Psychological Attributes of Individual Investors in Financial Markets

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1/17/2015

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Acknowledgments

I would like to thank Professor Neil Stewart, Professor Peter Ayton and the Psychology Department for giving me the opportunity to experience this journey, for continuous support and countless inspiring discussions. I am very grateful to Greg Davies for introducing me to the field of Behavioral Finance and for being a great friend. Also I would like to thank Daniel Egan for being a great collaborator and a friend over the years as well as Emily Haisley and the Behavioral Finance team at Barclays. Lastly I would like to thank all of my close friends and Dr. Walasek for the support and of course my parents who have continuously stood by all of my ideas and always respected my decisions.

Declaration

All material in this thesis is original, unless indicated otherwise in the text, and has not been previously submitted for a degree either at the University of Warwick or anywhere else. Chapter 3 has been accepted for publication in Journal of Economic and Behavior & Organization in its special edition on Behavioral Finance. Other material has not yet been published, although this is intended in the future.

ABSTRACT

The aim of this thesis is to understand which psychological attributes are important in explaining investors observed behavior within the financial markets and the economy. The dataset used for most part of the thesis consists of UK based individual investors. This research involves analysis of investors selective attention to information conditional on the past stock market returns and investors' personality trait of neuroticism. The study also includes cross-sectional analysis of investors' portfolio performance, risk preferences and trading behavior and how these relate to various self-reported psychological attributes. Lastly this study explores the impact of arousal and psychological attributes on investors' trading behavior within an experimental framework. Standard models of economics assume that individuals are omniscient rational utility maximizers with stable risk preferences and such models leave no room for individual differences and emotions. The results of the current research provide evidence that psychological attributes play an important role in financial decision making and account for significant variation in investors' information acquisition decisions, frequency of trades, risk preferences and portfolio performance. The objective of this thesis is to contribute to the growing field of behavioral finance by providing a finer picture of investors' behavior and by suggesting alternative explanations that better reflect the behavior of the agents that populate the real world.

CHAPER 1

Introduction

Contents:

Abstract

Chapter 1 introduces normative models of economics and finance and highlights examples of individual investors' behavior that is not consistent with such models. Studies exploring the anomalies within the financial markets as well as the proposed derivatives of the normative models, which incorporate insights from cognitive and personality psychology to account for the variance observed within investors' behavior, are also addressed. The chapter then outlines the research questions of the thesis, which focus on factors that drive individual investors' decision making processes. These include the impact of the market news, individuals' psychological attributes and incidental emotions. The objective of the thesis is to understand how individual investors make decisions and what are the main factors driving their behavior and decision making process. This is important as investors behavior is reflected back into the financial markets and the dynamics of the economy.

1.1 Motivation

Over the past decade, psychologists and behavioral scientists have documented robust and systematic violations of what is considered rational behavior according to normative models of economics and finance - questioning their validity as descriptive theories of decision making (De Bondt 1998). In this dissertation I use field and experimental evidence to corroborate previous findings from behavioral finance and to provide new evidence of behavioral deviations from the normative models. I offer insights from cognitive psychology to provide explanations of the observed phenomena.

Dominant theories of economics and finance such as the efficient markets hypothesis, posit that market prices fully reflect all available information (Fama 1970) and that an economic man adheres to the axioms of rational choice. A large body of empirical research highlights that real investors' behavior is not consistent with such models. For example as rational expected-utility maximizers, investors should have a demand for information as an input in their decision-making process because, under the standard assumption of economics, more information should lead to better decisions (Merton 1973). In such framework, utility should be impacted either via trading or changes in consumption, but not by the information (say about personal portfolio returns) itself. However, several recent studies have reported that individual investors selectively avoid or seek-out information. Loewenstein (1987) built a model which explains why people may bring forward bad experiences to shorten the period of dread while delay the pleasant experiences to savour it. Loewenstein, Read and Baumeister (2003) discuss why people may avoid going to the doctor even though such information could improve their health and wellbeing. It has been suggested that the observed behavior is not due to irrationality but rather due to individuals' interpretation of how information will make them feel. Loewenstein (2006) discusses cases where individuals seek out or avoid additional information conditional on their expectations of how such information will make them feel, independent of its informational value. Such behavioral could be considered rational as individuals weigh the hedonic costs associated with more information and the benefits of ignorance (Shani, van de Ven & Zeelenberg 2012). This trade-off of the informational value of information against its hedonic impact raises questions about the implications of this phenomenon for financial practice.

Exploring the economics of information Karlsson et al. (2009) presents a psychological decision-theoretic model of optimal attention for individual investors. In the model investors derive utility directly from information and with an assumption that definitive knowledge has a stronger effect on utility than simply suspecting something, investors will either seek out or avoid information. For example in the US dataset, provided by Vanguard Group, a 1% increase in prior averaged S&P500 returns increased the daily mean number of logins by 5-6%. Extending the study Sicherman et al. (2013) model how investor attention can impact the stability of the financial markets by inducing different types of price volatility and time-varying market risk premia. For example, when an investor is not paying attention to his portfolio he cannot trade. Therefore increased attention to the portfolio has a direct impact on the number of trades and is reflected in the overall volume traded as well as the asset (stock) pricing.

In psychology evidence that attention and information acquisition decisions are not independent of emotions has been accumulating since the 1940s. For example it has been suggested that anxiety, which is directly related to a personality trait of neuroticism (Mathews, Deary & Whiteman 2003), plays a role in selective attention to information (McGinnis 1949). Some research suggests that more neurotic people tend to be more perceptually defensive (e.g. Watt & Morris 1995), a phenomenon which is designed to delay the recognition of a threatening stimuli (Postman, Bruner & McGinnis 1948). Others have proposed that the attentional system of anxious individuals is abnormally sensitive to threat-related stimuli and that these individuals tend to direct their attention toward threatening information (Williams, Watt, MacLeod & Matthews 1988). In economics anticipatory emotions of anxiety have been considered when modelling asset pricing. Caplin and Leahy (2001), in their psychological expected utility theory, depart from the standard models by adding to the overall utility not only the value of consumption but also the level of anxiety associated with holding the risky assets to model the impact of anticipation on asset price. For example anxiety induced by the news could explain asset price "overreaction". The authors propose that conventional measures of risk aversion underestimate the effect of uncertainty on asset prices and risk premium when anxiety is excluded. Caplin et al. suggest that accounting for anxiety that investors have to live with while holding the volatile stock prior to the consumption date could explain market anomalies such as the equity premium puzzle - a phenomenon that describes the large difference between higher returns on stocks versus government bonds (Mehra & Prescott 1985[1]).

Modern portfolio theory posits that investors should hold minimal risk for maximum returns (Markowitz 1959). That is, investors should hold a well-diversified portfolio, a risk-management technique in which various assets are combined to reduce risk exposure. And in efficient markets investors should not be able to earn above average returns without accepting above-average risks. Additionally, given the normatively

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[1] In explaining the equity premium puzzle, Benartzi and Thaler (1995) propose two things. First they shift the utility function domain from consumption to returns and second due to investors' tendency to monitor portfolios frequently, such exposure to high return volatility causes people to demand higher compensation, even if there is no effect on consumption.

prescribed buy-and-hold strategy and the no-trades theorems (Aumann 1976; Milgrom & Stokey 1982; Tirole 1982) rational traders should not trade with other rational traders who have access to the same information. In light of the increase in on-line trading and growing interest in household finance, recent literature has begun to analyse individuals' economic behavior. Empirical evidence suggests that investors trade too much, failing to cover transaction costs (Barber & Odean 2001). They also hold losing positions too long and sell winners too soon, a phenomenon labelled as the disposition effect by Shefrin and Statman (1985). Even though the performance should be random, some investors systematically beat the market while others are systematic losers (Coval, Hirshleifer & Shumway 2005; Barber, Lee, Liu & Odean 2014; Korniotis & Kumar 2013). Moreover, investors hold under-diversified portfolios, which, according to standard portfolio theory, means investors are happy to hold more risk /volatility in their portfolios without any extra compensation.

To account for the observed phenomena, studies in behavioral finance have relied on cognitive psychology as the main source of inspiration. Majority of this work focused on one of the most robust biases, namely overconfidence. However, due to the limitations of the data availability and various proxies used to describe the same phenomenon, theoretical models and empirical findings do not agree. For example in theoretical models, overconfidence is modelled as miscalibration (Kyle & Wang 1997; Benos 1998; Odean 1998; Glaser & Weber 2007) whereby investors over-estimate the precision and usefulness of their information / knowledge and in turn have unrealistic beliefs about their trading profits. Such investors, by overvaluing their information end up trading more than they should. These models imply that trading frequency stems from investors' overconfidence and not from rational expectations. In testing the overconfidence theory, Barber and Odean (2001) used gender to proxy overconfidence. The authors found that men traded more than women and concluded that because men are generally considered overconfident, overconfident investors over-trade. In another study conducted by Dorn and Hubberman (2005) gender is related to trading, however, its effect drops once a risk tolerance measure is added to the model. So the effect of gender should be interpreted with caution as the effect is conditional on the model specification. In another example, when testing the same overconfidence theory, Statman, Thorley and Vorkink (2006) used past returns as a proxy for overconfidence. The authors found that strong past returns are associated with higher trading volume and concluded that higher past returns lead to overconfidence. Even when the proxies are constructed as per the model (a proxy for miscalibration), the results still vary. For example, in their field study Glaser and Weber (2007) do not find any relation between miscalibration and trading volume, nor any correlation between gender and trading volume.

They do find that above-average type of overconfidence, which is a cognitive bias that makes people overestimate their positive qualities compared to others, is associated with more trading.

Other psychological factors that have entered the overconfidence literature include a personality trait of locus of control (Rotter 1966), which captures the degree to which individuals feel that they are in control of their own life and have the capacity to influence their environment. While Barber and Odean (2002) find that investors with higher locus of control trade more, Dorn and Sengmuller (2009) do not find supporting results for locus of control. A related psychological factor called illusion of control (Langley 1975), which describes people's elevated perception of having control over chance events, has also been used as a proxy. For example Fenton-O'Ceevy, Nicholson, Sloane and Willman (2003) conducted a field study to test the effect of illusion of control and found that traders who are more susceptible to illusion of control performed worse.

Given the mixed results on overconfidence recent literature proposed an alternative explanation to account for the behavior. It has been suggested that investors derive utility directly from trading, from anticipating trading and from researching and planning various trading strategies. For example Dorn and Sengmuller (2009) found that investors who trade for entertainment, as measured by a self-reported survey, trade twice as much as their peers. A similar trading motivation was tested by Grinblatt and Kelojarju (2009). The authors used the number of speeding tickets to construct a sensation seeking measure and found that high sensation seekers exhibit higher trading volume. Although speeding tickets is a good measure for risk attitude in the recreational domain, it does not imply that the investors' risk attitude is the same in the financial domain as it has been well established that risk attitude differs across domains and situations (Weber, Blais & Betz 2002; Blais & Weber 2006).

Although over-trading may seem irrational especially from the normative point of view, it has been shown that some investors who trade more perform better than those who trade less. Studies have shown that intellectual abilities of investors can partially explain this. For example in analysing a Finish dataset Grinblatt, Keloharju and Linnainmaa (2012) constructed an intelligence score for each investor based on the responses to the Finish Armed Forces questionnaire and found that high IQ investors are better at timing the market and have better stock picking skills, therefore by trading more these investors are able to earn superior returns. Korniotis and Kumar (2013) have found similar results in their US dataset, although they used demographics as a proxy for smartness.

Investors' behavior is not independent from emotions. In psychology it is well established that emotions play an integral part of the decision making process and such view began to gain momentum in economics and finance. Loewenstein (2000) argues that emotions “propel behavior in directions that are different from that dictated by a weighing of the long-term costs and benefits of disparate actions” (p.426). Emotions have been shown to impact traders’ decision making and performance (Fenton O’Creevy, Soane, Nicholson, Willman 2011; Taffler & Tuckett 2010; Summers & Duxbury 2012). Within behavioral finance it has been proposed that emotions are rooted at the physiological level of individuals (Lo & Repin 2002; Lo, Repin & Steenbarger 2005). In analysing traders’ behavior, the authors presented psychophysiological evidence – measures of skin conductance and cardiovascular variables and survey data - that even seasoned traders go through an emotional rollercoaster during the trading hours. Moreover it has been suggested that emotions cause hormonal changes within traders. Coates and Herbert (2008) found that during volatile and uncertain market conditions a group of traders experienced an increase in the stress hormone cortisol. Such increase in the levels of cortisol, as would be expected during prolonged uncertainty such as the financial crisis, reduces risk-taking during the financial crisis when the risk taking is actually needed from traders. Traders however become more cautious, in turn possibly exacerbating the crisis (Kandasamy et al. 2014).

It is also widely accepted that emotions can carry over from one unrelated context to another, what Lerner, Small and Loewenstein (2004) referred to as the emotional-carryover hypothesis. Literature on such incidental emotions, which are induced by unrelated events in investors’ surroundings, suggests that supposedly rational investors are affected by feelings and the effect of feelings influences investment decisions and in turn the dynamics of the financial markets. For example in the financial literature it has been reported that stock-market price movement reflect external factors as the amount of sunshine (Hirshleifer & Shumway 2003) the duration of daylight (Kamstra, Kramer, & Levi 2003), geomagnetic activity (Krivelyova & Robotti 2003) and sports events (Edmans, Garcia & Norli 2007). For example Edmans et al. (2007) used international soccer results as a mood variable and found that significant stock market decline follows a soccer loss. The authors concluded that emotional arousal can impact asset pricing. This suggests that the markets are not driven purely by the market forces but also by the emotional state of the individual investors.

1.2 Research Objective and Research Questions

In this thesis we apply the insights from cognitive psychology to address the observed behavior of individuals in relation to information acquisition and investments decisions, contributing to the growing field of behavioral finance. Specifically, we analyse field and experimental datasets in order to explore what factors influence the selective attention of investors, what individual differences influence their trading decisions, risk preferences and investment performance and whether external factors such as incidental emotions unrelated to financial markets can impact traders' behavior.

Research question 1: Economics of information

Studying selective attention to information of market participants is important because of its potential impact on trading, asset prices and the dynamics of the financial markets. In Chapter 3 we attempt to corroborate previous findings that individuals do selectively attend to information and offer a psychological explanation for the observed behavior.

Research question 2: Psychometrics and performance, trading, risk preferences

In Chapter 4 we test which psychological attributes can explain investors' behavior. Much of the behavioral finance theoretical and empirical literature focuses on multiple measures of overconfidence amongst other psychometric attributes. However, due to limited data and the use of proxies such as gender for overconfidence, results in empirical findings that are not consistent and do not always support the theoretical models. Given our rich dataset we include multiple attributes in one model in an attempt to tease out the effects of each attribute and test how each correlates with investor's trading preferences, risk preferences and portfolio performance. We are primarily interested in how investors make decisions in the real world rather than what is expected of a rational investor as per normative models.

Research question 3: Negative arousal and trading

In an experimental setting using a real trading platform we test how negative arousal caused by an exogenous event unrelated to the financial markets, such as the terrorist attack or a negative event in individual's life, may impact trading behavior and whether individual differences interact with the emotional arousal. The experiment aims to test the effect of arousal, psychometric attributes and personality traits on investors' trading decisions. The details are provided in Chapter 5.

1.3 Outline of the Thesis

The structure of the thesis is as follows. In Chapter 2 we introduce methodology for Chapters 3, 4 and 5 including the rationale for the model chose, the survey method in collecting the field and experimental data, construction of variables and imputation of missing data. In Chapter 3 we explore economics of information. We present previous literature, models of investor's attention and offer psychological explanation of the observed phenomenon. We test the hypothesis that information has hedonic utility and find that information seeking and portfolio monitoring decisions are attributable to psychological factors, as anticipated by Karlsson et al. and Sicherman et al. (2013). We further test whether the variation in portfolio monitoring is psychological in nature and find that the personality trait of neuroticism accounts for heterogeneity on individual basis and investors' portfolio monitoring decisions. Our results suggest that, consistent with hedonic utility explanation, investors seek out positive information when the market is performing well. However, they also seek out information when the daily market returns are declining. This could possibly be explained by the desire to reduce the time dreading the bad news. Such increased monitoring given absolute changes in the market we call the *meerkat effect*. We also find that investors who monitor their portfolios given bad news are also more likely to trade.

In Chapter 4 we explore the impact of psychological attributes and individual differences on investors' portfolio performance, trading and diversification preferences. We address the classical models in finance and economics as well as the new theories that incorporate elements from psychology. We then discuss recent literature that reports empirical results, which are at odds with the models. To test previous theories and empirical findings we merge two datasets, one consisting of self-reported psychological attributes of individual investors and the other containing all portfolio and trading records of the same investors. We provide an insight as to why investors' behavior deviates from the normative models of finance and economics. We find that individual investors' cognitive and affective processes, avoidant behavior, risk tolerance, objective and subjective financial expertise, overconfidence and demographics account for significant variation in investors' investment decisions and trading preferences.

In Chapter 5 we consider the role of emotions and the impact of exogenous events on investors trading behavior. It has been shown that emotions experienced in one situation carry over to other unrelated situations caused by an associated shift in risk perception. We conduct an experiment in which participants use a real trading platform under two conditions, neutral and aroused. We also collect numerous psychometrics for each participant prior to the experiment. We do not find significant main effect of arousal, there are however mild interactions between the conditions and the psychometrics. Although the results are inconclusive we provide a discussion on limitations of the experiment and further work that could be conducted.

As is evident from the following chapters investors' behavior is not driven exclusively by the standard normative models of economics and finance as investors' selective attention, trading behavior, performance and risk preferences are underlined by psychological attributes of investors.

CHAPTER 2

Survey and Methodology

Contents:

Abstract

This chapter outlines the methodology used in the following chapters. Hierarchical modelling is applied in Chapter 3. Chapter 4 addresses various imputation methods and the rationale for using Multiple Imputation method to impute the missing psychometrics data in this study. Cross-sectional regressions are used to explore the relationship between psychometrics and the financial measures. The derivation of all financial measures is also provided. The description of the trading platform and the visual stimuli (International Affective Picture Systems) used in Charter 5 is discussed.

2.1 Introduction

Behavioral finance has relied on two methods to explore individual investor's behavior. The first is to use the actual trading datasets provided by brokerage houses or insurance companies and combine them with the available surveys. However, detailed datasets with transactions and portfolio positions for each investor are especially difficult to obtain. Furthermore, the few available surveys that could match the transactions dataset are limited to mostly demographics, which means proxies are constructed for various psychometric measures (see Chapter 1). For example in one of the leading studies by Barber and Odean (2001) gender was used as a proxy for overconfidence with male assumed to be more overconfident. However, the role of other variables that are related to gender, which could also impact the degree of overconfidence and trading, has not been addressed. This issue has been highlighted in the follow-up studies that demonstrated that the gender effect is not consistent and largely depends on the control variables in the model (Dorn & Huberman 2005; Durand, Newby & Sanghani 2008; Feng & Seasholes 2008). Another example of proxy construction based on demographics is sophistication (Graham, Harvey, Huang 2009). The authors used gender, education, income and investment to construct the variable. Such an instrument may not reflect the true general objective knowledge and the knowledge about the financial markets. Moreover, theoretical framework on overconfidence relies on miscalibration type of overconfidence in which investors overestimate the certainty of their information and give it more weight than they should. In studies that do have direct proxies for psychological attributes, the application of the proxies should also be questioned.

An alternative way to explore behavioral biases is through direct experimental manipulation. Although in psychology much of the work is conducted in the lab with many studies related to investment tasks, experimental work has been criticized. One shortfall is that student participants are used rather than the actual traders or investors therefore the economic behavior between the two groups may not be consistent as biases maybe eliminated amongst professionals (List 2003). Nonetheless, it has also been shown that the findings can be generalized to a wider audience. For example in exploring the theoretical account of myopic loss aversion - a tendency to take a short-term evaluation view on investments and be over-sensitive to losses - Haigh and List (2005) found that professional traders exhibited this bias to an even greater extent than the students. Another disadvantage of experiments is that participants face almost exclusively gains as financial outcomes, which cannot be compared to larger gains and losses that investors face within the real financial markets. On the other hand in a laboratory experiment the experimenter can control for factors that cannot be accounted for in the real world. In this thesis we use both methods, which are described below.

2.2 Research Methodology in Chapter 3

In the first section we analyse whether individual investors selectively attend to their portfolios (indexed by the frequency of daily portfolio logins) given changes in the daily stock market FTSE100 Index. We use trading data spanning six years, recording every transaction and portfolio login made. We then test whether a trait of neuroticism can account for the individual differences in investors' portfolio monitoring decisions. As we have a repeated measures design with multiple measurements per subject error terms in statistical models will tend to be correlated. There are (at least) two approaches to dealing with the repeated observations of logins for each investor. One approach is to fit a standard generalised linear model (Poisson for count data or logit or probit for binary data) and then to correct the standard errors for the clustering within investors (Cheah 2009). The other approach is to fit a mixed effects model (also sometimes referred to as Hierarchical equation modelling) with full random effects (Baayen, Davidson & Bates 2008). By including the random effects we no longer need to fix the standard errors of the fixed effects for clustering. In the generalised-linear-model-with-corrected-standard-errors approach the correction is only an approximation. In a simulation study, Cheah (2009) finds that the mixed effect approach performs better. Although both the mixed-effect approach and the generalised-linear-model-with-corrected-standard-errors approach deal with the repeated observations of logins for each investor, we prefer and subsequently apply the mixed-effects approach because the clustering is directly modelled. In our study we only deal with individuals but such modelling can include other random effects like states or companies, giving a multi-level-modelling approach. Such models also deal with unbalanced data (Baayen et al.).

2.3 Research Methodology in Chapter 4

In Chapter 4 we analyse the dataset consisting of the same 617 investors as in the previous section but with more psychological attributes added to the dataset. First we describe the survey construction process, then we explain the sample selection. Since our survey has data missing at random we address the method used for dealing with missing data and provide a simple numeric example from Baraldi and Enders (2010) to illustrate the rationale behind our chosen method. We then turn to the financial data and discuss how risk measures, portfolio performance, return on investment and propensity to trade are constructed for each investor.

2.3.1 Survey

Behavioral Finance team at Barclays Wealth conducted a panel survey of self-directed online investors at Barclays Stockbrokers, a UK direct brokerage. In constructing the questionnaire Barclays Wealth Management collected a wide range of potential candidate questions from industry financial questionnaires and academic studies. Overall such survey methodology has recently gained importance and acceptance in behavioral finance, and has allowed to test existing theories as well as explore investors' individual differences rather than focusing only on the aggregate market behavior. Three preliminary on-line surveys were conducted involving over 1500 affluent individuals from the UK population to develop the final set of questions and those are reported in the Appendix in Table 8.1.

The client base was stratified based on number of trades per year, the number of stocks within portfolio and portfolio value. Such stratification implies under-weighting of individuals who are less engaged with the financial market movements, are likely to have inactive accounts, hold too few positions and have low portfolio values. Such stratification was set-up partly to accommodate our collaborating bank's desire to under-sample clients who trade very little (Number of deals per year≤1) or had a relatively low portfolio value (Portfolio value<£1,000). As a result, the sample is not representative of the general client base, but is far more representative of the market-engaged client base. Over 85% of the sample had at least 5 stock holdings in their portfolio, 44% had at least £50,000 in their account, and 70% had traded at least 5 times in the previous year. Table 1.1 illustrates the stratified sample compared to all clients and those who were invited to take part in the survey.

Table 1.1 Sample of investors in this study compares to all Barclays stockbroker clients.

Portfolio value	All Clients	Invited	Panel
<£1k	35%	0%	0%
£1k to £10k	30%	19%	17%
£10k to £50k	23%	41%	40%
£50k to £100k	6%	19%	20%
£100k to £500k	5%	20%	23%
£500k to £1m	0%	1%	1%
>=£1m	0%	0%	0%
Deals/Year			
0	38%	3%	0%
1	10%	5%	1%
2 to 4	21%	12%	28%
5 to 9	11%	15%	25%
10 to 19	9%	27%	22%
20 to 39	6%	21%	13%
40 to 59	2%	7%	6%
60+	3%	10%	4%
Holdings			
0	21%	0%	1%
==1	18%	2%	3%
1 to 4	31%	22%	10%
5 to 9	15%	23%	13%
10 to 19	10%	32%	28%
20 to 39	4%	17%	25%
40 or more	1%	3%	20%

Note: Sample of investors compares to all Barclays stockbroker clients.

The first survey began in mid-September of 2008, shortly before what is in retrospect widely regarded as the climax of the financial crisis (the events around Lehman Brothers and AIG in the US, Northern Rock, HBOS, and other banks in the UK). The chosen sample of 19,251 clients (approximately 5% of customers) were invited via e-mail in late August/early September to participate in the first round. Of those, 4,520 (23%) opened the email. Of those who opened the email, 849 (20%) went to the website and in the end, 479 out of these 849 subjects completed the survey. This response rate is similar to other studies that have conducted surveys (Dorn & Huberman 2005; Glaser & Weber 2007). It took respondents on average 24 minutes to answer the survey. The 479 investors who answered the September 2008 survey were contacted again by email in late November 2008 and invited to participate in a shorter version of the earlier survey. Of those, 240 participated for a second time in December. In addition, Barclays Wealth sent out an email invitation to a different set of 700 customers who had not been previously contacted, in order to increase the sample size. This resulted in an additional 138 respondents who joined the panel in December 2008 and who completed the longer version of the survey at this point. In March 2009, all 617 investors who had previously participated in at least one round were contacted again and invited to participate in the consecutive rounds with the shorter versions of the survey. Subsequent rounds occurred in three month intervals for a total of nine rounds. The repeated observations of the same investors over time was for the bank's research question, in our study however we do not consider repeated questions and take only the first response in the event that the question was repeated in another round.

To identify potential selection biases, we compared those investors who participated only once with those that participated twice, three or four times. There are hardly any differences between the investor subgroups who participated once or more. Only the level of investable wealth, measured in 9 categories from 1 (£0 - £10,000) to 9 (> £1 million), differs significantly. Investors who participated only once had substantially lower investable wealth than investors who participated more frequently.

2.3.2 Imputation Method

Classification

There are multiple ways of imputing missing values. Prior to conducting any techniques it is important to understand why the data are missing. Rubin (1976) created a classification system for missing data that was further developed by Little and Rubin (2002). It explains why the data are missing based on the relationships between the probability of a missing data and the measured variables. The classifications include: missing completely at random (MCAR); missing at random (MAR); missing not at random (MNAR). MCAR occurs when there is no relationship between the probability of the missing data and the variables that are collected. An example of MCAR include a participant missing a survey round because he was stuck in traffic or a child who was part of the study who relocated and dropped out of the survey, or an administrative team that misplaced the survey results. All these missing data examples would be classified as MCAR. A MAR example is when there is an indirect relationship between the missing data and other variables in the study. For example, if the variable with a missing value is a specific age group, and because of prior restrictions on that age group the value for that age group is missing, such data would be classified as MAR. Lastly MNAR refers to a condition when there is a direct relationship between the missing value and the variable. For example drug users may skip answering questions related to drugs due to the fear of getting caught or the fear of admitting that they may have a problem. In the MNAR scenario omitting to control for drug addiction would not result in correct conclusion as the results would be biased.

Given the nature of our survey we classify our missing data as MCAR because the missing data are not related to any other variables measured within the study. The missing data is attributed to the timing of the survey and whether the investors participated in that round or not, therefore the responses are irrelevant to the questions that were asked. With MCAR classification all imputation methods described below should produce unbiased results, however, there are other issues to consider. With MCAR and MAR multiple imputation method and maximum likelihood method will provide unbiased estimates as is explained below. Notably, even when the data is classified as MNAR, the multiple imputation and the maximum likelihood methods would outperform alternative methods.

Imputation Methods

Data reported in Table 2.2 will be used as an example to illustrate the imputation the methods. The first column is the math aptitude score and the second column shows the course grade for twenty students. Figure 2.1 (a) illustrates a scatter plot for the full dataset. One old fashion way of dealing with missing data is to use a listwise deletion method, which excludes variables with missing observations. In doing so much of the data is lost. For example in Table 2.2 column 3 the course grade is missing for those students whose math aptitude score is lower than 6. The scatter plot (b) in Figure 2.1 shows the data, in which half of the observations are lost. Given that our dataset consists of numerous variables, applying such method would be considered as bad practice. Just a single missing value for any variable would result in deletion of the trader from the analysis. Another method of dealing missing data is to impute the missing values with the arithmetic means as is illustrated in column 4 in Table 2.2 and scatter plot (c) in Figure 2.1. However, such method does not account for the variability of the data. A third popular imputation method is to use a regression imputation as in column 5. Because of the perfect correlation between imputed variable and the predictor, as is illustrated in Figure 2.1 (d), the variability within the data is, once again, not accounted for. To fix this, an imputation by stochastic regression method has been developed. It uses the regression method to predict the missing value and then adds a random error, generated from a normal distribution with a mean of zero and variance equal to that of the regression's residual variance, to the predicted value. Column 6 in Table 2.2 provides an example of error terms, column 7 reports the new complete dataset and Figure 2.1 panel (e) plots the new dataset. Because the stochastic regression imputation method returns the variability to the data, the estimated parameters are unbiased under the MCAR and MAR classification. However because the added random error is simply a guess about the true value, this method produces standard errors that are too small as there is no adjustment made to account for the fact that the imputed value is a guess and not the true value.

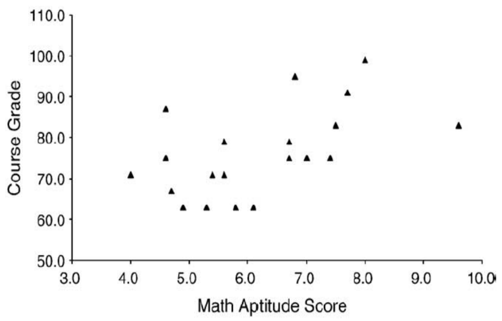
Table 2.2 Example of a dataset and imputation methods.

Math performance data set.

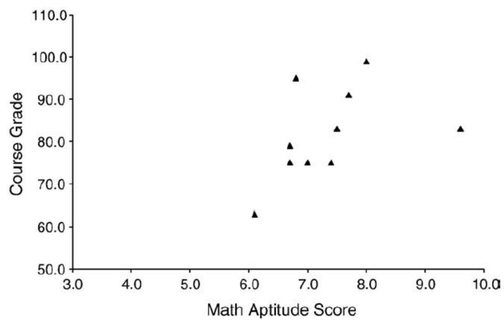
Complete data		Observed data	Mean imputation	Regression imputation [a]	Stochastic regression imputation [a]	
Math aptitude	Course grade	Course grade	Course grade	Course grade	Random error	Course grade
4.0	71.00	–	81.80	65.26	7.16	72.42
4.6	87.00	–	81.80	68.22	0.73	68.95
4.6	74.00	–	81.80	68.22	12.01	80.23
4.7	67.00	–	81.80	68.71	−7.91	60.81
4.9	63.00	–	81.80	69.70	−4.07	65.63
5.3	63.00	–	81.80	71.68	27.41	99.09
5.4	71.00	–	81.80	72.17	25.76	97.93
5.6	71.00	–	81.80	73.16	2.76	75.92
5.6	79.00	–	81.80	73.16	−11.77	61.39
5.8	63.00	–	81.80	74.15	−0.56	73.59
6.1	63.00	63.00	63.00	63.00	–	63.00
6.7	75.00	75.00	75.00	75.00	–	75.00
6.7	79.00	79.00	79.00	79.00	–	79.00
6.8	95.00	95.00	95.00	95.00	–	95.00
7.0	75.00	75.00	75.00	75.00	–	75.00
7.4	75.00	75.00	75.00	75.00	–	75.00
7.5	83.00	83.00	83.00	83.00	–	83.00
7.7	91.00	91.00	91.00	91.00	–	91.00
8.0	99.00	99.00	99.00	99.00	–	99.00
9.6	83.00	83.00	83.00	83.00	–	83.00
Mean	76.35	81.80	81.80	76.12		78.70
Std. Dev.	10.73	10.84	7.46	9.67		12.36

[a] Imputation regression equation: $\hat{Y}=45.506+4.938(\text{Aptitude})$.

Source: Baraldi and Enders (2010).

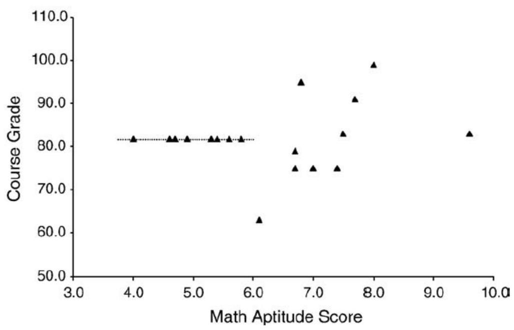


a. Complete dataset

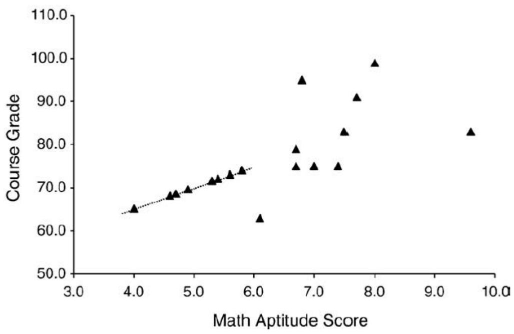


b. Post deletion method

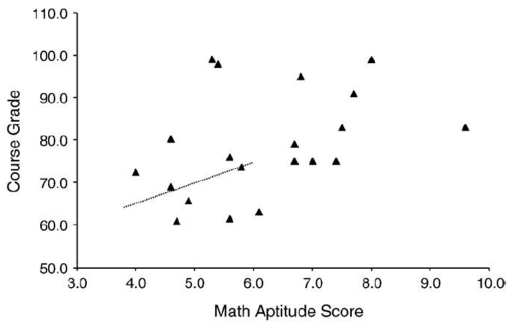
.



c. Mean imputed dataset



d. Regression imputed dataset



e. Stochastic regression imputation

Figure 2.1. The first scatter plot (a) shows the original complete dataset from the Table 2.1 above. The second scatter plot (b) shows results after the post deletion method of the math aptitude score. The third plot (c) shows the mean imputed scatter plot and the forth plot (d) shows regression imputed scatter plot. The last plot (e) is based on stochastic regression imputation method. Source: Baraldi and Enders (2010).

Full Information Maximum Likelihood based imputation (FIML) and Multiple Imputation (MI) are the two other methods that are considered to be "state of the art" missing data techniques which are more powerful than any of the traditional methods (Schafer & Graham 2002; Baraldi & Enders 2010). Both FIML and MI produce unbiased estimates and it is researcher's choice as to which one to use. FILM method has been more common due to software package development (Baraldi & Enders 2010). It does not impute or throw away any data but uses all available data to estimate most probable missing values that would have the highest probability (highest loglikelihood) of producing the data. Both MI and FIML are regarded as good techniques and produce similar results. For further detail see Baraldi and Enders (2010). Below we describe MI as it is the method we have chosen.

Multiple Imputation Method

In our study we proceed with MI, an idea first proposed by Rubin (1978). In short the MI method consists of the following tree steps:

1. Imputing phase: Impute missing values using an appropriate model that incorporates random variation. This is conducted M times producing M "complete" data sets.
2. Analysing phase: Perform the desired analysis as if the dataset was complete.
3. Pooling phase: Average out the parameter estimates and standard errors across the M datasets into one by calculating the standard errors as follows: (a) averaging the squared standard errors of the M estimates - within imputation variance (b) calculating the variance of the M parameter estimates across

samples - between imputation variance (c) combining the two quantities. See Rubin (1987) and Allisson (2002) for further details.

Multiple Imputation Example

Step 1.

An important step in the imputation methods is to choose the predictor variables. For example if participants' age is missing then it makes sense to include the grade he is attending as a predictor. Overall having more variables has been shown to be the preferred technique (Collins, Schafer & Kam 2001; Wayman 2002b). In this analysis we use all independent variables as predictors. Given that we have categorical variables in our dataset, we specify predictive mean matching method (PMM) for our regressions (Little 1988; van Buuren & Oudshoorn 2011). Such method imputes only values that are observed. For example if a regression estimate is 4.2 for a categorical variable that has a range from 1 to 5, PMM will fill in the missing value with an observed value of 4.

We build our multiple imputation regressions using a package in R called multiple imputation using chained equations (MICE, van Buuren & Oudshoorn 2000, 2011). In this method a model is specified on a variable by variable basis. So for categorical data, this could be a logistic regression model, while for count data, a Poisson regression model could be specified. Van Brueren and Oudshoorn propose that such concept is not new and has been previously referred to as: stochastic relaxation (Kennickell 1991), variable-by-variable imputation (Brand 1999), regression switching (van Buuren et al. 1999), sequential regressions (Raghunathan, Lepkowski, Van Hoewyk, & Solenberger 2001), ordered pseudo-Gibbs sampler (Heckerman et al. 2001), partially incompatible MCMC (Rubin 2003) and iterated univariate imputation (Gelman 2004). MICE imputes the missing values using a two-step iterative algorithm based on a statistical method outlines by Rubin (1987,1996) and Schafer (1997). For each of the datasets a procedure similar to stochastic regression is used to estimate the scores for the missing values. Then, given these values, Bayesian estimation principles are applied by the algorithm to estimate new parameters for the regression model, which is used to re-estimate the missing values again. This looping continues for 200 iterations, or as many times as is specified by the user. Once the first dataset is filled, the algorithm carries on for another 200 iterations to fill in the second dataset and so on. For further details on MICE refer to van Buuren and Oudshoorn (2011).

