________]4 $40,001 - $50,000
[________]5 $50,001 - $60,000
[________]6 $60,001 - $70,000
[________]7 $70,001 - $80,000
[________]8 $80,001 - $90,000
[________]9 $90,001 - $100,000
[________]10 $100,001 - $110,000
[________]11 $110,001 - $120,000
[________]12 $120,001 - $130,000
[________]13 $130,001 - $140,000
[________]14 $140,001 - $150,000
[________]15 $150,001 - $160,000
[________]16 $160,001 - $170,000
[________]17 $170,001 - $180,000
[________]18 $180,001 - $190,000
[________]19 $190,001 or more

Thank you for taking the time to complete this questionnaire. Your response to this survey is important to me. So, please check that you have answered every question and then return the questionnaire in the envelope provided. You can also post your questionnaires to: Reply Paid 300, Caulfield South, Vic., 3162, Australia.

A4 Reminder letter to potential investors

This research project has been approved by the Swinburne University Human Research Ethics Committee in line with the National Standard on Ethical Conduct in Human Research. If you have any concerns, or complaints about the conduct of this project, you can contact the Research Ethics Officer, Swinburne Research (H68), Swinburne University of Technology, P O Box 218, Hawthorn, Vic. 3122, 03 9214 5218 or resethics@swin.edu.au.

The Rational and Human Investor:
Opinions, Perceptions and Practices of Retail and Institutional Shareholders.

Dear Shareholder, 31st August 2010

I previously wrote to you on 13th August 2010 regarding the survey of retail and institutional investors. I am interested in shareholder opinions, perceptions and practices. Survey results may be used to help investors make more informed decisions, and ultimately, may have a positive impact on portfolio wealth.

As the survey is anonymous, I do not know who has already taken part in the survey. However, I would like to take the opportunity to thank those that have already participated in the survey. Their contribution is greatly appreciated.

As you may already be aware, we have undertaken every effort to ensure your privacy. We obtained your address details from a list provider solely for the purpose of two mail-outs for this research project and in accordance with its requirements. No contact details have been retained by the researchers. The use of reply paid envelopes ensures a secure, anonymous contact point for receipt of your completed survey. To ensure confidentiality and integrity of results, access to questionnaire data will be restricted to my supervisors and me. Questionnaire data will be stored for seven years in accordance with University regulations. Only unidentifiable group results will be reported in my thesis, and any other publications that may arise from it.

Ultimately, the results of this survey can only be as useful as those who take part in it. If you have not already done so, I encourage you to complete the attached questionnaire and post it in the reply-paid envelope provided. You can also post it to Reply Paid 300, Caulfield South, Vic., 3162. This questionnaire will take between 20 and 30 minutes to complete. As it is anonymous, feel free to complete it as openly and as honestly as you can.

For your information, a summary of overall, unidentifiable results will be available approximately two months from the date of this letter. If you have not already done so, and you would like to receive a copy of the overall results, please print your name and address on the attached form and send under separate cover to: Reply Paid 300, Caulfield South 3162. Please be assured that contact details used to post overall project results to you will not be retained beyond this purpose.

If you require any further information, please do not hesitate to contact Dr. Findlay (03 9214 8093), Professor Rahman (03 8662 0810) or myself (0418 149 506).

Thank you and best wishes,

Rachel Abramson

Rachel Abramson, PhD Student
Swinburne University
Faculty of Business and Enterprise
Reply Paid 300
Caulfield South, Vic., 3162
0418 149 506

I would like to receive a copy of the overall results. I understand that it will available in mid-November.

In this regard, I print my name and address details as follows:

NAME: ____
_

ADDRESS: ____

SUBURB: ____ POSTCODE: _____________

Please post this form, under separate cover, to:

REPLY PAID 300
CAULFIELD SOUTH, VIC, 3162.

