Overconfidence, Ability and Gender effects in an Experimental Financial Market

By

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Abstract

This thesis investigates individual's overconfidence bias within the context of an experimental asset market. I relate overconfidence, gender differences and ability in judgement to individual's trading performance and trading activities. The most robust finding that was found in the psychology of judgment issue, with people found to be generally overconfident and evidence of this overconfidence seen in several disciplines. In the financial market, the theoretical models predict that overconfident investors trade excessively. Consequently, trading too much is hazardous to investors' wealth and performances. To contribute to the emerging literature on this topic, overall, 376 participants were involved in an experimental study, through which their degree of overconfidence in judgement have been measured using subjective confidence interval estimation (miscalibration test). In addition to misclaribration score, other psychological bias measures and control variables are also included. During the financial experiments, those individuals were allowed to trade with the virtual agents or against other participants given certain endowments of both cash and shares, depending on the trading rules of each experimental market. By varying the market structure, trading data was collected which that enables us to obtain a much better picture in relation to the actual individuals' behaviour in this experimental environment.

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Chapter 1. Introduction

Rationality was widely assumed by financial economists, who believed that markets to be efficient and reflecting all the available information on stock prices (Fama 1970). However, growing evidence shows that the rational expectation model can not reconcile with witnessed financial market anomalies. For example, there is considerable evidence that when the trading volume is generally high, the consequent returns will be low (Barber and Odean 2000). In many empirical studies, trading volume in financial markets enormously exceeds what full rationality models can plausibly explain (Odean 1999, Barber and Odean 2000). Therefore, psychological bias affecting investor's behaviour has been hypothesized and tested by an accumulation of research, all of which contributes to providing explanations for financial market puzzles.

The most robust finding from previous research into the psychology of judgment is that most people are overconfident (Daniel et al 1998). Various definitions and manifestations of overconfidence bias are mentioned in previous literature (Daniel et al 1998, Scheikam and Xiong 2003). The Overconfidence effect has been defined as people tending to overestimate their ability and the accuracy of their knowledge in different contexts (Lichtenstein et al. 1982; Oskamp 1965; Alpert and Raiffa 1982; Brown 1988; Braumeister 1998). For instance, financial market theoretical models predict that an overconfident investor trades excessively compared to others in the financial market (Odean 1998). Financial economists therefore note that overconfidence can finally harm an investor's wealth due to irrationally aggressive trading. Men and women have also been found to behave differently when trading in the financial market. (Barber and Odean 2001).

The next chapter reviewing previous literature summarises a wealth of important research on this broad topic of overconfidence effect in the financial market. Both empirical and theoretical psychologial studies have predominantly found people are prone to overconfidence in terms of miscalibration. While miscalibration test has been discussed and modelled exclusively in different studies, limited research has been conducted to discover the impact of other manifestations of overconfidence bias on financial market performance. A further limitation of much of the research in this field has been the lack of emphasis on the mechanism how psychological bias affect financial market trading outcomes. Therefore, to uncover the channel by which overconfidence bias affects financial market behaviours needs to be investigated. To some extent, too few of studies have appropriately found the causality between miscalibration and trading volume either empirically or experimentally.

Lastly, a fundamental limitation of much of the research relating to this prominent topic has been overemphasis on overconfidence bias itself and neglect of the ability effect. Thus, it is important to identify the relationship between different psychological bias measures and trading performance to the extent that it contributes to the emerging literature on this topic to help explain behaviour bias in the financial market. To this end, this thesis attempt to characterize the nature of association between overconfidence bias, proxy of ability and financial market behaviours, and that many other factors are at play.

For this purpose, experimental research has been undertaken to simulate a naturally occurring market to investigate these relationships and associated channels. The analysed and designed experiments emphasise in the causality between financial market performance and key overconfidence measurements by controlling extraneous variables. Another advantage of the experimental study is that measures of overconfidence bias and trading data can be collected through surveys and electronic trading games directly, with participants having the incentive to report genuinely and trade seriously.

When analysing the experimental and survey data, we initially test the hypothesis of 'overconfidence generally reduces trading wealth, which is robust by using different overconfidence measures'. This finding contributes to existing literature on the linkage between overconfidence measures and trading losses. In addition to the overconfidence measures widely suggested by psychologists and financial economists, this study defines a new pair of possible measures as proxy variables of ability and overconfidence. To the best of my knowledge, this is the first study that contemporaneously considers that overconfidence rank and quantitative ability rank effect on trading performance. In particular, we found that overconfidence reduce wealth in terms of miscalibration score. Furthermore, overconfidence rank and ability rank affect trading wealth simultaneously in two different directions, extending the scope of previous literature by discussing overconfidence effect with the presence of ability effect.

Secondly, this thesis aims to make contribute to current knowledge by investigating the direct relationship between trading volume and psychological bias. However, no direct and significant association has been found in this experimental study. In contrast, we found that the male participants significantly traded more than their female counterparts under the different experimental set ups, highlighting that a significant gender effect is robust across different analytical models.

Finally, the key advantage of this study is that this experimental research utilizes limit order book data provided by the trading game software, to help shed light on a new perspective to investigate the mechanism how overconfidence bias affects trading performance. We found that subjects who is more aggressive in placing limit orders, have higher ability rank and end up with higher relative wealth.

In summary, this thesis sets out to establish associations between psychological bias and financial market behaviours, and the extent that the mechanism reveals complex causality.

This thesis is organized as follows. Chapter 2 presents previous literatures and sets out a theoretical background which motivate my experimental study. Chapter 3 discusses the experiments and variables. Chapter 4 summarizes empirical methods and descriptive analysis of the data, while Chapter 5, 6 and 7 report and discuss regression results. Chapter 7 concludes.

Chapter 2. Literature review

2.1 Overconfidence in judgement Background

The most robust finding found in the previous psychology of judgment research is that people are overconfident (DeBonbt and Thaler 1985; Lichtenstein, Fishhoff & Phillips 1982). Overconfidence is not just an artefact of psychological research but seems present in many real-life contexts. This argument is sufficiently evidenced in several contexts and supported by both theoretical and empirical findings. For example, studies show that overconfidence significantly affects investment performance (Hanauer 2014; Daniel et al. 1998).

Moreover, as Sakalaki et al. (2005) point out, overconfidence has essential implications to investment decisions. Furthermore, researchers found that overconfidence has impact on investment or saving for retirement (Parker et al. 2012), financial market activities (Glaser and Weber 2007; Statman et al. 2006; Odean 1998) and stock market participation (Xia et al. 2014). These works of literature on overconfidence have greatly enhanced our understanding of investor and decision-making behaviour in financial and economic markets.

In particular, studies on stock markets have brought the attention of many researchers (Odean 1999, Daniel et al., 1998). Indeed, overconfidence is perhaps the most widely investigated topic about behavioural bias involved in recent academic research in the spheres of finance and economics.

Although different definitions and various classifications of overconfidence are mentioned in the early literature (Daniel et al. 1998; Scheinkman and Xiong 203), overconfident behaviour has been widely defined as people tend to overestimate their ability and accuracy of their knowledge in the decision-making process (Lichtenstein et al. 1982; Oskamp 1965; Alpert and Raiffa 1982; Braumeister 1998). Recent studies in psychology have argued that there is strong evidence of different aspects of overconfidence effect. For instance, Odean (1998) found that people who are prone to overconfidence will overestimate the precision of the private information they receive.

In line with the conventional literatures of psychology, this definition is called the miscalibration effect, which is widely known as a psychological foundation of overconfidence (Alpert and Raiffa 1982; Lichtensten et al. 1982). After the term "overconfidence" has been widely used in psychological studies, more extensions of overconfidence effect have been discussed in finance and economics.

For example, as Daniel et al. (1998) put it, people who are prone to overconfidence tend to overestimate their private signals and lead to suboptimal trading decisions. Odean (1998) states that overconfident investors overestimate their ability and trade irrationally in the future. This irrationality may decrease trading profits and the expected utility of those overconfident investors (Barber and Odean 2000, 20001; Gervais and Odean 2001; Hilary and Menzly 2006).

According to Moore and Healy (2008), overestimation, overplacement and overprecision are precisely the most common concepts about overconfidence mentioned in prior studies. Firstly, as defined above, people tend to overestimate their ability and power of control (Grieco and Hogarth 2009). Secondly, Moore and Healy 2008 define overplacement as when people believe themselves to be better than others, which is also known as the “better-than-average” effect (BTA). BTA is commonly referred to the fact that investors classify themselves of "above average level" comparing to their counterparts. (Moore and Healy 2008; Scott et al. 1999; Menkhoff et al. 2006). T

he third definition is overprecision. It is also well known as “miscalibration", which refers to the fact that people are confident about the accuracy of their estimation (Moore and Healy 2008; Menkhoff et al. 2006). In addition, people may over-narrow confidence intervals around their answers of knowledge questions due to the excessive certainty of the accuracy of their estimations (Biais et al. 2005; Daniel et al. 1998; Cesarini et al. 2006).

Anecdotal evidence suggests that, in many markets, trading volumes are excessive (Dow and Gorton 1997). Various studies have argued that overconfidence can explain the active trading puzzle. As Odean (1998) points out, investors trade aggressively even when there is a transaction cost or expected negative payoffs. One possible explanation is that people are overconfident.

They argue that overconfident investors overestimate their ability and underestimate the risk, which results in increasing the differences of opinions between traders and higher trading volume in the market. Excessive trading volume is an inevitable consequence of overconfidence, which has also been tested empirically in many studies (Barber and Odean 2000; Barber Odean and Zhu 2009; Statman et al. 2007; Griffin et al. 2007; Chuang et al. 2014). These studies argue that high market returns in the past have led to investor overconfidence, while market turnovers can be used as a measurement of trading activity.

Moreover, evidence shows that people who are adopting online trading tended to trade more aggressively based on unusual past personal success. They attribute their past good performance to ability instead of chance (Barber and Odean 2002; Choi, Laibson and Metrick 2002). This connection helps to explain why stock market trading volume increases after high returns, as has been documented in a significant number of countries (Griffin, Nardari and Stulz 2007).

Statman et al. (2006) found that market turnover increases in the periods following higher returns. Regarding market performance, overconfidence may increase market depth and volatility (Odean 1998), while increasing trading activities (Griffin et al. 2007; Odean 1998, Statman et al. 2006). Another study conducted by Griffin et al. (2007) investigated this dynamic relationship in 46 different markets worldwide. They documented that market turnover is positively and strongly related to past returns, while that relationship is much stronger in markets of developing countries.

Chuang et al. (2014) extend these studies to cross-border investment. They find that trading activity has increased significantly in 10 Asian countries and that the overconfidence effect of excessive trading is more pronounced in markets with shortsale constraint. According to Scheinkman and Xiong (2003), overconfidence can lead to disagreements on asset fundamentals, while creating speculative bubbles caused by high trading volume and volatility.

In terms of theoretical studies, trading volume increases when price takers, insiders or market makers are overconfident. These are the most robust findings regarding overconfidence (Odean 1998). Odean (1998) also found that overconfidence increases trading volume and market depth, while decreasing the expected utility of the investor under different microstructure models. Evidence from recent theoretical studies shows that overconfidence plays a vital role in explaining trading anomalies in the financial market (Daniel et al. 1997; Odean 1998; Gervais and Odean 2001). Graham et al. (2009) argue that investors who over-relies on their knowledge and ability to lean toward undertaking high risks and so trading more. The argument suggests that competence may be another explanation for excessive trading in the financial market.

Daniel et al. (1997) argue that the asset price implications of overconfidence do not directly address investor's welfare. Daniel et al. (2001) then examined the pricing of securities regarding their risks and misevaluation. They found that the overconfidence bias implies stock market overreaction and correction, which is consistent with the empirical findings.

The significant effect of active trading by overconfident investors is the most popular conclusion among early studies of decision-making (Odean 1998). Most studies exploring the link between confidence or competence and trading activity define trading activity in terms of the size of trades, either relative to the initial size of the individual's portfolio (turnover) or in absolute value (Statman et al. 2006; Barber and Odean 2001; Glaser and Weber 2007).

In fact, various studies have shown that trading activity measured by either trading volume or volatility will decrease individuals' earning and performance (Gervais and Odean 2001). For example, theoretical models predict that overconfident investor trades excessively compared to others in the financial market (Daniel et al. 1997; Odean 1998), while psychological research has demonstrated that overconfidence would finally harm investor's wealth due to irrational trading behaviour (Barber and Odean 2000).

Overconfidence could thus be the decisive cause of frequent trading and below average performance (Barber Odeanm and Zhu 2009; Barber and Odean 2002; Choi Laibson and Metrick 2002).

Barber and Odean (2000) used the accounting data of 66465 households represented by a large discount broker during 1991-1996. They found high trading levels alongside the resulting poor performance of individual investors. Although evidence shows that trading frequency and returns are negatively related, investors regularly engage in active speculation when markets turn into boom phase (Magron, 2014; Odean 1999). Odean (1999) suggests that overconfident traders suffer from trading losses due to their tendency to overvalue their private information and ability as men and women behave differently in the financial market.

Odean (1998) was among the first to discover that the participation of overconfident investors in the market leads to high trading volume. In other words, overconfident traders overestimate their ability and underestimate the risk of investments, then trade more frequently in the subsequent period (Hishleifer and Luo 2001).

Benos (1998) found that investors overestimated the accuracy of the information which then led to an increased trading volume in an auction market study. Daniel et al. (1998) concluded that the average behaviour of overconfidence in financial markets might cause harmful effects. Investor overconfidence can even explain the forward premium puzzle in the manner that investors tend to overreact to their evaluation about future inflation (Burnside et al. 2011). Daniel and Hirshleifer (2015) state that the active investing puzzle is defined as the excessive trading behaviour of individual investors, which leads to a loss during active trades.

2.2. Measuring Overconfidence (Miscalibration and Other Measurements)

According to conventional psychological definitions, confidence is the subjective probability or belief related to what we “think” will happen. (Kahneman and Tversky 1982). Before the term “calibration” came into use, Adams and Adams (1961) proposed that “realism of confidence” is important for one to discriminate realistically between what he knows and what he does not know. It has also been called realism (Brown and Shuford 1973), external validity (Brown and Shuford 1973), the realism of confidence (Adams and Admas 1961), the appropriateness of confidence (Oskamp, 1962), secondary validity (Murphy and Winker 1971) and reliability (Murphy 1973).

The overconfidence effect has then been defined as “when confidence judgements are larger than the relative frequencies of the correct answers” (Gigerenzer, Hoffrage, Kleinbolting, 1991). In other words, when people are overconfident, they over-believe the accuracy of their judgement, thinking that they know more than they do know.

In some studies, overconfidence can be referred to as a “cognitive conceit” (Block and Harper 1991). More precisely, in terms of probability estimate of perceived likelihood, Koriat, Lichtenstein and Fischhoff (1980) propose that “an individual is well calibrated if, over the long run, for all answers assigned a given probability, the proportion correct equals the probability assigned.” The robust and consistent finding among psychological literature is that people are not well calibrated. (Lichtenstein, Fischhoff & Phillips 1982).

The measurement of overconfidence has been a fundamental topic for behavioural economics after overconfidence was introduced. Overconfidence in one’s judgement, which is measured by miscalibration, can explain loss-making (Biais et al. 2005).

Miscalibrated people tend to overestimate their ability and the precision of their information. This bias can be measured by using a confidence-interval task. The experiment of confidence -interval task has been widely adopted to measure “miscalibration” (Cesari et al. 2006; Glaser and Weber 2007; Sonsno and Regeve 2013).

Investors are asked to give confidence intervals estimates to questions concerning general knowledge with different domains. Overconfidence can then be measured by calculating the percentage of the accurate answer falling outside of the confidence interval. This percentage should equal significant level in the absence of overconfidence.