Using the same example as for previous imputation methods, Table 2.3 provides an example of the four new datasets produced by MICE (columns 2 through 6). Each column was generated using its own slightly different regression reported at the bottom of Table 2.3. The non-missing valued are identical across all datasets, however the difference of the imputed values reflect the uncertainty about what value to impute. For multiple missing variables MICE imputes missing values on a case by case bases, separately for each of the datasets.

Table 2.3 Example of Multiple Imputation Method

Imputed course grades from multiple imputation procedure.

Observed data		Imputed course grades			
Math aptitude	Course grade	Data Set 1 [a]	Data Set 2 [b]	Data Set 3 [c]	Data Set 4 [d]
4.00	–	51.48	67.91	69.38	72.45
4.60	–	59.53	62.59	74.19	57.38
4.60	–	62.34	59.77	67.43	46.47
4.70	–	68.45	53.56	71.39	56.99
4.90	–	75.47	63.79	72.54	85.96
5.30	–	81.81	57.16	70.99	68.71
5.40	–	61.05	90.47	56.25	74.11
5.60	–	77.72	46.92	69.14	52.91
5.60	–	71.49	70.79	73.89	72.44
5.80	–	68.36	59.98	67.04	77.53
6.10	63.00	63.00	63.00	63.00	63.00
6.70	75.00	75.00	75.00	75.00	75.00
6.70	79.00	79.00	79.00	79.00	79.00
6.80	95.00	95.00	95.00	95.00	95.00
7.00	75.00	75.00	75.00	75.00	75.00
7.40	75.00	75.00	75.00	75.00	75.00
7.50	83.00	83.00	83.00	83.00	83.00
7.70	91.00	91.00	91.00	91.00	91.00
8.00	99.00	99.00	99.00	99.00	99.00
9.60	83.00	83.00	83.00	83.00	83.00
Mean	81.80	74.79	72.55	75.51	74.15
SE	10.84	12.18	14.53	10.49	13.81

[a] Imputation regression equation: $\hat{Y}=6.03(\text{Aptitude})+33.92$.
[b] Imputation regression equation: $\hat{Y}=5.11(\text{Aptitude})+38.49$.
[c] Imputation regression equation: $\hat{Y}=5.62(\text{Aptitude})+41.15$.
[d] Imputation regression equation: $\hat{Y}=6.40(\text{Aptitude})+31.54$.

Source: Baraldi and Enders (2010).Columns 4 through 6 are generated datasets using MI.

Step 2.

In the second phase, after all the datasets have been filled, the desired statistical analysis is performed. The estimated will differ in each of the dataset due to the uncertainty about which value to impute. In the current study we use cross-sectional liner regressions as will be discussed in further detail in Chapter 5.

Step 3.

The pooling phase produces overall one set of estimates based on rules established by Rubin (1987). Although the average mean and the total average standard errors are computed automatically in the MICE package we will demonstrate the process using the example in Table 2.3. Combining the estimates of the parameter of interest is accomplished simply by averaging the individual estimates produced by the analysis of each imputed data set.

The standard errors are made up of two components: within and between imputation variance. The within standard errors are the average of the squared standard errors. The between-imputation variance is the variation of the means across the new datasets. In our example the within variance is: $W = \frac{\sum SE_t^2}{m}$ = (148.41+211.08+110.00+190.64) / 4 = 165.03 and between imputation variance is $B = \frac{\sum(\hat{\theta}_t - \bar{\theta})^2}{m\text{-}1}$ = ((74.79-74.25)^2 + (72.55-74.25)^2 + (75.51-74.25)^2 + (74.15-74.25)^2) / (4-1) = 1.59. The pooled standard error is $SE = \sqrt{W + B + B/m}$ = 12.92. Where t is the imputed dataset, m is the total number of datasets, $\hat{\theta}_t$ is the parameter estimate from the filled dataset t, $\bar{\theta}$ is the average parameter estimate. Due to the pooling of multiple datasets, random noise (between imputation variance) is accounted for. Therefore unlike in previous method such as the stochastic regression method, which underestimated standard errors because the imputed values are treated as real, in this method standard errors are corrected by the introduction of additional noise (between-imputation variance).

Overall MICE does not simply produce guesses about the values, but it restricts the imputations to the observed values, allows us to keep all the data, accounts for the variability in the data and preserves the non-linear relationships amongst the variables.

2.3.3 Portfolio construction and performance measures

Portfolio value & Performance measure

In the following section I will describe the financial variables used in Chapter 4 that measure investors' portfolio performance, risk and trading preferences. Given that the dataset has daily cash positions and all trading records for each investor we first reconstruct the daily portfolio value for each individual which enables us to derive the relevant performance measures. The *daily portfolio value* is the sum of the stock value and cash on a given day. To calculate the daily *stock value* we use the historic close prices from Bloomberg using the unique security identifier for each stock (the sedol) and the number of stocks traded on the day. The *cash value* position changes when there is a transaction for that amount (trade quantity× closing price×trade action). In our calculation we do not add interest to the cash positions and we do not account for dividends or corporate action.

Once we have the daily portfolio value we then calculate the *daily mean portfolio returns* for every trader for the whole period. Assessing daily mean portfolio returns, although of concern to investors, does not account for the portfolio risk that investors hold. For risk adjusted returns we use the *Sharpe Ratio*, which as calculated by dividing the total portfolio return by the standard deviation of the portfolio return. To calculate the risk of the portfolio, we measure portfolio *volatility*, which is the standard deviation of portfolio's daily returns. Volatility also accounts for how well diversified investor's portfolio is.

We also derive *return on investment (ROI)* by taking the difference between the average buy price for each stock per investor and the average sell price for each stock per investor and multiplying by the number of stock traded (same number of buys and sells) and then dividing this by the initial amount invested (buy price times quantity of stock). The measure could be interpreted in two ways. Either investors have made a profit on their investment and pulled the cash out of the market or investors have cut their losing positions with an intent to reinvest into potentially more profitable positions. Although at first it seems optimal to have positive return on investment, this could not always be the case. As per behavioral finance literature, the disposition effect (Shefrin & Statman 1985) investors tend to hold on to their losing positions too long and sell winners too soon. Therefore the ROI measure should be considered together with other portfolio performance measures as negative ROI might indicate that investors are getting out of unprofitable positions, in other words engaging in an optimal strategy.

Another measure that we will use is *notional*, which is the average size of the trade. Some investors might have preferences to trade in larger volume while others might be more cautious. We also consider trade frequency which we refer to as *deals*. It is the probability to trade over the whole time period on trading days and is calculated as the average of number of trades divided by the number of trading days. Lastly we consider *trade ratio*, which is the number of trades divided by the number of logins an investor has made. This measures whether an investor is more likely to trade once he has logged in or whether he simply logs into his portfolio to look.

Commissions

Is this study we leave commissions out of the analysis. We do however have the fee structure as per table below. Commission structure and its impact is something that can be explored in the future. Sometimes even if traders make a profit, the profit is wiped out by commissions.

Breakdown of commissions:

Comm. per trade	
1-12	£12.95
15-24	£9.95
25+	£6.95

Note: Charge of £12 per quarter if inactive.

2.4 Research Methodology in Chapter 5

Chapter 5 of the thesis is based on the experimental work. We use mixed effects modelling as in Chapter 3 for our analysis since we have a within subjects design. In a controlled environment we test whether exogenous variables impact participants trading decisions using a professional trading platform called Trading Technologies (TT), which is used by traders worldwide. We use International Affective Picture Systems (IAPS), one of the most widely used stimulus sets (Lang, Bradley & Cuthbert 1999) for inducing arousal. IAPS is a set of static images based on a dimensional model of emotion. The image set contains various pictures depicting mutilations, snakes, insects, attack scenes, accidents, contamination, illness, loss, pollution, puppies, babies, and landscape scenes, among others. It has been widely used in the experimental investigations of emotion and attention and obtained good reputation of worldwide psychological research labs with almost 9,000 articles siting it on Web of Science. Given the number of independent variables and a relatively small sample size we conduct factor analysis to reduce the model and to test for dominant factors. More detail about the experimental methods is provided in Chapter 5.

CHAPTER 3

The Meerkat Effect:

Personality and Market Returns Affect Investors' Portfolio Monitoring Behavior

Contents:

Abstract

Karlsson, Loewenstein and Seppi (2009) found that, following market downswings, investors are less likely to login to monitor their retirement portfolios. They concluded that, rather like (apocryphal) ostriches sticking their heads in the sand, investors avoid unpleasant information by reducing portfolio monitoring in response to news of negative market movement. We apply generalized non-linear mixed effects models to test for this selective information monitoring at an individual level in a new sample of active online investors. We see different behavior in this new sample. We find that investors *increase* their portfolio monitoring following both positive *and* daily negative market returns, behaving more like hyper-vigilant meerkats than head-in-the-sand ostriches. This pattern persists for logins not resulting in trades and weekend logins when markets are closed. Moreover, an investor personality trait – neuroticism - attenuates the pattern of portfolio monitoring suggesting that market–driven variation in portfolio monitoring is attributable to psychological factors.

3.1 Introduction

A standard assumption of the economics of information is that we should place value on information to the extent that it serves as input to decisions that enable us to obtain desired outcomes. However, recent studies have suggested that we can also value information for its own sake, and derive positive and negative utility directly from information. Loewenstein (2006) discusses cases where individuals seek out or avoid additional information conditional on their expectations of how such information will make them feel, independent of its informational value. For example, in the medical domain Loewenstein, Read and Baumeister (2003) describe how people choose not to book an appointment to see a doctor in order to avoid receiving potentially threatening information about their medical condition even if such information could potentially provide information that would improve the quality of their health and wellbeing. Recent studies in neuroscience (Berns et al. 2006) show that regions of the brain that are activated during the experience of a painful electric shock are also activated in individuals anticipating the impending painful experience. The brain activation increases as the time of the shock approaches - behavior consistent with the notion that the information that one is going to receive an electric shock is, like the shock itself, a source of misery. Indeed, thinking about the shock was so unpleasant that subjects in this study preferred more pain - a higher voltage shock - in order to reduce the time they spent dreading the impending shock.

As well as avoiding negative information people may seek out and relish positive information. Ehrilch et al. (1957) found that owners who recently purchased cars were more attentive to advertisements for the model which they bought compared to the other models they had considered buying. Similarly, Brock and Balloun (1967) found that smokers made more effort to listen to pro-smoking messages than non-smokers, and non-smokers made more effort to listen to a message affirming the link between smoking and lung cancer than smokers. The evidence indicates that, for both positive and negative information, people seek out or avoid information contingent on their expectation of its hedonic impact.

A recent study by Karlsson, Loewenstein and Seppi (2009) has found evidence that people selectively seek out and avoid information in a behavioral finance context. Given that the hedonic disutility of attending to bad news may outweigh its informational benefits, Karlsson et al. (2009) built a model that brings together information acquisition and hedonic utility of information. The model predicts that individuals rapidly seek out definitive information given positive news and avoid information in the face of adverse news or in other words, that they will have asymmetric preferences for the timing and resolution of uncertainty.

In their study Karlsson et al. (2009) explored two datasets. The first dataset from the Swedish Premium Pension Authority represented Swedish citizens' investments in equity and interest-bearing funds for their pensions aggregated across all clients. The second dataset, provided by Vanguard Group, one of the largest investment management companies, aggregated American investors who primarily had personal 401(k) plans - retirement savings plans that can be invested into various funds. In both datasets the authors found that investors selectively attended to information, as shown by portfolio monitoring increasing with rising markets. Karlsson et al. (2009) reported evidence that investors check the value of their portfolios more frequently following positive market movements. In the US dataset prior averaged market return[2] of 1% increased the daily mean number of logins by 5-6% and in the Swedish dataset by 1%.

Borrowing from an earlier study by Galai and Sade (2006), Karlsson et al. (2009) termed this pattern of information monitoring the *ostrich effect*. Galai and Sade's (2006) identification of the ostrich effect stems from their finding that the return on liquid assets was greater than that on equally risky illiquid assets and that this difference in returns was higher in periods of greater uncertainty. Galai and Sade (2006) attributed this observation to investors' willingness to pay a premium for the "bliss of ignorance" (p. 2758). Under a standard economic account people should demand a higher return for the illiquid assets, all other things being equal. The finding of the opposite pattern suggests that both because information about losses is particularly painful, and because information about the performance of illiquid assets is less accessible, investors are more willing to hold illiquid assets. Accordingly, Galai and Sade (2006) attributed investors' preference for illiquid assets over equally risky liquid assets to the avoidance of potentially negative or uncertain information.

More recently, using the same dataset as Karlsson et al. (2009), Sicherman, Loewenstein, Seppi and Utkus (2013) have extended the analysis of Vanguard clients' (mostly 401k) accounts over the 2007-2008 period to an individual account-level introducing a non-linear function (cf. Karlsson et al. 2009, who used a linear function) to relate market returns to logins to examine possible differences between the effect of positive and negative returns. Sicherman et al. (2013) confirmed the ostrich effect reporting a significant negative coefficient on a "down Dow" dummy variable which indicated whether the Dow index went down on the previous day. However, they found no corresponding increase in monitoring when the Dow increased; in fact monitoring slightly decreased across the range of positive returns. They confirmed the ostrich effect for negative market returns at both an aggregate and individual level; although many individual accounts had too few logins to enable detection of any effect, about 14% of their sample showed a significant return / login relation and, of

[2] Karlsson et al. (2009) define prior averaged market returns as the log change in the index relative to the average index level over the previous 4 days.

these, 79% of investors showed the ostrich effect, while 21% were “anti” ostriches as they had the opposite response to the market returns (increasing logins given negative market returns). Moreover, consistent with the view that the ostrich effect has a psychological basis, Sicherman et al. (2013) find that ostrich behavior is a relatively stable personal characteristic over time; individuals who displayed ostrich behavior in 2007 were more likely to display ostrich behavior in 2008.

In this study we test the effects of market returns on individual investors’ portfolio monitoring decisions in a new data set. Our data set is from 617 UK private individuals investing in equities from 2004-2009, and contrasts with the Vanguard and Swedish Premium Pension Authority investors allocating into pension funds in 2007-2008. We consider the effects of positive and negative daily market returns separately over a 6 year time period. To preview our results, like Karlsson et al. (2009) and Sicherman et al. (2013), we find that login behavior depends on market returns, but in our data the dependency is quite different. Rather than the ostrich effect pattern, where people login less after recent negative market returns, we find what we term a *meerkat effect* in which people login *more*, not less, in response to recent negative returns - *as well as* to positive returns.

In attempting to understand why login behavior should vary as a function of market returns we assume that investor logins may be motivated by different intentions. They may login to trade or merely for portfolio information. Regardless of a trader’s intentions both of these kinds of login could result in a trade - or not. In our modelling as well as considering all logins, we also consider just the subset of logins that did not result in a trade. This is because although logins that did not result in a trade do not necessarily reflect hedonic monitoring, these transaction-free logins can be considered more likely to reflect informational portfolio monitoring. We find that, for such non-trade logins investors increase their portfolio monitoring given both positive *and* negative daily market returns. To test this idea further we analyse weekend logins, days when investors cannot transact. We again find investors increase their portfolio monitoring for both positive *and* negative daily market returns - *a meerkat effect.* The fact that non-trade logins increase with positive daily market returns is consistent with the idea that investors seek - and gain - hedonic utility directly from positive information. However our findings of increased logins with negative market returns for daily non-trade logins and weekend logins are again the opposite of the ostrich effect for negative market returns found by Sicherman et al. (2013).

Karlsson et al. (2009) and Sicherman et al. (2013) propose that the ostrich effect is attributable to psychological factors, and our study was originally planned to seek corroborative evidence for this notion by exploring the possibility of a link between the psychological trait of neuroticism and individual differences in login behavior. The personality trait of neuroticism is associated with high levels of anxiety. While anxiety can be a mood or an emotion, *trait* neuroticism describes individual differences in base-line levels of anxiety; indeed some authors refer to anxiety as a personality trait (Wilt, Oehlberg & Revelle 2011). Neuroticism is one of the major human personality traits identified in the five factor model of personality (Costa & McRae 1992) and as more neurotic individuals experience greater anxiety and worry (Mathews, Deary & Whiteman 2003), we envisaged that this would be reflected in their reactions to negative market returns. In order to investigate the psychological basis of the ostrich effect, we construct a measure of the neuroticism personality trait for each investor and test whether investors' level of neuroticism interacts with the effect of daily market returns on logins. We hypothesise that there will be individual differences in logins conditional on the daily market returns. The next section introduces our dataset, definitions of variables, descriptive statistics and the generalized mixed effects model. Section 3.3 presents the results. In Section 3.4 we introduce the trait of neuroticism and its interaction with the meerkat effect. Discussion is presented in Section 3.5.

3.2 Dataset and Methodology

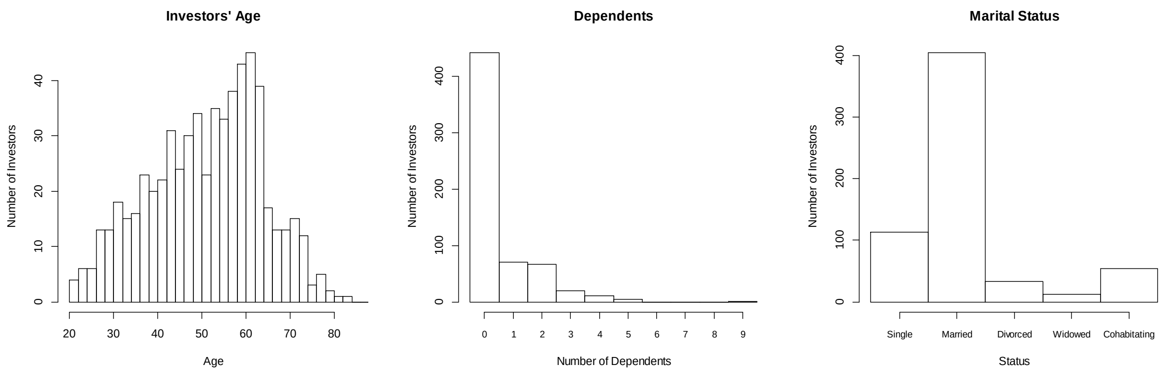
3.2.1 Data and sample characteristics

We study 617 clients from Barclays Wealth Management. For each client we have their logins and trading records over a 6 year period (2004-2009) and their self-reported demographics derived from a survey of the same 617 investors. The survey was conducted in a series of waves from September 2008 to December 2009 in order to explore investors' attitudes and disposition in relation to financial markets that were of interest to Barclays Wealth Management research objectives. As an incentive to participate in the survey respondents were promised a summary of the research findings. Overall, such survey methodology has become an important addition to finance (Graham & Harvey 2001, Lins, Servaes & Tufano 2010).

In this study our sample of investors was selected based on the activity and wealth of individual investors. Those with more than 1 trade per year and those with portfolio value of more than £1000 were invited to participate in the survey with a total of 19,251 of their clients invited to take part in an online survey via email. 4,520 clients opened the email and 849 proceeded to the on-line questionnaire survey. 617 clients completed the survey, which is in the same range of response rate as in similar studies by Dorn and Huberman (2005) and Glaser and Weber (2007).

Figure 3.1 provides demographic distributions of the panel sample of our 617 investors who took part in the survey and includes investors' age, number of dependents, investable wealth, income and marital status and the demographic survey questions. To identify potential selection biases, we compared survey participants to an adult British population based on the data reported by the Office for National Statistics. Overall our 617 investors have above average incomes compared to the British population; while the mean British income is around £30,000 our sample has a mean of £76,616 and a median of £60,000. 84% of the sample are the prime financial (investment and savings) decision makers of the household. The average age of survey participants is 51 years, four years older than the average British adult. Survey participants are also more likely to be married (0.74 vs. 0.52) or male (0.93 vs. 0.49) compared to the British average. Although our respondents are not representative of the typical British adult, their demographics are in-line with private investor populations analysed in other studies (Dorn & Huberman 2005).

Figure 3.2 plots the distributions of the daily market returns as measured by FTSE100 Index, the average daily number of logins per investor and the daily average number of logins per investor excluding those logins that resulted in a trade, or as we refer to, informational / hedonic logins. Investors in the sample login on 37% of the trading days. Figure 3.3 is a raw scatter plot of aggregate number of daily logins and daily market returns; the locally weighted scatterplot smoothing line clearly indicates non-linearity in the data showing increased logins responses to both market gains and losses.



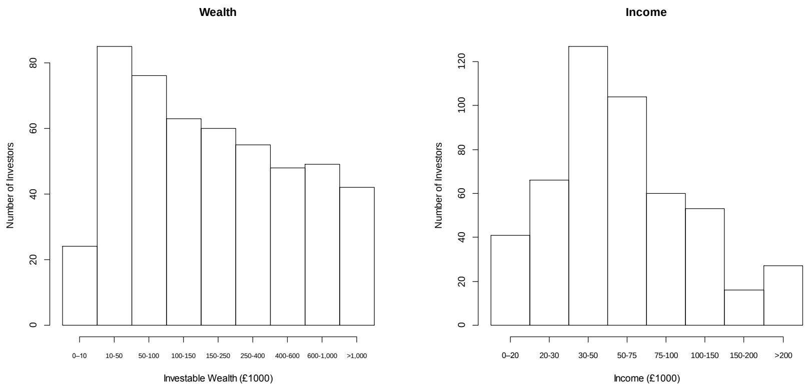


Figure 3.1. Demographics distributions: investors' age, number of dependents investors have, marital status, investable wealth and income. The survey questions were phrased as follows: How old are you? How many dependents do you have? What is your marital status? (Single; Married; Divorced; Widowed; Cohabitating). What is the approximate total value of all of your investable wealth - your stocks, bonds, investment funds, derivatives and cash holdings? What is your expected gross annual income for this year?

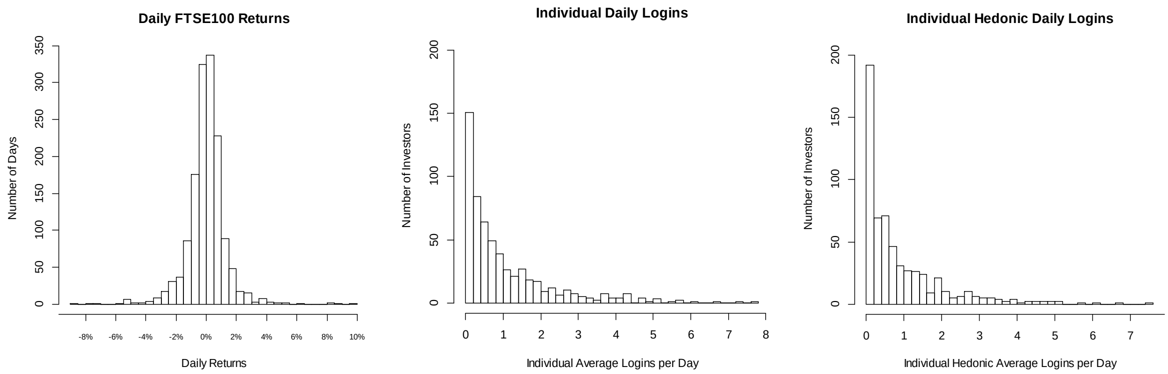


Figure 3.2. FTSE100 Index and logins distributions (trading days): FTSE100 Index ranging from January 2004 to December 2009 to match the transactions data, average daily logins per investor, average daily logins per investor excluding logins that resulted in a trade. Daily Market Returns = (FTSE100 Price $_{(t)}$ - FTSE100 Price $_{(t-1)}$) / FTSE100 Price $_{(t-1)}$. Closing prices are applied.

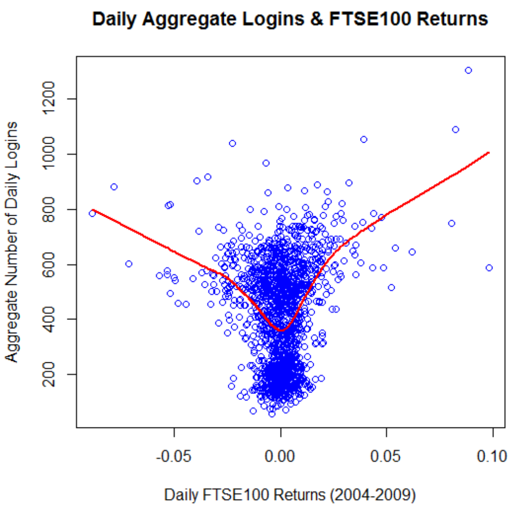


Figure 3.3. Aggregate logins and daily returns: The scatter plot shows the aggregate number of daily logins of our sample of investors and the daily FTSE100 returns with locally weighted scatterplot smoothing line.

3.2.2 Models:

Our data allows us to measure investors' portfolio monitoring behavior at an individual rather than the aggregate level. While we later describe analyses of logins that did not result in trades our first analysis includes all trading day logins. All models in this study include the full sample of 617 investors. Given that we have count data (the number of logins) we use a Poisson model and because we have repeated measures for each client we use a mixed effects model. This Poisson mixed effects model has random intercepts to account for each investor's propensity to login to their portfolio and random slopes to account for individuals' sensitivity to daily market returns. To directly test the sensitivity of investors' login behavior to changes in daily market returns separately for positive and negative domains, we use two dummy variables to indicate the sign of daily market returns, one to indicate a positive return (Up-Dummy) and one to indicate a negative return (Down-Dummy). We control for days of the week, age, gender, income, marital status and whether the individual is the prime financial decision maker in the household. We exclude weekends and holidays from the first part of the analysis as the stock market is closed therefore allowing us to focus on trading days; we consider weekend monitoring behavior in a later section 3.3.5. We fit four models. The first model uses daily market returns - returns between yesterday's and today's closing price - as the independent variable. The second model uses a 5-day moving average of daily market returns and the third model uses a 20-day moving average. The 5-day market return is the average of daily market returns for the week. For example if today is a Wednesday, the 5-day returns calculation would include daily market returns on the last Thursday though today. A similar method is used for the 20-day market returns calculation. It makes sense to look at market returns over several time periods: a recent daily return, a week's average return and a month's average return could cause varied portfolio monitoring behavior. The fourth model includes previous day's logins since a login on Tuesday might not be independent from a login on Monday. All four models gave very similar results.

3.3 Results

3.3.1 Daily Market Returns

The results in Table 3.1 show coefficients from our four Poisson mixed effects models. Across all models there are more logins on Mondays and Tuesdays compared to the rest of the trading days (Friday was the baseline in our regressions). There is also a significant gender effect in all models with males logging in more frequently, which is consistent with Sicherman et al.'s (2013) results. In Model 1, the significant positive coefficient for the interaction between daily market returns and the dummy for positive returns (Returns×Up-Dummy) indicates that given an increase in daily market returns investors monitor their portfolios more. The significant negative coefficient for the interaction between daily market returns and the dummy for negative daily market returns (Returns×Down-Dummy) indicates that the pattern is significantly different in the loss domain. Investors login more often with increasingly positive daily market returns and more, *not less*, after increasingly negative daily market returns. We call the increased monitoring as a function of increasing absolute daily market returns the *meerkat effect*[3] because investors increase their monitoring given changes. A t-test confirms that the absolute steepness of the slopes is significantly different ($p<.001$) in positive and negative domains. In summary, investors increase portfolio monitoring given both positive *and* negative daily market returns. The observed increase in portfolio monitoring given positive daily market returns is consistent with the ostrich effect; however, the increase in logins for negative daily market returns (relative to zero returns) is not consistent with what would be expected from an aversion to negative information.

3.3.2 Past Daily Market Returns

Model 2 replicates the analysis of Model 1, but replaces the daily market returns with the 5-day moving average, and we find the same significant meerkat effect – that is increased portfolio monitoring for both positive and negative market returns. Model 3 uses a 20-day moving average instead of the 5-day moving average and again we find the same significant pattern. Model 4 extends Model 1 by including a lagged login and it is consistent with the previous three models and shows that those investors who are more likely to login in the past are more likely to login today.

3.3.3 Hedonic monitoring

When people login they may do so with the intention of monitoring only or the intention of trading, and then once logged in, then can trade or not. Thus we have a 2x2 table of scenarios: (i) intending to trade and then trading, (ii) intending to trade but not trading, (iii) intending to monitor but then trading, and (iv) intending to monitor and then not trading. Of course, unfortunately, we do not know the intention at login, only the result - either a trade or not. We differentiate between portfolio logins for trading purposes versus pure informational purposes to explore the psychological effects of information. As non-trade logins can be considered more likely

[3] Typically one meerkat is on guard duty. Once faced with danger all meerkats come up and immediately begin jumping and growling.

Table 3.1

Poisson Models of All Weekday Logins

	Model 1 Daily Ret	P Value	Model 2 5-day Ret	P Value	Model 3 20-day Ret	P Value	Model 4 Login lag	P Value
(Intercept)	-1.004	0.007	-0.959	0.011	-0.949	0.011	-1.153	0.001
Monday	0.047	0.000	0.056	0.000	0.056	0.000	0.039	0.000
Tuesday	0.011	0.008	0.015	0.000	0.011	0.007	0.018	0.000
Wednesday	-0.011	0.008	-0.009	0.023	-0.012	0.004	-0.012	0.004
Thursday	-0.002	0.692	-0.007	0.096	-0.007	0.067	-0.002	0.592
Age	-0.004	0.383	-0.004	0.365	-0.004	0.361	-0.004	0.327
Decision Maker	-0.011	0.899	-0.011	0.901	-0.011	0.901	-0.014	0.867
Gender (Male)	0.615	0.011	0.611	0.012	0.611	0.012	0.563	0.011
Income	0.000	0.030	0.000	0.029	0.000	0.029	0.000	0.027
Married	-0.009	0.957	-0.007	0.965	-0.007	0.967	0.008	0.959
Divorced	-0.149	0.596	-0.147	0.602	-0.146	0.603	-0.126	0.622
Widowed	0.109	0.803	0.114	0.794	0.115	0.794	0.181	0.651
Cohabitating	0.373	0.118	0.374	0.117	0.374	0.117	0.337	0.121
Returns×Up Dummy	5.758	0.000					5.504	0.000
Returns×Down Dummy	-2.207	0.000					-1.567	0.000
Return 5-days×Up Dummy			4.997	0.000				
Return 5-days×Down Dummy			-1.669	0.000				
Return 20-days×Up Dummy					2.088	0.003		
Return 20-days×Down Dummy					-4.620	0.000		
Login 1 day lag							0.142	0.000
Marginal R^2	1.2%		1.2%		1.2%		3.0%	
Conditional R^2	48%		48%		48%		45%	

Note: The marginal R^2 describes the proportion of variance explained by the fixed factor(s) alone. The conditional R^2 describes the proportion of variance explained by both the fixed and random factors.

to reflect informational portfolio monitoring we subtract days with logins that resulted in a trade (trading days) from the dataset for each investor and conduct similar analyses as above to test the relationship between login days not involving transactions and daily market returns. Karlsson et al. (2009) addressed this issue by using the number of account logins less the number of portfolio reallocations in the Swedish dataset and aggregate S&P 500 trading volume as a proxy to control for transactional logins in the Vanguard dataset. Sicherman et al. (2013) also controlled for how much investors trade and performed analyses of weekend logins, which we consider in a later section.

Table 3.2 reports results from our four non-trade logins Poisson models. The Returns×Up-Dummy coefficients are, as before, significantly positive across all four model specifications suggesting investors' increased demand for positive information given rising markets. The fact that there are logins that do not result in trades is not, by itself, necessarily indicative of hedonic monitoring. However the observed *increase* in non-trade logins as a function of rising markets does support the notion that investors seek and obtain positive utility directly from information. Investors are more likely to monitor their portfolio given rising markets.

Given falling markets, the significant Returns×Down-Dummy coefficient in Model 1 implies that in response to daily market decreases, investors increasingly seek-out information; this is counter to the ostrich effect supporting our coining of the term meerkat effect. Model 4, which is similar to Model 1, but includes a term to control for the influence of logins on the previous day, also shows a meerkat effect. This model also shows that investors' login decisions are not independent of their logins the day before. However, Model 2 (the 5-day average return specification) shows the opposite pattern for these non-trade logins to that observed when logins involving trades were included. Instead of the meerkat effect there is a mild ostrich effect, such that with increasingly negative returns fewer non-trade logins are made. This possibly reflects the fact that because there is a larger proportion of logins that result in a trade when market declines (cf. Figure 3.4) there would be fewer opportunities for investors to record login days without trading over the 5-day period. Figure 3.4 shows a plot of the proportion of trades given a login across daily market returns and confirms that in falling markets investors' logins are increasingly likely to result in transactions; for rising markets the increase in transactions per login is not so steep. Model 3 (the 20-day return specification) shows that when the market declined over the previous month, investor logins without trades do not vary from their baseline level.

Table 3.2

Poisson Models of Non-Trades Weekday Logins

	Model 1		Model 2		Model 3		Model 4	
	Daily Ret	P Value	5-day Ret	P Value	20-day Ret	P Value	Login lag	P Value
(Intercept)	-1.297	0.001	-1.260	0.001	-1.253	0.002	-1.712	0.000
Monday	0.047	0.000	0.054	0.000	0.055	0.000	0.075	0.000
Tuesday	0.018	0.000	0.022	0.000	0.019	0.000	0.020	0.067
Wednesday	-0.002	0.678	-0.002	0.724	-0.003	0.493	-0.015	0.166
Thursday	0.007	0.145	0.002	0.586	0.002	0.677	0.003	0.803
Age	-0.003	0.570	-0.003	0.549	-0.003	0.544	-0.002	0.753
Decision Maker	0.005	0.957	0.005	0.954	0.005	0.954	-0.015	0.868
Gender (Male)	0.604	0.018	0.600	0.019	0.600	0.019	0.566	0.022
Income	0.000	0.021	0.000	0.021	0.000	0.021	0.000	0.015
Married	-0.002	0.989	-0.002	0.993	-0.001	0.994	-0.108	0.520
Divorced	-0.111	0.708	-0.109	0.714	-0.109	0.714	-0.207	0.469
Widowed	-0.055	0.905	-0.049	0.916	-0.049	0.916	-0.100	0.823
Cohabitating	0.409	0.103	0.409	0.103	0.409	0.103	0.195	0.421
Returns× Up Dummy	5.399	0.000					9.685	0.000
Returns× Down Dummy	-0.447	0.007					-2.104	0.000
Return 5-days×Up Dummy			5.431	0.000				
Return 5-days×Down Dummy			1.828	0.000				
Return 20-days×Up Dummy					4.887	0.000		
Return 20-days×Down Dummy					0.376	0.638		
Login 1 day lag							1.712	0.000
Marginal R^2	1.2%		1.2%		1.2%		16%	
Conditional R^2	51%		51%		51%		57%	

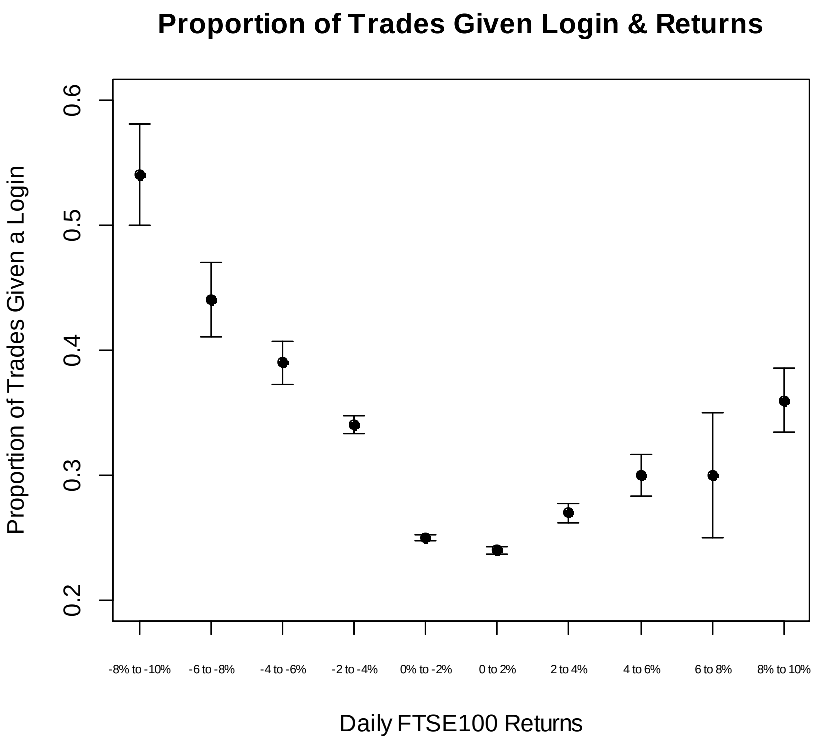


Figure 3.4. The plot shows proportion of daily trades given a login for daily market returns with bars showing the 95% confidence intervals.