A5 Summary feedback to investors

The Rational and Human Investor:
Opinions, Perceptions and Practices of Retail and Institutional Shareholders.
Summary of Research Findings

Dear Shareholder, 12th September 2013

I am writing to you because you had expressed an interest in receiving a summary of the results of the 2010 survey on retail and institutional investors. I am now pleased to provide you with this summary.

The objective of my research was four-fold: (a) to develop or adapt ten scales for use in investor surveys; (b) to explore the meaning of "don't know" and/or missing data responses throughout the survey; (c) to build a profile of retail and institutional investors; and (d) to develop a model of investor behavior.

Five hundred and twenty one retail and institutional investors took part in this survey. Overall, investors in this survey were typically 59 years old, with 21 years of investor experience and tertiary educated.

In this survey, institutional investors were somewhat younger than retail investors. Institutional investors typically had tertiary qualifications in finance, while retail investors typically had qualifications in fields other than finance. Institutional investors spent more time a week on their investments and held a greater number of different companies in their share portfolios. They were also more confident and more willing to take financial risks than were retail investors. This may express itself as overconfidence.

Overconfidence was more likely when investors had (a) finance qualifications, (b) investment experience, (c) knowledge of the companies in which they invest, (d) believe the share market to be increasing, (e) willing to take financial risks and (f) have the time to immerse themselves in the share market.

The model showed that the January effect, July effect, overreaction, psychological biases and social herding could play an impact on three-year wealth changes in the share market. These five variables in turn, were influenced by age, anxiety, impulsivity, information sources, education, financial education, overconfidence, propensity for financial risk and underconfidence. Some of these variables helped the investor maximize their wealth, while others had the reverse effect, leading us to think that

Benjamin Graham's (1949/1973, page xv) statement that "the investor's chief problem --- even his worst enemy --- is likely to be himself" may still be apt today.

Ultimately, a copy of my thesis will be made available through Swinburne University library. I will also be presenting two of my four research questions at the Australian Psychological Society annual conference in October this year. If you would like any further information about this research, please do not hesitate to contact Dr. Findlay (03 9214 8093) or myself (0418 149 506).

Best wishes,

Rachel Abramson

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Swinburne University
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P O Box 300
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0418 149 506

This research project has been approved by the Swinburne University Human Research Ethics Committee in line with the National Standard on Ethical Conduct in Human Research. If you have any concerns, or complaints about the conduct of this project, you can contact the Research Ethics Officer, Swinburne Research (H68), Swinburne University of Technology, P O Box 218, Hawthorn, Vic. 3122, 03 9214 5218 or resethics@swin.edu.au.

A6: Predicting Overconfidence, Overreaction and Underconfidence

Tables 45, 47 and 49 provide the respective hierarchical regression models for overreaction, overconfidence and count of "don't know" (as a marker of underconfidence). The models are based on 378 retail investors (and exclude the previously ungrouped investors).

Table 70 *Standardized Beta Weights for Overreaction*

Variables	**Block 1**	**Block 2**	**Block 3**	**Block 4**
Block 1: Demographic variables:				
Age	-.06	-.04	.01	.06
Gender	-.13*	-.02	-.01	.02
Marital status	.11	.07	.04	.07
Education	-.07	-.05	-.02	.01
Financial education	.06	.04	-.02	-.05
Years of investor experience	.00	-.02	-.02	-.05
Block 2:				
Natural log of C4: Hours spent on investments		.22***	.23***	.12
Natural log of C18: Companies followed		.17*	**.15***	.12
Natural log of C19: Companies in portfolio		-.01	-.00	-.06
Block 3: Personality variables:				
Anxiety			.07	.02
Lack of attention			.16**	.11
Lack of planning			-.07	-.02
Motor activity			.07	.01
Block 4: Behavioral practices:				
July effect				.40***
Information sources				.04
Appetite for financial risk				.10$^{n.s.}$

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant in retail only sample

R^2 *adjusted* = .31; $F_{16,305} = 9.97$; $p < .001$ bolded figures now significant