Kirchler and Maciejovsky (2002) used a confidence-interval technique and found evidence of overconfident in predictions of price variation. Deaves et al. (2009) found that calibration-based overconfidence does engender additional trade. Moreover, there is little evidence that gender influences trading activities. Indeed, Biais et al. (2005) found that overconfidence measured by calibration test reduces trading performance.

Psychological researchers have shown that people were particularly overconfident in their general knowledge judgement through a miscalibration test (Fischhoff et al. 1977; Lichetenstein et al. 1980). This type of miscalibration of subjective probability indicates that people tend to overestimate the accuracy of their knowledge (Alpert and Raiffa 1982; Lichetensteina and Fischhoff 1980; Fischhoff, Slovic and Lichtenstein 1977). Evidence from the previous studies shows that the overconfidence measured by miscalibration is high in difficulty (Koriat et al. 1980; Lichetenstein and Fischhoff 1980; Ronis and Yates 1987).

The mean percentage of miscalibration is 75 percent in Glaser and Weber's (2007) sample, which is much higher than the expected proportion (10% significant level in their study). This percentage range was between 40% and 70% in the most empirical studies. People may be overconfident in answering more difficult questions (Fischhoff et al. 1997; Lichtenstein et al. 1982; Yates 1990; Griffin and Tversky 1992).

In other words, over-confidence is generally found to be much more prevalent when the questions being asked for judgment are difficult. The measurement of difficulty was defined by the number of subjects who answer the question correctly (Sniezek et al.

1990; Arkes et al. 1987). The hard-easy effect of overconfidence in subjective probability judgement occurs when the degree of overconfidence of calibration test increases with the increase in the task's difficulty and where the difficulty level is measured by the percentage of correct answers (intervals) (Suantak et al. 1996; Gigerenzer et al. 1991). Klayman et al. (1999) also found that there are systematic differences between domains of questions were asked in over- or under-confidence, as well as systematic individual differences.

The point-estimates of overconfidence are another popular measurement in the literature. Both objective and subjective information is commonly used to derive the point measurement of overconfidence (She et al. 2013 ; Malmendier et al. 2011). Malmendier and Tate (2005, 2008) use the acquisition of company's stock and option exercise time to quantify the level of overconfidence. Such information is readily available in the market data (i.e. objective information) that can enhance the reliability and replicability of the findings.

According to the definitions of the overconfidence effect, miscalibration is only one manifestation of overconfidence (Moore and Healy 2008). Other aspects of investor trading behaviour are also consistent with overconfidence and the psychological processes that accompany it. For example, people sometimes expect good things to happen to them more often than to the peers. (Weinstein 1980; Kunda 1987). People are even unrealistically optimistic about pure chance events (Langer and Roth 1975; Irwin 1953) and people have unrealistically positive self-evaluations (Greenwald 1980). In addition, more than 50% of investors consider their stock selections skills to be better than the others (Statman et al. 2006; Daniel et al. 1998), which is statistically untrue.

Most individuals see themselves as better than average people and most individuals see themselves better than others see them (Taylor and Brown1988). In particular, the better- than-average effect (BTA), which is the tendency of people to rate their skills and virtues favourably relative to a comparison group, yields direct predictions for economic decision-making.

According to Moore and Healy 2008, there are three manifestations of the overconfidence effect: overestimate the “chance of good luck”(the illusion of control), overplacement (BTA) and miscalibration. The relationship between these different forms of overconfidence is discussed for instance, in various works of literature.

(Larrick, Burson and Soll 2007; Glaser, Langer and Weber 2009; Healy and Moore 2007).

Overestimation is diagnosed if people’s absolute evaluation of their own performance (e.g. correct answers in a knowledge test) exceeds their actual performance (Lichtenstein, Fischhoff & Phillips 1982, Moore & Healy 2008). Miscalibration then indicates overly narrow confidence intervals that are supposed to contain true values for a set of general knowledge questions under a certain probability (Russo and Schoemaker 1992; Alpert & Raiffa 1982).

Overplacement is typically called better-than-average effect when people rate themselves above average, which often occurs when people try to evaluate their competence in a certain domain relative to others (Alicke & Govorun 2005). Apart from the afore-mentioned over-optimism (Weinstein, 1980) and the illusion of control

(Langer 1975) are associated with overconfidence in a broad interpretation of the term.

It is well known that rationality assumption is long prevalent in financial and economic theory. Some researchers have modelled economies in which traders hold mistaken distributional beliefs about the payoff of a risky asset. (Harris and Raviv 1993; Kandel and Pearson 1995; Roll 1986; Hirshleifer, Subrahmanyam and Titman 1994; Figlewski 1978; Jaffe and Winkler 1976).

In recent literature, various approaches have been pursued to reconcile overconfidence with rational behaviour (Healy and Moore 2007; Benabou and Tirole 2002; Brocas and Carrillo 2002; Compte and Postlewaite, 2004; Koszegi 2006; Santos-Pinto and Sobel 2005). In the early overconfidence literature, overconfidence is modelled as the overestimation of the precision of private knowledge (Odean 1998; Glaser and Weber 2007; Daniel et al. 1998; Scheinkman and Xiong 2003). Microstructure models with private signals were then comprehensively developed by Grossman and Stiglitz (1980) and Kyle (1985).

Based on those conventional microstructure models, overconfidence can be introduced by modifying conditional variance and is defined as miscalibration effect (Odean 1998). This definition enables researchers to derive a new equilibrium under overconfidence and test hypotheses.

The causal relationship in the next stage of the research expresses how the level of overconfidence influences the magnitude of the prediction error. The prediction error reflects how much the predicted value of a security has deviated from its fundamental value in the preopening periods.

Odean 1998 forms a modelling perspective, in which overconfidence can promote orderly trade even in the absence of noise trading activities. He studies the markets with various types of investors respectively by assuming that trader, insiders and marketmakers may overestimate the precision of their signal. The overconfidence behaviour causes lower expected utility and higher trading volume.

De Long et al. (1990) have also shown in an overlapping generation model that overconfident traders who mis-perceive the expected price of a risky asset may have higher expected returns, though lower expected utilities than rational traders in the same economy. They demonstrate that the premium received by overconfidence traders is the compensation of the higher risk level that they create. Benos (1998) has looked at overconfidence in models based on Kyle (1985). In his model, investors are overconfident in their knowledge of the private signals of others, while they can also display extreme overconfidence in their own noisy signal, believing it to be perfect. Benos (1998) has derived similar results with Odean (1998) in an auction market. Kyle and Wang (1997) have also investigated overconfidence in models based on Kyle's (1985) model, where overconfidence is defined as an overestimation of the precision of people's own information. They demonstrate that overconfident traders may generate tighter distribution intervals of private signals which enable them to make more profit at the beginning compared to their rational opponents.

Gervais and Odean (2001) develop a multiperiod model in which trader's level of overconfidence is endogenously changing over the time. This dynamic of overconfidence level is due to trader's tendency to attribute his success

disproportionately to his own ability.

The model describes both the process by which traders learn about their ability and how a bias in this learning can create overconfidence. They find that an overconfident investor has a higher trading volume and volatility which decreases his trading performance.

In Daniel Hirshleifer and Subrahmanyam's (1998) study, rational risk-averse traders trade with risk-neutral traders who overact to private signals, properly weight public signals and grow more overconfident with success. They state that although overconfident traders are loss-making, they can earn exceed the profits made by rational investors in some cases. Kelley and Tetlock (2013) develop a structural model with informed and uninformed traders. They conclude that without the overconfidence effect, trading volumes would be much lower.

2.3 Gender and Other Characteristic Effects

Other characteristic variables can also affect overconfidence under some circumstances. Studies of the age indicator effect on overconfidence have been highlighted here (Grinbatt and Keloharju 2009; Menkhoff et al. 2013). Chuang and Sumel (2011) argue that financial market- related trading experience affect overconfidence. They found that professional traders with more past investment experience are less overconfident compared to their counterpart investors, while Lamber et al. (2012) find no overconfidence difference among students and professionals of investment decisions. Ekholm (2006) and Ekholm and Pasternack (2007) assume that overconfidence decreases with investor size.

Finally, motivated by psychological evidence that men are more overconfident than women in decision domains traditionally perceived as masculine, such as finance, investors' characteristics, such as gender, are another widely investigated area after excessive trading in the financial market. This line of research uses gender, past returns or experience as proxy variables of overconfidence effect to study market performance and investor behaviour.

Some empirical literatures studying household's trading data suggests that men and women trade differently (Barber and Odean 2000; Barber and Odean 2001). As Barber and Odean (2001) found, individual traders' turnover and profits are negatively related. Hence, they tested their conjecture that this is due to overconfidence by assuming that men are more overconfident than women. They find that men traded more than women such that the portfolio turnover of male participants was, on average, 45% higher by using brokerage data.

They tested the prediction of 'overconfident investors will trade too much' by partitioning investors on the basis of gender characteristics, which provides a natural proxy for overconfidence. They found that men trade more than women and thereby reduce their returns more than women do. However, Deaves et al. (2009) found little evidence of a gender effect in an experimental market.

2.4 Theoretical Background

To guide and motivate the subsequent empirical and experimental analysis, this chapter presents the related theoretical models and discusses how these models and the main assumptions relate to the my research questions build on my understanding of this broad topic. Much of the recent studies on asymmetric information and imperfect competition in an asset pricing model has relied upon extensive forms introduced by Kyle (1985) originally.

Kyle (1985) developed a single period Gaussian model. In his model setup, a risky asset has a random (ex post) liquidation value $\tilde{v}$, and normally distributed with mean of $\bar{v}$ and variance Σ_0, $\tilde{v} \sim N(\bar{v}, \Sigma_0)$, . Suppose there are three types of risk neutral traders in the market and two dates, $t = 0, 1,$ for simplicity. The insider (informed trader) can observe the true liquidation value $\tilde{v}$ and chooses the quantity $x = X(\tilde{v})$ to maximize expected profits. Secondly, the noisy trader (uninformed) can not observe $\tilde{v}$, and trade a net order flow $\tilde{u}$ exogenously, $\tilde{u} \sim N(0, \sigma_u^2)$ and independent of $\tilde{v}$. Market makers observe the total demand $\tilde{x} + \tilde{u}$ and set the price $\tilde{p} = P(\tilde{x} + \tilde{u})$ to clear the market.

Constant pricing rule assumption:

Suppose that for constant $\mu, \lambda, \alpha, \beta,$ linear function P and X are given by:

$$P(y) = \mu + \lambda y, \qquad X(v) = \alpha + \beta v$$

Profit Maximization assumption:

Insider's expected profit: $E\{\pi|\tilde{v}\}$ can be written as:

$$E[(\tilde{v} - \tilde{p})\tilde{x}|\tilde{v} = v]\ E\{[\tilde{v} -$$

$$P(\tilde{x} + \tilde{u})]\tilde{x}|\tilde{v} = v\}$$

Insider choose $\tilde{x}$ to maximize:

$$E\{[\tilde{v} - P(\tilde{x} + \tilde{u})]\tilde{x}|\tilde{v} = v\} = (v - \mu - \lambda x)x$$

First order condition yields:

$$v - \mu - 2\lambda x = 0$$

Which solves x:

$$x = \frac{v}{2\lambda} - \frac{\mu}{2\lambda}$$

Substituting the result into $x = X(v) = \alpha + \beta v$, yields:

$$\beta = \frac{1}{2\lambda};\ \alpha = -\frac{\mu}{2\lambda}$$

$$x = \beta(v - \mu);$$

Market efficient condition: Given the trading strategy and order flow $(\tilde{x} + \tilde{u})$

$$P(y) = E\{\tilde{v}|X(v) + \tilde{u} = y\}$$

$$\mu + \lambda y = E\{\tilde{v}|\alpha + \beta\tilde{v} + \tilde{u} = y\}$$

Which implies:

$$\mu + \lambda(x + \tilde{u}) = E[\tilde{v}|x + \tilde{u}]$$

Normality makes the regression linear and application of projection theorem gives:

$$x + \tilde{u} = \alpha + \beta\tilde{v} + \tilde{u}$$

$$Z = \frac{x + \tilde{u} - \alpha}{\beta} = \tilde{v} + \frac{\tilde{u}}{\beta}$$

Recall the assumption that $\tilde{v}$ and $\tilde{u}$ are normally distributed with:

$$\tilde{v} \sim N(\bar{v}, \Sigma_0)$$

$$\tilde{u} \sim N(0, \sigma_u{}^2)$$

$$Z = \tilde{v} + \tilde{\epsilon},$$

Where

$$\tilde{\epsilon} = \frac{\tilde{u}}{\beta} \sim N(0, \sigma_{\epsilon 2})$$

Bayesian updating of a normal distribution with a normally distributed signal gives a posterior distribution which is also normal. The conditional normal distribution(likelihood function) is

$$f(Z|\tilde{v}) = \frac{1}{\sqrt{2\pi\sigma_\epsilon^2}} e^{-\frac{1}{2\sigma_\epsilon^2}(Z-\tilde{v})^2}$$

Assumed normal prior with mean $\bar{v}$ and variance $h_v{}^{-1}$

$$f(\tilde{v}) = \frac{1}{\sqrt{2\pi\Sigma_0}} e^{-\frac{1}{2\Sigma_0}(\tilde{v}-\bar{v})\text{^}2}$$

According to proportionality, the posterior density is :

$$f(\tilde{v}|Z) \propto f(Z|\tilde{v})f(\tilde{v})$$

$$\propto \exp\left(-\frac{1}{2\sigma_\epsilon^2}(Z-\tilde{v})^2\right)\exp\left(-\frac{1}{2\Sigma_0}(\tilde{v}-v)^2\right)$$

$$\dots\dots$$

$$\propto \exp\left\{-\frac{1}{\frac{2\sigma_\epsilon^2\Sigma_0}{\sigma_\epsilon^2+\Sigma_0}}\left(\mu-\frac{\sigma_\epsilon^2\bar{v}+\Sigma_0 Z}{\sigma_\epsilon^2+\Sigma_0}\right)^2\right\};$$

which gives the normal distribution with mean $E(\tilde{v}|Z)$ and variance $Var(\tilde{v}|Z)$ are :

$$E(\tilde{v}|Z) = \frac{\sigma_\epsilon^2\bar{v}+\Sigma_0 Z}{\sigma_\epsilon^2+\Sigma_0}$$

$$Var(\tilde{v}|Z) = \frac{\sigma_\epsilon^2\Sigma_0}{\sigma_\epsilon^2+\Sigma_0}$$

Essentially, the market maker observes $(\tilde{x}+\tilde{u})$ which is the normally distributed signal about $\tilde{v}$, hence the posterior mean is updated to :

$$E[\tilde{v}|x+\tilde{u}] = E[\tilde{v}|Z] = \frac{\frac{\sigma_u^2}{\beta^2}\bar{v}+\Sigma_0 Z}{\frac{\sigma_u^2}{\beta^2}+\Sigma_0} = \frac{\beta\Sigma_0(x+\tilde{u})+\sigma_u^2\bar{v}-\alpha\beta\Sigma_0}{\beta^2\Sigma_0+\sigma_u^2}$$

$$= \frac{\sigma_u^2\bar{v}-\alpha\beta\Sigma_0}{\beta^2\Sigma_0+\sigma_u^2} + \frac{\beta\Sigma_0}{\beta^2\Sigma_0+\sigma_u^2}(x+\tilde{u}) = \mu+\lambda(x+\tilde{u})$$

Hence,

$$\beta\Sigma_0 \qquad \beta^2\Sigma_0\bar{v}+\alpha\beta\Sigma_0$$

$$\lambda = \frac{\beta}{{}_2\Sigma_0 + \sigma_u 2};\ \mu = \bar{v} - \frac{}{\beta 2\Sigma_0 + \sigma_u 2} = \bar{v} - \lambda(\alpha + \beta\bar{v})$$

The maximum likelihood estimate of $E[\tilde{v}|\tilde{x} + \tilde{u}]$ is best in the sense that it attains maximum efficiency and it also the minimum variances unbiased estimate, which is equivalently to the least square estimator[1] : Substituting in for the definitions of $\alpha = -\frac{\mu}{2\lambda}$; $\beta = \frac{1}{2\lambda}$, which are derived from insider's profit maximization problem yields:

$$\mu = \bar{v}$$

$$\lambda = \frac{1}{2}\frac{\sqrt{\Sigma_0}}{\sigma_u},$$

therefore, the equilibrium price, insider's demand and expected profit are:

$$p = v + \frac{1}{2}\frac{\sqrt{\Sigma_0}}{\sigma_u}(\tilde{u} + \tilde{x})$$

$$x = \frac{\sigma_u}{\sqrt{\Sigma_0}}(\tilde{v} - \bar{v})$$

$$E[\tilde{\pi}|v] = \frac{1}{2}\frac{\sigma_u}{\sqrt{\Sigma_0}}(v - v)^2$$

While Kyle (1985) assumes that insider can observe the realization of the true value $\tilde{v}$, Odean (1998) builds a model upon Kyle's model with different assumption. Instead observing $\tilde{v}$, he assumes that insider's private signal of the terminal value is noisy and that the insider is overconfident. In another word, prior to trading, a risk-neutral insider i receives a private signal

$$\tilde{s} = \tilde{v} + \tilde{\epsilon}$$

[1] See Appendix A for least square estimation steps.