3.3.4 Robustness tests

Because the system automatically logs-off inactive investors, multiple logins per day do not necessarily indicate a greater interest in portfolio monitoring; the most active investors could login just once and remain logged in - and monitoring - all day, while investors with a higher number of logins might be monitoring less and so being repeatedly logged out. For these reasons we tested a logit mixed effects model with a binary dependant variable for daily portfolio monitoring – measuring a login if an investor logged into his account any number of times on that day or no-login if an investor did not login on that day. As previously, we fitted four models for all logins (Table 3.3) and for non-trade logins (Table 3.4). Table 3.3 reports similar results to the Poisson models reported in Table 3.1 except that the returns and Down-Dummy interaction coefficients for Model 3 and Model 4 are non-significant. Results of the non-trade logins logit regressions in Table 3.4 are similar to the corresponding Poisson model specifications in Table 3.2 – except the returns and Down-Dummy interaction variable for Model 4 is non-significant. Though some effects are not significant over longer averaged returns the different criterion for logins tested with the logit models does not change the overall pattern of effects we observe.

Table 3.3

Logit Models of All Weekday Logins

	Model 1		Model 2		Model 3		Model 4	
	Daily Ret	P Value	5-day Ret	P Value	20-day Ret	P Value	Login lag	P Value
(Intercept)	-1.061	0.029	-0.991	0.041	-0.973	0.045	-1.430	0.000
Monday	0.063	0.000	0.074	0.000	0.076	0.000	0.039	0.000
Tuesday	0.040	0.000	0.049	0.000	-0.003	0.771	-0.012	0.010
Wednesday	-0.001	0.885	0.002	0.843	0.041	0.000	-0.006	0.186
Thursday	0.004	0.689	-0.002	0.816	-0.002	0.862	0.003	0.477
Age	-0.002	0.774	-0.002	0.742	-0.002	0.733	-0.003	0.487
Decision Maker	-0.022	0.847	-0.022	0.851	-0.022	0.850	0.000	0.999
Gender (Male)	0.687	0.029	0.683	0.030	0.681	0.030	0.552	0.018
Income	0.000	0.016	0.000	0.015	0.000	0.015	0.000	0.028
Married	-0.134	0.533	-0.133	0.536	-0.132	0.537	0.010	0.949
Divorced	-0.276	0.450	-0.272	0.457	-0.271	0.458	-0.097	0.720
Widowed	-0.149	0.794	-0.140	0.806	-0.138	0.808	0.010	0.982
Cohabitating	0.253	0.413	0.252	0.415	0.252	0.415	0.365	0.112
Returns×Up Dummy	9.221	0.000					5.293	0.000
Returns×Down Dummy	-3.954	0.000					-0.050	0.768
Return 5-days×Up Dummy			10.380	0.000				
Return 5-days×Down Dummy			-1.839	0.019				
Return 20-days×Up Dummy					9.784	0.000		
Return 20-days×Down Dummy					-2.805	0.111		
Login 1 day lag							0.150	0.000
Marginal R^2	1.3%		1.2%		1.2%		3.0%	
Conditional R^2	62%		61%		61%		48%	

Table 3.4

Logit Models of Non-Trades Weekday Logins

	Model 1		Model 2		Model 3		Model 4	
	Daily Ret	P Value	5-day Ret	P Value	20-day Ret	P Value	Login lag	P Value
(Intercept)	-1.295	0.009	-1.231	0.013	-1.221	0.014	-1.902	0.000
Monday	0.059	0.000	0.069	0.000	0.071	0.000	0.063	0.000
Tuesday	0.048	0.000	0.056	0.000	0.007	0.514	0.029	0.012
Wednesday	0.011	0.295	0.014	0.202	0.050	0.000	-0.003	0.792
Thursday	0.013	0.222	0.008	0.474	0.011	0.318	0.012	0.299
Age	-0.001	0.868	-0.001	0.836	-0.001	0.834	-0.001	0.834
Decision Maker	-0.008	0.949	-0.007	0.952	-0.007	0.953	-0.003	0.977
Gender (Male)	0.662	0.039	0.654	0.041	0.653	0.042	0.539	0.035
Income	0.000	0.013	0.000	0.013	0.000	0.013	0.000	0.014
Married	-0.132	0.547	-0.131	0.550	-0.131	0.551	-0.107	0.541
Divorced	-0.246	0.510	-0.243	0.515	-0.242	0.516	-0.181	0.542
Widowed	-0.260	0.655	-0.255	0.662	-0.253	0.664	-0.221	0.633
Cohabitating	0.279	0.378	0.278	0.380	0.278	0.379	0.225	0.371
Returns×Up Dummy	8.683	0.000					9.311	0.000
Returns×Down Dummy	-2.105	0.000					-0.413	0.326
Return 5-days×Up Dummy			11.080	0.000				
Return 5-days×Down Dummy			2.265	0.007				
Return 20-days×Up Dummy					12.500	0.000		
Return 20-days×Down Dummy					2.431	0.199		
Login 1 day lag							1.675	0.000
Marginal R^2	1.3%		1.2%		1.2%		15%	
Conditional R^2	62%		62%		62%		57%	

3.3.5 Weekend Monitoring

Our second strategy for examining psychological effects of information is to use weekend logins. As the market is closed at weekends we assume weekend logins will not be motivated by any intent to trade; with the exception of placing limit orders and market orders for immediate execution once the market opens, investors will be restricted to monitoring. Accordingly we investigated weekend logins using similar models as reported in previous sections. Treating the weekend as one period Table 3.5 reports results for weekend logins regressed on the previous Friday's returns using both Poisson and logit models (Model 1a and Model 1b). For the logit model we measured a login if an investor logged into his account any number of times on that weekend (Saturday or Sunday) or no-login if an investor did not login on that weekend.

Across both models we find support for the meerkat effect as investors significantly increase monitoring given both positive and negative market returns. We also used a similar strategy to test the effect of the previous week's returns on weekend monitoring behavior in Model 2a (Poisson) and 2b (logit). The only significant coefficient for these two models is a negative significant coefficient for the 5-day Return×Up-Dummy in Model 2a indicating that when the week is looking good investors chose not to monitor at the weekend – counter to both the meerkat and ostrich effects. This finding is difficult to interpret and different to what we have observed for the 5-day return on trading days – with or without excluding non-trade logins.

Table 3.5

Weekend Logins

	Model 1a Poisson	P Value	Model 1b Logit	P value	Model 2a Poisson	P Value	Model 2b Logit	P value
(Intercept)	-2.212	0.000	-2.607	0.000	-2.172	0.000	-2.545	0.000
Age	0.008	0.088	0.011	0.036	0.008	0.093	0.011	0.040
Decision Maker	-0.003	0.967	0.011	0.908	-0.002	0.984	0.012	0.901
Gender (Male)	0.342	0.137	0.479	0.066	0.339	0.140	0.476	0.068
Income	0.000	0.003	0.000	0.011	0.000	0.003	0.000	0.011
Married	-0.197	0.204	-0.180	0.304	-0.195	0.208	-0.179	0.306
Divorced	-0.679	0.011	-0.668	0.026	-0.668	0.012	-0.665	0.027
Widowed	-0.231	0.576	-0.279	0.550	-0.223	0.589	-0.272	0.560
Cohabitating	0.271	0.224	0.317	0.209	0.267	0.231	0.316	0.210
Returns×Up Dummy	1.928	0.011	4.279	0.000				
Returns×Down Dummy	-3.013	0.000	-4.835	0.000				
Returns 5-days×Up Dummy					-5.481	0.002	-3.019	0.273
Returns 5-days× Down Dummy					-0.150	0.915	-0.058	0.979
Marginal R^2	1.7%		1.8%		1.7%		1.8%	
Conditional R^2	45%		51%		45%		51%	

3.3.6 Double Weekend Logins

If investors login and check their accounts on Saturday and then login again on Sunday, Sicherman et al. (2013) hypothesize they are doing this more for psychological reasons rather than purely to get additional portfolio information since prices have not changed. Accordingly, like Sicherman et al. (2013), we investigated double weekend logins by fitting a logit model with 1= login happened consecutively on a Saturday and a Sunday and 0 otherwise. Results are reported in Table 3.6. A model regressed on the previous Friday's returns (Model A) shows a meerkat effect – double weekend logins increased for both increasing and decreasing Friday returns. No significant effects on double weekend logins were measurable based on the average market returns over the prior 5-day period (Model B).

Table 3.6

Double Logins

	Model A Friday Returns	P value	Model B Week Returns	P value
(Intercept)	-4.859	0.000	-4.826	0.000
Age	-0.004	0.661	-0.004	0.607
Decision Maker	0.001	0.995	0.003	0.988
Gender (Male)	0.699	0.163	0.716	0.156
Income	0.000	0.016	0.000	0.014
Married	-0.537	0.066	-0.485	0.100
Divorced	-0.907	0.068	-0.826	0.098
Widowed	-0.503	0.533	-0.403	0.619
Cohabitating	0.054	0.891	0.118	0.765
Returns×Up Dummy	5.549	0.081		
Returns×Down Dummy	-6.438	0.007		
Returns 5-days×Up Dummy			-8.024	0.285
Returns 5-days×Down Dummy			-5.916	0.304
Marginal R^2	2.7%		3.6%	
Conditional R^2	65%		65%	

3.4 Psychology of selective attention

3.4.1 Neuroticism

The psychological evidence that motives and expectations impinge upon human perception to the extent that people's attention and information gathering are influenced by the emotional content of information has been accumulating since the 1940s. For example Postman, Bruner and McGinnis (1948) observed that individuals subconsciously raised the sensory thresholds for the conscious recognition of “unacceptable stimulus objects” terming the phenomenon perceptual defence. Exploring this phenomenon further McGinnis (1949) measured participants' psychophysiological indicators (galvanic skin response) to assess people's emotional reactions and found that there was a selective emotional response to threatening stimuli - but not neutral ones. McGinnis concluded that: "perceptual defence is designed to delay the greater anxiety that accompanies actual recognition of the stimulus" (p.250). Anxiety is directly associated with a trait of neuroticism (Mathews, Deary & Whiteman 2003). *Trait* neuroticism describes individual differences in base-line levels of anxiety; indeed some authors refer to anxiety as a personality trait (Wilt et al. 2011). As earlier research has found that more neurotic people tend to be more perceptually defensive (e.g. Watt & Morris 1995) we hypothesize that the trait of neuroticism plays a role in portfolio monitoring behavior. At the time of planning this study we envisaged we would replicate the ostrich effect and then be able to measure its association with neuroticism. Such a result would offer direct corroboration of Karlsson et al.’s (2009) suggestion, that variation in portfolio monitoring with market returns is attributable to psychological factors. Although we have not replicated the ostrich effect, the rationale for studying the relationship between personality and variation in portfolio monitoring with market returns applies equally well to the meerkat effect. Indeed, some authors have proposed that the attentional system of anxious individuals is abnormally sensitive to threat-related stimuli and that these individuals tend to direct their attention toward threatening information (Williams, Watt, MacLeod & Matthews 1988).

3.4.2 Survey

The single measure of neuroticism was reported by the 617 investors as part of the survey questions collected by Barclays Wealth Management. Although the survey was conducted during turbulent financial times, it is well evidenced that personality traits are stable in adulthood and are seen as important inputs into social and economic outcomes by both psychologists and economists (Cobb-Clark & Shrurer 2011; Heineck & Anger 2010; Mueller & Plug 2006; Nyhus & Pons 2005). In the survey, which is based on the five-factor model of personality inventory (Costa & McRae 1992), each investor responded on a 1-7 Likert scale (labelled 1 “strongly disagree” to 7 “strongly agree”; 4 was labelled “neither agree or disagree”) to four personality statements. The resulting scores ranged from 4 to 28 points and then were scaled to have a mean of 0 and standard deviation of 1. Figure 3.5 reports the distribution of neuroticism and the survey statements used to construct the measure.

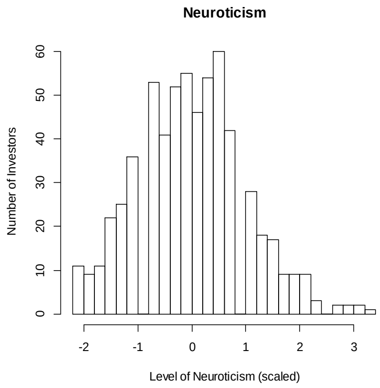


Figure 3.5. Distribution of trait neuroticism from least neurotic to most neurotic (scaled). Survey questions include the following: I am not easily bothered by things. I fear for the worst. I get stressed easily. Uncertainty makes me uneasy, anxious or stressed.

3.4.3 Personality Results

We apply similar analysis as in Section 3.3 using mixed effects with neuroticism added as a fixed effect variable into the model. As a robustness check we carried out both Poisson and logit regressions. As before, we also consider models with all logins and models with logins that did not result in a trade separately. Table 3.7 reports results for four models using the daily returns specification as in Model 1 in Section 3.3. The first and second columns report Poisson and logit models respectively with all logins. The third and fourth columns report Poisson and logit models with logins that did not result in a trade. The coefficient for Neurotic is negative but non-significant across all models, however of interest is the significant interaction between neuroticism and negative market returns (Returns×Neurotic×Down-Dummy) across all model specifications; the rate of increase in monitoring with negative market returns we characterise as the meerkat effect is more extreme for neurotic investors.

For positive market returns all logins and non-trade logins show that the rate of increase in logins is gentler for more neurotic investors. However this interaction is only significant for the Poisson model specifications (Models 1a and 1c). Figure 3.6 plots the fixed effects of returns, neuroticism, and their interactions from Model 1a.

Table 3.7

Poisson and Logit Models of Weekday Logins with Neuroticism

	Model 1a Poisson All logins	P Value	Model 1b logit All logins	P Value	Model 1c Poisson Non-Trade Logins	P Value	Model 1d logit Non-Trade Logins	P Value
(Intercept)	-1.005	0.007	-1.064	0.028	-1.298	0.001	-1.293	0.009
Monday	0.047	0.000	0.063	0.000	0.047	0.000	0.059	0.000
Tuesday	0.011	0.008	0.040	0.000	0.007	0.146	0.013	0.223
Wednesday	-0.011	0.008	-0.001	0.886	0.018	0.000	0.048	0.000
Thursday	-0.002	0.691	0.004	0.689	-0.002	0.673	0.011	0.295
Age	-0.004	0.416	-0.001	0.828	-0.003	0.596	-0.001	0.905
Decision Maker	-0.013	0.888	-0.025	0.832	0.004	0.964	-0.010	0.936
Gender (Male)	0.602	0.013	0.669	0.033	0.595	0.020	0.645	0.045
Income	0.000	0.027	0.000	0.014	0.000	0.020	0.000	0.012
Married	-0.005	0.977	-0.128	0.550	-0.001	0.997	-0.127	0.561
Divorced	-0.145	0.605	-0.269	0.461	-0.109	0.713	-0.241	0.518
Widowed	0.094	0.831	-0.172	0.763	-0.066	0.887	-0.279	0.632
Cohabitating	0.379	0.112	0.261	0.399	0.412	0.101	0.285	0.367
Neurotic	-0.053	0.361	-0.091	0.224	-0.038	0.537	-0.075	0.326
Returns×Up Dummy	5.727	0.000	9.235	0.000	5.380	0.000	8.696	0.000
Returns×Down Dummy	-2.219	0.000	-3.922	0.000	-0.456	0.006	-2.051	0.000
Returns×Neurotic×Up Dummy	-0.504	0.000	-0.516	0.161	-0.486	0.001	-0.431	0.272
Returns×Neurotic×Down Dummy	-0.364	0.008	-1.130	0.002	-0.781	0.000	-1.440	0.000
Marginal R^2	1.2%		1.5%		1.2%		1.4%	
Conditional R^2	48%		61%		51%		61%	

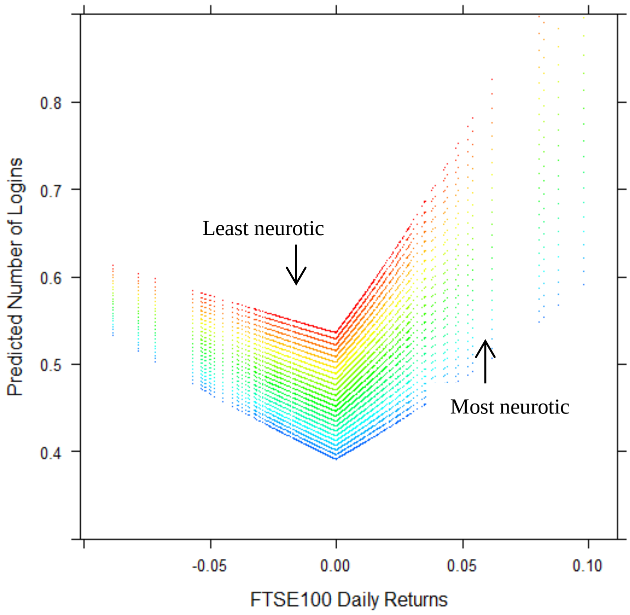


Figure 3.6. Number of logins and daily market returns: The plot illustrates predicted number of logins as a function of daily market returns and highlights effects of neuroticism, daily market returns and their significant interaction. The upper line represents those who scored the lowest on neuroticism and the lower line represents those who scored the highest on neuroticism.

3.4.4 Weekend monitoring and neuroticism

Conducting similar analysis as in the weekend monitoring section we find that neurotic investors login significantly less on the weekends across all model specification, however there are no interactions of neuroticism with market returns (see Table 3.8). We also find no interaction of neuroticism with market returns for double weekend logins. Given that neuroticism interacts with daily returns on weekdays, future research should explore the relationship between trading and the trait of neuroticism.

Table 3.8

Weekend Logins with Neuroticism

	Model 1a Poisson	P Value	Model 1b Logit	P value	Model 2a Poisson	P Value	Model 2b logit	P value
(Intercept)	-2.287	0.000	-2.696	0.000	-2.248	0.000	-2.640	0.000
Age	0.008	0.067	0.011	0.026	0.008	0.072	0.011	0.028
Decision Maker	-0.006	0.942	0.008	0.933	-0.005	0.955	0.009	0.926
Gender (Male)	0.314	0.170	0.443	0.088	0.312	0.174	0.441	0.090
Income	0.000	0.002	0.000	0.008	0.000	0.002	0.000	0.008
Married	-0.186	0.227	-0.166	0.342	-0.187	0.226	-0.168	0.335
Divorced	-0.665	0.012	-0.654	0.029	-0.665	0.012	-0.654	0.029
Widowed	-0.262	0.523	-0.310	0.504	-0.266	0.517	-0.318	0.493
Cohabitating	0.280	0.206	0.333	0.184	0.277	0.212	0.329	0.190
Neurotic	-0.179	0.016	-0.212	0.011	-0.184	0.013	-0.224	0.008
Returns×Up Dummy	1.955	0.035	4.293	0.002				
Returns×Down Dummy	-3.033	0.000	-4.555	0.000				
Returns×Up Dummy×Neurotic	0.053	0.960	0.034	0.984				
Returns×Down Dummy×Neurotic	-0.065	0.935	0.637	0.615				
Returns 5-day×Up Dummy					-4.735	0.028	-1.867	0.559
Returns 5-day×Down Dummy					-0.657	0.698	-1.130	0.660
Returns 5-day×Up Dummy×Neurotic					1.452	0.550	2.701	0.472
Returns 5-day×Down Dummy×Neurotic					-0.956	0.619	-2.560	0.397
Marginal R^2	2.1%		2.4%		2.1%		2.3%	
Conditional R^2	45%		51%		45%		51%	

3.5 Discussion

Our findings confirm that, as Karlsson et al. (2009) and Sicherman et al. (2013) have claimed, individual investors do indeed selectively monitor their portfolios as a function of market conditions. However, our observations differ markedly from those described before. The Vanguard and Swedish Premium Pension Authority datasets show that logins increase as returns move from negative to positive, whereas in our dataset portfolio monitoring increases as daily market returns move away from zero in either direction, indicating that the ostrich metaphor is inappropriate for our data. That is, rather than decrease portfolio monitoring when market conditions are negative and increase monitoring when market conditions are positive, we find that our sample of investors increased monitoring both when market conditions were positive *and* when they were negative. We term this phenomenon the meerkat effect to highlight the contrast with the previous observations of reduced monitoring (as apocryphal meerkats stick their heads up to look around whenever something happens). Our meerkats are logging-in to gain information (either to inform their decision making or for its own sake) and, unlike the ostriches from the Vanguard and Swedish Premium Pension Authority data sets, do not avoid negative information. This pattern of increased monitoring as a function of both increasing and decreasing daily market returns also holds when we consider 5-day and 20-day moving averages for the daily market returns.

Our meerkat effect has an asymmetry, with logins increasing more for positive returns than negative returns (the asymmetric V-shape in Figures 3.3 and 3.6). One possible cause of this asymmetry, suggested to us by Duane Seppi, is that the differential response to positive and negative market returns might be indicative of two effects, one of which masks the other: an effect on information monitoring that increases with changes in market returns in either direction and a hidden underlying ostrich effect that somewhat suppresses monitoring when returns are negative. Despite the possibility of a latent ostrich effect, in the plots of logins by daily returns there is, nonetheless, evidently a clear difference between the login behavior we report here and that found in the earlier studies showing an ostrich effect. For Sicherman et al. (2013, Figure 9) this shows fewer logins when returns are negative and more logins when returns are positive. For us, the scatter plot in Figure 3.3 shows more logins for increasing positive and increasing negative returns. Even accepting that there may be an underlying ostrich effect in our data leaves substantial differences between the data sets.

When we exclude those logins that involved trades from our dataset we again observe a meerkat effect - increasing non-trade logins for both rising and falling markets - *for immediate* (daily) returns. However, for returns over a longer (5-day) time periods we found a different pattern for non-trade logins - they reduced for negative weekly market returns – an ostrich effect. Nonetheless we again consistently observed statistically significant meerkat-like increasing logins with both up *and* down Friday market returns for weekend and double weekend logins when the markets are closed and investors cannot trade. Clearly the portfolio monitoring behavior observed here is qualitatively quite different to that observed by Karlsson et al. (2009) confirmed by Sicherman et al. (2013).

While there are differences between our data set and the Vanguard and Swedish Premium Pension Authority datasets, we all find that portfolio monitoring varies in relation to market movements. If, as Karlsson et al. (2009) and Sicherman et al. (2013) argued, the cause of variation in portfolio monitoring is psychological in nature then we might expect to see some association with psychological characteristics of our investors. Consistent with this rationale we find that the personality trait of neuroticism accounts for the behavioral heterogeneity on an individual basis and interacts with daily market returns in predicting investors' portfolio monitoring decisions. The more neurotic investors generally login less often than their less neurotic counterparts but, more interestingly, neuroticism interacts with the observed variation in logins with daily market returns. Investors generally increased their logins for negative market returns but neurotic investors increased their logins more than non-neurotic investors. For positive market returns, as described above, investors also generally increased their logins but neurotics were less responsive and increased their logins more gently than non-neurotic investors. These findings corroborate the notion of Karlsson et al. (2009) and Sicherman et al. (2013) that variation in portfolio monitoring is attributable to psychological factors – and this can be understood in terms of the different utility that different individuals may experience from any anxiety arising from contemplating portfolio performance.

Although our investigation focuses on the same behaviors as those studied by Karlsson et al. (2009) and Sicherman et al. (2013), we have noted that there are a number of differences between the datasets. Such results could be due to differences between the samples studied across the two studies – the Karlsson et al. (2009) and Sicherman et al.'s (2013) samples consisted of Swedish and USA nationals investing in their own pensions, which might perhaps entail more critical investments and with different time horizons than was at stake for the present sample who were not directly investing for their pensions and may have been involved in more discretionary trades. A clear difference in the behavior of the samples is evident when we compare the daily proportion of logins across the different datasets. From Karlsson et al.'s paper we can infer that the proportion of daily logins in the US dataset was about 2% and for the Swedish data was about 0.2% (Karlsson et al. Table 1), while in our sample the daily login base-rate is 37%.

Although Karlsson et al. (2009) and Sicherman et al. (2013) gave evidence in support of the rationale for observing an ostrich effect there is also evidence, cited by these authors, that people will sometimes hasten the experience of unpleasant experiences. In the introduction we referred to the study by Berns et al. (2006) who observed that people preferred more pain - a higher voltage shock - in order to reduce the time they spent dreading an impending shock. Of course the circumstances of this study are rather different to those of investors exhibiting the ostrich or meerkat effects. Nonetheless it may be that our investors who were likely trading over shorter time horizons than the Vanguard and Swedish Premium Pension Authority investors were more likely to feel that they should get any bad news over with; while the Vanguard and Swedish Premium Pension Authority investors, trading for their pensions, might have felt more able to defer monitoring poor portfolio performance in the short term.

The present study is not the only research finding at variance with the ostrich effect. Brown and Kagel (2009) used a trading laboratory experiment to test participants' information acquisition behavior. In their experiment participants chose one of twenty stocks to hold in 8 trials with 20 periods in each trial. At the end of each round participants were given the performance of their chosen stock and an option to view the past performance of the other nineteen stocks. Consistent with selective avoidance of negative information, the authors expected investors with losing stock to ignore the performance of other stocks that were not chosen so as to avoid the fear and the regret associated with learning that they made the wrong investment. However, their results indicate that, when holding a declining stock, a majority of participants sought more information about the performance of the other stocks they could have invested into; but when holding a winning stock, only a minority of participants chose to look at the performance of the other un-chosen stocks.

In Brown and Kagel's experiment, for a majority of decisions, participants chose to ignore information that could potentially have led to higher earnings. Plainly, this trade-off of the informational value of information against its hedonic impact raises questions about the implications of this phenomenon for financial practice. In relation to the financial markets Caplin and Leahy (2001) have even incorporated anxiety into the expected utility model and argued that it could account for the equity premium puzzle (Mehra & Prescott 1985; Benartzi & Thaler 1995). Similarly, Borghans, Duckworth, Heckman and ter Weel (2008) highlight the importance of personality in predicting various social and economic outcomes including the labour market, crime, educational attainment, schooling decisions, health and longevity, and suggest that personality traits should be incorporated into conventional economic models. Likewise, we have shown the role of individual differences and their importance in information acquisition decisions. With regards to financial markets, inconsistent information acquisition will be reflected in prices; consequently understanding fully how people respond to information is clearly vital to being able to predict prices and dynamics of the financial markets and the economy.

CHAPTER 4

Trading, Performance & Psychological Attributes of Individual Investors: Evidence from the Field

Contents:

Abstract

Combining survey responses and trading records of UK investors, this study tests the effect of self-reported psychological attributes on investors' observed daily trading behavior, transaction size, risk adjusted portfolio performance and portfolio risk preferences. The results indicate that investors' cognitive and affective processes, avoidant behavior, risk tolerance, objective and subjective financial expertise, overconfidence and demographics all contribute to explaining the variance (adjusted R^2) of the financial measures. Comparing only demographics to a full model with 32 psychological attributes increased the variance explained in average daily mean returns from .1% to 9%, investors' portfolio diversification from 11% to 21%, risk adjusted returns from 4% to 19%, propensity to trade from 2% to 30%, size of trades from 5% to 10%, trade ratio from 3% to 27% and return on investment from 1% to 13%. Individual differences in the psychology of investors explain a good deal more of investment behavior than just more traditional demographics. Because we have multiple psychological measures, we can also highlight that, focusing only on one at a time can be misleading. Including market engagement in the model attenuates the gender effect as well as better than average and competence effects on trading frequency. We also find that more frequent trading is not necessarily detrimental to performance: for more mature (older and wealthier) knowledgeable investors who use analytical decision making processes more trading leads to better performance (more diversified portfolios and higher risk adjusted returns), but for less mature sensation seeking investors and those with previous training, more trading leads to worse performance.

4.1 Introduction

Given the recent 2008 financial crisis and the growing interest in household finance, the theoretical and empirical literature in behavioral finance began questioning the overall market efficiency as investors' behavioral is often at odds with the normative theories of finance and economics. For example, according to efficient market hypothesis, stock markets should reflect all available information and, in the zero-sum game of trading, it should be impossible for investors to make systematic profits above the market returns. However, empirical evidence suggests that some investors are consistently better performers while others are systematic losers (Coval, Hirshleifer & Shumway 2005; Korniotis & Kumar 2009; Barber, Lee, Liu & Odean 2013). It has also been shown that investors do not behave as predicted by the modern portfolio theory (Markowitz 1959), according to which investors should hold a well-diversified portfolio and therefore get maximum returns for minimal risk. Yet studies have found that investors hold under-diversified portfolios (Goetzmann & Kumar 2008; Mitton & Vorkink 2007; Grinblatt, Keloharju 2011 & Linnainmaa; Barber & Odean 2013), and therefore investors do not minimize the idiosyncratic risk that is specific to each asset. Moreover, in contrast to normatively prescribed buy-and-hold strategy and no-trades theorems (Aumann 1976; Milgrom & Stokey 1982; Tirole 1982), which suggest that rational traders should not trade with other rational traders who have access to the same information, it has been found that investors trade too much (Barber & Odean 2001). This implies that investors believe they can win in the zero-sum game of trading. In most cases such over- trading results in wealth inhibiting portfolio performance due to perverse stock selection skills and transaction costs (Barber & Odean 2000, 2001; Dorn & Huberman 2005). However, the evidence suggests that some investors who trade more frequently can have superior portfolio performance (Barber et al. 2013).

Various violations of the normative models suggest that investors fail to act in an objective and rational manner. Instead, they may operate in accordance with the notion of bounded rationality (Simon 1955). Specifically, various individual differences and cognitive limitations may steer investors away from following the rules laid out by the axiomatic models of finance. Subsequently, the aim of the following study is to investigate psychological underpinnings of the behaviors that are at variance with the normative models. More specifically, this study investigates the role of individual investors' psychological attributes in financial decision making. Since the relevant field data are rare, only a handful of studies have tested the relationship between various psychometric measures and trading behavior, performance and risk preferences. This study introduces a new dataset consisting of UK-based private individual investors. The first part of the dataset consists of investors' self-reported psychometric measures including multiple measures of overconfidence, perceived competence, financial literacy, subjective numeracy, risk preferences, cognitive abilities, affective processes, aversive behavior and expertise (32 unique measures in total). The second part of the dataset includes individual investors' daily transactions and cash positions. To test investors' diversification preferences and performance we calculate daily portfolio performance, portfolio risk and risk adjusted returns for each investor.

For clarity, the psychological attributes are categorized into five sub-categories constructed based on previous literature. These sub-categories are Demographics, Overconfidence, Sophistication, Affective and Avoidance. The first part of the study tests the effect of demographic variables on trading behavior and performance as these are commonly used as proxies for various psychological measures. We then include all 32 psychological attributes into each of the models and compare the results of the full models with the univariate models, in which independent variables are regressed on their own. Lastly we conduct factor analysis and extract 11 factors, which we name as "Confidence", "Delegation", "Market Knowledge", "Sensation Seeking", "Analytical Decision Process", "Mature", "Income", "Training", "Impulsivity", "Level of Regret" and "Market Research". We use these factors to predict trading behavior and performance.

To pre-empt the results, we show that psychological attributes account for a significant part in explaining the observed trading behavior, trade size (notional), risk preferences as well as the portfolio performance of individual investors. For example the full model explains 15 times more variance in investors trading volume and 5 times more variance in risk adjusted portfolio performance than using simply demographics as predictors in the model. We provide new evidence that individual investors' cognitive and affective processes, avoidant behavior, risk tolerance, objective and perceived financial expertise/competence, overconfidence and demographics account for significant variation (adjusted R^2) in investors' portfolio diversification (21%), trading volume (30%), risk adjusted returns (19%), trade size (10%) and average daily mean returns (9%). The results also indicate that gender effect on trading is significant only when other variables are excluded from the model. The main components associated with more trading include high level of impulsivity, being always engaged with the market, having short investment horizons and believing that trading frequently is the optimal strategy.

We also find that a higher frequency of trading is not necessarily detrimental to the risk adjusted portfolio performance. However, predisposition to be sensation seeking and having previous financial training results in riskier portfolios and worse performance. Previous training and years trading is associated with worse risk adjusted performance. On the other hand better analytical skills and financial knowledge leads to behavior reminiscent to the predictions of the normative models. The outline of the paper is as follows. Section 4.2 introduces background and related research, Section 4.3 outlines the dataset, including descriptive statistics for the demographics, Section 4.4 introduces trading, performance and portfolio diversification details of the sample. Section 4.5 presents the model and the demographics of the dataset. Section 4.6 describes all psychometric measures used in this study and results. Section 4.7 reports the factor analysis and Section 4.8 concludes with a discussion.

4.2 Background and Related Research

To account for the inconsistencies between the normative models and the observed behavior of individual investors, studies in behavioral finance have relied on the insights from psychology to explain the observed phenomena. In psychology the validity of psychometric measures is well established in other domains. For example, Kuncel, Ones and Sackett (2010) compiled numerous studies that highlight the importance of personality traits and cognitive abilities in predicting the outcomes across important life events including educational attainment, test scores, school achievement, job performance, health status (Kern & Friedman 2011), crime (John, Caspi, Robins, Moffitt & Stoutharner-Loeber 1994; Vazsonyi, Pickering, Junger & Hessing 2001) and wages across numerous occupational categories (Almlund, Duckworth, Heckman & Kautz 2011). Barber et al. (2013) provide a comprehensive recent behavioral finance literature review of studies that rely on cognitive biases to explain behavioral anomalies within the financial markets and below we address those most relevant to our study. The studies we describe below all have in common the selection of a limited number of psychological measures which are then used to predict trading behaviors, risk preferences and performance. In Section 4.6, we contrast this single variable approach with the use of multiple measures in our study, to offer some explanation of why some effects appear to come and go in different studies.

One of the most prominent behavioral explanations for over-trading and underperformance has been overconfidence (Barber & Odean 2013); however the exact definition of it remains the subject of a debate in the literature. Theoretical models define overconfidence as miscalibration, whereby investors overestimate the precision of their private information about the value of a financial security. In these models investors' inaccurate beliefs about the available information cause them to trade more aggressively (e.g., Benos 1998; Odean 1998). Another interpretation of overconfidence is better than average: significantly more than 50% of the people claim to be better than average. An example of this cognitive bias was presented in a study by Svenson (1981) who surveyed US drivers and found that 93% of the sample believed their driving skills where in the upper 50% of the sample. To test the overconfidence hypothesis within the financial markets Glazer and Weber (2007) analysed a dataset provided by a German broker. The authors concluded that miscalibration was not related to trading volume. In an experimental financial market Biais, Hulton, Mazurier and Pouget (2005) did not find miscalibration to be related to trading volume. Glazer and Weber did find that the belief of being better than average was positively correlated with trading volume. In a field study Dorn and Huberman (2005) found that investors who believed they are more knowledgeable than average traded more frequently.

In their field study Barber and Odean (2001) used gender as proxy for overconfidence. Assuming that men tend to be more overconfident in general, Barber and Odean expected that they should trade more. The authors found that men trade 45% more than women and they have worse performance due to transaction costs. On the other hand, Dorn and Huberman (2005) found that the gender effect was reduced when a measure of risk tolerance was accounted for. That is, in Dorn and Huberman's study the difference between males' and females' trading behavior was explained by the gender difference in risk tolerance. Risk tolerant investors traded more and held riskier portfolios regardless of their gender. Similarly Dorn and Sengmueller (2009) found that adding a measure of trading-for-entertainment to a regression reduced the gender effect. Also Feng and Seasholes (2008) did not find support for the gender differences in their dataset that consisted of Chinese investors. In a laboratory environment Deaves, Luders and Luo (2008) did not find gender related trading differences among German and Canadian students, although they did observe increased trading to be associated with both miscalibration and better than average measures. Clearly, overconfidence captures psychological attributes that are relevant to trading behavior. Better understanding of the psychological factors contributing to overconfidence could explain the existence of gender effects in the financial markets.

The behavioral finance literature has considered locus of control (LOC, Rotter 1966) as an alternative explanation for the overconfidence-related overtrading. According to the LOC hypothesis, people can be separated into those who believe things happen mostly by chance (external locus of control) and those who believe things are caused by their own actions (internal locus of control). Believing that outcomes are a result of own actions can lead to an illusion of control (Langley 1975), which is an elevated perception of having control over chance events and overconfidence about own abilities. The illusion of control has been linked to lowered risk perception as individuals believe their skill can overcome the chance of negative events (Houghton, Simon, Aquino & Goldberg 2000). Barber and Odean (2002) argue that the illusion of control causes online investors to behave as if their personal involvement could influence the outcome of chance events. For example if investors seek out information and believe that it is superior to the information known by others, such beliefs lead to illusion of knowledge, increased overconfidence and ultimately elevated trading and a decrease in performance. Fenton-O'Ceevy et al. (2003) argue that traders, in contrast with other occupations, are particularly susceptible to illusion of control. In their field study Fenton-O'Ceevy et al. used traders' total annual package, self-ratings and the performance assessments of a senior manager as a proxy for performance and concluded that investors who exhibited a higher illusion of control performed worse. Notably, various studies do not find correlation between locus of control and trading volume (Dorn & Huberman 2005; Dorn & Sengmueller 2009; Deaves et al. 2008).