Table 71 *Standardized Beta Weights for Overconfidence*

Variables	Block 1	Block 2	Block 3	Block 4
Block 1: Demographic variables:				
Age	-.23**	-.20**	-.23***	-.22***
Gender	-.15*	-.01	-.02	-.03
Marital status	.01	-.04	-.03	-.02
Education	-.10 n.s.	-.08 n.s.	-.10 n.s.	-.09 n.s.
Financial education	.28***	.18**	.18**	.18**
Years of investor experience	.17*	.10	.11	.11
Block 2:				
Natural log of C4: Hours spent on investments		.17*	.17*	**.17***
Natural log of C18: Companies followed		.24**	.23**	.24**
Natural log of C19: Companies in portfolio		.13*	.14*	.14*
Block 3: Personality variables:				
Anxiety			-.12*	-.12 n.s.
Lack of attention			-.11 n.s.	-.11 n.s.
Lack of planning			-.07	-.07
Motor activity			.08	.07
Block 4: Behavioral practices:				
July effect				-.00
Information sources				-.06
Appetite for financial risk				.07

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant in retail only sample

R^2 *adjusted* = .31; $F_{16,222} = 7.67$; $p < .001$ bolded figures now significant

Table 72 *Standardized Beta Weights for the Square Root Count of "Don't Know"*

Variables	**Block 1**	**Block 2**	**Block 3**	**Block 4**
Block 1: Demographic variables:				
Age	-.06	-.11	-.09	-.08
Gender	.18*	.05	.06	.03
Marital status	-.09$^{n.s.}$	-.06	-.07	-.07
Education	-.01	-.02	-.01	.01
Financial education	-.23***	-.15*	-.14*	-.16**
Years of investor experience	-.02	.03	.02	.03
Block 2:				
C4: Natural log of hours spent on investments		-.06	-.06	-.06
C18: Natural log of companies followed		-.34***	-.34***	-.35***
C19: Natural log of companies in portfolio		.02	.02	.03
Block 3: Personality variables:				
Anxiety			.07	.08
Lack of attention			.10	.10
Lack of planning			-.04	-.03
Motor activity			-.06	-.08
Block 4: Behavioral practices:				
July effect				-.09
Information sources				.07
Appetite for financial risk				0.12*

*** $p < .001$ ** $p < .01$ * $p < .05$ n.s. not significant in retail only sample

R^2 *adjusted* = .23; $F_{16,305} = 6.99$; $p < .001$ bolded figures now significant

A7: Papers presented out of this research

Abramson, R., Rahman, S., & Buckley, P. (2005). Tricks and Traps in Structural Equation Modelling: A GEM Australia Example Using AMOS Graphics. Paper presented at the ABBSA Conference, Cairns, 5-7 August 2006.

Abramson, R., Rahman, S., & Buckley, P. (2005). A Financial and Psychological Model of Wealth Changes in the Share Market: A Theoretical Expose. Paper presented at the Australian Psychological Society 40th Annual Conference, Melbourne, October 2005 (Abstract only in conference proceedings).

Abramson, R., Rahman, S., & Buckley, P. (2006). Mapping 'Mr. Market': A conceptual model of investor behaviour underlying wealth changes in the share market. Paper presented at the Third International Business Conference, Melbourne, 20-22nd November 2006.

Abramson, R., Findlay, B., & Rahman, S. (2013). Reliability and factor structure of social herding, January effects, July effects, overreaction, overconfidence, information sources, psychological biases in decision making, propensity for risk, BIS15 and anxiety scales in sample of 521 retail and institutional share investors. Poster paper presentation. 48th APS Annual Conference, Cairns, 8-12th October 2013.

Abramson, R., & Findlay, B. (2013). A structural equation model of investor behaviour in a sample of 521 retail and institutional investors. Poster paper presentation. 48th APS Annual Conference, Cairns, 8-12th October 2013.