Where the random variables are normally distributed, as

$$\tilde{\epsilon} \sim N(0, h_\epsilon^{-1}),$$

$$\tilde{v} \sim N(\bar{v}, h_v^{-1}),$$

$$\tilde{u} \sim N(0, \sigma_u^2).$$

The insider believes the precision of $\tilde{\epsilon}$ *to be* κh_ϵ, $\kappa \geq 1$, and the precision of $\tilde{v}$ to be ηh_v, where $\eta \leq 1$. Same as in Kyle (1985)' model, insider demand for $\tilde{x}(v)$, noisy trader demand for $\tilde{u} \sim N(0, h_u^{-1})$, and market makers observe the total demand: $\tilde{x} + \tilde{u}$;

The insider conjectures that the market maker's pricing-setting function is a linear function of $\tilde{x} + \tilde{u}$, which gives

$$P = \mu + \lambda(\tilde{x} + \tilde{u}).$$

Insider choose to maximize his expected profit, $x(\tilde{v} - P)$, conditional on his signal $\tilde{s}$, and given his beliefs about the distributions of $\tilde{v}, \tilde{s}, \tilde{u}$, and the conjectured price function.

Market-maker conjectures that the insider's demand function is a linear function of $\tilde{s}$

$$x = \alpha + \beta\tilde{s}$$

Insider's expected profit: $E\{\pi|\tilde{v}\}$ can be written as:

$$E[(\tilde{v} - \tilde{p})x|\tilde{s}]$$

$$E\{[\tilde{v} - P(\tilde{x} + \tilde{u})]x|\tilde{s}\}$$

given that $E(\tilde{u}) = 0$:

$$E\{[\tilde{v} - P(\tilde{x} + \tilde{u})]\tilde{x}|\tilde{s}\} = (E(\tilde{v}|\tilde{s}) - \mu - \lambda x)x$$

First order condition gives:

$$E(\tilde{v}|\tilde{s}) - \mu - 2\lambda x = 0$$

$$x = \frac{E(\tilde{v}|\tilde{s})}{2\lambda} \quad \frac{\mu}{2\lambda} -$$

To solve $E(\tilde{v}|\tilde{s})$, applies Bayesian updating rule to the demand function :

Recall assumptions:

$$\tilde{s} = \tilde{v} + \tilde{\epsilon}$$

$$\tilde{\epsilon} \sim N(0, h_\epsilon^{-1})$$

$$\tilde{v} \sim N(\bar{v}, h_v^{-1})$$

For simplicity, $\bar{v} = 0$

The conditional normal distribution is

$$f(s|\tilde{v}) = \frac{1}{\sqrt{2\pi h_\epsilon^{-1}}} e^{-\frac{1}{2h_\epsilon^{-1}}(s-\tilde{v})^2}$$

According to proportionality, the posterior density is :

$$f(\tilde{v}|\tilde{s}) \propto f(\tilde{s}|\backslash\tilde{v}) f(\tilde{v})$$

Assume normal prior with mean $\bar{v}$ and variance h_v^{-1}

$$f(\tilde{v}) = \frac{1}{\sqrt{2\pi h_v^{-1}}} e^{-\frac{1}{2h_v^{-1}}(\tilde{v}-\bar{v})^2}$$

$$f(\tilde{v}|\tilde{s}) \propto f(\tilde{s}|\tilde{v}) f(\tilde{v})$$

$$\propto e^{-\frac{1}{2h_\epsilon^{-1}}(s-\tilde{v})^2} e^{-\frac{1}{2h_v^{-1}}(\tilde{v}-\bar{v})^2}$$

$$\propto \exp\left\{-\frac{1}{\frac{2h_\epsilon^{-1}h_v^{-1}}{h_\epsilon^{-1}+h_v^{-1}}}\left(\mu - \frac{h_\epsilon^{-1}\bar{v} + h_v^{-1}\tilde{s}}{h_\epsilon^{-1}+h_v^{-1}}\right)^2\right\}$$

which is the shape of normal distribution with mean $E(\tilde{v}|\tilde{s})'$ and variance $Var(\tilde{v}|\tilde{s})'$:

$$E(\tilde{v}|\tilde{s})' = \frac{h_\epsilon^{-1}\bar{v} + h_v^{-1}\tilde{s}}{h_\epsilon^{-1} + h_v^{-1}}$$

$$Var(\tilde{v}|\tilde{s})' = \frac{h_\epsilon^{-1}h_v^{-1}}{h_\epsilon^{-1}+h_v^{-1}}$$

If insider is overconfidence and believe the precisions are κh_{ϵ}, ηh_{v} , the updated distribution becomes:

$$E(\tilde{v}|\tilde{s}) = \frac{\kappa^{-1}h_{\epsilon}^{-1}\bar{v} + \eta^{-1}h_{v}^{-1}\tilde{s}}{\kappa^{-1}h_{\epsilon}^{-1} + \eta^{-1}h_{v}^{-1}}$$

$$Var(\tilde{v}|\tilde{s}) = \frac{\kappa^{-1}h_{\epsilon}^{-1}\eta^{-1}h_{v}^{-1}}{\kappa^{-1}h_{\epsilon}^{-1}+\eta^{-1}h_{v}^{-1}}$$

with couple of lines of calculations the above results can be written as:

$$E(\tilde{v}|\tilde{s}) = \frac{\kappa h_{\epsilon}\tilde{s}}{\eta h_{v} + \kappa h_{\epsilon}}$$

$$Var(\tilde{v}|\tilde{s}) = \frac{1}{\kappa h_{\epsilon} + \eta h_{v}}$$

Hence:

$$x = \frac{1}{2\lambda}\left(\frac{\kappa h_{\epsilon}\tilde{s}}{\eta h_{v} + \kappa h_{\epsilon}}\right) - \frac{\mu}{2\lambda}$$

If the linear demand conjecture holds:

$$\alpha = \frac{-\mu}{2\lambda};\ \beta = \frac{1}{2\lambda}\ \frac{\kappa h_{\epsilon}}{\eta h_{v} + \kappa h_{\epsilon}}(\quad)$$

Market efficient condition states:

$$P(x + \tilde{u}) = E\{\tilde{v}|x + \tilde{u}\}$$

$$\mu + \lambda(x + \tilde{u}) = E\{\tilde{v}|x + \tilde{u}\}$$

Suppose market maker observes a normally-distributed signal about $\tilde{v}$:

$$x + \tilde{u} = \alpha + \beta\tilde{v} + \tilde{u}$$

$$\frac{x+\tilde{u}-\alpha}{\beta} = \tilde{v} + \frac{\tilde{u}}{\beta}$$

Normality makes the regression linear and application of the projection theorem yields:

$$E(\tilde{v}|x+\tilde{u}) = E\left(\tilde{v}\Big|\frac{x+\tilde{u}-\alpha}{\beta}\right)$$

$$= \frac{-\alpha\beta h_\epsilon h_u}{\beta^2 h_u(h_\epsilon + h_v) + h_\epsilon h_v} + \frac{\beta h_\epsilon h_u}{\beta^2 h_u(h_\epsilon + h_v) + h_\epsilon h_v}(x+\tilde{u})$$

$$= \mu + \lambda(x+\tilde{u})$$

Substituting in for the definitions of ($\alpha = -\frac{\mu}{2\lambda}$; $\beta = \frac{1}{2\lambda}\frac{\kappa h_\epsilon}{\eta h_v + \kappa h_\epsilon}$) from insider's profit maximization problem yields:

$$\lambda = \frac{1}{2(\eta h_v + \kappa h_\epsilon)}\sqrt{\frac{\kappa h_\epsilon h_u(\kappa h_\epsilon + 2\eta h_v - k h_v)}{h_v}}$$

$$\beta = \sqrt{\frac{\kappa h_v h_\epsilon}{h_u(\kappa h_\epsilon + 2\eta h_v - \kappa h_v)}}$$

$$\alpha = 0$$

$$\mu = 0$$

where $\kappa h_\epsilon + 2\eta h_v > \kappa h_v$.

With some calculations, the trading volume can be expressed as:

$$E(|x| + |\tilde{u}|) = \sqrt{\frac{2\kappa(h_\epsilon + h_v)}{\pi h_u(\kappa h_\epsilon + 2\eta h_v - \kappa h_v)}} + \sqrt{\frac{2}{\pi h_u}}$$

which is an increasing function of κ, $when\ kh_\epsilon + 2\eta h_v > \kappa h_v$. In another word, overconfidence increases trading volume. Furthermore, the expected profit can be obtained as:

$$E(x, \quad (v-P)) = \frac{1}{h_v h_u} \sqrt{\frac{\kappa h_\epsilon (\kappa h_\epsilon + 2\eta h_v - \kappa h_v)}{2(\kappa h_\epsilon + \eta h_v)}}$$

which is an decreasing function in κ, and it implies that overconfidence decreases insider's expected profit.

2.5 Summary and Research Objectives

A review of relevant theoretical models shows that overconfidence measured as an overestimation (miscalibration) is related to trading performance and volume. While the theoretical model builds on my understanding of overconfidence and market anomalies, the principal aim of this experimental study has been brought to my attention.

Though existing literature has outlined a numerous meaningful studies on the issue of overconfidence effect, there is a certain numbers of limitations in the research on this broad topic. For instance, a fundamental limitation of much of the research overemphasise on overconfidence bias and neglect the influence of ability effect. This thesis attemps to contribute to existing literature by filling the gap in the prior research mentioned in the first chapter. Furthermore, this study is motived by the intention to answer the following research questions:

1. Literature and theoretical models generally suggest that overconfidence bias leads to a worse performance in financial market. To what extent do different overconfidence measures affect experimental financial market performance?
2. Observed excessive trading is one of the central questions in financial economics context. Does the experimental data in this study support literature of investigating the direct relationship between overconfidence bias and trading activity?
3. Does order book information help uncover the mechanism of the overconfidence bias effect in the financial market?

Chapter 3. Experiments

3.1. Introduction and some literature

The Last chapter reviewed a wealth of theoretical and empirical studies to investigate the complex relationship between psychological bias and financial market performance. For example, Daniel et al. (1997) consider the asset price implications of overconfidence but do not directly address investors' welfare, while some other papers listed below have studied the relationship between individuals' welfare and one's overconfidence level. In other words, overconfidence could be the decisive cause of frequent trading and below-average performance. Barber and Odean (2000) studied account data from 66,465 households at a large discount broker over from 1991-1996, finding that high trading levels resulted in poor performance by individual investors. Odean (1999) suggests that overconfident traders suffer from trading losses due to their tendency to overvalue their private information and ability. Barber and Odean (2001) tested the prediction that 'overconfident investors will trade too much' by separating investors on the basis of their gender characteristics, which provides a natural proxy for overconfidence, finding that men trade more than women and generated reduced returns by comparison.

Recall the model reviewed in the previous chapter that has been widely used to explain the effect of overconfidence on investors' trading behaviour (Odean 1998; Daniel et al. 1998; Daniel et al. 2001). In the simplest version of the information model, the private signal S has a normal distribution and is defined as:

$$s = \theta + \epsilon$$

where ϵ is a noise which is independent of θ, the true value of dividends and normally distributed $N(0, \sigma_{\theta}^{2})$. The precision $\rho_{\theta} = 1/\sigma_{\theta}^{2}$ of the distribution is the inverse of the variance. Overconfident people will underestimate variance (σ_{θ}^{2}) and overestimate precision (ρ_{θ}).

Odean (1998) points out that overconfident investors will overestimate the value of their private information, causing them to trade too actively and consequently earn belowaverage returns. He also found that under certain conditions, the overconfidence level has an increasing influence on per capita expected trading volume, with the overconfidence having a decreasing influence on expected profits. In addition to the direct relation between overconfidence and trading performance, the causal relationship that the level of overconfidence influences the magnitude of the prediction error should be considered as well. The prediction error reflects how much the predicted value of a security deviates from its fundamental value in preopening periods. We argue that the estimation of precision depends on overconfidence. The higher the overconfidence level is, the higher the prediction error.

Given this background, the literature identifies some research methodologies that have been used and that are based on theoretical frameworks or empirical analysis. A proper financial market experiment should be undertaken to collect such trading and prediction data and address the question of overconfidence in financial market. In experimental asset markets with different experimental designs, investor's behaviour can be studied to mimic real-world financial market performance.

The experimental research approach provides an alternative way for testing the excess trading hypothesis. Glaser and Weber (2007) studied a direct relation between investor overconfidence and trading volume through questionnaire and analysed in conjunction with investor trading data. They found that miscalibration, defined here as overly tight probability distributions and underestimation of volatilities, bears no relation to trading volumes, while only the better-than-average effect is demonstrated to correspond with higher trading volumes. Miscalibration is a concept that has been principally developed in cognitive psychology, and the level of miscalibration measured by the subjective probability, which is the percentage for number of correct answers fall outside the confidence interval given by participants. For example, student 1 were asked to answer 22 questions with 90% confidence level, 10 pairs of upper-lower bonds contains true answers, then 12 correct answers that fall outside the 90% confidence interval, therefore the miscalibration score is 12/22=54.5%.In another study of investor's trading behaviour that measures overconfidence directly, Grinblatt and Keloharju (2009) associate the trading behaviour of Finnish investors with the results of a psychometric test given to all Finnish males at ages 19-20 years. They found that investors who are overconfident and prone to sensation-seeking, trade more often. This irrational behaviour has sound cognitive psychological foundations and is identified in a wide range of experiments and surveys, although they are at odds with predictions of the standard economic theory and are labelled as market anomalies (see Odean 1998 for a review).

The existence of overconfidence in financial markets is demonstrated experimentally in varying conditions. Some investors are subject to the winner's curse and suffer from trading loss due to overestimating the precision of their signals in an experimental market (Bias, Hilton, Mazurier and Pouget 2005). Kirchler and Maciejovsky (2002) investigate individual's trading behaviour in an experimental financial market. They test four hypotheses:*1) Participants are overconfidence w.r.t. their created confidence intervals;2) Traders are overconfident with respect to the accuracy of their price prediction (Reject);3) The degree of overconfidence is highest in late trading periods and lowest in early trading periods;4) Trading volume is negatively correlated with individual earning.* In this experimental asset market where agents trade one risky asset, Maciejovsky and Kirchler (2002) found that the largest overconfidence towards the end of the experiment when the participants are more experienced than at the beginning and start to rely more heavily on their (overestimated) knowledge. Similarly, Biais et al. (2005) measured the overconfidence and self-monitoring of 245 participants in an experimental financial market. The trading behaviours observed suggest miscalibrationbased overconfidence reduce the trading performance, while self-monitoring enhances trading performance. They also found that gender characterises the experiment where the effect of the psychological variables is strong for men. As a part of their experiment, the overconfidence of participants is diagnosed through a general knowledge question set. Miscalibrated agents perform worse and earn lower trading profits than their bettercalibrated counterparts. Moreover, despite the fact that the miscalibration itself is approximately the same for both male and female, it decreases trading performance in the experimental market only for men, who turn out to be much more aggressive traders than women (Bias et al 2005).