Grinblatt and Keloharju (2009) used the Finish Armed Forces leadership assessment to derive a proxy for overconfidence. Assuming that the measure of self-confidence that they used is composed of competence and overconfidence, the authors regressed self-confidence on demographics and the intellectual ability score from the same assessment. The regression residuals were used as the overconfidence measure. In their study Grinblatt and Keloharju also constructed a measure of sensation seeking based on the number of speeding tickets individual investors had on file with Finnish Vehicle Administration database. Although it is a good proxy of risk preferences in the recreational context, this may not be true for the financial domain as studies have shown that people's risk attitudes vary across different domains (Blais & Weber 2006). Grinblatt and Keloharju found that both the overconfident and the sensation seeking investors traded more frequently.

Related to the sensation seeking measure, Dorn and Sengmueller (2009) suggest that investors derive utility from researching, anticipating and trading rather than just the profits associated with the investments as per normative models. The authors merged investors' trading data from German's discount brokers with a survey measuring the role of joy / entertainment in trading decision for the same sample of investors. Dorn and Sengmueller found that investors who strongly agree with "I enjoy risky investment" statement trade twice as much as those who disagree, while those who strongly agree with "games are only fun when money is involved" trade 75% more that those who strongly disagree with the statement. Dorn and Sengmueller also tested three overconfidence specifications - better than average, locus of control and the self-attribution bias (the tendency to overly attribute successes to skill) – and found that none were related to trading. Kumar (2009) points out that although sensation seekers could be considered as entertainment driven, sensation seekers may over-trade yet still hold a well-diversified portfolio. While those investors who like to gamble, that is have a preference for risker stocks, might not trade much, they will hold riskier investments. Kumar suggests that such preference for lottery-like stock[4] will lead to worse portfolio performance as such stocks tend to under-perform (Kumar 2009; Mitton & Vorkink 2007).

Investors' intelligence and perceived competence have also been considered in explaining trading behavior, portfolio performance and diversification preferences. For example Korniotis and Kumar (2013) differentiated their sample of US brokerage house investors into two groups classifying them as 'smart' and 'dumb' based on the demographics such as income, education, age and the size of social network as proxies for smartness. The authors found that 'smart' investors, while trading more actively, make better trading decisions and outperform 'dumb' investors by 3.5% annually. Korniotis et al. suggest that the investment decisions of investors with higher cognitive abilities reflect the use of superior information while the decisions of investors with lower cognitive abilities are more likely to be driven by psychological biases. In a US dataset, Graham, Harvey and Huang (2009) used demographics to construct a proxy for perceived financial expertise/competence and found that competent investors traded more frequently. In contrast, Dorn and Hubberman (2005) analysed a dataset from a German broker and constructed a perceived sophistication measure based on self-reported investment experience and perceived financial expertise/competence. Dorn and Hubberman found that more sophisticated investors churn their portfolios less frequently.

In analysing risk preferences, Goetzman and Kumar (2008) constructed a sophistication proxy based on demographics and found that sophisticated investors hold better diversified portfolios. Dorn and Huberman also found better diversified portfolios amongst those investors who perceived themselves as knowledgeable. Grinblatt, Keloharju and Linnainmaa (2012) proposed a better proxy to measure intelligence based on the responses to the Finish Armed Forces questionnaire, which measured cognitive functioning at the induction of the mandatory military duty. The authors found that while intelligent investors have better portfolio performance, they hold more diversified portfolios and are better at timing the market. These investors are also less susceptible to the disposition effect (Shefrin & Statman 1985), which refers to investors' tendency to hold onto losing investments for too long and to sell winning investments too soon. In another study Grinblatt, Keloharju, and Linnainmaa (2011) note that a high intelligence score predicts successful life outcomes, more stock market participation and better diversification.

[4] Lotteries have low price, low negative expected returns, payoffs are very risky (the prize distribution has extremely high variance), they have small probability of large reward (positively skewed payoffs).

The role of regret is yet another factor put forward to explain individual investors' trading preferences. Both anticipation and experience of regret have been shown to influence choice behavior. In behavioral finance the role of regret goes back to Shefrin and Statman (1985) as a possible explanation of the disposition effect. Shefrin and Statman suggest that people have a preference to avoid regret and seek out pride therefore selling a stock at a loss induces regret, selling it at a gain induces pride. The combination of these two factors leads to a disposition to realize gains and defer losses. Summers and Duxbury (2012) experimentally showed that it is the responsibility associated with regret that causes the disposition effect and the observed trading preferences. In an experimental financial market framework van Witteloostuijn, Muehlfeld and Tjalling found that students who have greater propensity for feelings of regret trade less. This is consistent with the findings showing that regret felt as a result of an action is more painful than regret following a failure to take an action (Gilovich & Medvec, 1995; Ritov & Baron 1995).

Previous literature highlights the importance of psychological factors in understanding investors' observed behavior. Given the unique dataset, which is described below, we will analyse the effects all factors in the models, compare the full models to univariate models and then perform factor analysis to determine the optimal variable structure.

4.3 Dataset

4.3.1 Data Source

The survey measuring psychological variables of individual investors was compiled in accordance with the Barclays Wealth Management's research objectives. Clients with more than 1 trade per year and portfolio value of more than £1000 were invited to participate in the survey, with a total of 19,251 (5% of customers) of their clients being invited to take part in an online survey via email. 4,520 clients opened the email and 849 proceeded to the on-line questionnaire survey. 617 clients completed the survey, which is in the same range of response rate to other similar studies (e.g., Dorn and Huberman (2005); Glaser and Weber (2009)). As an incentive to participate in the survey respondents were promised a summary of the research findings.

4.3.2 Survey

The self-reported survey was conducted in 9 rounds, every three months starting from September 2008. Measures included investors' expectations of future market movement, thoughts about investment strategies, emotional state, risk tolerance, cognitive abilities, previous investment experience, training, patience and inter-temporal discounting preferences amongst other psychological attributes. In the first part of this study, based on previous literature, we sub-grouped all measured psychological attributes into 5 categories. Summary of all variables and survey questions are outlined in Table 8.1 of the appendix and are described in more detail in a later section. All psychometric measures (IVs), which are introduced in detail in Section 4.6, are converted into z-scores.

4.3.3 Demographics

To identify potential selection biases, we compared survey participants to an adult British population based on the data reported by the Office for National Statistics. Overall our 617 investors have above average incomes compared to the UK population. While the mean British income is around £30,000 our sample has a mean of £76,616 and a median of £60,000. The average age of survey participants is 51 years, four years older than the average British adult. Survey participants are also more likely to be married (74% vs 48%) or male (0.93 vs. 0.49) compared to the British average adult. Although our respondents are not representative of the typical British adult, their demographics are in line with private investor population analysed in other studies (Dorn & Huberman 2005).

In the demographics category we also include a *liquidity* measure to account for one's need for urgent cash access. We would expect these investors to be more cautious with their investments. Lastly we include a measure of *income risk* as measured by individual's expected income fluctuation. We anticipate investors who have more volatile income to be more risk averse and more cautious in their trading strategy as opposed to wealthy individuals, who have been shown to trade more frequently (Vissing-Jorgensen 2003). Figure 4.1 shows the distributions of investors' age, wealth, income, number of dependents, marital status, income risk and liquidity measure.

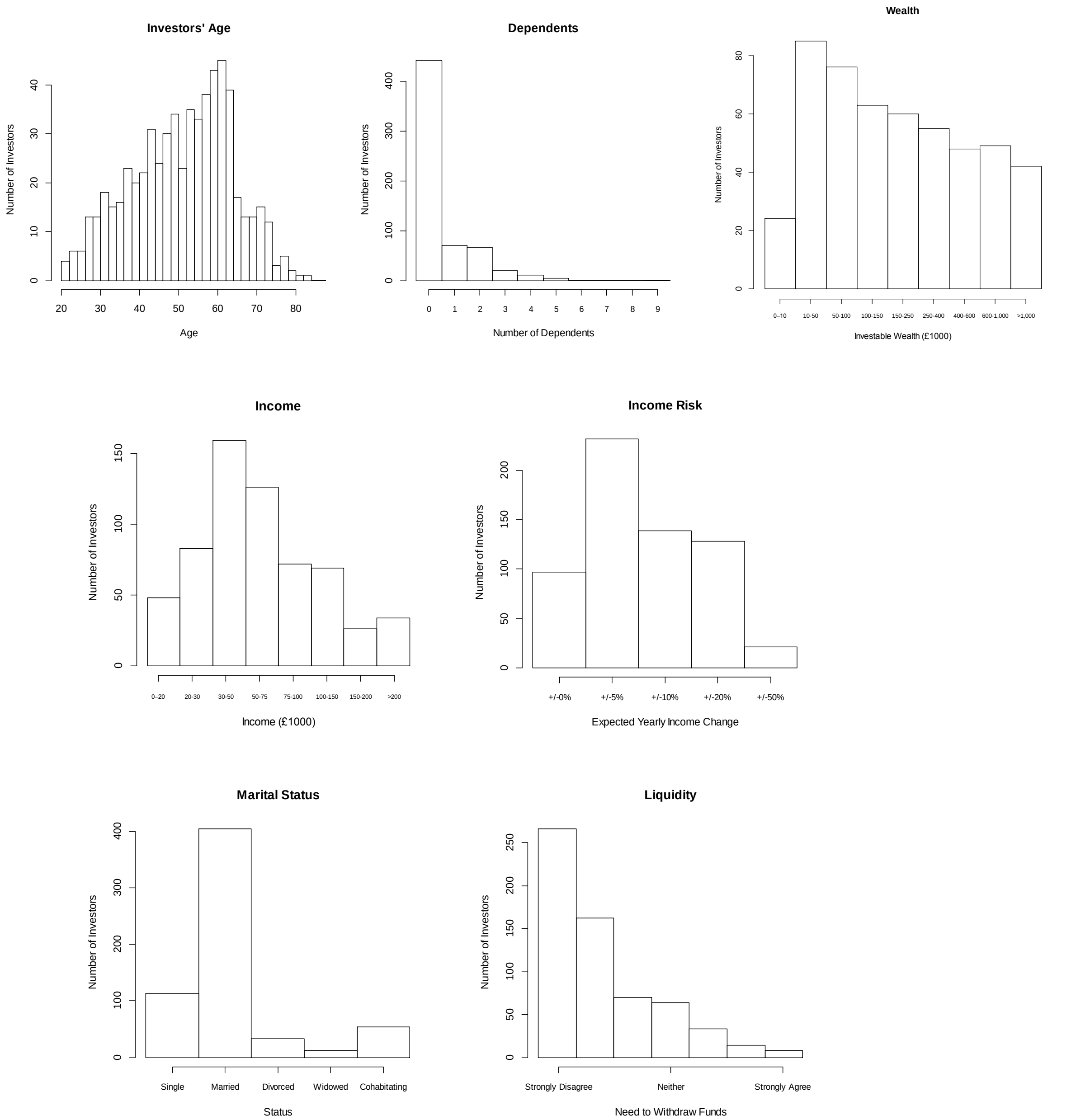
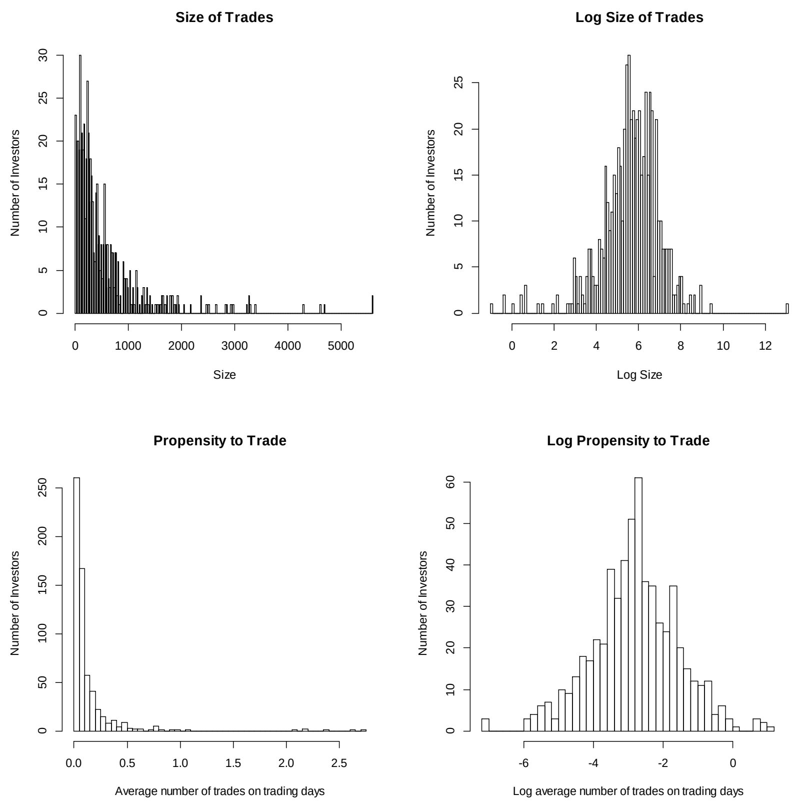


Figure 4.1: Distributions of: investors' age; number of dependents they have; investable wealth, income, income risk, marital status and liquidity. The average gross yearly income in the UK was ~ £30,000. Income risk questions: How much does your earned income fluctuate from year to year? Liquidity question: I often have an unforeseen need to withdraw a significant amount of money from my account; It is important for me to be able to withdraw money from my investment at short notice.

4.4 Trading, Performance & Diversification Measures

4.4.1 Trading

The second part of the dataset consists of individual investors' daily transactions details, cash held in the account as well as the daily records of stocks traded throughout 2004-2010 period. First we focus on analysing the relationship between individual investors' psychometric measures and the trading behavior. Given individual investors' daily transaction details we consider three unique variables related to trading. The first one is the *notional* size, defined as the average trade size per trade. The second variable is propensity to trade on each trading day (trades on the day/total trading days) referred to as *deals*, which is 13% of the time on average. Last is the *trade ratio*, which is the total number of trades divided by the total number of logins an investor has made to access his portfolio. Trade ratio measures whether investors are likely to trade once they are monitoring their portfolios or whether they are simply curious about the markets and portfolio performance. Figure 4.2 shows the corresponding distributions.



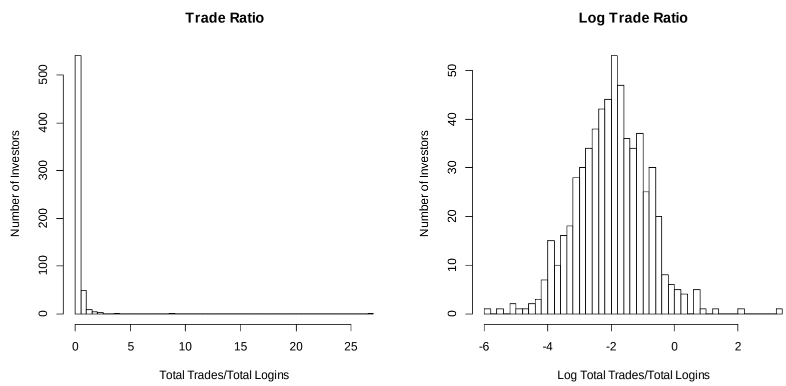


Figure 4.2. Distributions of investors' size of trades (notional), their propensity to trade (average number of trades per investor on any given trading day) throughout the 2004-2010 period and trade ratio (how many logins resulted in a trade).

4.4.2 Performance

Next we explore the relationship between individual investors' psychometric measures and portfolio performance. Based on the available data we reconstructed individual investors' portfolios over time. We use four measures to assess individual investors' performance and diversification. First we consider mean daily returns of individual investors' portfolios. It is calculated as the average daily change in portfolio value and accounts for daily changes in cash and stock positions. The second measure is investors' portfolio volatility (risk), or their diversification preferences, represented by the standard deviation of the daily mean portfolio returns. In the mean-variance framework of portfolio theory, the portfolio's aggregate volatility is the only measure of risk an investor should be concerned with. The third measure is risk adjusted returns. We apply Sharpe Ratio to measure 'smart investing' as it captures stock picking skills and timing-ability. It is calculated by dividing portfolio returns over the entire time by the standard deviation of the average daily portfolio returns. Sharpe Ratio indicates whether investors achieved superior returns for the risk that they hold in their portfolios. For example if an investor holds a very risky stock yet the return is similar to that of a less risky stock, the Sharpe Ratio would capture the risk/return trade-off. Lastly we introduce return on investment measure or realized gains (ROI) calculated as returns earned following a sale of the investment. We match quantities of buy and sell positions over the whole time period and use average purchase and average sell price to derive the ROI. We note that this could be somewhat misleading as corporate action (such as the stock split where a value of one stock becomes half of its value as there are now two stocks) in the six year period could have caused the stock price to change. Nevertheless this is a rare event and we dismiss any corporate action for the ROI calculation.

Figure 4.3 shows the distributions of all financial measures. See Section 2.3.3 for further details about the financial measures.

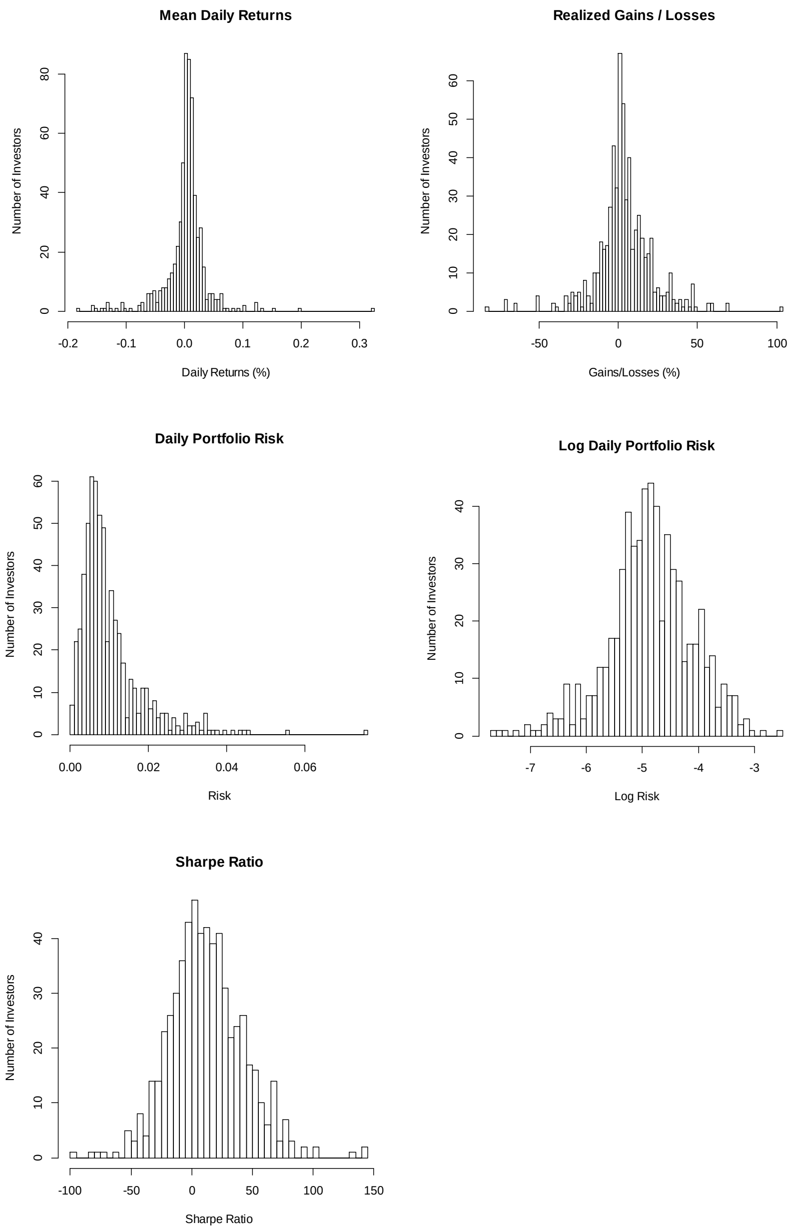


Figure 4.3. Distributions of averaged daily mean returns, realized gains and losses or return on investment (ROI), averaged daily portfolio risk (portfolio's standard deviation), the log of daily portfolio risk and averaged daily Sharpe Ratio per investor.

4.5 Model and Demographics

4.5.1 Model

As the survey was conducted in multiple rounds and not every investor participated in all rounds, we apply multivariate imputation by chained equations (va Buuren & Oudshoorn 2011) to impute the missing values using the predictive mean matching method (see Chapter 2 for details). We then use cross-sectional linear regressions to conduct our analysis. In our regression analysis all psychometric variables are scaled, but the DVs are kept in their original format. First we consider each psychometric category separately as described above to see what percent of variance is explained by each category. We then test the joined contribution of all variables in one model in an attempt to paint a full picture of individual investors' behavior within the financial markets. Given that the final model has 32 independent variables we conduct factor analysis and reduce the variables to 11 latent factors, and then repeat the regressions with these factors.

4.5.2 Demographics

In the first part we consider the effect of individual investors' demographics. Given the limited data availability many studies consider only the effects of demographics (Anderson 2013; Feng & Seasholes 2008; Korniotis & Kumar 2009) or use demographics to construct proxies for overconfidence (Barber & Odean 2001), sophistication (Goetzman & Kumar 2008), smartness (Korniotis & Kumar 2013) and competence (Graham et al. 2009). Below we discuss the relationship between just the demographics and the financial variables.

4.5.3 Demographics Results & Discussion

All regression results are reported in Table 4.1. In line with Barber and Odean (2000, 2001) we find that men trade more, although such finding should be interpreted with caution as women make up only 7% of our sample. Importantly, we do not find gender differences in performance, in contrast with Barber and Odean (2000, 2001) who found that women outperform men. It should be noted that we do not account for on-line transaction costs, and because men trade more they will incur larger costs and so performance after costs (which is what Barber and Odean also reported) could be worse.

We find that older and wealthier investors hold less risk and have higher risk adjusted returns, which is consistent with Anderson (2013) and Dorn et al. (2005) results. The finding is also consistent with the literature that suggests older investors have greater investment knowledge and are less prone to behavioral biases and gambling activities (List 2003; Feng & Seasholes 2005; Dhar and Zhu 2006; Goetzmann & Kumar 2008) and are more risk averse (Bakshi & Chen 1994; Campbell & Viciea 2002; Cocco, Gomes & Maenhout 2005; Gomes & Michaelides 2005). For example, Goetzmann and Kumar (2008) suggest that older and wealthier investors could be classified as more sophisticated and therefore they should exhibit more optimal behavior. Korniotis and Kumar (2009) also find that older and more experienced investors hold less risk, however investors' performance starts to decline sharply after the age of 70; in our sample the average age is 51 with only a few observations with age above 70.

Vissing-Jorgensen (2003) found that wealthier investors trade more frequently, in our sample wealthier investors trade in larger nominal value per trade, but not more frequently. We also found that higher income individuals are more likely to transact once they have logged into their portfolios. Given our dataset we are able to separate the marital status of investors. We find that divorced investors are less likely to trade while widowed investors are more likely to trade compared to single investors.

Table 4.1 Regression results with demographics

	Mean Return (%)		Log Risk		Sharpe Ratio		Log Deals		Log Notional		Log Trade Ratio		ROI	
Demographics	B	P value	β	P value	B	P value	β	P value	β	P value	β	P value	β	P value
(Intercept)	-0.009	0.333	0.691	0.000	-16.15	0.031	-3.186	0.000	4.887	0.000	-2.245	0.000	-0.069	0.131
Age	0.000	0.224	**-0.013**	**0.000**	**0.46**	**0.000**	-0.004	0.453	0.002	0.691	0.001	0.899	**0.002**	**0.031**
Gender (male)	-0.001	0.888	-0.066	0.581	-2.72	0.590	**0.525**	**0.019**	-0.106	0.643	*-0.305*	*0.093*	0.013	0.665
Married	0.002	0.694	0.021	0.819	-2.53	0.521	0.043	0.804	-0.121	0.498	0.060	0.674	-0.012	0.609
Divorced	-0.004	0.637	0.096	0.513	-6.77	0.275	**-0.634**	**0.021**	0.196	0.487	-0.208	0.351	0.052	0.168
Widowed	-0.008	0.527	0.140	0.541	-12.55	0.194	**0.883**	**0.038**	-0.420	0.339	0.526	0.130	-0.052	0.378
Cohabitating	**0.013**	**0.040**	0.172	0.152	4.71	0.353	0.210	0.347	-0.120	0.604	-0.216	0.236	0.055	0.078
Wealth	0.001	0.418	**-0.060**	**0.000**	**1.27**	**0.039**	-0.016	0.544	**0.130**	**0.000**	*0.037*	*0.093*	-0.003	0.418
Dependents	-0.001	0.580	0.025	0.316	0.82	0.439	0.046	0.322	0.003	0.947	-0.008	0.834	-0.006	0.330
Income	0.000	0.657	0.006	0.753	0.59	0.475	0.006	0.873	0.045	0.235	**0.084**	**0.005**	*0.010*	*0.056*
Adj. R^2	0.1%		11%		4%		2%		5%		3%		1%	

Note: Coefficients highlighted in bold indicate significance level with p-value<.05 and italicized indicate significance level with p-value <.1.

4.6 Psychometric Measures and Results

In this section we describe the set of psychological measures that we have used and their relationship to the previous literature, leaving the link between our measures and trading behavior for the next section. There is of course some inevitable degree of arbitrariness about our a priori categorisation of measures. Table 8.2 provides correlations amonst all independent variables.

4.6.1 Overconfidence measures

As we review above, within the behavioral finance literature overconfidence has been the main psychological factor to account for investors' investment and trading preferences. We consider six measures in the overconfidence category: *decision maker, risk taker, joy, better than average, locus of control,* and *winning* *investment*; all are explained below. We include a variable measuring whether an investor is the prime financial (investment and savings) decision maker within the household (in our sample 84% are prime decision makers). We also include a variable called risk-taking. It captures investors' risk preferences within the financial context and whether investors find it exciting to trade. Such variable is similar to Grinblatt and Keloharju's (2009) sensation seeking, but in a financial context rather than a recreation risk measure that is constructed based on the number of speeding tickets. A more common variable in this category is better than average (Dorn & Hubemnam 2005; Glazer & Weber 2007, Deaves et al. 2008, Graham, Harvey & Huang 2009; Dorn & Sengmueller 2009). Although theoretical work employs miscalibration to model overconfidence, empirical results show that miscalibration is not a significant predictor of behavior, while the results for better than average vary depending on the study (Dorn & Hubemnam 2005; Glazer & Weber 2007).

We also include a measure for investors' locus of control in this overconfidence category, which has been proposed to lead to elevated levels of illusion of control, over-confidence and increased risk taking (Barber & Odean 2002; Fenton-O'Creevy et al. 2003; Dorn & Hubemnam 2005; Deaves et al. 2008). Variable joy measures whether investors trade for entertainment and enjoyment reasons. Dorn and Sengmueller (2009) propose that entertainment can be driven by three motives: recreational, sensation seeking and an aspiration for riches. Entertainment driven investors enjoy following the market, get utility from realizing gains and seek intense novel sensations. The authors suggest that similar to the behavior of overconfident investors, those who trade for entertainment reasons should trade more frequently. Lastly we introduce a variable called winning investment, which accounts for investors who have preference for skewness and lottery-like investments (Mitton & Vorkink 2007; Korniotis & Kumar 2009). This is different from other variables as investors do not necessarily have to (over)trade but they should hold riskier portfolios. See Figure 4.4 for the distributions of all measures of overconfidence.

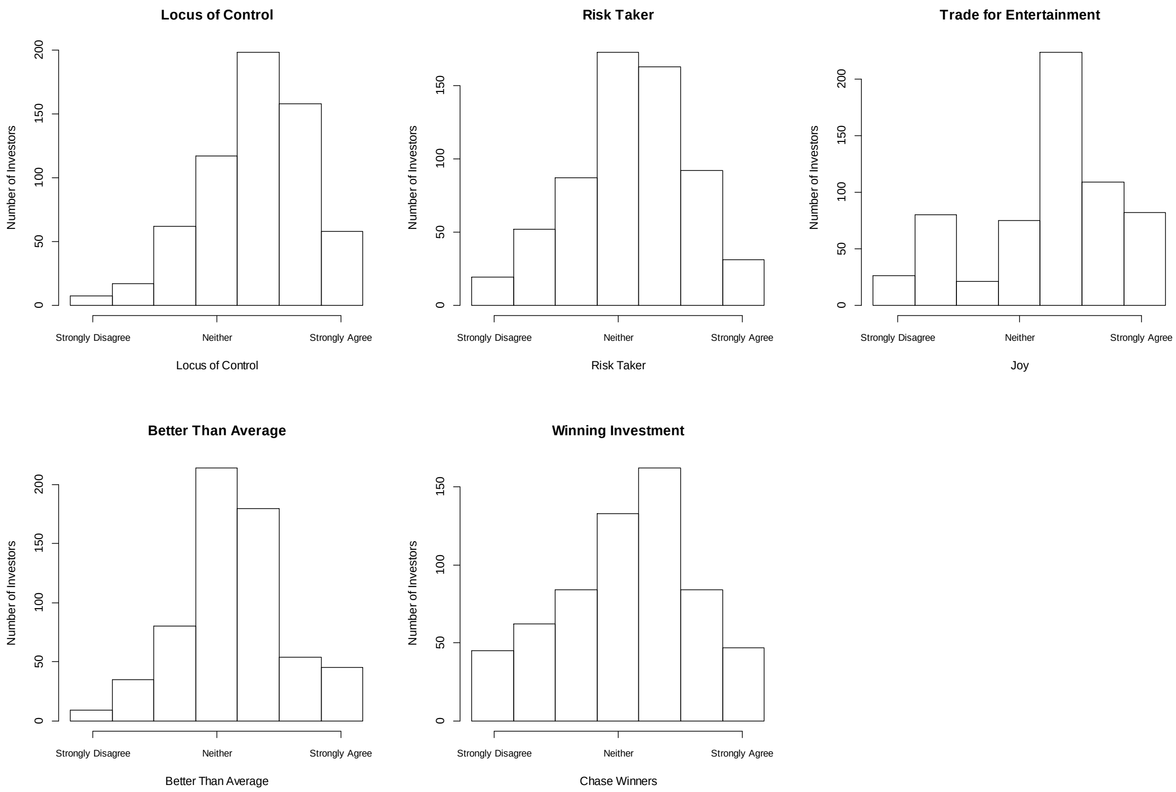


Figure 4.4. Distributions of: investors' locus of control measure, risk preferences, trading for entertainment measure (joy), better than average and whether investors aim to diversify their portfolio or chase a winning investment.

4.6.2 Sophistication Measures

Another large topic within the field of behavioral finance in explaining the observed investors' behavior is intelligence and experience. Our questionnaire includes 12 measures to account for these. The first one is *cognitive reflexion test* (CRT) (Frederick 2005), which captures investors' decision making process. The questions are aimed at testing whether individuals use analytical versus intuitive / impulsive strategy in answering the questions. We expect superior trading strategies and performance for those scoring higher on the CRT.

We also measure investors' subjective knowledge in financial markets, a variable we call *perceived financial expertise/competence*. This measure is similar to Graham, Harvey and Huang's (2009) perceived competence bias, defined as the subjective skill or knowledge level in a certain area (Heath & Tversky 1991). Graham et al.'s work is driven by studies in which subjects are more likely to bet on their own judgement rather than a matched chance lottery when they feel more knowledgeable. For example if an individual believes there is a 65% chance he can pick the winning team, in a situation when this individual feels competent, he would rather bet on his own judgment than a lottery that offers a 65% chance to pick the winning team. Perceived financial expertise/competence is different from overconfidence in a sense that the former is related to investor's beliefs while overconfidence inflates subjective probabilities. In the example provided above, one possibility is that an overconfident individual's subjective probability would inflate the chance of choosing the winning team from 65% to 70% therefore he would be even more likely to bet on his own belief.

Another measure that we introduce is *subjective numeracy,* which measures subjective perception of one's own numerical abilities. We also have a measure of investors' objective financial knowledge that we call *financial literacy* variable. It is based on a short quiz that tests investors' actual financial market knowledge. In this category we include a variable called *churning* - those who believe that frequent trading is an optimal strategy. Kimball and Shumway (2010) incorporated such measure into their "sophistication" proxy. In their study Kimball et al. concluded that sophisticated investors behave more in-line with normative models as they are more likely to diversify and to participate in the stock market.

We also have variables called *research hours* and *research use*. These capture how many hours per week an investor spends on searching for investment ideas and whether investors actually use research publications to make decisions, respectively. We account for previous education (*training),* number of years our investors have been trading (*years trading*) and whether they are more likely to plan for the future (*plan).* Lastly we have variables called *investment horizon* and *monitors.* The first one measures investor's timeframe for the investment and the second measures how intensely the investors monitors the market and own portfolio performance. Benartzi and Thaler (1995) suggested that investors who regularly monitor own portfolios trade more frequently, therefore less frequent monitoring and longer investment horizons would be beneficial for investors. We expect longer investment horizon and non-monitors to be negatively correlated with trading activity. Figure 4.5 shows the distributions for sophistication measures. Overall our sample of investors is highly literate in financial markets, which makes sense given the sample consists of 'frequent' traders and high net worth portfolios.

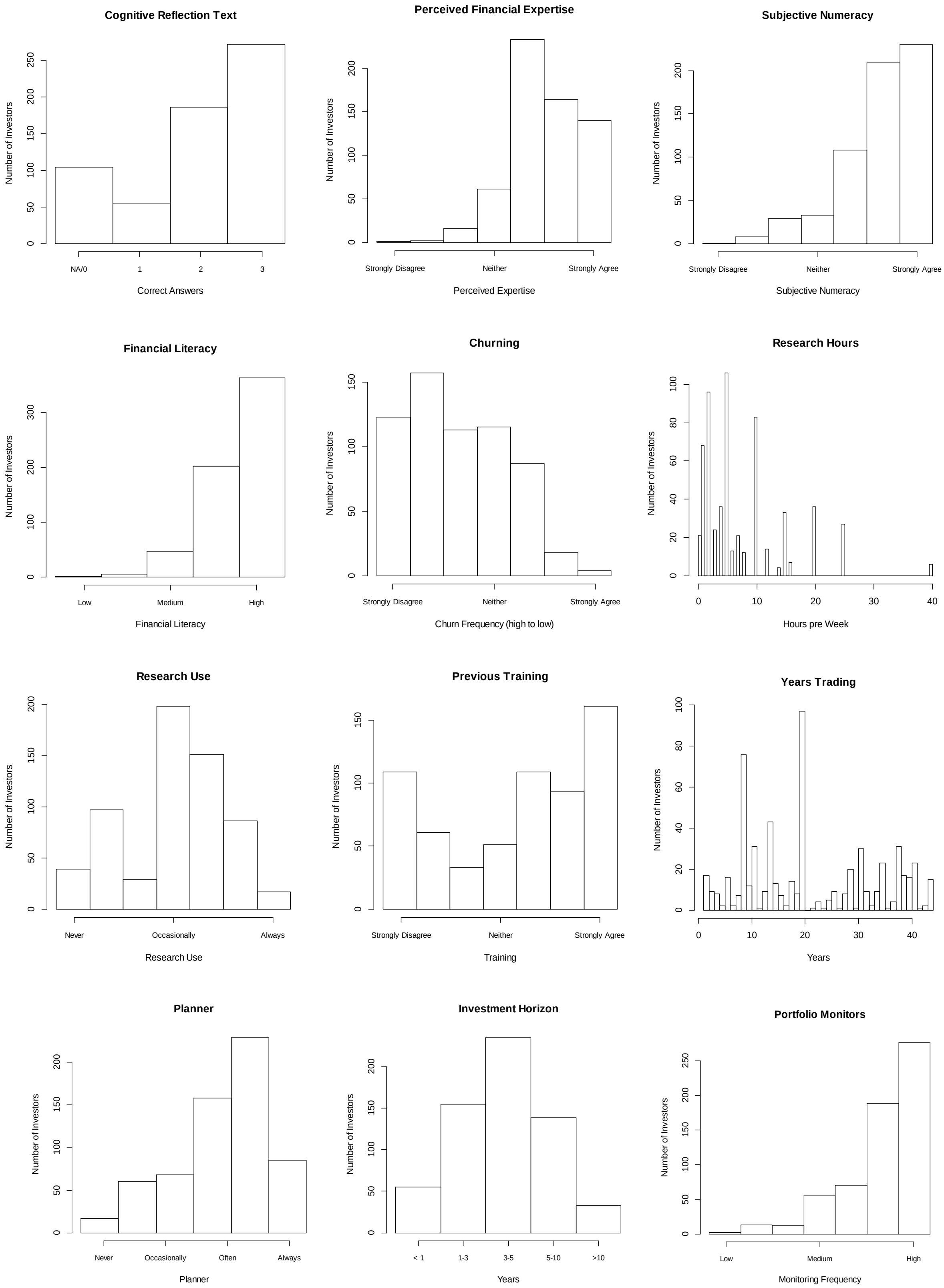


Figure 4.5. Distributions of investors' sophistication measures including cognitive reflexion test, perceived financial expertise (competence), subjective numeracy, financial literacy, churning preferences, research hours, research use, previous training, years trading, planning preferences, investment horizon and frequency of portfolio monitoring.

4.6.3 Affective processes

In this category we include four variables that are linked to affective processes of individual investors. These include *patience*, *discounting preferences*, *impulsiveness*, and *regret*. Patience measures the ability to postpone immediate gratification and wait for a larger payoff in the future. A well-known study on delayed gratification is the marshmallow experiment, in which children were presented with a choice of eating one piece of marshmallow immediately versus waiting until the experimenter returns to the room with one extra marshmallow. Such studies show that patient participants had better life outcomes as measured by SAT scores, educational attainment, body mass index and other life measures (Mischel 1974; Mischel, Shoda & Rodriguez 1989; Schlam, Wilson, Shoda, Michel et al. 2013; Shoda, Mischel & Peake 1990). Discounting preference measures how much a person is willing to accept a certain payoff today instead of a certain payoff in the future. Based on the intertemporal choice experiments, higher cognitive ability has been associated with patience and willingness to take more risks (Dohmen, Falk, Huffman & Sunde 2010). On the other hand Andersson, Tyran and Wengström (2013) found that cognitive abilities are unrelated to risk preferences. It has also been shown that impatient participants and those with higher discounting rate performed worse on the cognitive reflexion test (e.g., Frederick 2005). Preference for impulsiveness has been associated with affect-driven decision making without cognitive mediation (Schunk & Betsch 2006). Regret measures the tendency to compare a taken action to other alternatives. Predisposition to regret has been linked to influencing trading behavior (Shefrin et al. 1985; Summers et al. 2012; van Witteloostuijn et al. 2008). See Figure 4.6 for distribution of affective processes.

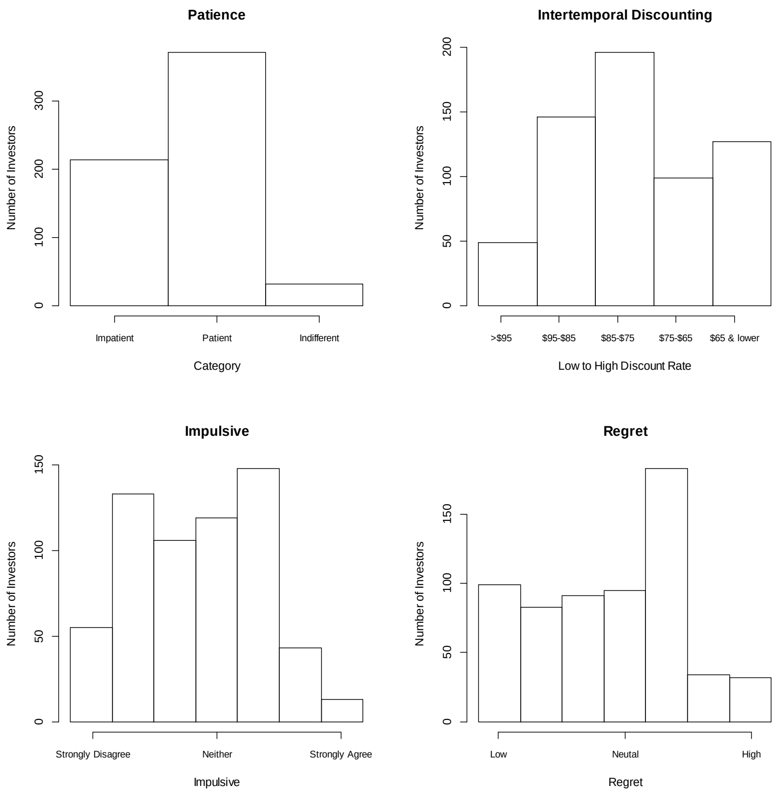


Figure 4.6. Distributions of investors affective processes: patience, intertemporal preferences, impulsiveness and tendency to experience regret.

4.6.4 Avoidant behavior

We introduce four variables that measure risk avoidant behaviors. The first variable assesses investors' risk perception by measuring the degree of *market aversion* in the financial context. The second variable is *delegation* of authority, which is a way investors may manage risk by distancing themselves from decisions (De Bondt 1998). Similar to delegation is a measure that assesses investors' *belief in advisor's* superior advice. Those investors who score high on these two measures can be seen as avoiding taking responsibility for the action. Lastly we consider investors' personality trait of *neuroticism* based on the Big Five personality profile (Costa & McCrae 1992), which is linked to anxiety and avoidance. The distributions of these measures are shown in Figure 4.7. Based on the *market aversion* and *delegation* variables our sample is more likely to take part in financial markets and are less likely to delegate their portfolio to an adviser, nevertheless they do believe advisors should provide useful information.

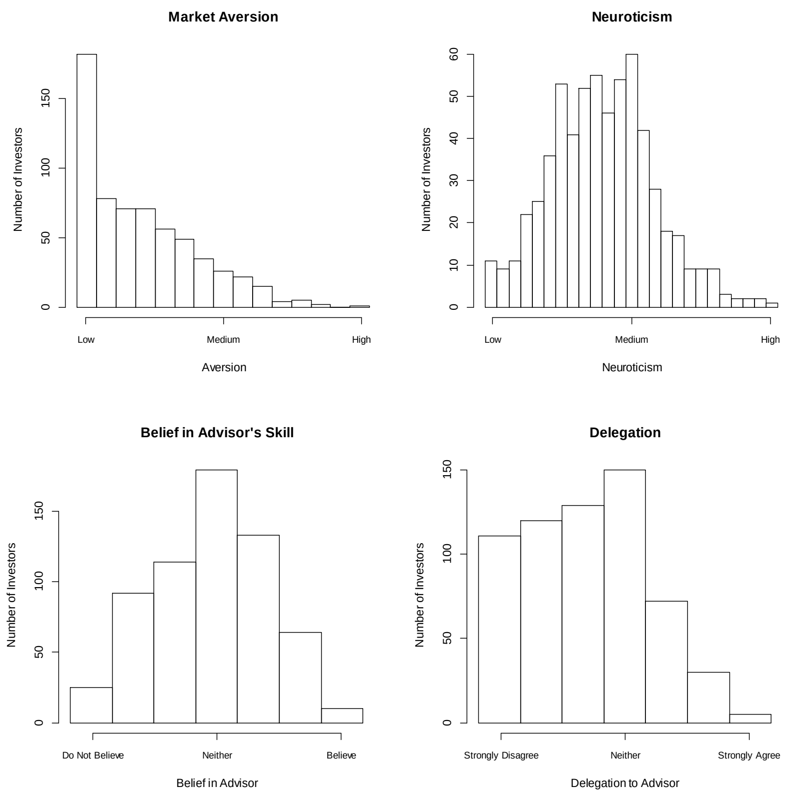


Figure 4.7. Distributions of investors market aversion preferences, neuroticism level, whether investors believe in adviser's superior market knowledge and whether investors prefer to have a portfolio manager.

4.6.5 Full Model and Results

One of the advantages of our dataset is the richness of the psychometric measures, the detail of the portfolio positions and the daily trading record. Table 4.2 reports seven regression models with all of the psychometrics included as dependent variables. The adjusted R^2 has significant improvement across all models from the demographics-only model. Relative to just using the demographics (Table 4.1), the daily mean returns variance explained (adjusted R^2) increased from .1% to 9%, for portfolio risk measure it increased from 11% to 21%, for Sharpe Ratio from 4% to 19%, for propensity to trade from 2% to 30%, for size of trades from 5% to 10%, for trade ratio from 3% to 27% and for ROI from 1% to 13%. To emphasize the importance of accounting for all psychometric measures we report regression results for each psychometric attribute separately in Table 4.3. We also report empirical findings from recent literature that are discussed in this study along with our finding from the full regression in Table 4.4 to highlight the differences and consistency in findings.

In the full model relative to the univariate model, of particular interest is the non-significant gender effect on trading frequency once all psychometric variables are included into the regression. Barber and Odean

(2001) made the link between gender and overconfidence in their study; however they did not provide any psychological measures to substantiate their claim. Our data provide evidence that those who follow the markets (monitors), who believe the optimal strategy is to trade frequently (churn), those who plan, have longer trading experience (years trading), scored as more reflective than impulsive on the CRT and are impulsive trade the most. Although not reported here, we found that accounting for investors, market engagement (monitors) changes the gender effect on trading non-significant.

Another variable of interest is financial expertise/competence. Graham et al. (2009) suggested that more frequent trading by males can be explained by investor competence. Although the effect of perceived financial expertise on trading is significant and does make the gender effect non-significant, including market engagement and perceived financial makes up for both gender and expertise/competence effects on trading. It means that the Barber and Odean (2001) and Graham et al. have selected a variable that is correlated with market engagement, and we have a variable that is more strongly related to trading. This is the case in our study.

In the full model wealth is another variable that becomes non-significant in predicting performance. Anderson (2013) and Kumar (2009) have found that wealthy investors perform better; however once we control for decision maker, perceived financial expertise, CRT and winning investment variables, the effect of wealth becomes non-significant. Yet consistent with Anderson and Dorn et al. (2005) wealthy investors hold less risk and trade less frequently. We also find that wealthy investors transact in larger notional value and are more likely to realize loses (or possibly cut loosing investments).

Joy is another variable of interest, which becomes significantly negatively correlated with trading frequency (deals) in the full model. However given a login, investors who enjoy trading are more likely to transact than their counterparts. While Dorn et al (2009) have found joy to be associated with higher trading volume, we believe our joy measure is slightly different. Rather than capturing investors' propensity to gamble or to seek entertainment, our investor who scores higher on variable joy, enjoy trading as a passive hobby.

In addition, more trading is not necessarily detrimental in our data set. For example those who scored as reflexive on the CRT and like to churn trade more, but they also have higher risk adjusted returns. This corroborates previously reported findings in relation to intelligence and trading frequency, better trading strategies and better execution skills (Grinblatt et al. 2012; Korniotis & Kumar 2013). That is, as Kornotis and Kumar (2013) suggested, we find that higher trading is not necessarily detrimental. We find that a 1 standard deviation increase on the CRT scale increases the Sharpe Ratio by nearly 7 points over a given time period. Barber et al. (2011) also found that some investors who traded with high frequency performed better than others. This could also reflect Seru et al.'s (2010) suggestion that some investors learn by trading. Also in the full model although impulsive investors trade more, the detrimental effect on risk adjusted performance, as observed in the univariate model, goes away.

In fact, in the full model, better than average, risk taker, winning investment, perceived financial expertise, financial knowledge training, patience and neurotic all become non-significant in predicting trading behavior. On the other hand divorced, wealth, CRT, monitors, subjective numeracy, research use, years trading, investment horizon, discount, impulsive, regret, aversion and belief in skill contribute to explaining propensity to trade with monitors and impulsive having the largest effect on trading volume.

Another interesting comparison between Table 4.2 and 4.3 is that in predicting the riskiness of the portfolio, all aversion measures become non-significant in the full model. The main attributes that account for risk are decision maker, risk taker, chasing winning investment, financial knowledge and previous training. The measure of aversion and belief in advisors' skill are negatively correlated with trading while the correlation with neuroticism becomes non-significant in the full model.

Considering risk adjusted returns variable, the significant correlations observed between discounting, impulsive and patient with risk adjusted returns all become non-significant in the full model. The main contributors in explaining the risk adjusted returns are CRT, perceived financial expertise/competence, financial knowledge that are all positively correlated with Sharpe Ratio, while decision maker, winning investment and previous training are all negatively correlated with Sharpe Ratio. The effect of risk taker on Sharpe Ratio becomes non-significant in the full model, once the winning investment variable is accounted for.

The results indicate that the number of years trading is negatively correlated with risk adjusted returns and positively correlated with trading frequency. It has been suggested that experience may lead investors to engage in excessive trading as it could inflate their overconfidence (Gervais & Odean 2001), although it can also lead to improved performance due to learning (Nicolosi, Peng & Zhu 2009; Seru, Shumway & Stoffman 2010). Longer investment horizon is correlated with fewer trades as predicted by Benartzi and Thaler (1995). Investors who are willing to delegate their portfolios earn better returns (marginally significant), are more likely to login and trade and are more likely to realize their losses; possibly because they are following an advice from an expert (De Bondt 1998). The effect of being a decision maker continues to have a strong effect on risk and performance. Overconfidence measure of locus of control in not related to trading, which is consistent with Deaves et al. (2008), Dorn et al. (2005) and Dorn et al. (2009). Investors who have high locus of control earn lower daily mean return, which is consistent with Fenton et al. (2003) who found worse performance for illusion of control.

Table 4.2 Regression results with all variables in the models.

	Mean Return (%)		Log Risk		Sharpe Ratio		Log Deals		Log Notional		Log Trade Ratio		ROI	
Full Model	β	P value	β	P value	β	P value	β	P value	β	P value	B	P value	β	P value
(Intercept)	-0.052	0.037	-3.484	0.000	-14.49	0.443	-1.765	0.021	5.179	0.000	-2.452	0.000	0.221	0.059
Age	**0.000**	**0.025**	**-0.009**	**0.007**	**0.49**	**0.000**	0.006	0.285	-0.001	0.856	**0.011**	**0.017**	0.000	0.900
Gender (male)	*-0.012*	*0.098*	-0.105	0.433	**-13.38**	**0.015**	-0.045	0.838	-0.328	0.216	**-0.908**	**0.000**	0.027	0.433
Married	0.001	0.786	0.009	0.920	-2.52	0.509	-0.071	0.644	-0.056	0.760	0.047	0.716	-0.028	0.236
Divorced	-0.004	0.632	0.087	0.545	-7.94	0.183	**-0.490**	**0.042**	0.153	0.594	-0.266	0.187	*0.067*	*0.068*
Widowed	-0.007	0.581	0.024	0.913	-7.22	0.434	0.509	0.173	-0.589	0.185	0.581	0.063	-0.087	0.129
Cohabitating	0.009	0.168	0.194	0.121	4.35	0.400	0.015	0.943	0.003	0.991	**-0.376**	**0.032**	0.046	0.146
Wealth	-0.001	0.503	**-0.044**	**0.009**	0.01	0.993	**-0.100**	**0.000**	**0.105**	**0.002**	-0.003	0.913	**-0.010**	**0.021**
Dependents	0.000	0.969	0.014	0.596	**2.61**	**0.015**	0.037	0.397	0.000	0.994	0.048	0.189	**-0.015**	**0.023**
Income	-0.001	0.382	0.024	0.236	-0.32	0.708	*0.057*	*0.096*	0.052	0.200	*0.051*	*0.073*	**0.019**	**0.000**
Better than average	0.003	0.160	-0.062	0.164	2.84	0.122	-0.087	0.242	-0.005	0.950	0.054	0.381	-0.003	0.776
Decision Maker	**-0.011**	**0.024**	**0.182**	**0.036**	**-8.56**	**0.017**	-0.019	0.896	**-0.415**	**0.016**	-0.167	0.167	-0.009	0.698
Joy	-0.001	0.406	0.024	0.225	*-1.38*	*0.099*	**-0.113**	**0.001**	0.035	0.377	**0.100**	**0.000**	**-0.025**	**0.000**
LOC	**-0.005**	**0.016**	0.023	0.545	-2.20	0.154	0.060	0.332	**0.203**	**0.006**	-0.073	0.160	0.004	0.690
Risk taker	0.002	0.354	**0.143**	**0.003**	1.07	0.583	0.124	0.115	0.149	0.113	-0.092	0.162	-0.014	0.250
Winning investment	-0.002	0.314	**0.070**	**0.034**	**-3.07**	**0.024**	0.017	0.759	-0.052	0.428	0.044	0.337	0.012	0.153
CRT	**0.006**	**0.002**	-0.041	0.252	**6.96**	**0.000**	**0.163**	**0.006**	-0.017	0.812	**0.107**	**0.033**	0.004	0.679
Monitors	0.002	0.477	0.032	0.457	-0.72	0.687	**0.439**	**0.000**	0.068	0.430	**-0.391**	**0.000**	**0.028**	**0.012**
Perceived Financial Expertise	0.003	0.386	-0.103	0.122	**7.58**	**0.006**	0.061	0.582	0.056	0.669	**0.259**	**0.005**	0.003	0.851
Subjective Numeracy	**0.005**	**0.020**	*-0.061*	*0.094*	1.05	0.489	**-0.250**	**0.000**	-0.020	0.786	0.049	0.334	**-0.021**	**0.028**
Financial Knowledge	**0.007**	**0.012**	**-0.141**	**0.006**	**4.45**	**0.034**	-0.070	0.409	0.065	0.520	0.064	0.368	0.015	0.246
Churn	*0.002*	*0.077*	-0.018	0.449	**2.20**	**0.022**	**0.144**	**0.000**	0.019	0.679	**0.147**	**0.000**	-0.004	0.534
Research hours	0.000	0.601	**0.010**	**0.042**	0.08	0.670	*0.014*	*0.069*	-0.015	0.111	**0.030**	**0.000**	**-0.005**	**0.000**
Research use	-0.002	0.243	*0.054*	*0.098*	0.13	0.924	**-0.280**	**0.000**	**0.134**	**0.039**	**-0.158**	**0.001**	-0.011	0.169
Training	**-0.008**	**0.000**	**0.064**	**0.005**	**-6.69**	**0.000**	0.043	0.253	0.032	0.476	0.014	0.650	-0.002	0.721
Years trading	0.000	0.654	0.004	0.193	**-0.26**	**0.024**	**0.014**	**0.002**	-0.003	0.586	-0.001	0.745	0.001	0.313
Planner	0.003	0.165	0.013	0.758	0.07	0.967	**0.239**	**0.001**	-0.032	0.707	0.042	0.488	0.013	0.241
Investment horizon	0.002	0.353	*-0.085*	*0.070*	-0.17	0.930	**-0.342**	**0.000**	**-0.309**	**0.001**	**-0.191**	**0.004**	**-0.031**	**0.010**
Discount	0.000	0.862	-0.015	0.613	*-2.16*	*0.070*	**-0.114**	**0.017**	-0.005	0.934	**-0.242**	**0.000**	0.012	0.106
Impulsive	-0.001	0.711	0.052	0.118	-1.09	0.428	**0.308**	**0.000**	0.027	0.678	**0.121**	**0.009**	0.010	0.258
Patience	-0.002	0.377	-0.047	0.323	-1.20	0.543	-0.104	0.191	-0.008	0.932	0.105	0.115	-0.020	0.105
Regret	0.001	0.424	-0.020	0.325	*1.40*	*0.097*	**-0.152**	**0.000**	-0.010	0.802	**-0.092**	**0.001**	**-0.019**	**0.000**
Neurotic	0.000	0.950	-0.044	0.300	-1.62	0.358	-0.057	0.422	0.083	0.326	-0.031	0.600	0.013	0.229
Aversion	-0.001	0.744	0.030	0.553	0.29	0.892	**-0.173**	**0.042**	0.131	0.197	*-0.121*	*0.091*	**0.030**	**0.023**
Belief skill	-0.003	0.246	-0.008	0.866	-1.98	0.335	**-0.286**	**0.001**	-0.133	0.180	-0.068	0.326	**-0.023**	**0.069**
Delegation	**0.005**	**0.036**	-0.066	0.152	*3.32*	*0.079*	-0.028	0.710	0.009	0.925	**0.186**	**0.004**	**-0.036**	**0.002**
Adj. R^2	9%		21%		19%		30%		10%		27%		13%	

Table 4.3 Univariate regression results

Independent Regressions	Mean Return (%)		Log Risk		Sharpe Ratio		Log Deals		Log Notional		Log Trade Ratio		ROI	
	β	P value	β	P value	B	P value	β	P value	β	P value	B	P value	β	P value
Age	0.000	0.140	**-0.017**	**0.000**	**0.47**	**0.000**	-0.005	0.270	**0.009**	**0.038**	0.005	0.180	0.074	0.204
Gender (male)	-0.002	0.804	-0.087	0.478	-0.75	0.880	**0.486**	**0.025**	0.062	0.784	-0.177	0.321	1.785	0.550
Married	0.003	0.371	**-0.202**	**0.012**	**7.09**	**0.033**	0.053	0.715	0.178	0.242	*0.198*	*0.094*	0.270	0.891
Divorced	-0.001	0.805	-0.094	0.528	0.96	0.875	**-0.667**	**0.012**	0.404	0.148	-0.094	0.665	6.896	0.593
Widowed	-0.002	0.836	-0.280	0.219	2.68	0.775	0.642	0.113	0.013	0.975	**0.754**	**0.024**	-2.544	0.649
Cohabitating	**0.013**	**0.006**	0.161	0.196	6.52	0.204	0.211	0.340	-0.032	0.890	-0.134	0.461	*5.758*	*0.060*
Wealth	0.001	0.297	**-0.083**	**0.000**	**2.16**	**0.000**	-0.011	0.637	**0.140**	**0.000**	**0.068**	**0.000**	0.074	0.809
Dependents	-0.001	0.520	0.005	0.816	1.17	0.207	0.055	0.169	0.044	0.289	0.050	0.129	-0.509	0.358
Income	-0.001	0.643	-0.012	0.464	1.02	0.140	0.027	0.363	**0.105**	**0.000**	**0.090**	**0.000**	0.513	0.214
Better than average	0.001	0.360	-0.017	0.642	2.00	0.175	**0.135**	**0.035**	*0.130*	*0.053*	0.057	0.280	-0.524	0.545
Decision Maker	*-0.080*	*0.065*	**0.254**	**0.002**	**-10.961**	**0.001**	-0.186	0.216	**-0.605**	**0.000**	-0.161	0.194	-3.256	0.115
Joy	0.001	0.803	**0.070**	**0.000**	*-1.46*	*0.054*	-0.011	0.745	-0.016	0.675	0.023	0.384	**1.636**	**0.000**
LOC	-0.002	0.221	-0.007	0.830	0.31	0.833	*0.111*	*0.082*	**0.198**	**0.002**	-0.009	0.862	-0.692	0.429
Risk taker	0.000	0.868	**0.269**	**0.000**	**-3.33**	**0.032**	**0.337**	**0.000**	0.073	0.304	-0.027	0.625	-1.316	0.158
Winning investment	-0.002	0.189	**0.20**	**0.000**	**-4.913**	**0.000**	**0.136**	**0.007**	-0.043	0.410	-0.051	0.218	0.275	0.690
CRT	**0.005**	**0.002**	*-0.054*	*0.055*	**4.84**	**0.000**	0.035	0.485	*0.101*	*0.053*	0.031	0.457	0.262	0.703
Monitors	*0.004*	*0.087*	**0.085**	**0.035**	0.59	0.719	**0.525**	**0.000**	*0.128*	*0.090*	**-0.324**	**0.000**	**2.037**	**0.039**
Perceived Financial Expertise	0.004	0.123	-0.078	0.119	**5.61**	**0.006**	**0.217**	**0.014**	**0.255**	**0.006**	**0.151**	**0.037**	0.151	0.901
Subjective Numeracy	**0.005**	**0.003**	0.021	0.490	0.15	0.904	-0.021	0.703	-0.024	0.672	0.043	0.334	-1.053	0.157
Financial Knowledge	0.003	0.229	**-0.196**	**0.000**	**4.33**	**0.018**	**-0.161**	**0.043**	0.257	0.002	**0.174**	**0.008**	0.695	0.526
Churn	-0.001	0.298	0.031	0.136	-1.04	0.220	**0.100**	**0.007**	-0.009	0.813	**0.091**	**0.003**	-0.630	0.216
Research hours	0.000	0.207	**0.019**	**0.000**	-0.32	0.066	**0.043**	**0.000**	0.003	0.694	**0.024**	**0.000**	**-0.291**	**0.005**
Research use	0.000	0.901	-0.027	0.369	*2.14*	*0.085*	**-0.149**	**0.006**	**0.206**	**0.000**	-0.063	0.157	-0.616	0.409
Training	**-0.005**	**0.000**	0.030	0.143	**-4.41**	**0.000**	0.037	0.319	0.047	0.226	*0.053*	*0.079*	-0.592	0.241
Years trading	0.000	0.774	-0.002	0.553	-0.15	0.159	0.007	0.123	0.004	0.357	0.006	0.131	-0.071	0.250
Planner	*0.004*	*0.053*	-0.023	0.530	0.628	0.672	0.087	0.179	0.001	0.984	-0.010	0.847	0.142	0.874
Investment horizon	0.002	0.411	**-0.170**	**0.000**	-0.32	0.860	**-0.400**	**0.000**	**-0.354**	**0.000**	-0.062	0.345	*-2.092*	*0.057*
Discount	-0.002	0.112	**0.097**	**0.000**	**-3.67**	**0.000**	*0.074*	*0.098*	-0.015	0.748	**-0.190**	**0.000**	0.599	0.329
Impulsive	-0.001	0.335	**0.126**	**0.000**	**-2.54**	**0.038**	**0.229**	**0.000**	0.055	0.325	0.063	0.149	-0.169	0.818
Patience	0.000	0.938	**-0.135**	**0.002**	**3.46**	**0.050**	**-0.229**	**0.003**	0.043	0.600	**0.219**	**0.001**	-1.369	0.198
Regret	-0.001	0.273	0.023	0.190	-0.53	0.459	**-0.126**	**0.000**	0.036	0.277	**-0.091**	**0.000**	-0.580	0.179
Neurotic	0.001	0.806	**-0.084**	**0.044**	0.36	0.833	**-0.157**	**0.033**	0.105	0.174	-0.092	0.131	1.263	0.214
Aversion	0.000	0.996	**-0.119**	**0.010**	2.812	0.136	**-0.381**	**0.000**	0.059	0.498	-0.014	0.841	1.552	0.170
Belief skill	-0.002	0.253	*0.069*	*0.073*	*-2.98*	*0.058*	*-0.130*	*0.059*	**-0.158**	**0.028**	-0.007	0.906	**-2.696**	**0.004**
Delegation	-0.001	0.684	0.031	0.383	-2.122	0.149	-0.160	0.012	-0.092	0.172	0.093	0.076	-3.088	0.000

Table 4.4 Overview of the results from previous literature and this study

Article	Dependent (DVs) & Independent Variables (IVs)	Dataset	Main Findings from previous literature	Current Findings (based on full model in Table 4.2 unless referenced otherwise)	Differences
Anderson (2013)	DVs: Trading, diversification and performance IVs: Demographics	Swedish online broker	Lower income, poorer, younger and less educated trade more, perform worse and hold more risk. Wealthier have better performance.	**Replicated:** Young hold more risk and have better performance. Poorer hold more risk and trade more and have worse performance in a univariate model. Less financial knowledge is linked to more risk and worse performance. **Not replicated**: Age is not related to trading frequency. But older trade more once logged into portfolio.	**Effect goes away**: In full model wealth effect on performance goes away once adding variables: decision maker, perceived financial expertise, winning investment and CRT.
Barber Odean(2001)	DVs: Trading and performance IVs: Overconfidence: Gender as proxy	US household data 1991-1996	Men trade more than women therefore men underperform women	**Replicated:** Men trade more in univariate model. Men perform worse in full model.	**Effect goes away**: No gender differences in full model. It is Monitors and Impulsive investors who trade more. **New effect:** In the full model men earn lower returns.
Deaves, Luders, Luo (2008)	DVs: Trading IVs: Overconfidence (locus of control, better than average, miscalibration)	German and Canadian students	Miscalibration and better than average was associated with a higher trading volume; no gender effect	**Replicated:** No gender effect in full model, better than average is positively correlated with trading only in the univariate model.	**Effect goes away**: Better than average becomes non-significant, it is Monitors and Impulsive that account for trading.
Dorn and Huberman (2005)	DVs: Trading IVs: Demographics, risk tolerance, overconfidence	German Broker 1995-2000	Risk tolerant hold more risk and trade more frequently. Those who think themselves more knowledgeable than the average trade more. More knowledgeable hold better diversified portfolios. Wealthy hold less risk and trade less.	**Replicated:** In a univariate model risk tolerant (risk taker) hold more risk and trade more. Better than average and perceived financial experts trade more. More knowledgeable (Financial Knowledge) hold better diversified portfolios. Wealthy do hold less risk and trade less in the full model.	**Effect goes away**: The effect of risk taker and above average on trading goes away. Monitors and Impulsive trade more. **New effect:** Wealthy trade less in the full model.
Dorn Sengmueller (2009)	DVs: Trading IVs: Joy, LOC, BTA	German Broker 1995-2000	Entertainment doubles trading frequency; overconfidence fails to explain trading (BTA, LOC); wage and age decrease trading volume; men trade more.	**Replicated:** BTA and LOC are not related to trading in the full model. Men trade more in the univariate model. **Not replicated:** Investors who trade for joy trade less but are more likely to trade once they are logged into their portfolio. Wage and age are not related to trading in the full model.	**Effect goes away**: No gender differences in full model. Monitors and Impulsive trade more.
Feng and Seasholes (2008)	DVs: Trading and performance IVs: Gender	Chinese Broker 1999-2000	Men and women trade and perform the same after controlling for various factors.	**Replicated:** In full model men and women trade the same **Not replicated:** men perform worse in the full model.	
Fenton-O'Creevy et al. (2003)	DVs: Performance IVs: Illusion of control	UK Investors Field Study	Greater illusion of control is related to worse performance.	**Replicated:** Locus of control is associated with lower daily mean returns.	
Goetzmann Kumar (2008)	DVs: Diversification IVs: Demographics	US Broker 1991-1996	Young, low-income, less-educated and less sophisticated (advanced asset trading) hold underdiversified portfolios.	**Replicated:** Wealthy, older and higher financial knowledge lead to less riskier portfolios even after controlling for all the variables.	
Glazer and Weber (2007)	DVs: Trading IVs: BTA	German Broker 1997-2001	Investors who think they are better than average in terms of investment skills trade more. No gender effect on trading. No relations of overconfidence and performance.	**Replicated:** No better than average or gender effect on trading. No relation of better than average on performance.	

Graham Harvey and Huang (2009)	DVs: Trading, diversification IVs: Competence (perceived financial expertise)	UBS survey of US investors	Investors who feel competent trade more and have better diversified portfolios.	**Replicated:** Perceived financial expertise/competence trade more only in the univariate model.	**Effect goes away**: Perceived financial expertise non-significant in full model. Monitors and Impulsive trade more.
Grinblatt Kelohaju (2009)	DVs: Trading IVs: Overestimation of confidence (self-assessment of skill vs outcome) and sensation seeking (speeding tickets)	Finish equity traders 1995-2002	Overestimation of confidence and sensation seeking are positively correlated to trading. No gender effect.	**Replicated:** High perceived financial expertise/competence trade more in the univariate regression. Risk takers and winning investment trade more in univariate models. (In factor analysis section we find sensation seekers trade more.)	**Effect goes away**: Perceived financial expertise, risk taker, winning investment are all non-significant in full model. Monitors and Impulsive trade more.
Grinblatt Keloharju Linnainmaa (2011)	DVs: Diversification IVs: IQ: Survey from military files (mathematical, verbal, and logical reasoning)	Finish equity traders 1995-2002	High IQ investors have better diversified portfolios.	**Replicated:** Better financial knowledge and scoring higher on CRT (analytical decision making investors) leads to better diversified portfolio.	**Effect goes away**: CRT non-significant in full model. Adding Financial knowledge makes the effect non-significant.
Grinblatt Keloharju Linnainmaa (2012)	DVs: Trading and performance IVs: IQ (as above)	Finish equity traders 1995-2002	High-IQ investors exhibit superior market timing, stock-picking skill and trade execution.	**Replicated:** Better financial knowledge and scoring higher on CRT (analytical decision making investors) earn higher risk adjusted returns.	
Kimball and Shumway (2007)	DVs: Diversification IVs: Sophistication (14 question quiz)	US Consumer Survey	Sophisticated investors are better diversified.	**Replicated:** Better financial knowledge is related to better diversification.	
Korniotis Kumar (2009)	DVs: Performance IVs: Demographics	US Broker 1991-1996	Age (above 70) deteriorates cognitive abilities therefore causes performance to decline.	**Replicated:** Older investors perform better (but our sample is much younger, so overall the results are confirmed)	
Korniotis Kumar (2013)	DVs: Performance IVs: Cognitive abilities	US Broker 1991-1996	Demographically based cognitive ability predicts performance. Smart investors outperform dumb investors.	**Replicated:** Better financial knowledge and scoring higher on CRT (analytical decision making investors) earn higher risk adjusted returns.	
Kumar (2009)	DVs: Diversification, Performance IVs: Socioeconomic characteristics and gambling	US Broker 1991-1996	Young, low-income, less-educated single men go for lottery-like stocks (more risk) in turn they underperform.	**Replicated:** Poorer, younger, less educated hold more risk and have worse risk adjusted performance.	**Effect goes away**: In full model wealth effect on performance goes away once adding variables: decision maker, perceived financial expertise, winning investment and CRT.
Nicolosi, Peng & Zhu (2009)	DVs: Performance IVs: Trading frequency	US household data 1991-1996	Trading experience improves performance	**Not replicated:** Previous trading experience leads to more trading and worse performance.	
Seru, Shumway & Stoffman (2010)	DVs: Performance IVs: Performance Trading years	Finish equity traders 1995-2003	Experienced investors trade more.	**Replicated:** Previous trading experience (years trading) leads to more trading.	
van Witteloostuijn , Muehlfeld, Tjalling (2008)	DVs: Trading IVs: Personality	34 Economics students from Europe	Propensity to regret leads to less trading; Impatient are more likely to accept limit orders.	**Replicated:** Propensity to regret leads to less trading and impulsivity (impatience) leads to more trading.	

4. 7 Factor Analysis

4.7.1 Factor Analysis and Results

Given the number of variables in our model we conducted factor analysis in order to extract the most important components and reduce the model to eleven factors. We chose the more commonly used varimax method (although promax gives similar results). Such orthogonal rotation produces factors that are uncorrelated; the promax method allow the factors to correlate. Given that our survey method was intended for the variables not to correlate, we chose the varimax rotation technique. As per Figure 4.8 below, we chose the optimal number of factors based on the Parallel Analysis, which is considered the recommended technique (Costello & Osborne 2005). Table 4.5 shows the eigenvalues and the factor loadings for items loadings above .30. The eleven extracted factors are "Confidence", "Delegation", "Market Knowledge", "Sensation Seeking", "Analytical Decision Process", "Mature", "Income", "Training", "Impulsivity", "Level of Regret" and "Market Research". These 11 factors still only account for about half of the variability in the original 30 items. This means that, as planned, the 30 original measures are indeed mostly all measuring different things. Further, for most factors, only a small number of items load onto that factor. Again this indicates that our 30 original items are mostly unrelated. Exceptions are Overconfidence and Sensation Seeking factors, which each have a reasonable number of items loading onto them.

The regression coefficients for the eleven factor model are reported in Table 4.6. With these eleven factors significant amount of variance is explained as measured by the R^2 in each of the models, however not nearly as much as is explained by the full model (Table 4.3 compared to Table 4.6). That is, in reducing our 30 items to 11 factors, much explanatory power is lost. Nonetheless overall the results are consistent with those observed in the main regression. Mature and more analytical investors with better financial knowledge are the successful investors. On the other hand previous training leads to too much portfolio risk and worse risk adjusted performance. Preference to delegate and propensity to regret results in less frequent trading. Those who are sensation seekers and are engaged with the market trade more and hold more risk.

Figure 4.9a and Figure 4.9b illustrate the relationship between the psychometric attributes and the new 11 factors as well as the relationship between the new 11 factors and the financial variables. For clarity the Figure 4.9 is split into two parts, with Figure 4.9a showing the first five extracted factors from the factor analysis and Figure 4.9b showing the other 6 extracted factors. The signs on arrows indicate positive/negative relationships. The numbers amongst the psychological variables are the correlation coefficients (above .25).

Only those psychological variables that have loading of above .3 onto the new factors are illustrated in the figure.

Factors 1 and 2 are the most important each explaining 6% and 5% of the total variance, respectively. The first factor Confidence has positive loadings on better than average, subjective expert, subjective number, monitors and planner; negative loadings on aversion and neuroticism. The combination of these variables implies that these investors are active market followers who believe they are knowledgeable in a certain area (Heath & Tversky 1991). From Table 4.6 we see that these investors trade more, but the risk or portfolio performance in not affected. The second factor is Delegation with high positive loading on both belief in skill and delegation variables. These investors believe that advisors should have superior knowledge about investing and they also prefer to have portfolios managed on their behalf. Delegation is correlated with less trading and smaller notional, which is also consistent with previous findings. For example De Bondt (1998) suggests that investors who are willing to delegate their portfolio to a financial advisor are able to manage risk by distancing themselves from decisions and avoid taking responsibility for their action. We also find a significant negative coefficient for ROI, which indicates that these investors are also more likely to cut their losing positions, possibly implying that they are less prone to the disposition effect.

The third factor is Market Knowledge, which loads positively on financial knowledge and negatively on churning and time discounting. These investors hold more diversified portfolios (less risk), enjoy higher risk adjusted returns, trade less and are more likely to log-into their portfolios to trade rather than just look: behavior more consistent with the rational models of finance. Complete opposite behavior is seen from investors who have Sensation Seeking qualities, which is factor four. It loads positively on winning investment, joy, risk taker and negatively on investment horizon. Sensation Seeking investors have lower risk adjusted returns and hold more risk and trade more frequently, which is consistent with Grinblatt and Keloharju's (2009) findings that show sensation trade more and have inferior performance. This is also in-line with Dorn and Segmueller's (2009) findings that those who trade for entertainment trade twice as much. The fifth factor is Analytical Decision Process, which loads only on the CRT variable. Investors who scored high on CRT hold less risk and have higher daily mean returns and higher both risk adjusted returns. Our results are in-line with Korniotis et al. (2013) and Grinblatt et al. (2012).