Deaves et al. (2009) measured overconfidence in three manifestations while investigating the relationship between overconfidence measurements and trading activity. They found miscalibration-based overconfidence measurement plays a vital role in explaining higher trading volume and there is not much of evidence shows that gender influences trading activity.

3.2. Experimental Design

The objective of this thesis is to investigate the relationship between the degree of overconfidence and final wealth using accessible data sources, which could provide a superior explanation for trading behavioural bias in real financial markets. In the experiment, individuals are placed in a controlled market setting and given certain endowments of securities and cash. By varying the market structure, we can learn a great deal about the actual behaviour of economic agents in a simple competitive environment.[2]

Then we next go on to get psychological data. There are limited studies supporting the precise interpretation of the measurements of overconfidence, and the relationships surrounding those measurements attribute to overconfidence the intuitive appeal

[2] The variables are defined in the next section.

connecting trading activity in the financial markets. Some of the studies have utilised measures of overconfidence directly from a survey or within an experimental framework (Biais et al. 2005; Kirchler and Maciejovsky 2002).

Overconfidence in one's judgement, as discussed in Chapter 2, which can be measured by miscalibration, can offer an explanation for loss-making (Biais et al. 2005). Mis-calibrated people tend to over-estimate the precision of their information. This bias can be measured by using a confidence-interval task. Inspired by the theoretical frameword, Kirchler and Maciejovsky (2002) used a confidence-interval technique and found evidence of overconfidence in predictions of price variation. Deaves et al. (2009) found that calibration-based overconfidence engenders additional trade. There is however little evidence that gender influences trading activities. Biais et al. (2005) found that overconfidence measured by the calibration test reduces trading performance. The survey experiments of miscalibration test, as will be shown below, follows psychological research that has shown that people are especially overconfident in their general knowledge judgements when miscalibration tests are used (Fischhoff et al. 1977; Lichetenstein et al. 1980).

This kind of overconfidence measured by miscalibration is particularly task depends (Koriat et al. 1980; Lichetenstein and Fischhoff 1980; Ronis and Yates 1987). In other words, over-confidence is generally found to be much more prevalent when the questions being asked for judgment are difficult.[34] Klayman et al. (1999) also found systematic differences between domains of questions that are asked and that are related to over- or under-confidence, as well as finding systematic individual differences.

[3] Difficulty is measured by the number of subjects who answered the questions correctly (Arkes et al.
[4] ; Sniezek et al. 1990).

Following the studies mentioned above, we calibrated subjects' overconfidence level with 22 general knowledge questions to get miscalibration score. The subjects were asked to provide estimated intervals, for which they are 90 per cent confident that the intervals contain the correct answers for each question. People being generally prone to overconfidence indicates that the provided intervals are too narrow on the basis of assumed 90 per cent confidence level. The alternative to report overconfidence measures from this general knowledge survey method, in which the widths of each the intervals were documented, provides another possible measure of overconfidence level. The smaller the interval, the higher the overconfidence degree. [5]

Our basic analysis focuses on the direct association between overconfidence level of the participants and their trading performance. As well-mentioned above, the subjects have to participate in two experiments, which are a survey experiment and a trading game experiment.

3.2.1. Survey Experiment

The survey experiment is designed to collect psychological measures and characteristic measures.

In order to analyse the direct consequences of miscalibration and other overconfidence measures in the financial market, a well-established quantifiable approach is used in this thesis.

[5] The definitions of different measures are shown in the section of 'Defining variables'.

We follow Lichtenstein, FIschhoff and Phillips (1982), Klayman et al. (1999) and Bias et al 2005 by using a confidence interval test in which subjects are asked to specify interval estimations for which that they are 90 percent sure that the true answer of each question falls within the range provided. If subject is said to be overconfident or miscalibrated, it typically means that the subject has given intervals that are too narrow to contain the true answer more than 10 percent of the time.

For example, Biais et al 2005 found that university students had the correct answer within the stated range of an average 36 percent of the time. While the mean degree of overconfidence in Klayman et al 1999's study was 48 per cent, indicating that the correct answer fell inside the subject's confidence intervals 52 per cent of the time. Russo and Schoemaker (1992) also found that the correct answer fell inside their participants' confidence interval from 42% to 62% of the time. Utilizing the same miscaliration procedure to elicit interval estimations, this study has found that the participants to be generally prone to overconfidence in judgment and have an average 72% overconfidence level.

Method

The survey experiments presented in this study used two questionnaires to look for psychological bias measures and participants' characteristics. We collected participants' characteristic measures, including gender, age, trading experience and others. In addition, participants were asked about the questions to measure the illusion control.[6] Furthermore, after the financial market experiments, they have to fill the postexperiment questionnaire.

[6] The last five questions on Questionnaire 2 shown in Appendix B. The definition is in section of "Defining Variables" in this chapter.

The experiment of survey questionnaires used the same procedure to ascertain the miscalibration score as Bias (2005). These experiments were conducted to investigate miscalibration, better-than-average effect, the illusion of control and provide other possible measures of psychological bias.

Participants

Two groups of students from Cardiff Business School participated in the experiments as part of their coursework assessments in the module "Investment and Electronic Trading". 281 postgraduate students participated in an network experiment in 2017. 90 postgraduate students participated in an stand-alone experiment as a robustness check.

Design:

Participants were asked to respond to 22 questions of questionnaire 2 and provided a pair of lower bound and upper bound for each question, such that they were 90 per cent sure the correct answer fell into the range. This technique of confidence interval estimation was conducted to measure miscalibration score and other associated measures. In addition, participants were asked to fill the questionnaire 1 to provide some basic information about themselves, for example, gender and age. [7] The last five questions in the questionnaire 1 were also asked to generate the illusion of control measure as well. [7]

Procedure:

[7] The corresponding questionnaires used for experiments are shown in Appendix B. [7] The definitions of all the variables are shown in Chapter 4 [8] Required by University Research Committee. [9] Questionnaire is shown in appendix B.

Prior to the financial market experiments, participants were asked to sign a consent form[8] to consent to the use of their information and trading data in this experimental research. The students were instructed to participate in completing questionnaire 1 and 2 in the experiments. As per the requirements by Ethics Committee, the subjects can choose not to answer any of those questions and opt out the experiments at any time. After completing the financial market experiments (trading games), the participants were asked to fill in a post-experimental questionnaire, which asked them to compare their performance with the peers.[9]

3.2.2. Financial market experiments

To gain further insights into the mechanism behind the association of overconfidence and trading performance, the experimental trading games were designed to gather experimental trading data after survey experiments.

Following the theoretical literature, we consider 2 experimental financial markets in which assets are bought and sold by participants. These experiments are in-module experiments whereby all of the students from this module were randomly assigned to trading game groups. All students had previously taken a lecture and tutorials about financial market activities and therefore had basic information and knowledge of the experimental financial market.

The main difference between two experiments concerns the rule of each trading game. The first experiments conducted with students in 2015 was a stand-alone trading game, while the second experiment in 2017 was a network game. The network game allows students to trade against each other in the same group. Each trading experiment lasts for approximately 60 minutes, including instruction and practice. There was a sequence of six trading sessions in an experimental financial market, each of which lasted five minutes. At the end of each period, the asset will be paid out as dividends.

Software and trading rules

Teaching and Research Electronic Simulator (TRETS) was used to simulate a singleasset financial market, in which participants can place limit orders and market orders[8]. A distinguishing feature of the limit order markets is that investors can provide liquidity by submitting limit orders or consume liquidity by submitting market orders. Limit orders specify a price and the number of shares available for sale or purchase. The price is pre-specified, so they can not always be matched with orders on the other side upon arrival. They are then stored in a limit order book while waiting to be executed. Market orders are executed with certainty at the best available quoted prices on the market. The trading statistics and limit order book information are stored for empirical analysis automatically after each trade. All of the participants were postgraduate students with no previous experience in any similar experiment and had been involved in Survey Experiments illustrated in this chapter. At the beginning of each trading session, before any trading took place, participants were given private information regarding the value of the true dividend per share, with this information shown on a ticket or computer screen. After receiving the privately distributed dividend signal, participants were required to write down their own prediction about the realization of the true dividend value. Hence, the prediction error could be calculated based on the

[8] The brief introduction about the software is shown in Appendix B.

absolute value of the difference between the true dividend and each participant's prediction.[9]

Before any trade occurred, each participant had the same amount of cash (300 experimental currency) and share endowments (50 shares of a single risky asset). Figure 2 shows the sequence of the events in the experiment. For each session, subjects could buy and sell any number of shares subject to having sufficient funds and shares.[10] At the end of the experiment, the participants' performances were privately marked, with this mark accounting for 10 per cent of their final grade of this module's assessment, which was the incentive and was documented in the instructions.

Another advantage of this analaytical designed financial market experimental market is that it can report the details of each order submitted by participants and this wealth of limit order book information is able to shed light on the study of aggressiveness behaviors and overconfidence bias.

3.3. Defining variables

A survey experiment is an important resource for different research disciplines because it helps to collect characteristic variables. Together with the panel data set obtained from trading experiments, the unique nature of the data sets allows this study to analyse how behaviours and performance of individuals change over time. This thesis empirically analyses both survey data and trading experimental data. The average value of each variable is defined for cross sectional analysis. The variables with both time and crosssectional dimensions are collected for panel data estimation.

[9] The definition of prediction error in is the next chapter.

[10] Short selling and borrowing money are restricted in our experiments.

Relative Final Wealth:

The Final wealth of each student includes cash and the value of holding shares at the end of each session, which is defined as end of session positions multiplied by true dividend of the group in the session plus end of session cash. Let W_{ij} denotes relative final wealth which measures how far the individual i's final wealth in session j differs from the group average or initial wealth.[13]

Suppose individual q' s final wealth in session j of group k is $W_{qj}{}^{k}$, where $j = 1, 2, 3,4,5,6$, which indicates that there are 6 sequences of sessions; $k = 1,2,3..K, K \leq 6$, which represents that there are maximum 6 groups in each session. $q = 1,2,3, \dots Q, Q \leq 9$; there are a maximum of 9 traders in each group.

In a network game, then the group k' s average of Q traders in session j is :

$$\bar{W}_j^k = \frac{\sum_{q=1}^{Q} W_{qj}^k}{Q}$$

Then the relative wealth of individual i among all the participants is: [14]

[13] For financial market experiment 1 (stand alone game), the relative final wealth =student i's final wealth / his or her initial wealth; for experiment 2(network game), the formula is shown in the next page.

[14] In a stand alone game, relative final wealth:

$$W_{ij} = \frac{W_{qjk} - \bar{W}_{ijk0}}{\bar{W}_{ijk0}}$$

Where $\bar{W}_{ij}{}^{k}{}_{0}$ is individual $i's$ initial wealth of each session j.

$$W_{ij} = \frac{W_{qjk} - \bar{W}_{jk}}{\bar{W}_{jk}}$$

Where $i = 1,2 \ldots n$, n is the total number of the participants, n=281. The percentage difference is defined as the nature log term of relative final wealth formula shown above multiplied by 100. The first dependent variable from our data can be written as:

$$y_{it} = LnW_{ij} \approx Ln\left(\frac{W_{qjk}}{W_{jk}}\right) * 100$$

In order to show the crude association between psychological measures and trading performance, the cross sectional regression is needed. Therefore, the average performance across 6 sessions of each individual i:

$$y_{1i} = \frac{\sum_{j=1}^{6} LnW_{ij}}{6}$$

Trading activity:

The first proxy variable of trading activity in this paper is the total number of shares transacted in each session. Suppose individual q bought $b_{qj}{}^{k}$ shares and sold $s_{qj}{}^{k}$ shares in session j group k, then the total absolute volume is calculated as follows:

$$y_{ij} = Vol_{ij} = Vol_{1kj} = b_{qjk} + s_{qjk}$$

$$y_{2i} = \frac{\sum_{i=1}^{6} Vol_{ij}}{6}$$

Where y_{2i} is the average absolute volume across six sessions for cross sectional analysis.

Overconfidence measurements:

A number of overconfidence-related variables were ascertained from the experimental survey data. Generally speaking, the higher the value of the overconfidence variable, the higher the overconfidence level. To measure overconfidence through survey questions, the first question is whether the answer is verifiable as the degree of confidence level in judgement. Therefore, a well-mentioned quantifiable approach is converting the degree of belief into an estimation of the subjective probability that the judgment is correct.(Kahneman and Tversky (1982), Gigerenzer hoffrage and kleinbolting 1991, DeFinetti 1962). The subjective probability is one's estimation about the probability of a judgement is of being correct, and which has been frequently expressed as confidence. (Adams and Adams 1961). For example, saying " I am 90 % sure that stock price will be £1 per share" indicates a degree of uncertainty and have a small margin of room for error. Suppose we are interested in the judgement of a student on questions about his or her general knowledge. In principle, we can measure the overconfidence level as how this student is miscalibrated.

Miscalibration score(Miscal): is a concept that has been principally developed in cognitive psychology, and the level of miscalibration measured by the subjective probability, which is the percentage for number of correct answers fall outside the confidence interval given by participants.

$$x_{1i} = avgMiscal_i = \frac{No.\ of\ intervals\ do\ not\ contain\ correct\ answers}{22}$$

For example, student 1 were asked to answer 22 questions with 90% confidence level, 10 pairs of upper-lower bonds contains true answers, then 12 correct answers that fall outside the 90% confidence interval, therefore the miscalibration score is 12/22=54.5%.

Rank of disability/Ability: The confidence-range tasks of the survey capture the overconfidence level based on subjective probability. The subject is said to be miscalibrated if the proportion of correctness is less than confidence level (90%). In another word, the subject is overconfidence if the intervals are too narrow to include the true answers for more than 10% of the time. Therefore, here we define another two measures relate to confidence-range questions to elicit overconfidence or psychological bias.

ocRankgood(ability): Rank of ability is the measure of ability of individual i. The score of ability equals to the average widths of intervals of 5 easiest (most accurate) questions as follows:

$$AbS_i = \frac{\sum_j^5 |Width\ of\ interval|_{ij}}{5}$$

Where $j = 1st, 8th, 11th, 15th, 22th$ questions in the survey. Then the rank of ability is defined as:

$x_{2i} = ocRankgood_i = Rank[AbS_i]$ The individual with smallest average width has highest rank of ability *ocRankbad: (disability)*: Rank of disability is the measure of overconfidence of individual i . The score of overconfidence equals to the average widths of intervals of 6 hardest (least accurate) questions as follows:

$$OcS_i = \frac{\sum_j^6 |Width\ of\ interval|_{ij}}{6}$$

Where $j = 9th, 12th, 13th, 17th, 18th, 20th$ question in the survey. Then the rank of overconfidence is defined as:

$$x_{3i} = ocRankbad_i = Rank[OcS_i]$$

The individual with smallest average width has highest rank of overconfidence As mentioned in previous chapter, this confidence-range test is highly depending on the difficulty or the domains of tasks are being asked. For answering more difficult questions, the subject is more prone to overconfidence because of lower rate of accuracy, which is known as “hard-easy effect”. (Suantak et al 1996). The hard-easy effect of overconfidence in subjective probability judgement occurs when the degree of overconfidence of calibration test increases as task difficulty increases and where difficulty is measured by the percentage of correct answers (intervals) (Suantak et al. 1996; Gigerenzer et al. 1991). In addition, we have noticed that the subjects response to easy or hard questions differently.