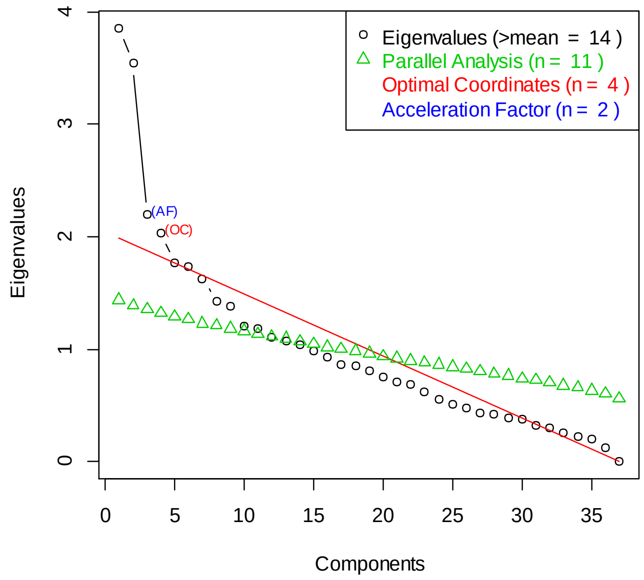


Figure 4.8. Factor analysis illustrating Parallel Analysis solution(a Monte Carlo simulation technique) and Eigenvalues solution (a Kaiser criterion, which suggests to choose factors with eigenvalues greater than one)[5].

The sixth factor is Mature, which loads positively on age, wealth and research use. We would expect those who score high on this measure to be well-established investors. Consistent with previous studies (Anderson 2013; Goetzmann & Kumar 2008) the regression coefficients indicate that they do in fact hold better diversified portfolios (less risk), have higher risk adjusted returns and trade in larger size. The seventh factor is Income which loads positively on income, income risk, wealth and number of dependents. Investors who score high on this variable trade more and in larger size. Such investors, who have extra funds to play with, are more likely to make large and frequent transactions. The eighth factor is Training which loads positively on the training variable and liquidity. It leads to less diversified portfolios and lower daily mean returns as well as risk adjusted returns, as in the full regression results. The ninth factor is Impulsivity and these investors trade more and hold more risk. Results are as expected given that in behavioral economics literature more "anomalous" preferences and stronger behavioral biases such as greater level of impatience and impulsivity are linked to lower levels of cognitive abilities (e.g., Frederick 2005; Dohmen et al. 2010). This could also be linked to Dorn and Sengmueller (2009) suggestion that "impatient" investors would trade more as they would be more likely to abandon current trading ideas, as well as hold more volatile portfolios with positively skewed returns in order to reach a higher level of wealth sooner - aspiration driven investors.

[5] Practical Assessment, Research and Evaluation, Costello and Osborne (2005)

Table 4.5: Factors extracted from Factor Analysis

Variables	**Confidence**	**Delegation**	**Market Knowledge**	**Sensation Seeking**	**Analytical Decision Process**	**Mature**	**Income**	**Training**	**Impulsivity**	**Level of Regret**	**Market Research**
Eigenvalue	2.32	1.65	1.49	1.47	1.45	1.42	1.38	1.35	1.27	1.21	1.09
Variance Explained	0.06	0.05	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.03	0.03
Cumulative Variance Explained	0.06	0.11	0.15	0.19	0.23	0.27	0.31	0.35	0.38	0.42	0.45
Factor Loadings:											
BTA	0.62										
Perceived financial expertise	0.73										
Belief in Skill		0.99									
Delegation		0.64									
Discount			-0.66								
Financial Knowledge			0.64								
Winning Investment				0.75							
CRT					0.98						
Age						0.83					
Income category							0.8				
Training								0.97			
Impulsive									0.96		
Regret										0.96	
Research hours											0.62
Gender (male)											
Married											
Wealth category						0.42	0.44				
Dependents							0.48				
Churn			-0.33								
Decision maker											
Joy				0.31							
LOC											
Aversion	-0.39										
Risk taker				0.45							
Subjective numeracy	0.35										
Monitors	0.34										
Patience											
Planner	0.48										
Income risk							0.35				
Investment horizon				-0.38							-0.34
Liquidity								0.36			
Neurotic	-0.34										
Research use						0.35					
Years trading											

Note: We used varimax rotation but promax gives similar results.

The tenth factor is Level of Regret, which loads highly on the regret variable. Similar to the full regression results these investors trade less and in larger size and have less trades per login compared to other investors. The last factor is Market Research. It loads positively on the variable research and negatively on investment horizon. Given the amount of hours these investors spend on research could result in behavior analogous to overconfidence as we observe more trading and high notional. Moreover, as mentioned earlier, shorter investment horizon is associated with more trading. It makes sense that these investors hold more risk, execute more trades in bigger size and are more likely to trade once they have logged into their accounts. These investors engage in active strategies, which ground investment decisions in research and seek to exploit perceived inefficiencies; however it seems that other active and clever traders walk away with a profit in this zero-sum game.

Table 4.6: Regression results with the 11 factors extracted from the factor analysis.

	Mean Return (%)		Log Risk		Sharpe Ratio		Log Deals		Log Notional		Log Trade Ratio		ROI %	
Factors	β	P value	β	P value	β	P value	β	P value	β	P value	B	P value	β	P value
(Intercept)	-0.008	0.019	-4.740	0.000	2.447	0.325	-2.901	0.000	5.494	0.000	-2.020	0.000	3.430	0.033
Confidence	0.003	0.103	0.006	0.837	1.146	0.381	**0.177**	**0.002**	0.061	0.325	-0.027	0.579	-0.557	0.510
Delegation	-0.001	0.346	0.026	0.344	-1.459	0.213	**-0.119**	**0.018**	*-0.096*	*0.086*	0.026	0.545	**-2.196**	**0.004**
Market Knowledge	0.002	0.304	**-0.142**	**0.000**	*2.693*	*0.056*	**-0.238**	**0.000**	0.103	0.125	**0.166**	**0.002**	-0.092	0.919
Sensation Seeking	-0.001	0.423	**0.248**	**0.000**	**-4.556**	**0.001**	**0.290**	**0.000**	0.054	0.413	-0.064	0.219	0.585	0.515
Analytical Decision Process	**0.005**	**0.001**	**-0.055**	**0.035**	**5.005**	**0.000**	0.019	0.681	0.064	0.214	0.019	0.638	0.160	0.820
Mature	0.002	0.179	**-0.203**	**0.000**	**6.670**	**0.000**	0.045	0.409	**0.261**	**0.000**	0.059	0.219	1.138	0.169
Income	-0.002	0.252	-0.009	0.765	1.429	0.281	**0.116**	**0.042**	**0.227**	**0.000**	**0.222**	**0.000**	0.263	0.758
Training	**-0.008**	**0.000**	**0.062**	**0.027**	**-7.733**	**0.000**	0.045	0.372	0.047	0.403	*0.079*	*0.068*	-0.642	0.395
Impulsivity	0.000	0.850	0.056	0.049	-0.623	0.598	**0.177**	**0.001**	0.041	0.470	*0.073*	*0.098*	0.171	0.823
Level of Regret	-0.001	0.743	-0.009	0.747	1.266	0.279	**-0.231**	**0.000**	*0.108*	*0.054*	**-0.140**	**0.001**	-1.169	0.122
Market Research	-0.002	0.196	**0.075**	**0.032**	-0.232	0.873	**0.345**	**0.000**	**0.213**	**0.002**	**0.140**	**0.010**	-0.769	0.413
Adj. R^2	6%		20%		15%		17%		7%		8%		1%	

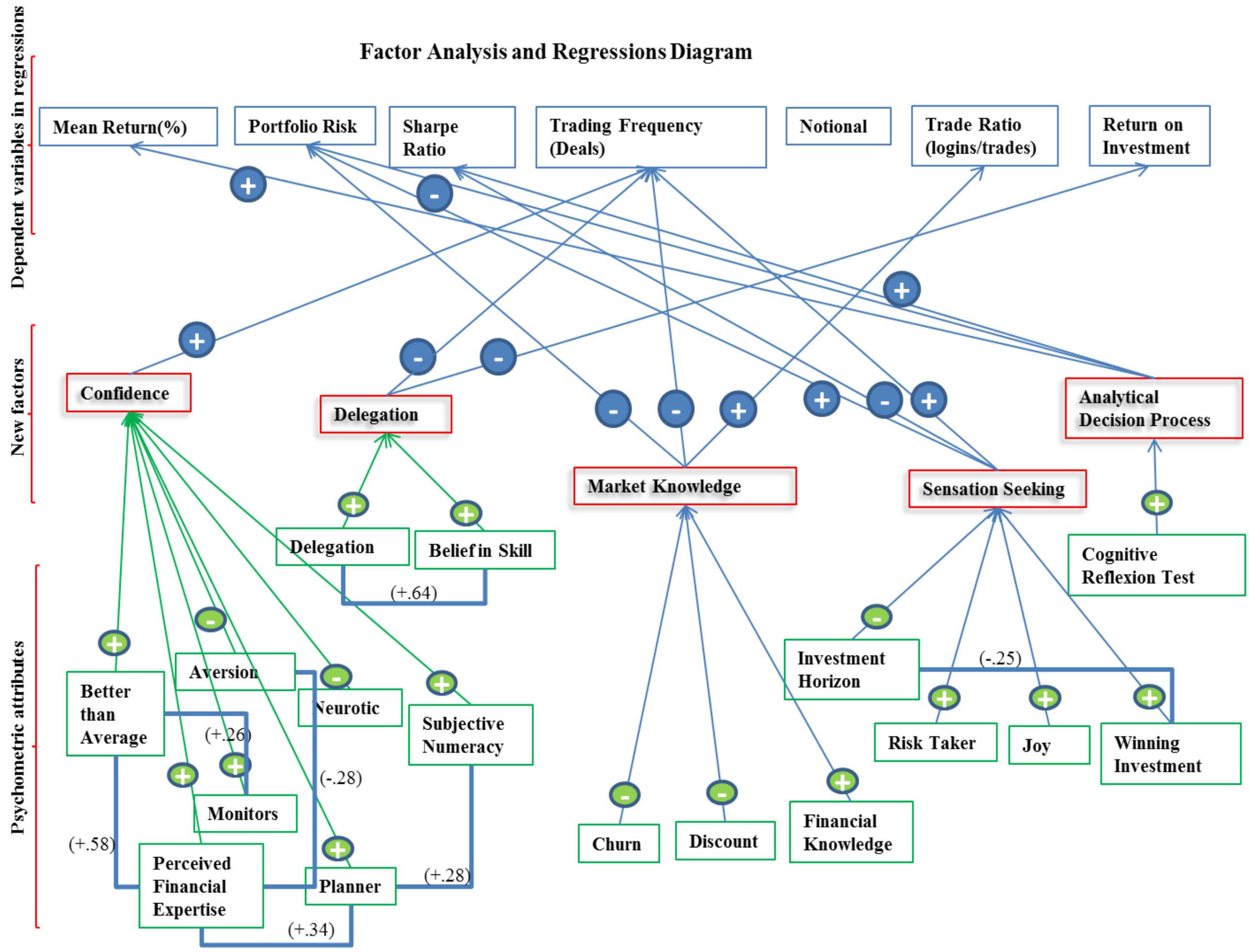


Figure 4.9a. The Figure illustrates the seven dependent financial variables at the top in blue. The first five extracted factors from the factor analysis are in the middle of the diagrams (the Figure 4.9 is split for clarity into a and b with Figure 4.9b illustrating the remaining 6 factors). The arrows from the new factors show the relationship between these and the financial variables from the regressions in Table 4.6. The initial psychometric attributes that where factor analysed are at the bottom of the diagram in green. The positive and negative signs from the psychometric attributes to the new factors show loading (+/-). Only factors with loading above .3 are shown. Amongst the psychological attributes correlations above .25 are noted.

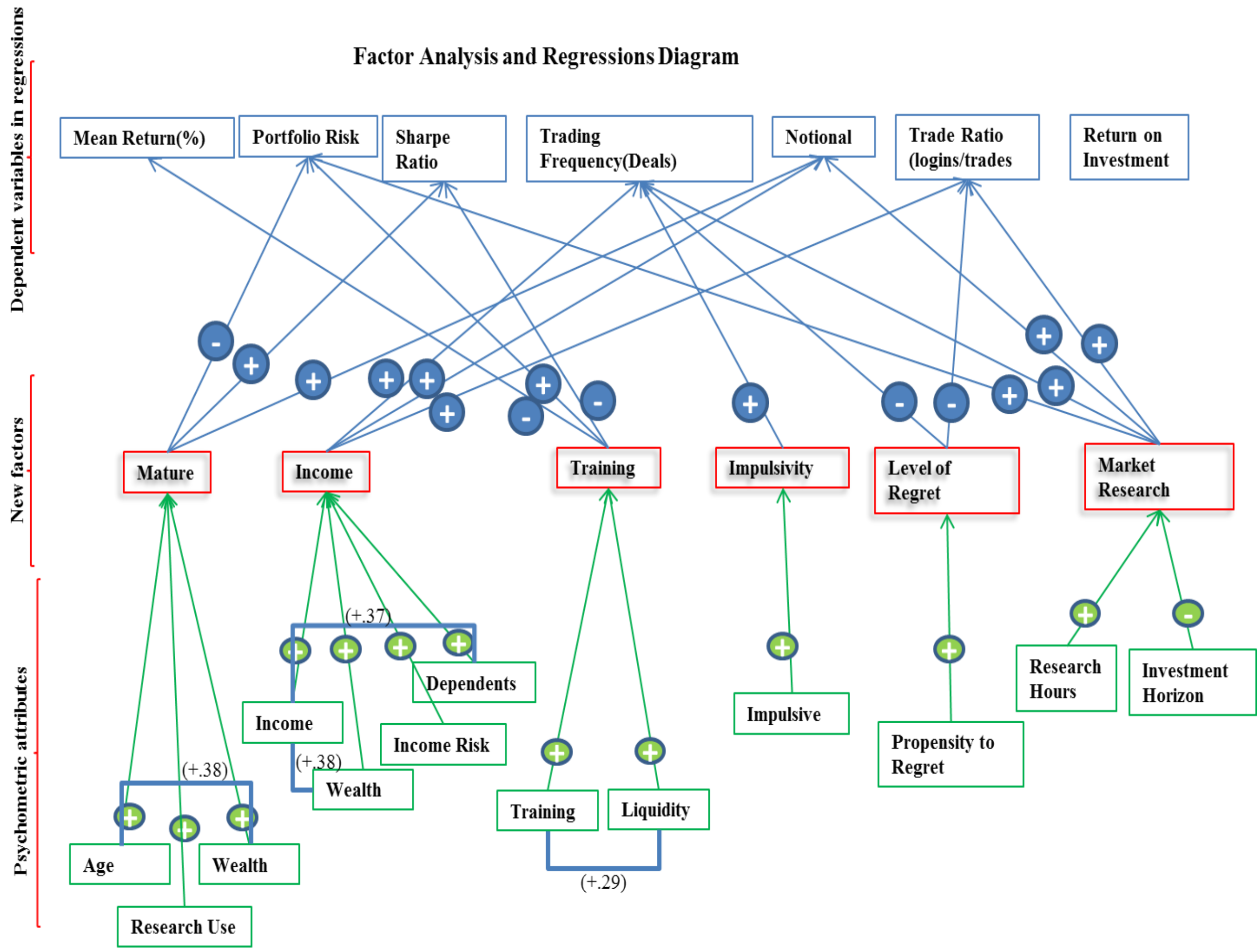


Figure 4.9b.

4.8 Summary and Conclusion

This study provides the first comprehensive analysis of individual investors' psychological attributes and the effects of individual differences on risk preferences, trading behavior and portfolio performance. The detailed daily transactional dataset allows us to conduct a much more granular analysis and to directly compare which attributes and biases are relatively more important. Unlike previous studies, rather than attributing investors' portfolio performance and trading behavior to one category, such as demographics or overconfidence, we introduce thirty two self-reported psychological variables to capture the multiple aspects of the individual. First we analyse the effect of only demographics. Then we build one model with all psychometric attributes as well as univariate models for each of the attributes. Lastly we conduct factor analysis to reduce the model size.

Using only demographics in the model as is frequently done in other studies leaves much of the variance unexplained compared to the full model. Comparing explanatory power of demographics to the full model, the daily mean returns variance explained increased from .1% to 9%, for portfolio risk measure it increased from 11% to 21%, for Sharpe Ratio from 4% to 19%, for propensity to trade from 2% to 30%, for size of trades from 5% to 10%, for trade ratio from 3% to 27% and for ROI from 1% to 13%. This study also shows that including only one variable in the model can miss the real attribute that is causing the effect. For example while Barber and Odean's (2001) results suggest that men trade more than woman - and so do we when considering only demographics – when other psychometric variables are added to the model, the gender effect goes away completely. In this study we found that it is market engagement and impulsiveness that are the underlying psychological attributes driving higher volume of trading. Moreover, Graham et al. found that the gender effect becomes non-significant once perceived financial expertise/competence was added to the model. We find this too; however, we find that perceived financial expertise/competence also becomes non-significant in relation to trading once we account for market engagement in the model. Another example is the lack of correlation between better than average type of overconfidence (Dorn & Huberman 2005;Glazer & Weber 2007) and risk taker (Dorn & Huberman 2005) and trading activity in the full model, effects which were significant in the univariate model. Accounting for market engagement (monitors) in the model causes the better than average and risk taker effects to become non-significant.

We also find that more trading does not necessarily lead to worse performance, as per Barber and Odean's (2001) suggestion. For example in the full regression the analytical (rather than intuitive) investors as measured by the CRT and those whom we have classified as churners, do trade more; however, they also have higher risk adjusted returns. On the other hand investors who have been trading for many years also trade more, yet they have worse risk adjusted performance.

Corroborating previous findings that higher IQ is correlated with better performance (Grinblatt et al. 2012, Korniotis & Kumar 2013), better trade execution and better diversification, our results suggest that those investors with higher cognitive abilities - measured by CRT, financial literacy and believe they have superior financial knowledge - earn higher risk adjusted returns, and are better at trade execution. We find that older investors hold less risk and earn higher returns. Investors with a preference for lottery-like stocks, as predicted by previous literature, hold riskier portfolios and have poor performance, without necessarily trading more frequently.

Factor analysis results imply that investor confidence is the most definite factor, which has perceived financial expertise/competence loading positively and neuroticism and market aversion loading negatively on the factor. With the eleven factors, the reduced model leaves much of the variance unexplained compared to the full models. For example in explaining propensity to trade the demographics model the factor analysis model and the full model have adjusted R^2 of 2%, 17% and 30% respectively. The factor analysis results suggest that mature investors with good market knowledge and analytical rather than intuitive decision making process exhibit behavior more in-line with the normative models. On the other hand investors who have had finance related training and are sensation seekers end up holding extra risk and have poor performance. Higher income, confidence, impulsivity and sensation seeking preferences all lead to frequent trading.

Although in theory all market participants have access to the same information, the observed portfolio performance, trading behavior and portfolio risk preferences clearly depend on various psychological attributes and not simply on demographics and socio-economic characteristics that are mainly considered to differentiate people in the literature. Hirshleifer (2001) quite rightly starts his paper with a hypothetical deficient market hypothesis: that prices inaccurately reflect all available information including mispricing proxies, the amount of sunlight and other mood indicators that could do a better job at predicting future returns. Understanding individual differences is vital as investors decisions lead to variances in information acquisition decisions, trading and risk preferences which are then fed back into the market and are reflected in the asset prices and the financial markets.

CHAPTER 5

The Effects of Arousal and Personality in a Trading Experiment

Contents:

Abstract

This paper examines the role of incidental emotions and their impact on trading volume and tests whether participants' psychological attributes mediate this relationship. Previous studies highlight the importance of affect in judging the risk and benefit associated with choices. It has been suggested that emotions alter risk perception, believes and can overpower cognitive decisions. Using a professional trading platform (TT) we conduct an experiment with two conditions in which level of arousal was manipulated (high vs. neutral). The results show that individuals with preference for intuition are more affected by the high arousal condition. Participants trade more in the aroused condition but the effect is not statistically significant. It was also found that older investors tend to trade less. We propose that the lack of effect of arousal may be due to the novelty of trading using TT platform and the difficulty or excitement associated with trading itself.

5.1 Introduction

In classical economic models decision making is based on rational objective calculations with an assumption of constant and stable risk preferences. For example in the expected utility framework individuals make risky decisions based on the expected utility of the final outcome. However, the role of emotions in guiding human behavior as well as the dynamics of stock markets and the economic cycles has been advocated since the late 1930's. Keynes (1936) introduces the idea of animal spirits, which focuses on the importance of emotions, and believed that relying on the efficiency of the markets is not a solution to the underlying cause of for example the Great Depression. Recently Akerlof and Shiller (2009) recovered the animal spirits idea and highlighted the limitations of the current economic theory, suggesting that human psychology should be addressed.

It has been proposed that emotions are rooted at the physiological level of individuals. For example Lo and Repin's (2002) presented psychophysiological evidence – measures of skin conductance and cardiovascular variables and survey data - that even seasoned traders go through an emotional rollercoaster during the trading hours. Coates and Herbert (2008) suggested that emotions cause hormonal changes within individuals thereby alter their risk preferences. For example Coates et al. found that during volatile and uncertain market conditions a group of traders experienced an increase in the stress hormone cortisol. In a follow up experimental study, Kandasamy et al. (2014) found that elevated levels of cortisol caused by prolonged stress (chronic stress experienced by real traders), as would be expected during prolonged uncertainty such as the financial crisis, reduced risk-taking since the stress hormone cortisol increased investors' risk aversion. Such results imply that, for example, during the financial crisis, when the risk taking is actually needed from traders, they could become more cautious, in turn exacerbating the crisis.

Literature in psychology highlights that emotions and cognition are not independent of psychometric measures and personality traits. For example Schunk and Betsch (2006) found that participants with a preference for intuition rely of affective-based decision making and deliberative people base their decisions on the stated values. The authors estimated participants' utility functions using lottery based choices and also assessed participants Preference for Intuition and Deliberation (PID, Betsch, 2004) to find more curved utility function for those participants with a preference for intuition and a more linear utility function for those with a preference for deliberation. The authors suggest that the feeling of risk becomes integrated in the judgment, resulting in risk-averse or risk-seeking behavior. In exploring framing effect[6] (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991, 1992) , Seo and Barrett (2010) ran an online stock investment simulation and found that when individuals experienced large gains and had pleasant feelings, they were not risk averse, but instead were risk seeking. Conversely, when individuals simultaneously experienced pleasant feelings and large losses, they became less risk seeking. When participants felt especially pleasant, the framing effect of loss was mostly eliminated. Linking emotions with personality, Gross and John (2003) suggested that although emotion regulation can be acquired though experience, it is likely that emotion regulation is influenced by personality traits such as neuroticism and extroversion. This view is supported by Lerner, Gonzalez, Small and Fischhoff (2003) who conducted a post 9/11 survey on a national representative sample of Americans and found elevated perception of risk amongst those who scored higher on the anxiety scale, which implies that neurotic or anxious individuals were more influenced by the 9/11 event.

This study explores an emotion-based framework of decision making. Lowenstein, Weber, Hsee and Welch (2001) distinguish between anticipatory emotions and incidental emotions. In economics emotions are expected consequences of the outcomes, yet Loewenstein et al. suggest that incidental emotions that are experiences during the decision can bypass the cognitive decision making process and drive the decision. This study tests the role of incidental emotions induced by exogenous negative valence visual stimuli while investors trade. The goal is to also test whether individual differences such as investors' personality, PID and risk preferences mediate the effect of emotions on trading behavior. In a field study, one is unable to control for outside environment given the number of exogenous factors in the real world. In a laboratory environment we can control for the conditions that introduce specific emotional responses. In the experiment we have a neutral and an aroused (negative valence only) conditions and use a professional trading platform. To test role of individual differences in trading behavior and interacting with emotions we collect participants' psychological attributes including personalities, sensation seeking preferences, predisposition to regret, cognitive abilities and whether they use deliberate versus intuitive decision making system. The structure of the paper is as follows. The next section provides theoretical overview and previous literature. Section 5.3 describes the methodology and procedure and results. Section 5.4 reports the results for factor analysis and Section 5.5 concludes.

[6] The tendency to be risk averse when a decision is framed in terms of gains and to become risk seeking when a choice is framed in terms of losses.

5.2 Theoretical Orientation and Literature Review

In psychology the role of emotions in decision making is well recognized. For example Rottenstreich and Hsee (2001) suggested that emotions and cognition are integrated and that emotions influence risk perception and risk choice. In Rottenstreich et al.'s model the role of affect can explain the weighing function of the prospect theory (PT, Kahneman & Tversky 1979). PT introduces a distinction between losses and gains domains, an s-shaped value function to account for the attractiveness of the outcomes (convex in the negative domain and concave in the positive domain) and a weighting function (inverse s-shaped in the positive and the negative domain) to account for the impact of probabilities. The computation of the value and the weighting function establish the utility of an outcome. It is different from the expected utility model as according to PT individuals transform the probabilities into subjective weights (Kaheman & Tversky 1984) whilst making a decision. In their model, Rottenstreich et al., rather than explaining the inverse s-shaped weighting function as caused by moving away from impossibility (0) to certainty (1), the authors use emotions of hope and fear. At the left hand-side the overweighting of the small probability of wining is caused by some hope versus no hope (certain loss), and on the right hand side the underweighting is caused by some fear (probability of wining is less than 1) to no fear (certain win). Moreover, while in PT the probability weight of the outcome and the value of the outcome are independent ($\Sigma w(p_i)v(x_i)$), in Rottenstreich et al.'s model weighting of an outcome is not independent of their affective content. The outcomes that are more affect-rich will produce a stronger (inverted) s-shaped weighing function than the monetary outcomes. In other words people will overweight small probabilities more in the affect-rich condition and under-weight large probabilities less in the affect-rich condition. For example in one of the experiments in a low probability condition (1%) participants were willing to pay on average \$7 to avoid an electric shock versus \$1 to avoid a \$20 penalty. On the other hand in a high probability condition (99%) participants were willing to pay on average \$10 to avoid the electric shock and \$18 to avoid the monetary penalty. Participants over-weighted the affect-rich probability of electric shock (\$7) and underweighting affect-rich high probability condition (\$10). However in this account the focus is on anticipated emotions, which are not experienced at the moment of a decision.

Other studies have claimed that rather than integrating information through expectation based calculations, emotional and cognitive systems work in parallel. One example is Damasio's (1994) work on somatic marker hypothesis. Damasio suggests that through experiences, learning, conditioning and memory representations of objects, events and outcomes are marked to positive and negative emotions. So an image of an outcome would be associated with the positive or negative feeling. These anticipatory emotions are the somatic markers that drive the decision. In his study Damasio (1996) found that in individual's whose prefrontal cortex was damaged, these individuals had significant impairment in risky decision making. Even though individuals' memory, cognitive and learning abilities were intact, the abnormalities in emotional system led to inferior performance. The patients had no physiological activation as measured by the skin conductance responses prior to making the risky choice. Damasio concluded that emotions can lead to better performance because emotional signals (i.e., somatic markers) develop in healthy individuals to warn them against making a bad choice. Similarly Finucane, Alhakami, Slovic, Johnson (2000) proposed that when making decision, individuals use affective cues that are attached to objects and events to make decisions, which is faster than the computing required by the information-integration models. The authors term this as affect heuristic. They also use affect to describe the observed inverse relationship between perceived risk and benefit (Alhakami & Slovic 1994) in which, for example, a 'liked' activity would lead to higher benefit perception and a lower risk perception.

An alternative view is known as the risk as feeling hypothesis (Lowenstein et al. 2001), which posits that in evaluating risk, emotional state plays a crucial role during the decision making process. Furthermore, unlike in the affect heuristic or the somatic marker hypothesis in which emotions play an informational or complementary role in decision making, in risk as feeling hypothesis emotions can diverge with what the individual views as the optimal outcome. The risk as feeling hypothesis emphasises that emotions guide the reaction to risk at its first occurrence. In this context feelings react to immediate risk and probabilities without entering the cognitive process and these emotion driven decision can even overpower the cognitive decision.

In psychology it is also widely accepted that emotions can carry over from one unrelated context to another, what Lerner, Small and Loewenstein (2004) referred to as the emotional-carryover hypothesis. This is in-line with the appraisal-tendency framework (Lerner & Keltner, 2000, 2001; Lerner & Tiedens 2006), which differentiates between integral emotions and incidental emotion. While integral emotions are relevant to the task at hand, incidental emotions are irrelevant to the situation yet they can still influence decision-making process in an unrelated task and normatively unrelated economic decisions (Andrade & Ariely 2009; Philippot 1993; Andrade & Cohen 2007; Vohs, Baumeister & Loewenstein 2007), influence how much people eat (Grunberg & Straub 1992), help (Manucia, Baumann & Cialdini 1984), trust (Dunn & Schweitzer 2005), procrastinate (Tice, Bratslavsky, & Baumeister 2001), and price different products even when real money is at stake (Lerner et al. 2004[7]).

Borrowing from the insights of psychology and neuroscience, recent developments in behavioral finance began to acknowledge the role of emotions in explaining individual investors' behavioral anomalies (Lo, Repin 2002; Lo, Repin & Steenbarger 2005) and recognize that emotions play an important role in influencing traders' risk perception, trading behavior and in turn their portfolio performance (Au, Chan, Wang & Vertinsky 2003; Lo, Repin & Steenbarger 2005). For example Au et al. found that participants who were in a good mood were more confident, less accurate with their investment strategies and more risk seeking. Lo et al. (2005) used a survey (the Mood Adjective Check List, Mathews et al. 1990) that tracked traders' psychological profile for 25 days before and after trading. The authors found that worse performers experienced stronger emotional reactions implying a negative correlation between successful trading behavior and emotional reactivity. On the other hand, Fenton O'Creevy et al. (2011) conducted a field study with real traders to find that a stronger emotional reaction experienced by a trader is not necessarily a bad thing for performance. The authors claim that experienced traders were able to use emotions as informational cues - similar to what Slovic et al. (2002) refer to as the affect heuristic - which resulted in more successful trading strategies. On the other hand low performing investors engaged in avoidant behavior (such as taking breaks and leaving the desk) and required more cognitive effort to control their emotional responses. In a follow up psychophysiological study, Fenton et al. (2012) suggested that emotion regulation comes with trading experience and learning throughout the career. Similar results were reported by Seo and Barrett (2007). The authors conducted a 20-day internet-based investment simulation with investment club members as participants. Seo et al. found that those participants who experienced stronger emotions were better performers and those who understood their emotions during the decision making process (gave a more vivid description of feelings) were top performers. The authors concluded that those investors who have strong emotion during the decision making process and are aware of them are most successful.

Emotions have also been found to account for a widely cited phenomenon in behavioral finance. For example Lowenstein et al. (2001) suggested that the equity premium puzzle described in Chapter 4 could be analogous to the Damasio's (1996) experiment, in which the control group had normal physiological activation, over time learned to stay away from the riskier condition while those with the damaged brain area was

[7] In their study the authors found that sadness and disgust reduced selling prices.

insensitive to the high monetary punishment. Loewenstein et al. suggest that ‘fear’ could explain why investors choose to stay away from investing into equities. Another widely explored phenomenon is called the disposition effect, in which investors sell their winning investments and hold on to losing positions for too long (Shefrin & Statman 1985). Although Shefrin and Statement suggested the role of psychology in explaining the disposition effect, the effect has been mainly explained by the PT’s s-shaped value function, concave in the domain of gains and convex in the domain of losses. In the domain of gains investors are predisposed to be risk averse therefore by simply experiencing gains they are likely to sell the stock and lock in the gains in order to avoid losses. On the other hand in the domain of losses investors are considered risk seeking, and consequently are more likely to keep the losing investment. In exploring the psychology of the disposition effect Summers and Duxbury (2012) proposed an alternative explanation. The authors experimentally showed that experiencing a positive or a negative emotion - elation and regret - can explain the disposition effect. If these emotions are not present during the decision making process, then individuals are not necessarily risk averse for gains and risk seeking for losses as predicted by the PT. For example in the disappointment condition (when participants are not responsible for the choice in the loss scenario) there is no evidence of disposition effect, while in the regret condition (when participants are responsible for a choice) disposition effect is observed. It is the change in the emotion caused by gains and losses and the responsibility associated with it that evoke the disposition effect rather than a just a change in gains and losses as per PT. Without specific emotions, the risk preferences, as suggested by the S-shaped value function of the prospect theory, are not observed.

Research on incidental emotions is not unique to psychology. For example Edmans, Garcia and Norli (2007) examined 39 countries’ stock price momentum and found that a country’s important sports game defeat was followed by a significant decline in the country’s stock market. The authors concluded that emotional arousal can impact asset pricing. Other external factors which have been indirectly reflected in the stock-market price movement and trading behavior include the amount of sunshine (Saunders 1993; Goetzmann & Zhu 2005; Hirshleifer & Shumway 2003). These authors found that on sunny days the returns were higher and attributed such finding to investors’ increased optimistic behavior when it is sunny. The lunar cycle has been found to affect the stock market in 25 different countries with daily returns around the new moon nearly double the returns around the full moon (Dichev & James 2001) as investors are depressed and pessimistic. The decrease in daylight (Kamstra, Kramer & Levi 2003) and increase in geomagnetic activity (Krivelyova & Robotti 2003) have been linked to a declining market as investors become depressed and risk-averse. On an individual investor level, Au et al. (2003) found that traders who were in a good mood (elicited by music) had inferior performance and were more overconfident while those in a bad mood made better decisions and were more conservative with their trading. In their experimental and field data analysis, Guiso, Sapienza and Zingales (2014) found that investors became risk averse after witnessing a scary event (induced by watching a scary movie trailer) regardless of whether an investor has experienced an economic loss or not.

Within the behavioral finance context, studies have also explored the role of personality traits of daily traders and their influence on financial decision making. For example Fenton-O'Creevy, Nicholson, Soane, and Willman (2004) conducted a study among 118 professional traders employed at investment banking institutions, and found that successful traders tend to be emotionally stable introverts open to new experiences. Similarly, Durand et al. (2008) found that personality traits are correlated with investment decisions. They assessed 21 traders across Australia using the Big Five personality inventory (Costa & McRae, 1992) to find that higher anxiety and higher risk taking propensity were associated with increased trading behavior, while investors who were more extraverted had a lower propensity to trade. Witteloostuijn and Muehlfeld (2008) found that personality traits affect trading behavior with those who have stronger regret disposition and dislike sensation seeking trade less frequently. Contrary to these results, Lo et al. (2005) found lack of correlation between personality traits and trading performance suggesting that the differences could be visible only on the physiological and neurological levels.

5.3 Methodology

5.3.1Participants & Psychological Attributes

Students of University of Warwick were invited to take part in the experiment via SONA recruitment system with a total of 55 participants from various disciplines including Economics, Finance, Business Management, Mathematics, Physics, Psychology, Engineering and Computer Science taking part over the three identical experiments (23 students in round 1, 18 students in round 2 and 14 students in round 3). We stopped testing once we had achieves 50 participants as planned. To control for gender differences only males were invited to take part in the experiment. The age ranged from 18 to 29 with a mean of 21. Many participants took part in the experiment because they were keen to learn how to trade and they were also financially incentivised to take part and to perform well. Following participants registration to the experiment they were asked by email to follow a link and to complete an online questionnaire on Qualtrics. The questionnaire gathered various information including individual's demographics, predisposition to regret, cognitive reflection test, risk preferences, intuitive versus deliberate decision making style, whether they are patient or impulsive when making a decision and their personality profile. The source and the description of the questions and psychological attributes are outlined in Table 5.1. All questions are provided in the Appendix. In total the participants answered 158 questions, and on average it took 21.27 minutes to complete the questionnaire.

Table 5.1 Description of psychological attributes and survey questions.