More precisely, when the question is easy, subject’s judgement is correct with a high probability and when the probability is higher than confidence level, the subject is said to be under confidence. Comparing to two participants with same confidence –task, they all have 90% accuracy and they are all well calibrated, but one subject’s average width of intervals is smaller than the other one. Based on miscalibarition score, they are the same, but the width is telling you that the smaller the width the better skilled subject with higher knowledge.

Thereby, the smaller the confidence intervals are, the higher the ability with easiest questions, while the smaller the width of confidence intervals are, the higher the overconfidence with hardest questions.

Thus, our finding can also confirm that the significant hard-easy effect of overconfidence exists in this experimental environment.

Other measurements of psychological variables:

According to the definitions of overconfidence, people tend to overestimate their ability and accuracy of their knowledge. Miscalibration and ranks of overconfidence/ability measure overconfidence through subjective probability, while we argue that the intuitive prediction errors could also provide some quantifiable measures of overconfidence.

Prediction error of survey questions(Svpred): individual i 's percentage prediction error of the accuracy of 22 survey questions.

$$x_{4i} = avgsvpred_i = \ln\left(\frac{individual\ i's\ prediction}{No.\ of\ intervals\ contain\ correct\ answer}\right)$$

Dividend prediction error(avgpderr): is the average absolute deviation of individual i' s dividend prediction from true dividend

$$x_{5i} = avgpredderr_i = \frac{\sum_{j=1}^{6} |Ture\ Dividend_j{}^k - Prediction_{ij}{}^k|}{6}$$

Prediction error of Better-than-average(bta_i)

The better-than-average score and the illusion of control scores are designed to capture the overconfidence effect. Following Glaser and Weber (2007)'s study, the subjects in this experiment were asked to provide a percentage estimate of how many participants of their peers would have better performance than themselves. And the prediction error of this better-than-average score is expressed as:

$$bta = \frac{50\% - estimate_i}{50\%}$$

Average score of illusion of control(ioc_i)

The illusion of control is defined as inappropriate confidence of a subject if he attributes the chance of success to his ability(Langer 1975). The illusion of control score is the cognitive error and defined as:

$$ioc_i = \frac{5 - answer_i}{4}$$

$$ioc = \frac{\sum_{i=1}^{5} ioc_i}{5}$$

There are five questions about the illusion of control measure and is shown in questionnaire 1 in the Appendix. The illusion of control score is the average score across 5 questions, with the highest value of 1 and lowest value of 0.

Other control variables

In this section, we also introduce other characteristics of the subjects. The data set is conducted from questionnaire 1 through survey experiment. The variables are defined as follows:

Gender: $Gender_i = 1$ for female subject.

Nationality: $n_i = 1$ for Chinese;

Academic Background: $bc_i = 1$ for Frist class graduated;

$s1_i = 1$ for IEBF students;

$s2_i = 1$ for FE students;

Experiences: $emp_i = 1$ for subject who was employed in financial market;

$st_i = 1$ for subject who has self-online trading experience.

Order book information:

In an order driven market like our trading game, participants can submit both limit orders and market orders.

We conduct a number of variables from order book data in the network trading game.

In particular, we thus constructing the elicited individual's expectations about execution prices from each time period. In order to characterize such individual beliefs by order price they indicate, we compute the order aggressiveness as following steps.

Order aggressiveness:

p_{ij}^{n} is individual i' s nth order 's price, s_{ij}^{n} is the order size. where $n = 1,2, \ldots . N,$ in session j , group k. p^{n} is nth order's transaction price. Then the first order aggressiveness measure is calculated by comparing order price and the bid/ask prices in the limit order book at the time of the submission. We write individual $i\,'s$ rank of aggressiveness of order n as follows:

$$Rank[AGS1]^{n}_{ij} = \begin{cases} 6, & Market\ order \\ 5, & p_{ij}^{n} > Best\ ask\ for\ a\ buy\ order; p_{ij}^{n} < Best\ bid\ for\ a\ sell\ order \\ 4, & p_{ij}^{n} = Best\ ask\ for\ a\ buy\ order; p_{ij}^{n} = Best\ bid\ for\ a\ sell\ order \\ 3, & Best\ bid < p_{ij}^{n} < Best\ ask \\ 2, & p_{ij}^{n} = Best\ bid\ for\ a\ buy\ order; p_{ij}^{n} = Best\ ask\ for\ a\ sell\ order \\ 1, & p_{ij}^{n} < Best\ bid\ for\ a\ buy\ order\ ; p_{ij}^{n} > Best\ ask\ for\ a\ sell\ order \end{cases}$$

$$m1_{ij} = \frac{\sum_{n=1}^{N} Rank\ [AGS1]_{nij}}{N}, n = 1,2, \ldots . N,$$

Where p_{ij}^{n} is individual i' s nth limit order $'s$ price in session j group k. Therefore $m1_{ij}$ denotes the aggressiveness measure of student i in session j which is calculated by the ranking rule above. Consequently, a higher rank indicates higher overall aggressiveness of orders and associated attitude towards risk, while lower valueo $m1_{ij}$ suggest lower aggressiveness and more risk averse.

Trading Activity

Recall that each network trading game group has 8 traders. As we are interested in the ranked activities in each network-trading group, we calculated the total share size which elicits the demand for individual i in session j as follows:

$$AGS2_{ij} = \sum_{n=1}^{N} s_{ijn}$$

$$m2_{ij} = Rank[AGS2_{ij}],$$

where s_{ij}^{n} is the order size of nth order in session j. We write $Rank[AGS2_{ij}] = 8$ of the individual with highest $AGS2_{ij}$ in the group.

We define another trading activity variable from limit order book information which builds on $m2_{ij}$ as follows:

$$AGS3_{ij} = \frac{AGS2_{ij}}{N}$$

$$m3_{ij} = Rank[AGS3_{ij}]$$

$AGS3_{ij}$ denotes the average trading activity per order and the $m3_{ij} = Rank[AGS3_{ij}] = 8$ of the individual with highest $AGS3_{ij}$ in the group.

VWAP-Price

The last variable has been conducted from order book data is the measure of the deviation between (limit) order price and VWAP. The VWAP is shown in the Trading Statistics panel of the software when the market is opened. [11]

[11] The screenshot of the software's user interface is shown in appendix B.

$$\tilde{p}_m$$

$$AGS4_{nij} = \{VWA_{ij} - PVWA_n - pP_{ijmijn} \text{ ,,} buysell\ ordersorders$$

$$_{ij}$$

$$m4_{ij} = \frac{\sum_{n=1}^{N} AGS4_{nij}}{N},$$

Where $\tilde{p}_{ij}^m$ denotes individual i' s mth order $'s$ transaction price in session j and $VWAP_{ij}^n$ is the $VWAP$ figure shown on individual$'s$ trading software screen at the time when the order m is executed at price $\tilde{p}_{ij}^m$.

In real life trading market, VWAP is used sometime as a proxy for fair price, which can help investors consider if their execution prices were consistent and in line with fair market prices. Simply say, a negative value of $AGS4^n_{ij}$ indicates better performance and a positive value indicates underperformance. In another word, the higher the value of 4^n_{ij} , the lower the performance of nth order. Hence the average order performance of individual i can be expressed as:

$$m4_{ij} = \frac{\sum_{n=1}^{N} AGS4_{nij}}{N},$$

Chapter 4. Methodology

As we have seen previous discussions, the principle aim of this thesis is to investigate in an experimental financial market. To analysis experimental data, regression plays an exceptionally critical role. To review the fundamental properties and implications of regression methods, we next go on to the discussion of OLS regression method to start with.

4.1 OLS

To gain the crude empirical association between different measures of overconfidence and financial market performance, I firstly estimate a single equation multivariate linear model using Ordinary Least Square method for cross sectional data set and panel data set as follows relation (1):

$$y_i = \alpha + \beta_1 Overconfidence_i + \Gamma X' + \epsilon_i$$

Where y_i is individual $i's$ average performance across six sessions and refers to average relative final wealth or average absolute volume. α, β_1, Γ, are unknown parameters and need to be estimated.The key variable of interest is the impact of $overconfidenc_i$ on y_i , which refers to different overconfidence bias measures collecting from survey experiments. The coefficient β_1 of $overconfidence_i$ indicate the separate and marginal effects of overconfidence measures. I also include a group of control variables X' which can be collected from survey and refers to gender, age, and other characteristics of the subjects, for example, including academic background and working experiences. ϵ_i is unobserved error term with certain properties and refers to

the part of y_i left unexplained by $overconfidence_i$.

4.2 Dummy Variables in Regressions

Recall the previous multivariate regression model:

$$y_i = \alpha + \beta_1 Overconfidence_i + \Gamma X' + \epsilon_i,$$

Where X' is expressed by a group of dummy variables to indicate the presence or absence of demographical effect. Suppose $X' = D_i$, $D_i = 0$ or 1. The above equation becomes to:

$$y_i = \alpha + \beta_1 Overconfidence_i + \gamma D_i + \epsilon_i,$$

With constant effect of D_i on outcome, the conditional expectation of the above equation can be expressed as:

$$y_{1i} = E[y_i|D_i = 1] = \alpha + \beta_1 Overconfidence_i + \gamma + E[\epsilon_i|D_i = 1]$$

$$y_{0i} = E[y_i|D_i = 0] = \alpha + \beta_1 EOverconfidence_i + E[\epsilon_i|D_i = 0]$$

Then the observed outcome (y_i) shifts to $y_{1i} = \alpha + \beta_1 Overconfidence_i + \gamma + \epsilon_i$ if $D_i = 1$; or $y_{0i} = \alpha + \beta_1 Overconfidence_i + \epsilon_i$ if $D_i = 0$. Therefore the outcome y_i can be expressed as:

$$y_i = y_{0i} + (y_{1i} - y_{0i})D_i + \epsilon_i,$$

Where the estimate of $(y_{1i} - y_{0i}) = \hat{\gamma}$. For example, $D_i = 1$, if individual i is female; 0 otherwise. The regression of y_i on D_i presents the causal effect of interest, $\hat{\gamma}$. Then the estimation result of $\hat{\gamma}$ suggests that the outcome of y_i for a female trader is higher than the outcome of a male trader by about $\hat{\gamma}$ amount. In the following empirical chapters, we consistently estimate γ and test if there is significant gender effect among the subjects. If $\hat{\gamma}$ is significantly positive, which indicate a gender difference effect on the outcome and female individual's performance are much higher. There are also other control dummy variables describe student characteristics such as age, academic background, financial market experiences.

If these controls are uncorrelated with $overconfidence_i$, then they will not affect the estimate of β_i. In another word, estimate of β_1 in the long regression:

$$y_i = \alpha + \beta_1 Overconfidence_i + \Gamma X' + \epsilon_i,$$

will be close to the estimate of β_1 in the short regression of no control dummies. Inclusion of control variables X', although not necessary in the study of overconfidence effect, may generate more precise estimators of the causal effect of interest, β_1 . Although the control variables are uncorrelated with D_i , they have substantial explanantory power for y_i.

Therefore regression is a useful and straightforward tool for the discussion of causal issue, with the presence of experimental or survey data.

4.3 Panel data model

As discussed in Chapter3, the experimental trading game in this study was designed to collect trading data of the subject across six trading periods. The analysis of panel data estimation is applicable has been widely by economists. Before we get into the next important question of which panel data model is appropriate, It is conductive to review the nature of panel data and highlights the advantages of using panel data for regressions. The use of panel data has increased dramatically since the pioneering research of financial market experiments. Before proceeding to review the panel data estimating methodology, a quick review of various conceptual definitions of panel data regression and data properties. A data set containing observations with both time dimension and cross-section dimension is called panel data (Wooldrige 2002). Panel data analyses do not require that the time period in which different individuals or sampling units are observed are exactly the same. Unbalanced panel is acceptable for regression. Baltagi (2008) suggests that, depending on the superior nature of panel data, panel data estimation reduces the volume of multicollinearity problems when comparing to crosssection and time series analysis.

The financial experiments carried out in this study provide trading data for each individual i and across six periods. In order to determine the impact of survey measured overconfidence bias in the experimental financial market, we use panel data analysis as the main econometric analysis technique in addition to cross sectional OLS estimation. Consider the following linear panel model with unobserved effect:

$$y_{it} = \alpha + \beta x_{it} + c_i + u_{it},$$

where c_{it} is the unobserved effect; $i = 1,2, \dots n, t = 1,2, \dots T$. x_{it} is a $1 \times K$ vector that contains all the regressors. The error terms can be denoted as :

$$\epsilon_{it} = c_i + u_{ij},$$

where:

$$E(\epsilon_{i1}\epsilon_{i2}|x) = E[(c_i + u_{i1})(c_i + u_{i2})|x] = E(c_i c_i + c_i u_{i2} + u_{i1}u_{i2})|x]$$

$$= E(c_i c_i|x) + E(c_i u_{i2}|x) + E(c_i u_{i1}|x) + E(u_{i1}u_{i2}|x) = E(c_i c_i|x)$$

$$\neq 0$$

Therefore, the "No serial correlation " assumption of OLS regression is violated.

Viewed in this light, it is apparent that OLS regression cannot obtain "consistent" estimators (Wooldrige, 2002). It is necessary, therefore, to find an alternative method to OLS regression. Two commonly applied alternatives are random effects methods and fixed effect methods. Both of these methods assumes $E(u_{it}|x, c_i) = 0$. The random effect methods assumes that $E(c_i|x_i) = 0$, while the fixed effect method dose not retain any such assumption.

4.3.1 Fixed effect model(FE)estimators

$$y_{it} = \alpha + x_{it}\beta + c_i + \epsilon_{it}$$

where γ_i is the unobserved effect and $cov(x_i, \gamma_i) \neq 0$

Within Estimator:

$$y_{it} - \bar{y}_i = (c_i - c_i) + (x_{it} - \bar{x}_i)'\beta + (\epsilon_{it} - \bar{\epsilon_i})$$

$$y_{it} - \bar{y}_i = (x_{it} - \bar{x}_i)'\beta + v_t$$

Where $v_t = (\epsilon_{it} - \bar{\epsilon_i})$.

Within estimator is the OLS estimator of above equation, within estimator of FE model is consistent.

$$Cov(v_t, v_{t-1}) = E\left((\epsilon_{it} - \bar{\epsilon_i})(\epsilon_{i,t-1} - \bar{\epsilon_i})\right)$$

$$= 0 - \frac{\sigma_{\epsilon}^2}{T} - \frac{\sigma_{\epsilon}^2}{T} + \frac{\sigma_{\epsilon}^2}{T}$$

$$= -\frac{\sigma_{\epsilon}^2}{T}$$

$$\hat{c_i} = \bar{y}_i - \bar{x}_i{}'\beta_W,$$

Problem: T must be large for consistency of $\hat{\alpha}_i$.

LSDV-Least square dummy variable Fixed effect estimator:

$$\begin{bmatrix} y_1 \\ \vdots \\ y_N \end{bmatrix} = \begin{bmatrix} e & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & e \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} + \begin{bmatrix} X_1 \\ \vdots \\ X_N \end{bmatrix} \beta + \begin{bmatrix} \epsilon_1 \\ \vdots \\ \epsilon_N \end{bmatrix}$$

where $D = \begin{bmatrix} e & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & e \end{bmatrix}$ is the cross-sectional dummy variable.

First difference estimator:

$$y_{it} - y_{i,t-1} = (c_i - c_i) + (x_{it} - x_{i,t-1})'\beta + (\epsilon_{it} - \epsilon_{i,t-1})$$

First difference estimator is the OLS estimator of the above equation. It is consistent.

$$\omega_t = (\epsilon_{it} - \epsilon_{i,t-1})$$

$$Cov(\omega_t, \omega_{t-1}) = E\left((\epsilon_{it} - \epsilon_{i,t-1})(\epsilon_{i,t-1} - \epsilon_{i,t-2})\right)$$

$$= 0 - 0 - \sigma_\epsilon^2 - 0$$

$$= \sigma_\epsilon 2$$

Though, the fixed effect estimators can generally provide unbiased and consistent estimators, it has other drawbacks. In this thesis, we aim to investigate the impact of overconfidence bias onto financial market performance. As stated before, the timeinvariant variables will be eliminated by the data transformation of fixed effect mode. Therefore, random effect model can be carried out but with more strict assumptions to hold.