Group	Source	Measure	Description
Demographics		Age and major	All participants were male
Regret Scale	Schwarts et al (2002); Marcatto & Ferrante (2008)	5 questions ; 7 point likert scale (1 = completely disagree to 7 = completely agree)	Assesses how individuals deal with decision situations after the decision has been made, specifically the extent to which they experience regret.
Barrat Impulsivity Scale	Patton, Stanford & Barratt (1995)	30 question using 4-point ratings (1 = never/rarely, 2 = occasionally, 3 = often, 4 = almost always/always)	Assess the personality traits of patience and impulsiveness.
Cognitive Reflection Test	Frederick (2005)	3 brainteaser items using a free-response format	Assess a specific cognitive ability. Tests individuals' ability to suppress an intuitive and spontaneous ("system 1") wrong answer in favour of a reflective and deliberative ("system 2") right answer.
Sensation Seeking/ Risk attitude (SSS-V)	Zuckerman, Eysenck, & Eysenck (1978)	40 items using forced-choice format	Assess the personality traits of thrill and adventure seeking, disinhibition, experience seeking, and susceptibility to boredom; measure of risk preferences.
Intuition / Deliberation	Schunk & Betsch (2006)	18 questions; 1-5 scale (1 = completely disagree to 5 = completely agree)	Assesses an individual's tendency to use an intuitive mode or the one seized on in the moment of decision. A rational way of elaborating information (a deliberative system) or an experiential way of elaborating information (an intuitive system).
NEO-FFI (Five Factor Theory of Personality)	Costa & McCrae (1992)	60 items using 5-point ratings (1 = strongly disagree to 5 = strongly agree)	Openness: Fantasy, aesthetics, feelings, actions, ideas, values Conscientiousness: Competence, order, dutifulness, achievement striving, self-discipline, deliberation Extraversion: Warmth, gregariousness, assertiveness, activity, excitement seeking, positive emotions Agreeableness: Trust, straightforwardness, altruism, compliance, modesty, tender-mindedness Neuroticism: Anxiety, angry hostility, depression, self-consciousness, impulsiveness, vulnerability

5.3.2 Visual stimuli

In the experiment we had two visual stimuli conditions: aroused and non-aroused. Participants were presented with 5 minutes of images from the picture stimulus in the International Affective Picture Systems (IAPS) (Lang, Bradley, & Cuthbert, 1999). IAPS contains 1196 static images based on a dimensional model of emotion in which emotions can be captured in two or three dimensional space. IAPS dataset has been widely used in the experimental investigations of emotion and attention and obtained good reputation of worldwide psychological research labs. Moreover, unlike visual stimuli that rely on widely known movies, the IAPS images are not typically shown in any media outlet, publications or reports in order to maintain the novelty and efficacy of the stimuli set within research experiments. The images include various pictures depicting mutilations, snakes, insects, attack scenes, accidents, contamination, illness, loss, pollution, puppies, babies, and landscape scenes, among others. Each image is rated on affective valence, arousal and dominance based on a 9-point scale, with 9 being the highest rating score and 1 being the lowest rating point. Valence indicates how pleasant or unpleasant the emotional state is and arousal measures how activated or reactivated the emotion of the participant is.

In the current study we selected 100 pictures from IAPS visual images for each of the conditions. For the aroused condition the selected images rated above 5.5 (out of 9) on the arousal scale and below 2 on the valence scale (not pleasant). For the non-arousal condition images were chosen based on the arousal and valence rating between 3.5 and 6. To make sure participants engaged with the images, and to provide a manipulation check, our participants used a 7 point scale to rate the images on valence and arousal, with valence ranging from Nasty to Nice and arousal ranging from Mild to Strong.

5.3.3 Trading and trading platform

X_TRADER (TT) is a professional trading platform used by market makers around the globe. For the experimental trading sessions we used two historical indices, the DAX and the S&P500. During the training session participants traded S&P Index futures and during the experimental trading sessions they traded DAX Index futures. Participants were shown how to place market orders (immediate execution) and limit orders (executed at a specified price in the future). Participants were allowed to trade (go long or short) up to 10 contracts to avoid extreme positions. At the end on the experiment all participants were required to have a closed position of 0 units. Participants could not see the performance of others at any point of the experiment.

5.3.4 Procedure

Prior to conducting the experiment we received an institutional ethical approval with the Ethical Application Reference of 94 /12-13 Info-Ed Reference: 37773 from the Humanities and Social Sciences Research Ethics Committee at Warwick. The experiment was conducted over two days: 2 hours on the first day and 30 minutes on the second day. At the beginning of the experiment all participants signed a consent form which outlined what to expect and that at any point of the experiment they could discontinue the experiment. As an incentive to take part in the study participants were paid £10 for their participation and a further £15 bonus was awarded to two top performers. All participants were required to attend on both days and payments were made at the end of the experiment on day two.

On the first day participants spent an hour and a half learning about the trading platform, how to use TT, what strategies to consider when placing trades and analytical procedures. They were encouraged to ask questions and to practice placing limit and market ordered for as long as needed. Following the training session and prior to being able to participate in the experiment, participants were required to complete a 5 question quiz testing their knowledge of the TT platform and trading strategies as an understanding check (See Table 8.3 of the Appendix).

Participants were informed at the start that those who do not pass the quiz will not be allowed to take part in the experiment and will leave with £5. Only one participant failed the quiz and was not allowed to take part. Following the quiz participants took a ten minute break and as soon as they returned to their cubicles they had to rate the images for five minutes. Half of the participant took part in the negative arousal condition and the second half of the participants took part in the neutral condition. This was followed by thirty minutes of trading.

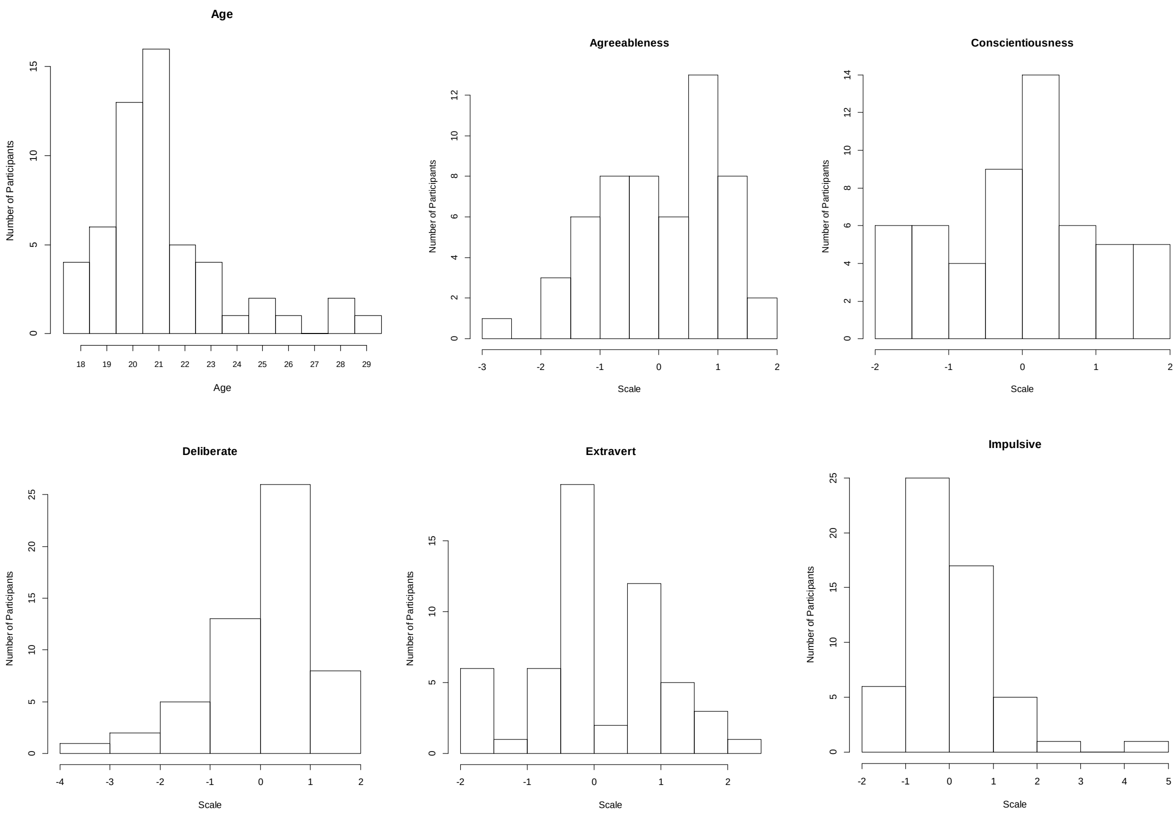
On the second day the two conditions were swapped. Following a trading refresher session participants rated the set of images they have not seen before and then traded for thirty minutes. At the end of the experiment participants were asked to fill out a feedback form with three open ended questions including the following:

1. What did you think of the experiment?
2. What do you think the experiment was about?
3. How could we improve the experiment?

Based on the feedback majority of participants were excited about to learn how to trade and enjoyed the experiment. They also said it was very challenging to trade and to be able to make profit. All participants were paid just before leaving the laboratory.

5.3.5 Summary Statistics and Results

The distributions of psychological attributes are presented in Figure 5.1 and have all been scaled to mean=0 and standard deviation=1. The distribution of CRT stands out from the rest as we have 6 participants who did not answer any questions correct, 9 with 1 question right, 14 with 2 correct and 26 who answered correctly on all 3 questions. The number of three correct answers is high compared to the original study in which only 17% of participants responded correctly to all 3 questions (Frederick 2005). This could be due to our participants being mostly from mathematics, engineering and computer science backgrounds or it could be that some participants have seen the CRT questions before.



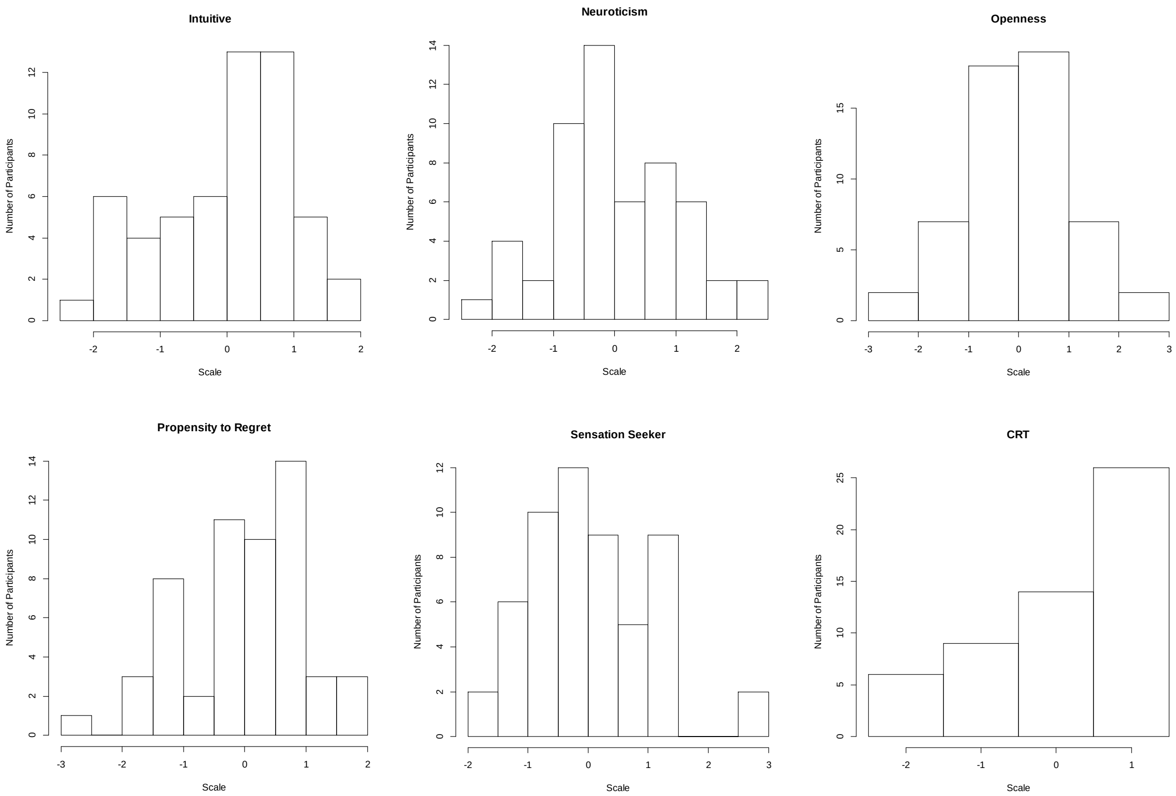


Figure 5.1.Distributions of participants' psychological attributes collected via Qualtrics.

Table 5.2 reports the 95% confidence intervals amongst the collected psychological attributes with correlations above .30 highlighted in bold. When constructing the questionnaire the aim was to capture various aspects of the individual differences, however, because a variety of tests were used, there should be some correlations. Age and deliberate decision making system are negatively correlated with being impulsive, while neuroticism is positively correlated with impulsiveness and propensity to regret. Extraversion and agreeableness, which are positively correlated with one another, are both positively correlated with intuition and negatively correlated with neuroticism. Conscientiousness is positively correlated with deliberate decision making style and negatively correlated with impulsiveness.

Table 5.2 The table shows 95% confidence intervals amongst the collected psychological attributes with correlations above .30 highlighted in bold.

	Age	Regret	Deliberate	Intuitive	Impulsive	CRT	Neurotic	Extravert	Openness	Agree	Conscien-tious	SSS
	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.	95% C.I.
Age	1.00											
Regret	-0.31 0.22	1.00										
Deliberate	-0.08 0.43	-0.04 0.47	1.00									
Intuitive	-0.21 0.32	-0.21 0.32	-0.15 0.37	1.00								
Impulsive	**-0.59 -0.13**	-0.24 0.29	**-0.64 -0.21**	-0.30 0.23	1.00							
CRT	-0.10 0.42	-0.15 0.37	-0.18 0.35	-0.36 0.16	-0.39 0.13	1.00						
Neurotic	-0.43 0.08	**0.04 0.52**	-0.40 0.12	-0.44 0.07	**0.13 0.59**	-0.38 0.14	1.00					
Extravert	-0.27 0.27	**-0.51 -0.02**	-0.30 0.23	**0.05 0.53**	-0.19 0.34	-0.31 0.22	**-0.61 -0.16**	1.00				
Open.	-0.07 0.44	-0.31 0.22	-0.31 0.22	-0.22 0.31	**-0.52 -0.04**	-0.21 0.32	-0.38 0.14	-0.16 0.36	1.00			
Agree.	-0.25 0.28	-0.17 0.36	-0.18 0.35	**0.12 0.58**	-0.27 0.26	-0.16 0.36	**-0.54 -0.06**	**0.13 0.59**	-0.28 0.25	1.00		
Conscien-tious	**0.05 0.53**	-0.24 0.29	**0.15 0.60**	-0.15 0.37	**-0.60 -0.15**	-0.26 0.27	-0.48 0.03	-0.20 0.33	-0.20 0.33	-0.10 0.42	1.00	
SSS	-0.27 0.26	-0.24 0.29	-0.16 0.36	-0.33 0.20	-0.26 0.27	-0.23 0.30	-0.30 0.23	-0.18 0.35	-0.16 0.36	-0.45 0.06	-0.20 0.33	1.00

Valence and Arousal

As a manipulation check Figure 5.2 shows the rating results of the images and provides the summary statistics. It is reassuring that the images confirm what was intended by the task. In the arousing condition participants' ratings indicate that the images were strong in valence (we used negative valence only) and strong in emotional arousal. In the non-arousal condition the rating of the images was neutral for both valence and arousal scales.

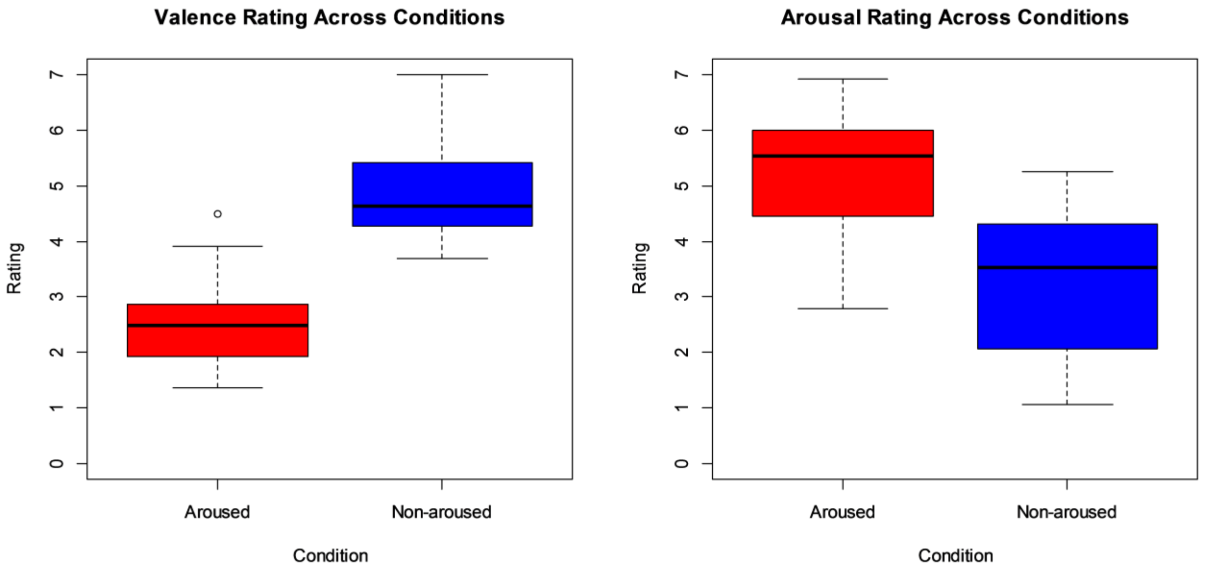


Figure 5.2. Boxplots of participants' aggregated responses by condition. The first window shows ratings for valence scale and the second window shows ratings for arousal scale. The boxes capture the interquartile range (IQR) with outliers below Q1 – 1.5×IQR and above Q3 + 1.5×IQR, which mark the endpoints of the whiskers.

<u>Trading Statistics</u>

Figure 5.3 illustrates the trade volume distribution in panel (a) and its log in panel (b). Figure 5.4 shows a boxplot for the number of trades between the aroused and non-aroused conditions as well as number of trades across the two days or two sessions. The mean number of trades for aroused condition is 308 and for non-aroused is 287 while the means across days are 268 for first day and 327 for the second day.

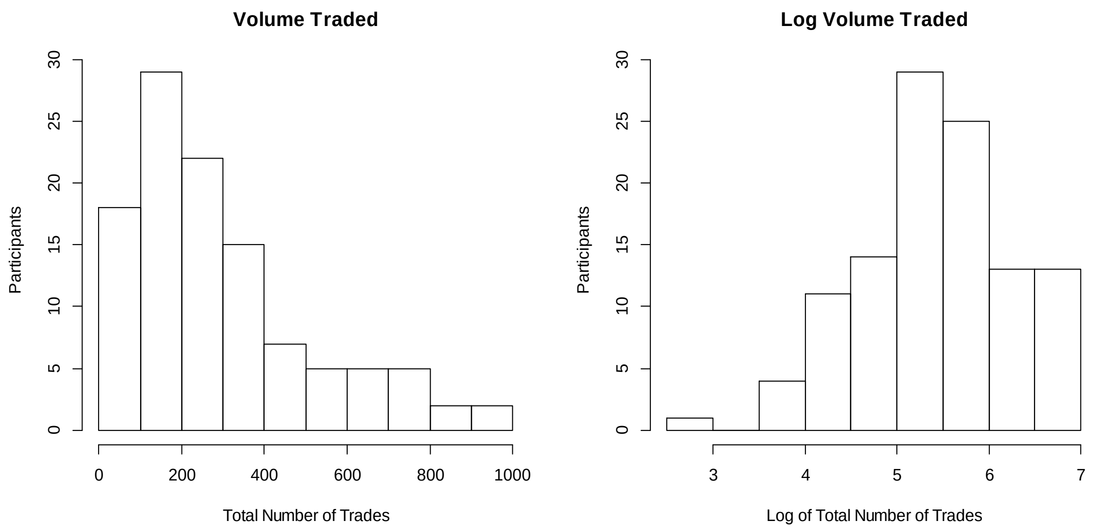


Figure 5.3. The first histogram (a) shows the total number of trades per participant for both sessions. The second panel (b) shows the log of total number of trades.

Although there are more trades in the aroused condition, accounting for the within-subject design there is no effect across conditions. The within subject ANOVA on log transformed trading volume is not significant with $F(1, 54) = 0.639$, $p = 0.427$, and a non-parametric Friedman test on the trading volume across conditions is also not significant with $\chi^2(1) = 1.85$, $p = 0.17$. We also tested whether there is a difference in trading volume across the two days. The within subject ANOVA on log transformed trading volume is: [$F(1,54)= 3.475$, $p= 0.067$)] although it is significant on the non-transformed trading volume [$F(1,54)= 5.099$, $p= 0.028$)]. The non-parametric Friedman test confirms that there is no significant difference $\chi^2(1) = 1.19$, $p = 0.2$. As it is known that the effect of emotion wears off with time (Lerner & Keltner 2006), we have also tested the influence of conditions over 5 minute time periods and found that trading volume does declines with time ($\beta = -0.09$, $p < .01$).

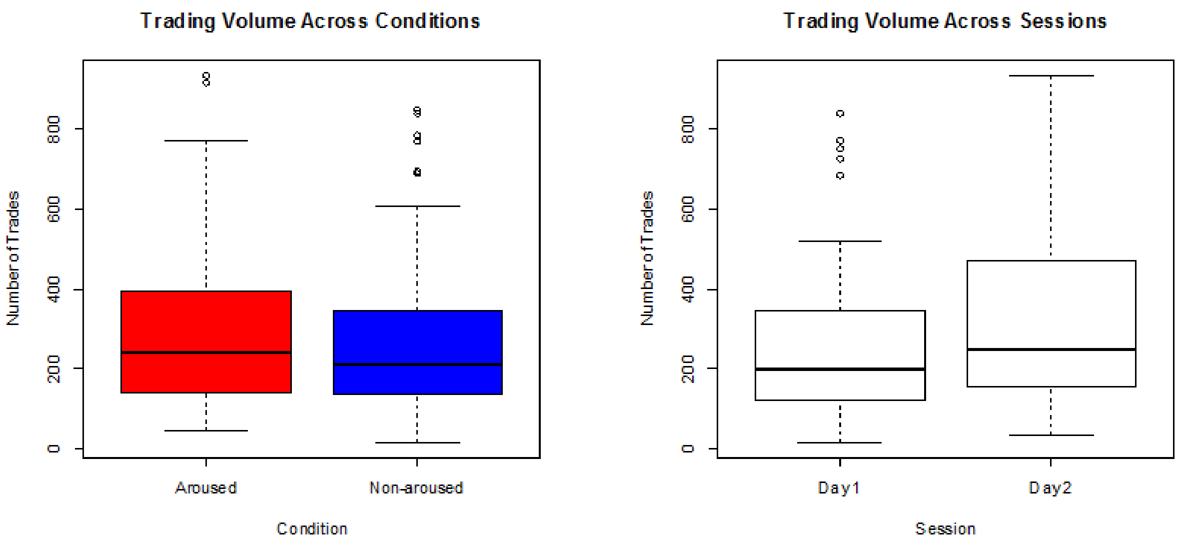


Figure 5.4. The first boxes capture the IQR distribution of trades by condition and the second boxplot show the trading volume across the two days. Outliers are below Q1 – 1.5×IQR and above Q3 + 1.5×IQR, which mark the endpoints of the whiskers.

Given that the study has a within subject design and number of transactions as a dependent variable we used a mixed effects Poisson model. The model includes full random effects, with by subject adjustments to the intercept and by-subjects adjustment to the slopes for the effect of condition (the only within subjects variable in the analysis). The regression results are reported in Table 5.3. The main effect of the condition is non-significant, in agreement with the nonparametric analysis reported above. Overall older participants are less likely to transact. The 95% confidence intervals indicate that only age is significant. The interactions between CRT and neutral condition as well as the interaction between intuitive and neutral condition is marginally significant. This means that those scoring higher on intuition and CRT are more affected by the arousal condition and are marginally less likely to transact. Schunk et al. (2005) did suggest that intuitive individuals use affective decision making processes therefore they could have been more affected by the negative valance images. Given the unexpected nature of these interactions, their marginal significance, the number of main effects and interactions included, we do not make theoretical claims for these. In an analysis with 25 tests, we would expect to see a number of type I errors.

Table 5.3 Poisson mixed effects model results

	Transactions	**P Value**	**95% Confidence Intervals**	
(Intercept)	7.684	0.000	5.956	9.412
Age	**-0.103**	**0.013**	**-0.184**	**-0.022**
CRT	-0.105	0.282	-0.297	0.087
Deliberate	0.005	0.965	-0.223	0.233
Agree	0.155	0.165	-0.064	0.374
Conscientious	0.027	0.800	-0.182	0.236
Open	0.052	0.595	-0.140	0.245
Regret	0.130	0.219	-0.077	0.336
SSS	-0.046	0.636	-0.234	0.143
Impulsive	0.114	0.368	-0.134	0.362
Extravert	-0.077	0.499	-0.301	0.147
Intuitive	-0.103	0.306	-0.301	0.094
Neurotic	-0.015	0.896	-0.246	0.216
Neutral condition	-0.868	0.336	-2.636	0.900
Age ×neutral condition	0.035	0.404	-0.048	0.118
CRT × neutral condition	**0.181**	**0.070**	**-0.015**	**0.377**
Deliberate × neutral condition	-0.179	0.133	-0.411	0.054
Agreeable × neutral condition	-0.133	0.244	-0.357	0.091
Conscientious × neutral condition	0.076	0.487	-0.138	0.289
Open × neutral condition	-0.076	0.448	-0.273	0.121
Regret × neutral condition	0.056	0.600	-0.155	0.267
SSS × neutral condition	-0.043	0.664	-0.236	0.150
Impulsive × neutral condition	0.080	0.536	-0.173	0.333
Extravert × neutral condition	0.042	0.720	-0.187	0.271

Intuitive × neutral condition	**0.195**	**0.059**	**-0.007**	**0.396**
Neurotic × neutral condition	-0.115	0.339	-0.351	0.121

5.4 Factor Analysis and Results

5.4.1 Factor analysis

Given that we have numerous measures and 55 participants we conducted factor analysis to reduce the number of factors as previous results are inconclusive. Figure 5.5 is a scree plot, which shows the optimal number of factors to extract. Based on eigenvalues and parallel analysis we continue with a 5 factor model (the 3 factor model gives very similar results), which explains about half of the variance. Table 5.4 reports the factors extracted from the analysis as well as the eigenvalues and the factor loadings. Deliberate, conscientious and age load positively on the first factor while impulsive and neurotic load negatively. Extravert, agreeable and intuitive load positively on the second factor with neuroticism loading negatively. The fourth factor consists of openness variable. Lastly sensation seekers load positively on the fifth factor and agreeable load negatively on it. The main factors are arbitrarily named as "Thoughtful", "Bubbly", "Regretful", "Openness" and "Risk Seeker".

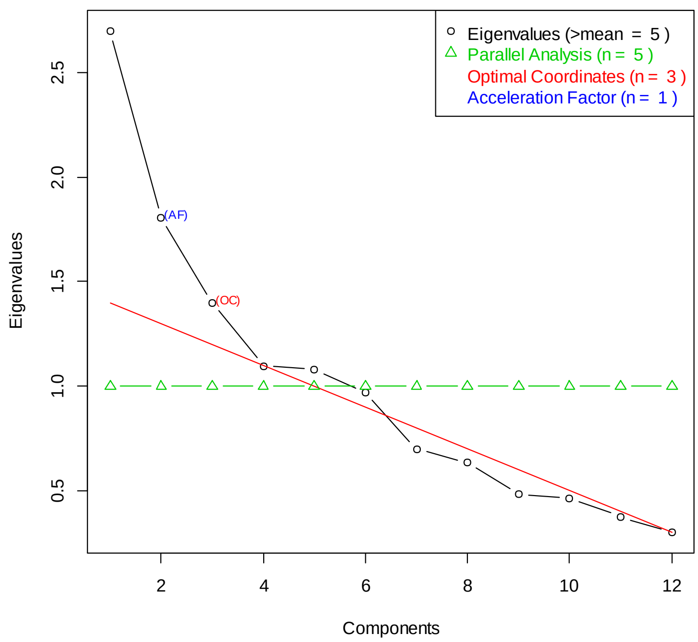


Figure 5.5. Scree plot illustrating optimal factor analysis solution variants.

Table 5.4 Factors extracted from factor analysis

Variables	**Thoughtful**	**Bubbly**	**Regretful**	**Openness**	**Risk Seeker**
Eiganvalues	1.88	1.6	0.94	0.72	0.51
Variance Explained	0.16	0.13	0.08	0.06	0.04
Cumulative Variance Explained	0.16	0.29	0.37	0.43	0.47
Factor Loadings					
Deliberate	0.67				
Impulsive	-0.83				
Conscientious	0.53				
Extravert		0.71	-0.33		
Agree		0.78			-0.38
Regret			0.73		
Open				0.73	
Age	0.45				
Intuitive		0.49			
CRT					
Neurotic	-0.41	-0.43	0.44		
SSS					0.49

5.4.2 Factor Analysis Results

As previously we use a Poisson mixed effects model to find marginal significant negative main effect for Thoughtful and a marginal significant positive main effect for regretful (Table 5.5). The conditions however are non-significant. The 95% confidence intervals suggest that the factor Thoughtful is just on the borderline of significance.

Table 5.5 Poisson mixed effects model results with factors extracted from factor analysis.

	Transactions	**P Value**	**95% Confidence Intervals**	
(Intercept)	5.489	0.000	5.302	5.676
Cond.Neutral	-0.113	0.256	-0.307	0.082
Thoughtful	**-0.205**	**0.052**	**-0.411**	**0.000**
Bubbly	0.056	0.594	-0.150	0.261
Regretful	**0.218**	**0.063**	**-0.012**	**0.448**
Openness	-0.012	0.905	-0.201	0.178
Risk Seeker	-0.087	0.469	-0.321	0.148
Thoughtful×Cond.Neutral	-0.047	0.666	-0.261	0.167
Bubbly×Cond.Neutral	0.049	0.652	-0.164	0.262
Regret×Cond.Neutral	-0.113	0.355	-0.351	0.126
Open×Cond.Neutral	-0.036	0.723	-0.233	0.162
Risk×Cond.Neutral	-0.004	0.971	-0.248	0.239

5.5 Discussion

The aim of the current study was to test whether incidental emotions influence trading behavior in an experimental set up and whether psychometric attributes mediate the effect of arousal on trading behavior. In this experiment we had two conditions, aroused and non-aroused. We also collected participants' psychometrics to test for individual differences. The results indicate that older participants trade less---even though our participants' age ranged from 18 to 29 years of age. Looking at the psychometrics, of marginal significance is the interaction between CRT and arousal. In an aroused condition those who have preference for intuition trade less than their counterparts. As addressed in the introduction, Schunk et al. (2005) found that individuals with preference for intuition are more likely to use affect-based reasoning therefore in our study such individuals could have had a stronger reaction to the negative valance condition. From the factor analysis we find that Thoughtful participants trade less. As it loads highly on the variable "deliberate", it is consistent with the results from the main regression analysis.

Although the trading volume is higher in the aroused condition, which is consistent with previous studies on arousal valence and risk-preferences (Mano 1994) the main effect is non-significant. One explanation for such a result could be because participants were already excited about learning how to trade using the professional platform. In the feedback form conducted at the end of the experiment participants noted that trading was difficult yet very exciting. This could mean that the aroused condition was dominated by the task at hand. In terms of the appraisal tendency framework integral emotions caused by the trading task could have dominated the incidental emotions brought about by viewing the images. One solution is to conduct the experiment over a longer time period as was done by Seo et al. (2007, 2010). Lo et al. (2005) also conducted their study over 25 days and measured traders' psychological profiles via survey before and after trading. The authors found correlation between emotional reactivity and performance. Conducting an experiment in such a away would significantly reduce the novelty of trading and minimize the effect of integral emotions caused by the task at hand. Moreover the trading itself could have been so demanding that it blocked the arousal manipulation. Also, in the future rather than using simply the trading volume, limit and market orders should be considered to measure the change in the aggression of the orders conditional on arousal and psychological attributes.

In light of the current results it would be optimistic to provide any definite links between arousal personality and trading preferences. However given the mentioned experimental limitations, the relationships should not be dismissed. Such relationships could be applied for practical investment advice, better understanding of individual investors' behavior as well as the understanding of the inconsistencies within the financial markets and asset pricing. Further investigation could contribute to the understanding of how traders react in abnormal market environment and how the reactions are reflected in the market volatility for example. While financial and economic models all assume stable and consistent preferences, the behavior evoked by emotions, personalities and exogenous factors could be an under-appreciated cause for market dynamics.

CHAPTER 6

Conclusion

Contents:

Abstract

This chapter summarizes the research objectives of the thesis. It highlights the empirical findings from each section and addresses the importance of psychological research within the fields of finance and economics. The behavior of real investors has a direct impact on the dynamics of the financial markets and asset pricing. For each research question the chapter highlights limitations as well as possible improvements, future research ideas and strategies for investors and policy makers. It concludes by suggesting that incorporating insights from psychology into economics can paint a more realistic picture of investors' behavior, their role within the financial markets and the effects on the economy.

6.1 Introduction

The objective of the current study was to test whether insights from psychology can explain investors' behavior within the financial markets including their selective attention, trading behavior, risk preferences and portfolio performance. Individual investors do not behave in accordance with the assumptions of rational economic theory. Instead, agents' trading behavior can be largely explained by a myriad of psychological factors, which include stable individual differences (e.g. personality), emotions and individual responses to exogenous factors. The following chapter summarizes the empirical findings of the previous chapters and outlines how the research questions and goals of this thesis were achieved. The summary of the main finding in Chapters 3, 4 and 5 is presented in Table 6.1. Section 6.2 offers a further discussion of the results including a summary of main successes, limitations and directions for future research. Lastly this chapter concludes with a note on the importance of this research for the field of behavioral finance.

Table 6.1: Main summary points in Chapters 3, 4 and 5

<u>Chapter 3:</u>

- Investors monitor portfolio as meerkats not ostriches as previously suggested (Karlsson et al. 2009; Sicherman et al. 2013). Investors monitor their portfolio more following both positive and negative market returns.

- Investors' portfolio monitoring depends on the personality trait of neuroticism. Neurotic investors are less sensitive to returns given positive market returns and are more sensitive given negative market returns.

- Given that investor has loged in to monitor own portfolio, the investor is more likely to transact in the falling market than in the rising market, but they login to monitor portfolio more in the rising market.

<u>Chapter 4:</u>

- A number of psychological attributes contribute to explaining significant amount of variance in trading behavior, risk preferences and portfolio performance.

- Using inconsistent proxies for psychological attributes and univariate regressions to explain trading behavior, risk preferences and portfolio performance and can lead to incorrect conclusions. For example, below is a table highlighting attributes which are significant in the univariate models yet non-significant in the multivariate models. Attributes that are significant in full models are also provided.

Dependent Variables	**Attributes with Effect in Univariate Model & Non-significant in the Full Model**	**Significant Attributes in the Full Model, (Direction of the effect is indicated by (+/-))**
Mean Returns	Cohabitating	**(+)** Age, CRT, Subjective Numeracy, Financial Knowledge, Delegation **(-)** Decision Maker, LOC, Training,
Risk (portfolio diversification)	Married, Joy, Monitors, Investment horizon, Discount, Impulsive, Patient, Neurotic, Aversion	**(+)** Wealth, Decision Maker, Risk Taker , Winning Investment, Research Hours, Training **(-)** Age, Financial Knowledge
Sharpe Ratio (risk adjusted returns)	Married, Wealth, Risk Taker, Discount, Impulsive, Patient	**(+)** Age, Dependents, CRT, Financial Knowledge, Churn **(-)** Male, Decision Maker, Winning Investment, Training, Years Trading
Deals (trading frequency)	Gender, Better than Average, Risk Taker, Winning Investment, Perceived Financial Expertise/Competence, Financial Knowledge, Research Hours, Training, Patience, Neurotic	**(+)** CRT, Monitors, Subjective Churn ,Years Trading, Planner, Impulsive, **(-)** Divorced, Wealth, Joy, Numeracy, Research Use, Investment Horizon, Discount, Regret, Aversion, Belief in Skill
Notional(average size of the trade)	Age, Income, Perceived Financial Expertise/Competence	**(+)** Wealth, LOC, Research Use, **(-)** Decision Maker, Investment Horizon
Trade Ratio (propensity to trade given a login)	Widowed, Income, Financial Knowledge, Patience	**(+)** Age, Joy, CRT, Financial Expertise, Churn Research Hours, Impulsive, Delegation. **(-)** Gender, Cohabitating, Monitors, Research Use, Investment Horizon, Discount, Regret
Return On Investment	Perceived Financial Expertise	**(+)** Income, Monitors, Aversion **(-)** Wealth, Dependents, Joy, Subjective Numeracy, Research Hours, Investment Horizon, Belief in Skill, Delegation.

- Frequent trading is not necessarily detrimental. Investors using analytical rather than intuitive decision making processes, who are more knowledgeable about the market and those who prefer to trade frequently transact more *and* have higher risk adjusted returns. The opposite is true for investors who had training in finance or a related field.

- Regression analysis with new factors form factor analysis indicate that superior investors are more mature (older and wealthier) and use analytical rather than intuitive decision making process. Worse performing investors are sensation seeking and those who have had previous financial training.

Chapter 5:

- Older participants trade less.

- Negative affect makes participants trade more, although the main effect of the manipulation is not significant.

- Intuitive investors are more affected by aroused condition than their counterparts.

6.2 Chapter Review: Successes, Limitations and Future Research

The first chapter introduces an overview of the thesis. It presents the classical theoretical framework from economics and the behavioral finance. Recent empirical evidence is introduced, which suggests that within financial markets real investors do not behave like the agents from the rational models. Chapter 1 highlights the inconsistencies between the normative models and the investors' observed behavior based on a review of empirical literature. It also introduces various psychological explanations that could account for investors' behavior. At the same time, the review points out to the lack of agreement between different studies and theoretical accounts. . Based on this summary, Chapter 1 sets up the rationale for the research questions and outlines the research goals, which are subsequently addresses in detail in Chapters 3, 4 and 5.

Chapter 2 introduces the methodology used throughout the thesis. In analysing investors' selective attention to their portfolio performance we use hierarchical equation modelling. Next, the chapter describes the investor sample selection process, how the psychometrics survey was constructed and how the data were collected. Given the nature of the survey, missing data was unavoidable as not every investor answered all the questions. In order not to lose any information caused by non-responses, the missing data were imputed. Chapter 2 describes various imputation techniques, provides examples and introduces the multiple imputation method that was adopted to impute the missing data. The chapter also introduces all the financial variables and how they were constructed. Lastly, it briefly discusses the trading platform (TT) and the visual stimuli used in Chapter 5.

Chapter 3 explores economics of information. Karlsson et al. (2009) presented a psychological decision-theoretic model to account for selective attention. This chapter investigates individual investors' portfolio monitoring decisions and tests the selective attention hypothesis. The results imply that investors selectively monitor their portfolio; however, the behavioral pattern is somewhat different from that reported in earlier studies. Karlsson et al. and Sicherman et al. (2013) found that their investors login to monitor their portfolio and to trade more given positive market returns and "stick their heads in the sand" given negative market returns. The results in this study suggest that, in this active sample, investors increase monitoring given both positive and negative news, a pattern we call the meerkat effect. While previous studies suggest the selective attention is driven by the psychological factors, this study actually tests this by introducing a trait of neuroticism to find that neurotic investors and their counterparts have different preferences for information. Given positive market returns all investors monitor their portfolios more, but the neurotic investors are less sensitive to positive returns than non-neurotic investors. Following negative market returns, neurotic investors monitor increasingly more than non-neurotic investors. This study also finds that although there are fewer logins after negative market returns, these logins are more likely to result in a trade.

There are many reasons why it is important to understand information acquisition decisions. First according the efficient market hypothesis all available information should be reflected in the asset pricing. According to normative models more information is better as it enables individuals to make better decisions and investors should have a stable demand for information. The concept that information has a direct impact on investors' utility has not been recognized within the standard economic paradigm in which utility is only affected at the final consumption or at a trading point. This study shows that investors face a trade-off between objective value of information and its hedonic value, behavior which is at odds with the rational models. Second, selective monitoring has a direct impact on trading volume. For an investor to trade he must log into the account. If all investors decide to login at once and trade, this could lead to an overreaction in the market as increased trading would increase the volatility in the markets in turn causing sharp market movement. This is highlighted in the model presented by Sicherman et al. (2013) that links investors' selective attention and its impact on the stability of the financial markets induced by different types of price volatility and time-varying market risk premia.

Third, the role of personality trait of neuroticism, which is associated with high levels of anxiety, should not be dismissed. Indeed some authors refer to anxiety as a personality trait (Wilt, Oehlberg & Revelle 2011). Caplin and Leahy (2001) have incorporated anxiety into the expected utility model and argued that it could account for the equity premium puzzle (Mehra & Prescott 1985; Benartzi & Thaler 1995). In Caplin and Leahy's model individuals not only are concerned with the final consumption as predicted by the normative models of choice, but also with the anxiety associated with holding the investment. Forth, the instability in the financial markets impacts the economy and has spill over effects outside of financial markets.

Future research should consider investors trading behavior in more depth. Firstly separating buying and selling decisions within the positive and the negative market returns domains and then separating these buys and sells based on the individual characteristics of investors. For example, a widely studied phenomenon within behavioral finance is the disposition effect (Shefrin & Statman 1985). In this context, if the effect is present, it could be attributed to a specific group of investors with certain psychological factors. Exploring who buys and who sells at each turning point of the stock market could shed light on investors' trading strategies. Future research could also consider past portfolio returns rather than market returns as the predicting variable. For example in analysing investors trading behavior Glaser and Weber (2009) found that both past market returns and past portfolio returns increase trading, however only past portfolio returns increase the amount of risk investors are willing to hold in their portfolio and they attribute such behavior to self-attribution bias.

Considering limit orders and market orders is another avenue for future research. For example it could address the question of whether an investor logs in to monitor portfolio or to place a limit order. While the limit order data is not available in this dataset, one option is to see whether monitoring over a weekend is related to the number of trades executed on a Monday. If Monday's trading is related to the weekend monitoring, it could be indicative of investors' strategic trading behavior over the weekend. Furthermore, studies could test whether mood inducing events such as the amount of sunshine (Hirshleifer & Shumway 2003) or geomagnetic activity (Kamstra, Kramer & Levi 2003) have an impact on monitoring and trading behavior. Lastly as an extension of this research it would be interesting to consider the influence of other psychological attributes such as risk preferences and financial expertise on portfolio monitoring and trading preferences.

Chapter 4 tests whether psychological attributes can explain the reasons and motives for the observed investors' trading behavior, risk preferences and investors' portfolio performance. Investors' psychological attributes account for significant variation (adjusted R^2) in investors' portfolio diversification, trading volume, risk adjusted returns, trade size and average daily mean returns. Moreover including multiple attributes in one model makes previously reported effects non-significant. Modern portfolio theory (Markowitz 1959) and capital asset pricing model (Sharpe 1964; Lintner 1965; Mossin 1966) dictate that investors should hold a well-diversified portfolio in order to minimize the idiosyncratic risk related to each of the assets, which means holding a variety of assets in order to maximize portfolio returns for minimal risk. Yet empirical evidence suggests that investors hold underdiversified portfolios (Goetzmann & Kumar 2008; Grinblatt, Keloharju & Linnainmaa 2011; Kimball & Shumway 2007; Kumar (2009). According to efficient market hypothesis all information should be reflected in the value of the asset, therefore investors should not trade with one another as it should be impossible to make profits above the market returns. However recent literature highlights that investors overtrade (Barber & Odean 2001; Deaves et al. 2008; Dorn & Huberman 2005; Dorn & Sengmueller 2009; Graham et al. 2009; Grinblatt & Kelohaju 2009) and some investors' portfolios under (over) perform (Anderson 2013; Fenton-O'Creevy et al. 2003; Grinblatt et al. 2012; Korniotis &Kumar 2013; Seru et al. 2010). The normative framework cannot account for the observed anomalies in the financial markets, the recent models in behavioral finance are also at odds with the empirical findings and empirical finding exploring the same phenomenon is inconsistent.

Recent literature attempted to explain investors' behavior in terms of psychological biases. Many studies use either proxies for psychological attributes such as gender for overconfidence (Barber & Odean 2001) or use models with only one or two psychological attributes. Given the rich dataset, this study shows the importance of looking at multiple psychological attributes. We fist consider the effect of demographics on all financial measures. Then we build models with all 32 attributes as well as univariate models for comparison. Lastly we conduct factor analysis and reduce the model to 11 factors. The gender effect on trading, although significant in the univariate model and consistent with Barber and Odean's (2001) suggestion becomes non-significant in the full model with other psychometric measures. Therefore using demographics as proxies for psychological attributes should be considered with caution. In the full model investors who monitor the market, plan ahead and score high on impulsivity trait, trade most frequently. Also in relation to previous literature that found correlations between trading and better than average (Glazer & Weber2007), risk taker (Grinblatt & Keloharju 2009), perceived financial expertise/competence (Graham et al. 2009; Dorn et al. 2009), in the full model these attributes become non-significant. In relation to investors who chase winning investment, the results in the full model support Kumar's (2009) suggesting that those who chase lottery-like stock do not necessarily trade more but do hold riskier portfolios. Moreover, trading more frequently is not necessarily detrimental. For example those investors who are more analytical (rather than intuitive) in decision making and those who prefer to churn stocks, tend to trade more frequently *and* have better risk adjusted returns. On the other hand those investors who have trading experience also trade more yet they have negative risk adjusted returns. This corroborates Gervais and Odean's (2001) suggestion that experience may lead investors to engage in excessive trading caused by inflated overconfidence.

From factor analysis we can conclude that successful investors have superior financial market knowledge, they use analytical rather than intuitive reasoning and they are more mature in terms of age and wealth. Least successful investors are sensation seekers and those who have had previous training in finance or a related field.

The results could be applied both in practical and theoretical frameworks. For example for a wealth management advisor it would be beneficial to know what type of client they are dealing with and also be aware of own characteristics prior to recommending any investments. For example if an investor is impulsive then a self-control mechanisms could be arranged, which would prevent him from trading too frequently. Such an investor could also employ someone to manage their portfolio rather than have an on-line trading account. Furthermore, financial models should incorporate psychological insights. The results also indicate what personal characteristics are important to be a successful investor. For example while previous training in finance or a related field has a negative effect on performance, more specific financial knowledge has a positive effect on performance. Although much of the high-frequency trading is done using algorithms, it is still important for advisors and for individual investors to understand what influences investment decisions. Future research could experimentally test whether being aware of own behavior can improve investment decisions as per the example above. While in the current study the main focus was the effect of individual differences, future research could also consider time-series analysis and incorporate market returns and portfolio returns to the current static framework.

In an experimental framework, Chapter 5 tests whether incidental emotions affect participants' trading behavior and whether psychological attributes mediate the effect. Older participants trade more and those in the negative affect condition compared to neutral condition also trade more, yet the main effect of arousal is non-significant. Participants with a preference for intuition are more affected by the aroused condition than their counterparts. Whereas the role of affect has gained an important role within psychology, it has yet to be explored within the behavioral finance. Some theories in psychology posit that emotions work in parallel with cognition such as the somatic marker hypothesis (Damasio 1994); some say emotions are used as heuristics (Finucane et al. 2000). Others suggest that emotions are at the core of the decision making and can even overpower the cognitive decision for example as in risk as feeling hypotheses (Lowenstein et al. 2001). Nevertheless all agree that emotions play a crucial role in decision under risk and uncertainty and have been considered as explanations for the well-known puzzles in the finance literature such as the disposition effect and the equity premium puzzle.

Although literature in psychology and behavioral finance highlight the importance of emotions in decision making, we believe that the novelty, the excitement and the difficulty of trading itself overpowered the negative affect in the aroused condition. Future research could consider reducing the novelty of trading for participants. One way of achieving this is to have participants trade for a number of days and then on the last day add the aroused condition. Another alternative is to simply use experienced traders. Moreover other methods of inducing arousal should be explored. For example, rather than having participants judge the images that they were not responsible for choosing, participants could write an affect-rich memorable story. Lastly, measuring the change in the level of aggression could be an alternative to measuring trading volume via the gap difference between the market and limit order pricing of trades across the conditions. If arousal causes changes in the differences between the market and the limit order, it could partially explain the market volatility as observed in the real financial markets.

6.3 Conclusion

The main findings of this work suggest that individuals have information-dependent utility and that psychological attributes play an important role in financial decision making. Although all investors are exposed to the same information, their psychological attributes account for significant variation in their information acquisition decisions, portfolio performance, trading and risk preferences. For example an overconfident investor may perceive his information to be superior and therefore trade, while an impulsive investor might simply not be able to resist trading more frequently. We propose that certain traditional concepts used in economics should be modified to reflect the real investors, not those currently populating the models of economics. Much work remains to be done in synthesizing a body of empirical knowledge in cognitive and personality psychology into economics.

Given the increased on-line trading and the desire for immediate performance, investors should have greater awareness about cognitive biases and the impact of emotions in financial decision making. For example as Warren Buffett said “I often make more money when I am snoozing than when I am active” implying that patience is the key to successful trading. However, in the financial markets impulsiveness is hard to resist. Removing cost and illiquidity as barriers to entry is one of the causes for such potential investor impatience. Introducing self-control measures could result in better performance. As for policy implementation, given the differences in the selective attention, individuals will react differently to new policies and market news. Individuals’ possible reaction and the consequences should be taken into account prior to releasing the information to the public. Not only is understanding of individual differences important for economics and finance but also for other fields. For example in a recent court ruling the supreme court of justice for the first time the decision was based on the fact that it acknowledged that the markets are inefficient (Haliburton Co. Et Al. v Erica P. John Fund Inc.).

Lo (2004) proposed the adaptive market hypothesis, a hybrid of efficient markets with behavioral finance. It is an evolutionary model in which individuals adapt to the changing environment, and given that we can measure changes in investors' preferences, environment and investor population, more suitable portfolios could be tailored to each individual's needs. Similarly, economics theory could accommodate insights from psychology, in turn the economic analysis and the models would paint a finer picture as to how financial decisions are made, what impacts the asset pricing and what is the effect of individual differences within the dynamics of the financial markets and the economy.

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8. Appendix

Table 8.1 Definitions of variables

Variable Name	Questions
I (Overconfidence & Sensation-seeking)	
Better Than Average	I believe my investing skill is above average.
Locus of Control	Success in investing is due to hard work and skill, not luck.
Risk Taker	I have invested a large sum in a risky investment for the excitement of seeing whether it went up or down in value.
	It is likely I would invest a significant sum in a high risk investment.
	Compared to other people, I am prepared to take higher financial risks.
	In order to achieve high returns I am willing to choose high risk investments.
	I am willing to risk a significant amount of my wealth in order to get a good return.
	I am a financial risk taker.
	Even if I experienced a significant loss on an investment, I would still consider making risky investments.
	I enjoy making speculative investments in specific assets with portions of my wealth.
Winner	I want to pick winning investments rather than minimize my risk through diversification.*
Joy	I enjoy investing and trading for its own sake.
II (Sophistication Measures)	
Cognitive Reflexion Test (Binary coded)	A bat and a ball cost £1.10 in total. The bat costs £1.00 more than the ball. How much does the ball cost?
	If it takes 5 machines 5 minutes to make 5 widgets, how long would it take 100 machines to make 100 widgets?
	In a lake, there is a patch of lily pads. Every day, the patch doubles in size. If it takes 48 days for the patch to cover the entire lake, how long would it take for the patch to cover half of the lake?
Churn (Financial Lit)	To do well in the stock market, you have to buy and sell your stocks often.(Kimball/Shumway 2007)
Subjective Numeracy (Binary response)	When people tell you the chance of something happening, do you prefer that they use words ("it rarely happens") or numbers ("there's a 1% chance")?
(Fagerlin, A., Zikmund-Fisher, B.J., Ubel, P.A., Jankovic, A., Derry, H.A., & Smith, D.M. Measuring numeracy without a math test: Development of the Subjective Numeracy Scale (SNS). Medical Decision Making, 2007: 27: 672-680)	How good are you at calculating a 15% tip?
	When reading the newspaper, how helpful do you find the tables and graphs which are part of a story?
	How good at you at working with percentages?
	How often do you find numerical information to be helpful?
	When you hear a weather forecast, do you prefer predictions using percentages (e.g., “20% chance of rain today”) or predictions using only words (e.g., “a small chance of rain today”)?*
Perceived Financial Expertise/Competence	I have confidence in my ability to make good financial decisions.
	Compared to an average person, I am (choose one) informed about current financial conditions.

	Compared to an average person, I am (choose one) informed about investing in general.
	I have more experience with investing than the average person.
Planner	In general, how much do you think about and plan for your future?
Monitor	I frequently check my investments just to know the value.
	I like to be constantly aware of how my investments are performing.
	I frequently check my investments to reassess my opinion of future performance.
Investment Horizon	When investing a significant amount, what do you consider to be an appropriate investment horizon?
Years trading	For how long have you been investing directly, i.e using a stock brokerage service to make investments?
Financial Literacy	When an investor spreads money among different assets, does the risk of losing money:
	0- Do not know; 1- Increases; 2- Decreases; 3 - Stays the same
	If the interest rate rises, what should happen to bond prices?
	0- Do not know; 1- Rise; 2- Fall; 3- Stay the same
	Suppose you had £100 in a savings account, the interest rate was 10% per year and you never withdraw the money or the interest payments. After 5 years, how much do you think you would have in the account in total? 0- Do not know; 1- More than £150; 2- Exactly £150; 3- Less than £150
	Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account?
	0- Do not know; 1- More than today ; 2- Exactly the same; 3- Less than today
Research Hours	How many hours a week do you spend trading or researching potential investments? *(range 0-40h)*
Research Use	How often do you use research publications or analyst advice?
Past Training	I work in, or have significant training in finance, economics, mathematics or statistics.
III (Affective Processes)	
Impulsive	I am an impulsive person.
Patience	Which would you prefer? A) £1,000 today or B) £1,100 one year from now?
Regret	Whenever I make a choice, I try to get information about how the other alternatives turned out and feel bad if another alternative has done better than the alternative I have chosen.
Discount Rate: (higher value=lower rate)	Imagine someone offered you a guaranteed £100 one year from now if you give them money today. What is the maximum you would be willing to pay now for this guaranteed £100 in one year?*
IV (Avoidant Behavior)	
Market Avoidance	I put my money into banks rather than investments because I want my money to be safe from risk.
	I hold cash rather than stock-market investments because I want to be safe from risk.
	Compared to holding cash, buying stocks and shares is too risky.
	I hold cash rather than stock-market investments because I want to be safe from risk.
	In general, investing directly in financial markets is too risky.

	Investing in shares is something I don't do, since it is too risky.
	I would not put even a small amount of my money into high risk investments.
Delegation	I want an investment manager to do the work for me.
	I would like to have independent external advice about my investments.
	I could trust an investment manager to manage my portfolio effectively.
Belief in skill	I believe it is worth paying for the skill of an investment manager.
	Investment managers are able to get better returns than the market average for their investors.
	I would want my investment manager to be using the most sophisticated techniques available.
Liquidity	I often have an unforeseen need to withdraw a significant amount of money from my account.
	It is important for me to be able to withdraw money from my investment at short notice.
Neuroticism	I am not easily bothered by things.*
	I fear for the worst.
	I get stressed easily.
	Uncertainty makes me uneasy, anxious or stressed

Note: This Table shows the questions that investors answered. These were used to construct the independent variables. The resulting scores were normalized: mean = 0 and standard deviation=1. Reverse coded questions are market with *.

Table 8. 2 Correlations of all independent variables

	Age	Male	Status	Weath	Dependents	Income	BTA	Churn
Age	1.00	-0.02	0.00	0.36	0.02	-0.08	-0.07	0.15
Male	-0.02	1.00	-0.09	0.07	0.09	0.20	0.11	-0.06
Married	0.00	-0.09	1.00	0.01	0.02	0.06	-0.03	0.08
wealthCat	0.36	0.07	0.01	1.00	0.15	0.40	0.16	-0.12
Dependents	0.02	0.09	0.02	0.15	1.00	0.36	-0.01	0.00
incomeCat	-0.08	0.20	0.06	0.40	0.36	1.00	0.14	-0.02
BTA	-0.07	0.11	-0.03	0.16	-0.01	0.14	1.00	-0.11
Churn	0.15	-0.06	0.08	-0.12	0.00	-0.02	-0.11	1.00
Dm	-0.09	-0.19	0.11	-0.12	-0.01	-0.01	-0.01	0.05
Joy	-0.16	0.16	0.18	-0.18	-0.07	-0.03	0.07	0.04
Loc	0.03	0.00	-0.01	0.08	-0.02	0.00	0.17	0.10
aversion	0.18	-0.15	-0.01	-0.02	-0.02	-0.11	-0.18	0.13
risktaker	-0.40	0.10	0.06	-0.12	0.04	0.10	0.21	-0.04
subjectiveexpert	-0.09	0.13	0.01	0.26	-0.04	0.14	0.59	-0.29
SubjNum	-0.28	0.02	0.02	0.01	0.05	0.14	0.19	-0.21
winInvest	-0.23	0.13	0.10	-0.29	-0.01	-0.05	0.02	0.06
CRT	-0.08	0.25	0.06	0.21	-0.17	0.18	0.24	-0.21
Discount	-0.01	-0.24	-0.03	-0.22	0.06	-0.09	0.05	0.18
impulsive	-0.21	-0.01	-0.09	-0.11	0.02	0.11	0.06	0.02
monitors	-0.01	0.08	0.03	0.02	-0.03	-0.07	0.27	-0.11
Patience	0.11	0.08	0.03	0.14	0.06	0.23	-0.05	-0.17
Planner	-0.04	0.01	0.05	0.17	0.10	0.04	0.24	-0.21
Regret	-0.14	-0.08	0.00	-0.17	-0.11	0.08	0.10	0.11
beliefSkill	-0.13	-0.06	0.02	-0.25	-0.07	-0.09	-0.09	0.19
delegation	-0.15	-0.03	0.01	-0.18	-0.02	-0.03	-0.17	0.17
incRisk	-0.19	0.05	0.08	0.20	0.18	0.27	0.14	-0.14
invHorizon	0.01	-0.07	0.02	0.02	-0.01	0.01	-0.02	-0.08
Liquidity	0.00	0.02	-0.02	-0.10	0.08	-0.08	-0.07	0.24
Neurotic	0.05	-0.06	0.03	0.05	-0.02	-0.12	-0.20	0.07
researchhours	-0.23	0.03	-0.18	-0.02	-0.11	-0.06	0.16	0.04
researchuse	0.21	0.06	-0.17	0.16	-0.05	-0.02	0.09	-0.08
Training	-0.07	-0.04	-0.04	0.09	-0.07	0.07	0.37	0.08
finKnowledge	0.09	0.08	0.01	0.25	-0.02	0.16	0.09	-0.20
yearstrading	0.07	0.15	0.03	0.27	0.01	0.11	0.13	0.14

	Decision Maker	Joy	Locus of Control	Aversion	Risk Taker	Subjective Expert	Subjective Numeracy	Winning Invest
Age	-0.09	-0.16	0.03	0.18	-0.40	-0.09	-0.28	-0.23
Male	-0.19	0.16	0.00	-0.15	0.10	0.13	0.02	0.13
Married	0.11	0.18	-0.01	-0.01	0.06	0.01	0.02	0.10
wealthCat	-0.12	-0.18	0.08	-0.02	-0.12	0.26	0.01	-0.29
Dependents	-0.01	-0.07	-0.02	-0.02	0.04	-0.04	0.05	-0.01
incomeCat	-0.01	-0.03	0.00	-0.11	0.10	0.14	0.14	-0.05
BTA	-0.01	0.07	0.17	-0.18	0.21	0.59	0.19	0.02
Churn	0.05	0.04	0.10	0.13	-0.04	-0.29	-0.21	0.06
Dm	1.00	0.11	0.01	-0.02	0.03	-0.09	0.05	0.07
Joy	0.11	1.00	0.01	-0.01	0.12	0.08	0.09	0.22
Loc	0.01	0.01	1.00	-0.05	-0.01	0.20	0.04	0.03
aversion	-0.02	-0.01	-0.05	1.00	-0.45	-0.29	-0.12	-0.13
risktaker	0.03	0.12	-0.01	-0.45	1.00	0.22	0.23	0.40
subjectiveexpert	-0.09	0.08	0.20	-0.29	0.22	1.00	0.21	-0.01
SubjNum	0.05	0.09	0.04	-0.12	0.23	0.21	1.00	0.16
winInvest	0.07	0.22	0.03	-0.13	0.40	-0.01	0.16	1.00
CRT	-0.05	0.21	0.04	0.02	0.09	0.22	0.30	-0.05
Discount	0.05	0.12	0.03	-0.06	0.12	-0.11	-0.11	0.09
impulsive	-0.14	-0.01	-0.07	-0.11	0.33	-0.02	0.02	0.28
monitors	-0.06	0.14	0.17	-0.12	0.16	0.25	0.16	0.21
Patience	-0.04	-0.04	-0.18	0.02	-0.03	0.02	-0.11	-0.13
Planner	0.13	0.05	0.00	-0.13	0.00	0.34	0.31	-0.06

Regret	0.13	0.16	0.07	0.10	0.06	0.03	-0.04	0.09
beliefSkill	0.05	-0.08	0.10	0.09	0.09	-0.20	-0.05	0.22
delegation	0.06	-0.09	0.00	0.14	0.03	-0.28	-0.07	0.16
incRisk	0.06	0.08	0.00	-0.11	0.23	0.14	0.10	0.04
invHorizon	0.08	-0.05	-0.07	-0.03	-0.17	0.02	0.12	-0.24
Liquidity	0.08	0.00	-0.06	0.12	0.06	-0.21	-0.20	0.11
Neurotic	-0.01	-0.04	-0.01	0.23	-0.15	-0.17	-0.20	-0.06
researchhours	-0.08	0.11	0.23	-0.12	0.14	0.16	-0.04	0.01
researchuse	-0.20	-0.06	-0.04	-0.01	-0.04	0.12	-0.05	0.06
Training	0.01	-0.07	0.02	-0.07	0.10	0.26	0.16	-0.05
finKnowledge	-0.07	-0.08	0.10	-0.05	-0.04	0.25	0.02	-0.10
yearstrading	0.03	0.17	0.04	-0.10	0.00	0.22	0.09	-0.06

	CRT	Discount	Impulsive	Monitors	Patience	Planner	Regret	Belief Skill
Age	-0.08	-0.01	-0.21	-0.01	0.11	-0.04	-0.14	-0.13
Male	0.25	-0.24	-0.01	0.08	0.08	0.01	-0.08	-0.06
Married	0.06	-0.03	-0.09	0.03	0.03	0.05	0.00	0.02
wealthCat	0.21	-0.22	-0.11	0.02	0.14	0.17	-0.17	-0.25
Dependents	-0.17	0.06	0.02	-0.03	0.06	0.10	-0.11	-0.07
incomeCat	0.18	-0.09	0.11	-0.07	0.23	0.04	0.08	-0.09
BTA	0.24	0.05	0.06	0.27	-0.05	0.24	0.10	-0.09
Churn	-0.21	0.18	0.02	-0.11	-0.17	-0.21	0.11	0.19
Dm	-0.05	0.05	-0.14	-0.06	-0.04	0.13	0.13	0.05
Joy	0.21	0.12	-0.01	0.14	-0.04	0.05	0.16	-0.08
Loc	0.04	0.03	-0.07	0.17	-0.18	0.00	0.07	0.10
aversion	0.02	-0.06	-0.11	-0.12	0.02	-0.13	0.10	0.09
risktaker	0.09	0.12	0.33	0.16	-0.03	0.00	0.06	0.09
subjectiveexpert	0.22	-0.11	-0.02	0.25	0.02	0.34	0.03	-0.20
SubjNum	0.30	-0.11	0.02	0.16	-0.11	0.31	-0.04	-0.05
winInvest	-0.05	0.09	0.28	0.21	-0.13	-0.06	0.09	0.22
CRT	1.00	-0.14	-0.11	0.21	0.17	-0.04	0.03	-0.05
Discount	-0.14	1.00	0.09	0.12	-0.17	0.04	0.05	-0.03
impulsive	-0.11	0.09	1.00	0.06	0.11	-0.20	0.16	0.09
monitors	0.21	0.12	0.06	1.00	-0.16	0.18	-0.05	0.04
Patience	0.17	-0.17	0.11	-0.16	1.00	-0.03	-0.10	0.08
Planner	-0.04	0.04	-0.20	0.18	-0.03	1.00	-0.15	-0.09
Regret	0.03	0.05	0.16	-0.05	-0.10	-0.15	1.00	-0.01
beliefSkill	-0.05	-0.03	0.09	0.04	0.08	-0.09	-0.01	1.00
delegation	-0.15	-0.01	0.13	-0.11	0.11	-0.17	-0.01	0.64
incRisk	0.07	-0.04	-0.13	-0.01	-0.05	0.16	-0.06	-0.06
invHorizon	-0.06	-0.16	-0.08	-0.18	0.12	0.03	-0.11	-0.07
Liquidity	-0.03	0.20	0.15	-0.04	-0.01	-0.13	0.14	0.12
Neurotic	0.02	0.00	-0.01	-0.09	-0.05	-0.06	0.20	0.02
researchhours	0.02	0.11	0.08	0.17	-0.12	0.08	-0.16	-0.08
researchuse	0.08	-0.05	0.07	0.15	0.15	0.14	0.02	0.03
Training	0.11	0.04	-0.01	0.02	-0.03	0.06	0.15	-0.05
finKnowledge	0.04	-0.40	-0.04	-0.03	0.19	0.08	0.05	-0.11
yearstrading	0.18	-0.10	-0.10	0.04	-0.08	0.01	0.04	-0.03

	Delegation	Income Risk	Investment Horizon	Liquidity	Neurotic	Research Hours	Research Use	Training
Age	-0.15	-0.19	0.01	0.00	0.05	-0.23	0.21	-0.07
Male	-0.03	0.05	-0.07	0.02	-0.06	0.03	0.06	-0.04
Married	0.01	0.08	0.02	-0.02	0.03	-0.18	-0.17	-0.04
wealthCat	-0.18	0.20	0.02	-0.10	0.05	-0.02	0.16	0.09
Dependents	-0.02	0.18	-0.01	0.08	-0.02	-0.11	-0.05	-0.07
incomeCat	-0.03	0.27	0.01	-0.08	-0.12	-0.06	-0.02	0.07
BTA	-0.17	0.14	-0.02	-0.07	-0.20	0.16	0.09	0.37
Churn	0.17	-0.14	-0.08	0.24	0.07	0.04	-0.08	0.08
Dm	0.06	0.06	0.08	0.08	-0.01	-0.08	-0.20	0.01
Joy	-0.09	0.08	-0.05	0.00	-0.04	0.11	-0.06	-0.07

Loc	0.00	0.00	-0.07	-0.06	-0.01	0.23	-0.04	0.02
aversion	0.14	-0.11	-0.03	0.12	0.23	-0.12	-0.01	-0.07
risktaker	0.03	0.23	-0.17	0.06	-0.15	0.14	-0.04	0.10
subjectiveexpert	-0.28	0.14	0.02	-0.21	-0.17	0.16	0.12	0.26
SubjNum	-0.07	0.10	0.12	-0.20	-0.20	-0.04	-0.05	0.16
winInvest	0.16	0.04	-0.24	0.11	-0.06	0.01	0.06	-0.05
CRT	-0.15	0.07	-0.06	-0.03	0.02	0.02	0.08	0.11
Discount	-0.01	-0.04	-0.16	0.20	0.00	0.11	-0.05	0.04
impulsive	0.13	-0.13	-0.08	0.15	-0.01	0.08	0.07	-0.01
monitors	-0.11	-0.01	-0.18	-0.04	-0.09	0.17	0.15	0.02
Patience	0.11	-0.05	0.12	-0.01	-0.05	-0.12	0.15	-0.03
Planner	-0.17	0.16	0.03	-0.13	-0.06	0.08	0.14	0.06
Regret	-0.01	-0.06	-0.11	0.14	0.20	-0.16	0.02	0.15
beliefSkill	0.64	-0.06	-0.07	0.12	0.02	-0.08	0.03	-0.05
delegation	1.00	-0.07	-0.07	0.12	0.08	-0.10	0.02	-0.06
incRisk	-0.07	1.00	-0.07	-0.01	-0.02	0.10	-0.04	0.17
invHorizon	-0.07	-0.07	1.00	-0.13	-0.05	-0.21	-0.14	0.04
Liquidity	0.12	-0.01	-0.13	1.00	0.09	0.00	0.00	0.27
Neurotic	0.08	-0.02	-0.05	0.09	1.00	-0.05	-0.01	-0.09
researchhours	-0.10	0.10	-0.21	0.00	-0.05	1.00	0.05	0.13
researchuse	0.02	-0.04	-0.14	0.00	-0.01	0.05	1.00	0.04
Training	-0.06	0.17	0.04	0.27	-0.09	0.13	0.04	1.00
finKnowledge	-0.08	0.05	0.07	-0.18	0.06	-0.05	0.22	0.22
yearstrading	-0.04	-0.01	0.10	0.01	-0.02	-0.02	0.07	0.23

	Financial Knowledge	Years Trading
Age	0.09	0.07
Male	0.08	0.15
Married	0.01	0.03
wealthCat	0.25	0.27
Dependents	-0.02	0.01
incomeCat	0.16	0.11
BTA	0.09	0.13
Churn	-0.20	0.14
Dm	-0.07	0.03
Joy	-0.08	0.17
Loc	0.10	0.04
aversion	-0.05	-0.10
risktaker	-0.04	0.00
subjectiveexpert	0.25	0.22
SubjNum	0.02	0.09
winInvest	-0.10	-0.06
CRT	0.04	0.18
Discount	-0.40	-0.10
impulsive	-0.04	-0.10
monitors	-0.03	0.04
Patience	0.19	-0.08
Planner	0.08	0.01
Regret	0.05	0.04
beliefSkill	-0.11	-0.03
delegation	-0.08	-0.04
incRisk	0.05	-0.01
invHorizon	0.07	0.10
Liquidity	-0.18	0.01
Neurotic	0.06	-0.02
researchhours	-0.05	-0.02
researchuse	0.22	0.07
Training	0.22	0.23
finKnowledge	1.00	0.14
yearstrading	0.14	1.00

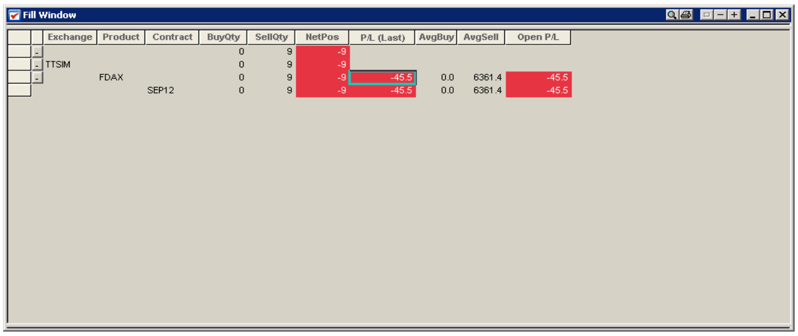
Table 8.3 The quiz participants took prior to trading

Please enter your cubical ID number:___________

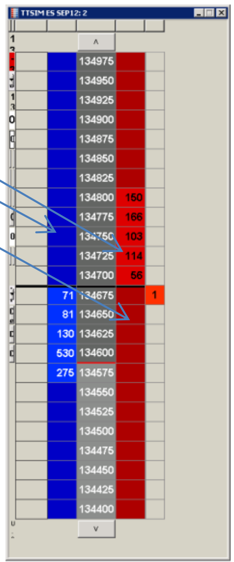
Please answer the following questions.

Use the charts next to the question.

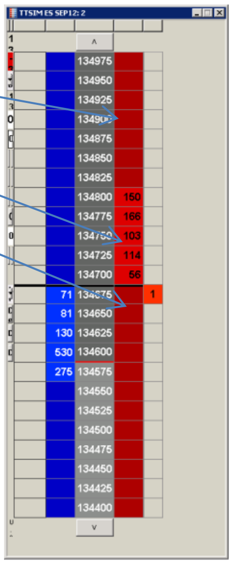
1. You are -9 units, to get back to zero units you should buy 9 units:



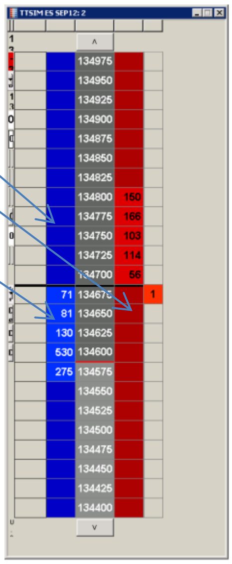
a) Click here 9 times
b) Click here 9 times
c) Click here 9 times



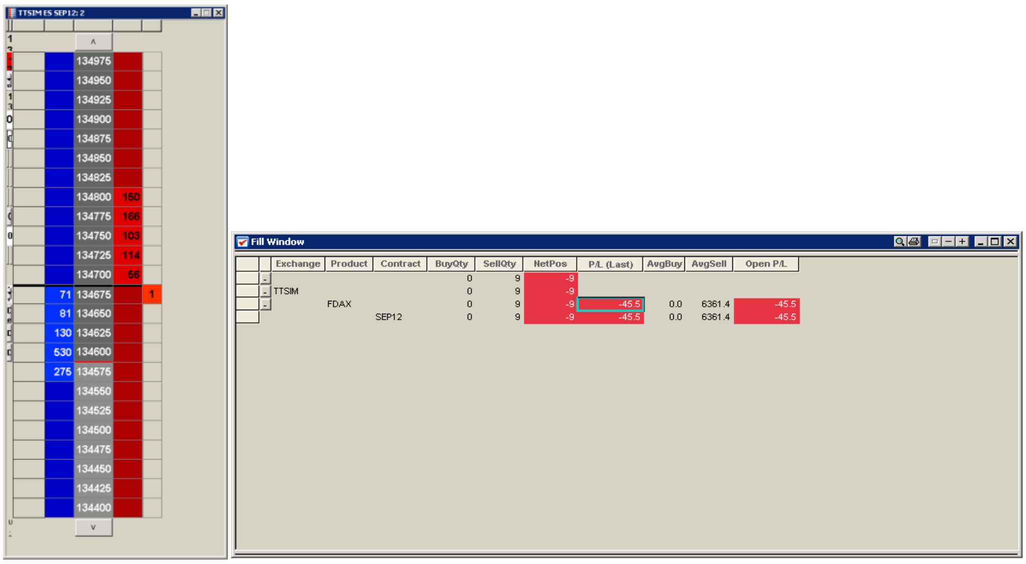
2. How can you sell 5 units at 134725?
   a) Click here 5 times
   b) Click here 5 times
   c) Click here 5 times



3. You want to buy two units **immediately**:
   a. Click here 2 times
   b. Click here 2 times
   c. Click here 3 times



4. How many units do you need to buy to get back to zero units:
   a) 134657 units
   b) 9 units
   c) -45.5 units



5. If I want to delete my current buy limit order of 134575 I should:
   a) Click here
   b) Click here
   c) Click here