4.3.2 Random effect model(RE)

$$y_{it} = c_i + x_{it}\beta + \epsilon_{it}$$

where α_i is the unobserved effect and $cov(c_i, x_i) = 0$. Random effect models belong to the method of GLS estimation. The key issue is whether the random effect model should be used in the panel data given the assumption that $E(u_{it}|x_{it}, c_i)$ (Wooldrige, 2002).

<u>Between estimator:</u>

$$\bar{y}_i = \alpha + \bar{x}_i\beta + (\gamma_i - \alpha + \bar{\epsilon}_i)$$

where $\bar{y}_i = \frac{1}{T}\sum_{t=1}^{T} y_{it}$, $\bar{x}_i = \frac{1}{T}\sum_{t=1}^{T} x_{it}$, $\bar{\epsilon}_i = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{it}$

<u>GLS estimator:</u>

$$y_{it} = \gamma_i + X_{it'}\beta + \epsilon_{it}$$

$$y_{it} = X_{it'}\beta + (\gamma_i + \epsilon_{it})$$

$$y_{it} = X_{it}'\beta + u_{it}$$

Since $u_{it} = \gamma_i + \epsilon_{it}$ is serial correlated over times and OLS estimator is not efficient, GLS is consistent and efficient for RE models.

$$Cov[(\gamma_i + \epsilon_{it}), (\gamma_i + \epsilon_{is})] = \begin{cases} \sigma_\gamma^2, & t \neq s \\ \sigma_\gamma^2 + \sigma_\epsilon^2, & t = s \end{cases}$$

$$\Omega^{-\frac{1}{2}} y_i = \Omega^{-\frac{1}{2}} W_i \delta + \Omega^{-\frac{1}{2}} (\gamma_i + \epsilon_i)$$

$$y_{it} - \hat{\lambda}\bar{y}_i = (1 - \hat{\lambda})\mu + (x_{it} - \hat{\lambda}\bar{x}_i)'\beta + v_{it}$$

where $v_{it} = (1 - \hat{\lambda})\gamma_i + (\epsilon_{it} - \hat{\lambda}\hat{\epsilon_i})$ and $\hat{\lambda}$ is consistent estimator for $\lambda = 1 - \frac{\sigma_\epsilon}{(T\sigma_\gamma^2 + \sigma_\epsilon^2)^{\frac{1}{2}}}$

The feasible GLS(FGLS) estimator is the OLS estimator of β in the above model. FGLS is consistent and full efficient for RE models but is inconsistent for FE model. Still use OLS even when heteroscedasticity is suspect, but to adjust standard errors and test statistics so that they are valid in the presence of arbitrary heteroscedasticity[16].

4.3.3 Hauman and Taylor model

It is possible that some random individual unobservable effect are correlated with repressors, $cov(c_i, x_i) \neq 0$. If the strict exogenous assumption of $cov(c_i, x_i)=0$ is not hold, the random effect estimator is biased and inconsistent. For the purpose of investigate the change of time-invariant variable (Overconfidence bias, eg.), with possible $cov(c_i, x_i) \neq 0$, Hausman and Taylor (1981) suggest a panel data model to address this issue.

$$y_{it} = x_{1}'_{it}\beta_1 + x_{2}'_{it}\beta_2 + z_{1}'_{i}\alpha_1 + z_{2}'_{i}\alpha_2 + c_i + u_{it}.$$

[16] Asymptotic Normality of OLS estimator:

$$y_i = x_i\beta + u_i$$

$$\beta_{OLS} = \beta + \left(N^{-1}\sum_{i=1}^{N} x_i'x_i\right)^{-1}\left(N^{-1}\sum_{i=1}^{N} x_i'u_i\right)$$

The asymptotic distribution of OLS estimator:

$$\sqrt{N}(\hat{\beta} - \beta) = \left(N^{-1}\sum_{i=1}^{N} x_i'x_i\right)^{-1}\left(N^{-\frac{1}{2}}\sum_{i=1}^{N} x_i'u_i\right)$$

therefore asymptotic variance of OLS estimator:

$$A\,v\hat{a}r(\beta) = (X'X)^{-1}\left(\sum_{i=1}^{N} \hat{u}_i^2 x_i'x_i\right)(X'X)^{-1}$$

$\sqrt{\sum_{i=1}^{N} \hat{u}_i^2 x_i' x_i}$ is the White standard errors or Huber standard errors, or Heteroskedasticityrobust standard errors used for the estimations of the following chapters.

In this model, x_{1it} is time varying and uncorrelated with c_i; z_{it} is time-invariant variable and uncorrelated with c_i. x_{2it} and z_{2i} are allowed to correlate with c_i.

Hausman and Taylor (1981) assume that:

$$E[c_i | x_{1it}, z_{1i}] = 0 \quad E[c_i | x_{2it}, z_{2i}] \neq 0$$

$$Var[c_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \sigma_c^2$$

$$Cov[u_{it}, c_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = 0 \quad Var[u_{it} + c_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \sigma^2 = \sigma_u^2 + \sigma_c^2$$

σ_c^2

$$Corr[u_{it} + c_i, u_{is} + c_i | x_{1it}, z_{1i}, x_{2it}, z_{2i}] = \rho = \sigma\_\_2$$

The model assumes that some of the regressors are correlated with random effect c_i, therefore leads to convergence problem of either OLS or GLS estimators. Hausman and Taylor (1981) then propose that, to get consistent estimators, the mean-LSDV method is applied to get valid instruments:

$$(y_{it} - \bar{y}_i) = (x_{1it} - \bar{x}_{1i})'\beta_1 + (x_{2it} - \bar{x}_{2i})'\beta_2 + (\epsilon_{it} - \bar{\epsilon_i})$$

$x_{1it} - \bar{x}_{1i}$ *and* $x_{2it} - \bar{x}_{2i}$ act as instruments that produce unbiased estimates (Christopher and Ruper, 1988).[12]

4.4 Regression models

In viewed of the above methods, the following single equation regression models are built up and run as described to test the different hypotheses of each empirical chapters from Chapter 5 to Chapter 7.

Model 1: Cross sectional regression

$$y_i = \alpha_1 + \beta_1 Overconfidence_i + BX + \epsilon_i$$

Model 2: Pool OLS regression of Panel data

$$y_{it} = \alpha_1 + \beta_1 Overconfidence_i + BX + \epsilon_{it}$$

Model 3: Random effect model of Panel data

$$y_{it} = \alpha_1 + \beta_1 Overconfidence_i + BX + c_i + \epsilon_{it}$$

Model 4: Hausman Taylor mode of Panel data

$$y_{it} = \alpha_1 + \beta_1 Overconfidence_i + BX + M_{it} + c_i + \epsilon_{it}$$

[12] Hausman and Taylor model steps are shown in Appendix C.

Where:

y_i= *Average relative final wealth or volume across 6 sessions of student* i

y_{it} = *Relative final wealth or volume of student i for 6 sessions.* $i = 1,2, \dots, n$; $t =$

1,2,3,4,5,6

$Overconfidence_i$ =*difference overconfidence measurement variables defined in the previous chapter. They are Miscalibartion, overconfidence and ability as a pair of measurements, better-than-average effect, the illusion of control, prediction errors.*

M_{it} *:Ordre book measurements,* $m1_{it}$, $m2_{it}$, $m3_{it}$, $m4_{it}$ *, which refers to order aggressiveness, total order size, shares per order, VWP-price difference*

$X = (bc_i, s1_i, s2_i, emp_i, st_i, gender_i, age_i, n_i, transcost_i)'$*: are the control variables defined in the previous chapter.*

$B = (\beta_2, \beta_3, \beta_4, \beta_5, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10})$*: are the coefficients of control variables.*

s_t= *unobservable time fixed effect.*

c_i= *unobservable individual effect.*

4.5 Data and Descriptive Statistics.

According to the section of "Defining Variables" in Chapter 3, the data sets have been collected from trading game experiments and survey experiment.

Table 1 summarizes descriptive statistics for relative final wealth and absolute volume. Column 1 reports mean, median, minimum, maximum, skewness, kurtosis and the numbers of observations for average relative final wealth across six sessions used in cross-sectional regressions. Further, column 3 presents the same statistics for relative final wealth used in Panel Data analysis with both cross-sectional and time dimensions. The sample shows that the mean for relative final wealth is negative and close to zero, which highlights that the average for deviations from individual's final wealth to the group mean is close to zero.

Table 1. Summary statistics of Relative Final Wealth and Absolute Volume

	Cross-Sectional		Panel Data	
	Relative Final Wealth W_i	Absolute Volume V_i	Relative Final Wealth W_{ij}	Absolute Volume V_{ij}
Mean	-0.01	59.21	-0.02	59.44
Median	-0.13	50.20	-0.05	49.00
Standard Deviation	1.16	40.47	2.19	52.56
Min	-3.10	6.33	-9.34	0.00
Max	4.70	243.67	8.35	425.00
Skewness	0.82	1.77	0.06	2.33
Kurtosis	4.78	7.21	5.12	11.04
Observations	281	281	1686	1686

Figure 1A and Figure 1B plots histograms for relative final wealth under both crosssectional level and panel data level to characterise skewness and kurtosis. Skewness measures symmetry while, kurtosis measures the shape of tails relative to a normal distribution. As can be seen that the distributions are nearly symmetric and bell-shaped with slightly more weight in the tails.

Figure 1a Histogram of Average Relative Final Wealth ($\bar{W}_i$)

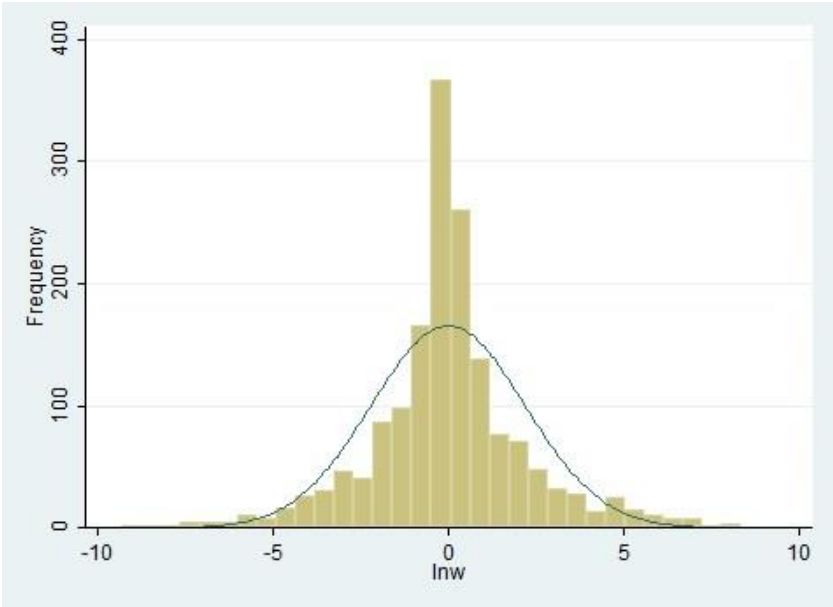
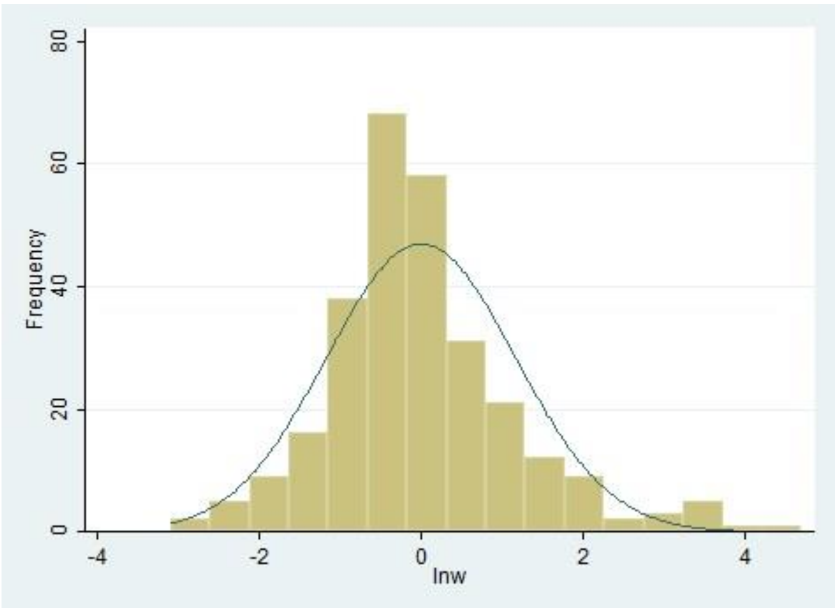


Figure 1b. Histogram of Relative Final Wealth (W_{ij})



By way of preliminary analysis of psychological variables, Table 2 presents the descriptive statistics for the survey measurements. Miscal's mean is 0.74 which is slightly higher than previous studies of 0.50 (Biais, et al. 2005). A possible explanation for the average higher miscalibration found in our study is that the subjects are Chinese students. According to Yates, et al (1989) pointed out, region, age and background affect the probability judgement of the subjects. Menkhoff et al. 2013 argue that students tend to be more overconfident than professionals according to miscalibration test. Table 3 presents the statistics of dummy variables that control the characteristics of subjects. Table 4 presents the correlation analysis results for overconfidence variables and gender. It is observed that, in general, the independent variables are not highly correlated.

Table 2. Summary Statistics of Survey Measurements

	ocRankgood	ocRankbad	avgsvpred	MisCal	avgpder	bta	ioc
Mean	25.90	44.33	0.08	0.74	0.60	0.15	3.08
Median	25.90	44.33	0.08	0.74	0.50	0.15	3.08
Standard Deviation	5.64	8.52	1.37	0.12	0.68	0.17	0.38
Min	2.20	2.00	-1.00	0.23	0.17	-0.99	1.40
Max	42.60	71.33	10.00	0.95	5.96	0.99	4.60
Skewness	-0.40	-0.28	3.01	-0.72	6.91	-0.20	-0.03
Kurtosis	4.32	5.39	18.64	4.28	53.31	14.29	5.32
Observations	281						

Table 3. Summary Statistics of Demographic Variables

	n	bc	s1	s2	emp	st	gender
Mean	0.01	0.45	0.73	0.18	0.07	0.36	0.66
Median	0.00	0.00	1.00	0.00	0.00	0.00	1.00
Standard Deviation	0.11	0.50	0.45	0.39	0.25	0.48	0.47
Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Max	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Skewness	8.68	0.21	-1.02	1.63	3.42	0.57	-0.67
Kurtosis	76.35	1.04	2.03	3.67	12.70	1.32	1.45
Observations	281						

Table 4. Correlation Coefficients

	ocRankgood	ocRankbad	avgMisCal	avgsvpred1	avgpder	ioc	bta	gender
ocRankgood	1.00							
ocRankbad	0.38	1.00						
avgMisCal	0.16	0.44	1.00					
avgsvpred1	0.08	0.07	0.19	1.00				
avgpder	-0.02	-0.07	0.00	0.03	1.00			
ioc	-0.02	-0.01	-0.04	-0.13	0.08	1.00		
bta	-0.04	0.01	0.04	-0.04	-0.01	0.13	1.00	
gender	-0.08	0.03	0.12	0.00	0.01	-0.04	0.04	1.00

Chapter 5. Investigating Overconfidence Measures Effects on Final Wealth (network experimental market)

5.1. Introduction

To date, a strong relationship between overconfidence bias and financial market trading performance has been established. (Statman et al. 2006; Barber and Odean 2000; Barber and Odean 2001). Previous studies suggest that this cognitive biases may have a significant role in affecting an individual's decision-making behaviours in different markets (Scheinkman and Xiong 2003). Some different manifestations of overconfidence biases have been documented in the literature, and the associated impact on financial market behaviours have been investigated (Cesarini 1999; Menkhoff 2006; Daniel, et al. 1998; Biais, et al. 2005).

It has been found that investors are prone to overconfidence in terms of miscalibration (Daiel et al. 1998). Many people tend to think that their knowledge and abilities are better than average (Menkhoff 2006). People sometimes believe that they have more power to control event outcomes than they actually have. The illusion of control causes them to place too high a probability on their success (Langer 1975; Scott et al. 2003). The literature generally supports the hypothesis that overconfidence, in terms of miscalibration, reduces the trading profits, final wealth, and market performance, and that a gender effect is also observed, with male traders having a larger trading volume than female traders (Barber and Odean 2001). The gender effect is also explored in more details in the next chapter.

Glaser and Weber (2007) argue that it is not only important to investigate into the linkage between overconfidence bias and trading, but it is also crucial to identify whether and which psychological biases affect trading behaviour. More precisely, it is interesting to establish which kind of overconfident, i.e, miscalibration, BTA, with respect to one's knowledge, ability in judgement, or the misperception of the accuracy of information, is able to forecast market outcomes, which, in turn, might inspire future research on how to attenuate such biases.

This chapter aims to contribute to the academia in this field by assessing the relationship between trading performance and overconfidence bias measures, looking at the effects of various overconfidence bias measures, gender and other demographic variables in an experimental financial market (see the design in chapter 3). This experiment builds on the stand alone experiment by expanding the experimental design into a network trading market.

However, the studies of cognitive bias have often failed to evaluate the ability effect on trading performance because it was a variable that was left-out. While the effect of miscalibration and gender on trading performance have been found in the previous literature, too few studies have taken a detailed look at how overconfidence and ability can simultaneously affect trading performance. This chapter will also attempt to investigate the impact of a pair of overconfidence and ability measurements defined in this study (see the definitions in Chapter 3) on trading performance.

It is noted across the existing literature that better-than-average effect and illusion control appear to affect trading performance and decision-making (Menkhoff 2006; Langer 1975). This chapter will also investigate the extent of the relationship between other measurements mentioned in previous literature of overconfidence bias and trading performance.

5.2. Hypothesis

The hypotheses are:

1. *Mis-calibration reduces relative final wealth in an experimental financial market.* The result makes contributions to the literature on experimental analysis of overconfidence effect. We can see significant and consistent miscaibration effect on relative final wealth.
2. *Overconfidence and ability measurements defined in this chapter affect relative final wealth.*

This chapter is the first quantitative study of the relationship of calibrated ability and overconfidence and experimental financial market performance. We found that ability rank enhance relative final wealth, while overconfidence reduce relative final wealth.

3. *Better-than-average, the illusion of control, prediction error as other forms of overconfidence are found to reduce relative final wealth.*

This chapter also attempts to contribute to the literature looking at various measures of overconfidence experimentally and empirically. However, there is no significant effect of other measures onto relative final wealth in this study.

4. *There is a significant gender difference in relative final wealth.*

We can not see any gender difference among the subjects in their relative final wealth.

5.3. Regression Results and Discussions

This section presents and discusses the findings of cross-sectional and panel data regression results using network experiments data. The principle aims of this chapter are investigating the impacts of different time-invariant overconfidence measures on relative final wealth, with OLS and Random effect models being run as described in chapter 4. Though the fixed effect estimator is efficient and consistent, we focus on the change on the time-invariant variables, which are eliminated by fixed effect models. As can been seen from Table 5 Panel1, Miscalibration score(Miscal), dividend prediction error (pderro) are negative correlated with relative final wealth(lnw) after fitting different regression models (Pool OLS, Random Effect-GLS and Random Effect Maximum Likelihood), while better-than-average effect(bta) and ability measurement(ocRankgood) are positively correlated with relative final wealth. In addition, they are statistically significant at 1% , 5% or 10% significant levels. In another word, the negative and significant coefficients of Miscalibration and Dividend prediction error predict a loss of relative final wealth in our data. According to Daniel et al 1998, Scheikam and Xiong 2003, overconfidence in one's judgement, which is measured by Miscalibration, is negatively correlated with people's wealth. The findings of negative correlations are consistent with the existing literatures. In column 1 shown in the table, the relative final wealth is predicted to decrease 1.7 when overconfidence measured by Miscalibration score goes up by one, and decrease by 0.41 when overconfidence level measured by dividend prediction error increase by one.

As introduced in Chapter 2, "better-than-average" effect (bta) is defined as when people believe themselves to be better than others, which is also known as the overplacement (Moore and Healy 2008). "better-than-average" effect (bta) is commonly referred to the fact that investors classify themselves of "above average level" comparing to their counterparts. (Moore and Healy 2008; Scott et al. 1999; Menkhoff et al. 2006). Following Greico and Hogarth (2009),Menkhoff (2006), BTA and the illusion of control can be used as proxy variables of overconfidence, which have been found significantly reduce trading performance in terms of both profit and wealth. BTA here is positively correlated with relative final wealth, which is in contrast to the findings of previous studies. The BTA score in this study is calculated based on post-experimental questionnaire. The ex-post positive BTA effect may suggest that the subjects updated their beliefs correctly about their past performance comparing to their peers. Therefore, this ex-post BTA effect in my study may capture the ability effect in terms of predicting trading performance. If their expectations are correct, with higher BTA score, their relative performance are higher. Similarly, another ability measure (ocRankgood) is positively correlated with relative wealth, which suggests that participants with higher ability level of answering survey questions, have higher trading performance(relative final wealth).

So far, we have found that some aspects of overconfidence decrease relative final wealth, while some aspects of ability increase relative final wealth. The findings of negative correlations between different aspects of overconfidence level with trading performance are consistent with the existing studies. Furthermore, the findings of positive correlations between ability and trading performance contribute to the emerging literature of explaining psychological bias.

A lagged dependent variable in a regression is often used to capture some of the dynamic effects in learning process. After including lagged relative final wealth in the regressions, as can be seen from column 2-4, the statistics of R^2 and $F\ statistics$ are both improved. Additionally, the significance of coefficients of lagged relative final wealth, fitting in the different models, suggest that current session's trading performance measured by relative final wealth is significantly correlated with previous session's trading wealth. The better the previous trading performance the better the current performance. One possible explanation is that, during the 6 sequence of sessions in the experiment, participants were learning through trading. This learning process may refer to the learning of the market, being familiar with the software, or their own impact on the market. Unfortunately, we are not able to precisely measure which aspects of learning process has driven up the trading performance. However, we can still conclude that the positive and significant relationship between previous trading performance and current session's trading performance suggests that the learning effect has been found in our data.

Table 5: Regress Relative Final Wealth on all overconfidence related measures and all other controls (Including lagged relative final wealth)

	Relative Wealth	Relative Wealth	Relative Wealth	Relative Wealth
	Pool OLS	Pool OLS	RE-GLS	RE-MLE
Lagged lnw		0.12^{**}	0.10^{**}	0.12^{**}
		(2.03)	(2..08)	(2.11)
Panel 1: Overconfidence Measures:				
Miscal	-1.74^{*}	-1.37	-1.37	-1.37
	(-1.75)	(-1.25)	(-1.25)	(-1.30)
pderro	-0.41^{**}	-0.45^{**}	-0.48^{***}	-0.45^{**}
	(-2.19)	(-2.17)	(-2.94)	(-2.25)
ioc	0.04	0.04	0.02	0.04
	(0.12)	(0.10)	(0.05)	(0.10)
bta	1.98^{**}	1.39^{*}	1.39^{*}	1.39^{*}
	(2.52)	(1.74)	(1.69)	(1.70)
svpred	-0.26	-0.18	-0.20	-0.18
	(-1.48)	(-0.94)	(-0.90)	(-0.98)
ocRankbad	-0.02	-0.03	-0.03	-0.03
	(-1.30)	(-1.56)	(-1.44)	(-1.62)
ocRankgood	0.09^{***}	0.08^{***}	0.08^{***}	0.08^{***}
	(3.84)	(3.20)	(3.09)	(3.32)

Panel 2: Other Controls:				
bc	0.21	0.29	0.29	0.29
	(0.90)	(1.11)	(1.04)	(1.16)
s1	-0.16	-0.40	-0.41	-0.40
	(-0.35)	(-0.78)	(-0.69)	(-0.80)
s2	-0.32	-0.37	-0.36	-0.37
	(-0.58)	(-0.62)	(-0.54)	(-0.64)
emp	-1.03*	-1.50**	-1.48**	-1.50**
	(-1.68)	(-2.15)	(-1.96)	(-2.23)
st	0.52*	0.43	0.43	0.43
	(1.95)	(1.44)	(1.29)	(1.50)
gender	0.50**	0.42	0.44	0.42
	(1.99)	(1.47)	(1.41)	(1.53)
age	0.05	0.07	0.06	0.07
	(0.62)	(0.73)	(0.73)	(0.76)
n	0.14	0.25	0.21	0.25
	(0.13)	(0.20)	(0.30)	(0.21)
transcost	-0.18	-0.24	-0.21	-0.24
	(-0.43)	(-0.50)	(-0.47)	(-0.52)
session=2	0.41	0.00	0.00	0.00
	(1.06)	(.)	(.)	(.)
session=3	-0.15	-0.56	-0.54	-0.56
	(-0.38)	(-1.43)	(-1.32)	(-1.49)
session=4	0.03	-0.37	-0.36	-0.37
	(0.08)	(-0.91)	(-0.76)	(-0.94)
session=5	-0.46	-0.84**	-0.83**	-0.84**
	(-1.14)	(-2.14)	(-2.36)	(-2.22)
session=6	0.11	-0.21	-0.21	-0.21
	(0.28)	(-0.53)	(-0.61)	(-0.55)
Constant	-1.47	-0.85	-0.74	-0.85
	(-0.58)	(-0.31)	(-0.32)	(-0.32)
R^2	0.104	0.137		

F 1.99 2.18 *t* statistics in parentheses

---

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

As shown in Chapter 6, we haven't found any significant impact of overconfidence measures on trading volume. However we have discovered that there is a significant gender difference in our data sample. For example, as in the table above, the coefficients of gender dummy variable indicate that female participants significantly traded less than their male counterparts. Barber and Odean (2001) have found that males are more aggressive and tend to trade excessively comparing to females by using a large brokerage data sample. In column 2-4, the coefficients of lagged volume are positively correlated with current volume in different regression models. The finding suggests if 'learning' takes places in trading, as discussed above, participants will enhance their understandings about the market, the software, or their own impact on the market. Consequently they will perform better as suggested by table , while they will trade more aggressively. According to Benos (1998) point out that trading activity is associated with some aspects of overconfidence. Hence, the 'learning' process encourages participant to trade more by increasing their overconfidence level. This empirical finding is consistent with the theoretical work about learning and overconfidence.

Before discussing about learning process in this chapter, we have assumed that overconfidence level is fixed and not changing over time. The finding of learning increases trading volume may contribute to the existing studies about overconfidence impact on trading behavior by releasing the assumption of constant overconfidence level.

Table 6 : Regress Absolute Volume on

all overconfidence related measures and all other controls

(Including lagged volume)

Note: The regressions models here have the same dependent variable sets as the previous table, but this table has omitted the regression results of the variables that are not significant.

	Volume	Volume	Volume	Volume
	Pool OLS	Pool OLS	RE-GLS	RE-MLE
Lagged volume		0.09***	0.09*	0.09***
		(3.20)	(1.83)	(3.31)
Gender	-4.53**	-4.61*	-4.61	-4.61*
(=1 if female)	(-2.13)	(-1.82)	(-1.44)	(-1.89)
Constant	-3.56	1.00	1.00	1.00
	(-0.17)	(0.04)	(0.07)	(0.04)
R^2	0.861	0.841		
F	109.21	76.87		

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Relationship 1: Miscalibration and Relative Final Wealth

The first objective of this chapter is to ascertain the extent of the miscalibration effect on relative final wealth. Initially, cross sectional multivariate models were run to show the crude relationship between different overconfidence measurements and relative final wealth, in which other demographic variables are also included.

The regression results reported in Table 5 suggest a robust relationship between miscalibration and relative final wealth with different model specifications. As expected, the coefficients for miscalibration in different models are very similar. All the coefficients of miscalibration are significantly negative.

The first column in Table 5 presents the estimates for cross-sectional OLS regression. The dependent variable is average relative final wealth for the 6 sessions of each student. Miscalibration significantly lowers average relative final wealth (the estimated coefficient is -1.1822, with a t-statistic of -1.79), whilst the impact of other demographic variables on relative final wealth is not significant. The point estimate of age is -0.0772, with t-statistic of -1.29; the t-statistics for the other variables are all smaller. This Table also presents Pool OLS regression for the panel data estimates for Mis-calibration and other controls in column 2. The point estimated coefficients indicate a robust impact by miscalibration on relative final wealth.

In the next two columns, it is assumed that there is an unobserved individual effect and that all the independent variables in the model are strictly exogenous. The point estimates for the Random effect GLS and Random effect Maximum Likelihood are 1.29 respectively, with t-statistics of -1.76 and -1.84. Unsurprisingly, GLS and Maximum Likelihood provide similar estimates.

Table 5. Regressions Of Relative Final Wealth Onto Miscalibration And Other Controls. *T* Statistics In Parentheses, * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.

	Cross Sectional OLS	Pool OLS	Random Effect GLS	Random effect ML
Dep. Var.:	W_i	W_{ij}	W_{ij}	W_{ij}
Miscal	-1.1822* (-1.79)	-1.32** (-2.43)	-1.29* (-1.76)	-1.29* (-1.84)
bc	-0.0334 0.01 0.02 0.02	(-0.18) (0.08)	(0.08) (0.08)	
s1	-0.2032 (-0.70)	-0.12 (-0.47)	-0.11 (-0.31)	-0.11 (-0.33)
s2	-0.0995 (-0.29)	-0.04 (-0.13)	-0.02 (-0.05)	-0.02 (-0.06)
emp	0.0348 (0.06)	0.17 (0.41)	0.21 (0.38)	0.21 (0.39)
st	0.0927 (0.41)	0.03 (0.20)	0.04 (0.19)	0.04 (0.20)
gender	-0.0729	0.03	0.02	0.02

	(-0.32)	(0.17)	(0.09)	(0.09)
age	-0.0772	-0.07	-0.08	-0.08
	(-1.29)	(-1.44)	(-1.23)	(-1.25)
n	0.5390	0.58	0.60	0.60
	(1.09)	(1.04)	(0.81)	(0.84)
transcost	-0.0572	-0.08	-0.01	-0.02
	(-0.15)	(-0.32)	(-0.02)	(-0.07)
session=1		0.00		0.00
		(.)		(.)
session=2		-0.09		-0.11
		(-0.38)		(-0.50)
session=3		0.04		0.02
		(0.16)		(0.07)
session=4		-0.08		-0.10
		(-0.31)		(-0.44)
session=5		-0.22		-0.23
		(-0.90)		(-1.03)
session=6		0.13		0.10
		(0.51)		(0.44)
Constant	2.8600*	2.73**	2.85	2.88*
	(1.88)	(2.06)	(1.64)	(1.71)
R^2	0.040	0.013		
F	0.9564	0.81		
Observations	172	927	927	927

As column 1 in Table 8 shows, the standard errors for the coefficients are generally lower than in the Pool OLS regressions. According to the discussions in Chapter 4, if the assumptions of OLS are hold, the OLS estimator is the best linear unbiased estimator. Table 8a column 1 present Breush-Pagen LM test results. The null hypothesis in the

BPLM test is that variance across individuals is zero. In other words, there is no significant difference across individuals and no unobserved random effect.

Table 8 Standard Errors Of Coefficients From Regressing Relative Final Wealth Onto Different Psychological Variables.

	ocRankgood	Mical	ocRankbad
Pool OLS	0.541	0.013	0.009
RE GLS	0.730	0.017	0.011
RE MLE	0.701	0.016	0.011

As column 1 in table 8a shows, $\chi^2 = 44$ (p-value<0), so we can reject the null hypothesis of no systematic difference and conclude that random effect model is appropriate. This evidence that the significant unobserved effect across individuals.

Table 8a Breush-Pagan LM Test

	χ^2	p-value
Mical	44	0
goodbad	36.56	0
bta	47.59	0
pderro	30.93	0
svpred	21.41	0

Relationship 2: Ability Rank and Overconfidence Rank as new measurements of Psychological Bias

Suantak et al. (1996) point out that the hard-easy effect of overconfidence occurs when the degree of overconfidence increases as the difficulty of the questions increases.

According to the literature mentioned in section 1, the difficulty of the general knowledge questions involved in such experiments affects the level of overconfidence. We calculated the average overconfidence measurement of the five most accurate questions and the five least accurate questions and named them ocRankgood and ocRankbad. We expected the five least accurate questions to provide a better measurement of overconfidence based on the confidence intervals of these questions. However, for those high accuracy questions, we expect the intervals of the questions to be narrow. Narrow intervals with high accuracy cannot imply overconfidence but may indicate an effect from ability on trading performance. The higher the ability to get a correct interval with a narrow width, the better performance a subject should be able to obtain.

The second objective is to further check the impact of the newly defined psychological bias measures on relative final wealth. As Table 6 shows, ocRankgood and ocRankbad are negatively and positively correlated with relative final wealth, with p-value<0.01. Also the results of BG-LM test shown in Table 8a suggests random effect is appropriate, indicating that there is unobserved random effect. The consistent and robust regression results from varying model specification suggest that ability (calibrated by ocRankgood) increases relative final wealth, while overconfidence (calibratied by ocRankbad) reduces relative final wealth. This finding contributes to the emerging literature about psychological bias.

Table 6 Regressions Of Relative Final Wealth Onto Ability Rank/Overconfidence Rank And Other Controls. *T* Statistics In Parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Cross Sectional OLS	Pool OLS	Random Effect GLS	Random effect ML
Dep. Var. :	W_i	W_{ij}	W_{ij}	W_{ij}

ocRankbad	-0.0319**	-0.03***	-0.03***	-0.03***
	(-2.59)	(-3.66)	(-2.85)	(-2.90)
ocRankgood	0.0531***	0.05***	0.05***	0.05***
	(2.79)	(4.12)	(3.21)	(3.26)
bc	0.0124	0.00	0.01	0.01
	(0.07)	(0.01)	(0.04)	(0.04)
s1	-0.2679	-0.29	-0.28	-0.28
	(-1.01)	(-1.26)	(-0.95)	(-0.97)
s2	-0.2481	-0.28	-0.27	-0.27
	(-0.77)	(-1.09)	(-0.81)	(-0.82)
emp	-0.0075	-0.06	-0.04	-0.04
	(-0.01)	(-0.19)	(-0.09)	(-0.09)
st	0.1789	0.17	0.17	0.17
	(0.82)	(1.09)	(0.89)	(0.90)
gender	-0.0722	-0.05	-0.06	-0.06
	(-0.34)	(-0.36)	(-0.31)	(-0.31)
age	-0.0862	-0.07	-0.08	-0.08
	(-1.39)	(-1.44)	(-1.24)	(-1.26)
n	0.6269	0.62	0.63	0.63
	(1.22)	(1.15)	(0.91)	(0.93)
transcost	0.0287	-0.01	0.02	0.02
	(0.08)	(-0.05)	(0.06)	(0.06)
session=1		0.00	0.00	0.00
		(.)	(.)	(.)
session=2		-0.05	-0.07	-0.07
		(-0.23)	(-0.33)	(-0.33)
session=3		0.03	0.01	0.01
		(0.14)	(0.05)	(0.06)

session=4		-0.04	-0.06	-0.06
		(-0.17)	(-0.29)	(-0.29)
session=5		-0.11	-0.12	-0.12
		(-0.49)	(-0.57)	(-0.57)
session=6		0.19	0.17	0.17
		(0.82)	(0.77)	(0.78)
Constant	2.2540	1.88	2.02	2.01
	(1.30)	(1.40)	(1.19)	(1.21)
R^2	0.091	0.028		
F	1.4261	1.80		
Observations	173	1016	1016	1016

Relationship 3: Other Measurements of Overconfidence Effects on Relative Final Wealth

The aim of this section is to investigate the extent to which the impacts of other overconfidence measures.

Following Greico and Hogarth (2009),Menkhoff (2006), BTA and the illusion of control can be used as proxy variables of overconfidence, which have been found significantly reduce trading performance in terms of both profit and wealth. Table 7 presents estimated results for the different models about these measures, with BTA being significant in the cross sectional OLS and Pool OLS specifications. BTA here is positively correlated with relative final wealth, which is in contrast to the findings of previous studies. The BTA score in this study is calculated based on post-experimental questionnaire. The ex-post positive BTA effect may suggest that the subjects updated their beliefs correctly about their past performance comparing to their peers. If their expectations are correct, with higher BTA score, their relative performance are higher.

Table 7. Regressions Of Relative Final Wealth Onto Other Overconfidence Measures And Other Controls. *T* Statistics In Parentheses, * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.

	Cross Sectional OLS	Pool OLS	Random Effect GLS	Random Effect MLE
Dep. Var. :	W_i	W_{ij}	W_{ij}	W_{ij}
ioc	0.0895	0.08	0.08	0.08
	(0.37)	(0.46)	(0.37)	(0.38)
svpred	0.0269	0.06	0.07	0.07
	(0.40)	(0.41)	(0.45)	(0.46)
pderro	-0.0147	-0.04	-0.05	-0.05
	(-0.09)	(-0.41)	(-0.59)	(-0.59)
bta	1.0955*	0.75*	0.80	0.79
	(1.69)	(1.70)	(1.38)	(1.41)

Relationship 4 Gender effect

So far, we have not found any significant gender effect on relative final wealth through testing overconfidence measures. A simple t-test is presented to test the equality between female and male participants' relative final wealth. As Table 9 shows, the null hypothesis of equality, at least, can not be rejected at any significant level below 10.62%. It concludes that there is not a significant difference between female and male for relative final wealth.

Table 9. Two-Sample T Test With Equal Variances Of Relative Final Wealth (By Gender)

diff = mean(0) - mean(1) ; Ho: diff=0	
Ha: diff != 0	Pr(|T| > |t|) = 0.1062
Ha: diff < 0	Pr(T < t) = 0.9469
Ha: diff > 0	Pr(T > t) = 0.0831

Relationship 5 Prediction Error

Miscalibration of overconfidence and accuracy in subjective probability of judgment were first mentioned by Admas and Admas (1961). The overconfidence effect was defined as systematic overestimation of the precision of one's ability and overestimation of the accuracy of one's predictions in decision making (Yate 1990). To study the effect of overconfidence on the accuracy of prediction, we performed statistical analysis of prediction errors and overconfidence measurements. We argue that the process underlying the formation of overconfident beliefs in the trading game (dividend prediction error) is similar to that underlying the formation of overconfident judgements when answering the calibration questionnaire (miscalibration score). Both reflect overestimation of the private information or accuracy of one's own knowledge, and underestimation of conditional risk. For example, overconfident subjects response to the miscalibration questions by overestimating their knowledge and provide excessively narrowed confidence intervals. Similarly, it is expected that overconfident trader in the financial experimental market also overestimate the precision of their information or public cues. They also correspondingly underestimate the variance of true dividend in the experiment.

As Table 10 presents, no significant relationship has been found for miscalibration and prediction error. However, ocRankgood lower prediction error suggests that people with higher ability rank tend to make smaller prediction errors. Also, employment positively correlates with prediction error under Pool OLS and Random effect Maximum Likelihood methods. This also has been found in Menkhoff (2013) 's study, with professionals who has more working experience tend to be more overconfident and overestimate their ability and knowledge.

Table 10 Regressions Of Dividend Prediction Error Onto Miscalibration And Other Controls. *T* Statistics In Parentheses, * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$.

	Pool OLS	Random Effect GLS	Random effect ML	Pool OLS	Random Effect GLS	Random effect ML
Miscal				-0.28	-0.32	-0.32
				(-1.26)	(-0.76)	(-0.91)
ocRankbad	0.00	0.00	0.00			
	(1.13)	(0.57)	(0.60)			
ocRankgood	-0.02***	-0.02	-0.02**			
	(-3.78)	(-1.51)	(-2.48)			
bc	-0.05	-0.05	-0.05	-0.05	-0.06	-0.06
	(-0.80)	(-0.68)	(-0.62)	(-0.81)	(-0.64)	(-0.62)
s1	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.10)	(-0.06)	(-0.03)	(-0.03)	(-0.06)	(-0.03)
s2	0.13	0.14	0.14	0.11	0.11	0.11
	(1.13)	(0.74)	(0.81)	(0.89)	(0.61)	(0.58)
emp	0.55***	0.53	0.53**	0.69***	0.71	0.71***
	(3.64)	(1.13)	(2.40)	(3.95)	(1.11)	(2.62)
st	-0.06	-0.05	-0.05	-0.05	-0.04	-0.04
	(-0.95)	(-0.78)	(-0.55)	(-0.74)	(-0.55)	(-0.38)

gender	0.05	0.04	0.03	0.09	0.08	0.07
	(0.71)	(0.45)	(0.36)	(1.28)	(1.14)	(0.70)
age	0.03*	0.04	0.04	0.03	0.04	0.04
	(1.68)	(0.78)	(1.32)	(1.55)	(0.67)	(1.21)
n	0.23	0.26	0.26	0.24	0.27	0.26
	(1.06)	(0.66)	(0.76)	(1.07)	(0.63)	(0.75)
transcost	0.10	0.11	0.11	0.13	0.11	0.11
	(1.10)	(1.27)	(1.13)	(1.27)	(1.17)	(1.08)
session=1	0.00	0.00		0.00	0.00	
	(.)	(.)		(.)	(.)	
session=2	-0.03	0.00		-0.05	-0.01	
	(-0.34)	(0.03)		(-0.44)	(-0.14)	
session=3	-0.02	-0.01		0.00	0.01	
	(-0.24)	(-0.14)		(0.00)	(0.13)	
session=4	0.02	0.04		0.03	0.05	
	(0.21)	(0.57)		(0.33)	(0.71)	
session=5	-0.00	0.01		0.02	0.03	
	(-0.04)	(0.10)		(0.20)	(0.33)	
session=6	0.07	0.08		0.09	0.10	
	(0.68)	(1.09)		(0.89)	(1.34)	
Constant	0.09	-0.04	-0.02	-0.05	-0.18	-0.15
	(0.17)	(-0.04)	(-0.03)	(-0.10)	(-0.15)	(-0.19)
R^2	0.048			0.044		
F	2.80			2.50		
Observations	904	904	904	829	829	829

5.4. Robustness check with Stand-alone experiment

A robustness check is a common exercise in applied econometric studies. It refers to investigating how certain regression coefficient estimates behave when the specification is modified by adding or removing regressors (White and Lu 2014). For an experimental data set, robustness is a sort of generality.

Before the network experiment was continued in 2017, a stand-alone experiment was designed to generate a rough idea of what we expect. The following section discusses the regression results in details.

Firstly, we set the stage by focusing on the bivariate linear regression results. In the first group of bivariate regression models, the dependent variable is average wealth (W_i) of individual' i and the explanatory variables are overconfidence variables and prediction error. As Table 11 shows, the coefficients of miscalibration and survey prediction error are negative. For example, the average wealth decrease is accompanied by a large increase in overconfidence variable (miscalibration and prediction error (svpred). The estimated coefficient for miscalibration is more significant, and the model having more explanatory power. These estimates are negative, which is consistent with the existing literature and our hypothesis of 'higher overconfidence lowering final wealth'.

Table 11. Regression Average Wealth Onto Miscalibration Or Prediction Error

	coeff	t-stat	R-squared
miscalibration	-5.163	-2.116	0.038
svpred	-0.142	-0.454	0.003

Gender characteristics

According to the basic equality test of the groups partitioned by gender characteristics, we cannot reject the null hypothesis of the same mean of average wealth for men and women, which is consistent with our network experimental results. However, Barber and Odean (2001) assume that men are more overconfident than women and found that men have a lower average return.

Prediction error

According to the theoretical literature, the prediction error caused by overconfidence lowers final wealth and trading performance. We regress the average wealth on miscalibration together by adding prediction error. As can be seen from Table 12 and Table 13, there is no strong effect of miscalibration onto prediction error. But the sign of miscalibration in Table 12 suggest that there is a weakly negative correlation was found.

Table 12. Regressing Average Wealth Onto Both Miscaibration And Prediction Error

	Coefficient	t-Statistic
C	0.911	0.386182
miscalibration	-3.929	-1.576737
svpred	-0.212	-0.921087
R-squared	0.050	

Table 13. Regressing Prediction Error Onto Miscalibration

	Coefficient	t-Statistic
C	2.104	1.292
miscalibration	0.641	0.531
R-squared	0.041	

Overconfidence and ability

As can be seen from Table 14, all of the coefficients of ocRankbad are negative. ocRankbad is defined as a measurement of overconfidence according to the width of the five least accurate questions' confidence intervals. Therefore, the higher the value of ocRankbad, the higher the overconfidence level. The coefficients and corresponding tstatistics indicate that ocRankbad is significantly and negatively correlated with final wealth. The estimates of ocRankgood are positively correlated with final wealth. The results conclude that final wealth decreases as the degree of overconfidence increases, where overconfidence is measured using the width of the least accurate questions' confidence intervals. Final wealth increases as ability increases, where ability is measured by the average confidence intervals of the most accurate questions. The finding is consistent with the findings from the network experimental result.

Table 14: Sensitivity check of Regressing Average Wealth onto Ability Rank and Overconfidence Rank.

	Regression 1		Regression 2		Regression 3	
	Coeffi.	T-Stat.	Coeffi.	T-Stat.	Coeffi.	T-Stat.
C	-0.903	-0.805	-4.804	-3.640	-0.560	-0.461
ocRankgood	-0.068	-2.575			-0.067	-2.500
ocRankbad			0.021	0.741		
D1					-0.622	-0.828
R_2	0.067		0.006		0.074	

	Regression 4		Regression 5		Regression 6	
	Coeffi.	T-Stat.	Coeffi.	T-Stat.	Coeffi.	T-Stat.
C	-4.333	-2.685	-2.485	-1.769	-2.194	-1.343
ocRankgood			-0.092	-3.148	-0.091	-3.012
ocRankbad	0.019	0.612	0.060	1.904	0.057	1.713
D1	-0.607	-0.749			-0.417	-0.528
R_2	0.013		0.108		0.112	

As can be seen in Table 15, the first column presents the estimates of coefficients. The estimated coefficient of ocRankbad is statistically significant with the absolute t-statistic values well above 2.

Table 15. Sensitivity Check of Regressing Prediction Error onto Ability Rank and Overconfidence Rank.

	Regression 1		Regression 2		Regression 3	
	Coeffi.	T-Stat.	Coeffi.	T-Stat.	Coeffi.	T-Stat.
C	1.967	3.440	2.256	4.505	1.306	2.609
ocRankgood	0.013	1.046			0.000	0.036
ocRankbad	-0.027	-2.218	-0.021	-1.955		
R_2	0.062		0.048		0.000	

Table 16. Sensitivity Check of Regressing Average Wealth onto Ability Rank and Overconfidence Rank, with Dropping each session sequentially.

Dep.V	ADEW-1		ADEW-2		ADEW-3	
Ind.V	Coeffi.	T-Stat.	Coeffi.	T-Stat.	Coeffi.	T-Stat.
C	-3.259	-1.914	-2.000	-1.357	-2.308	-1.250
ocRankgood	-0.090	-2.803	-0.053	-1.857	-0.100	-2.928
ocRankbad	0.055	1.477	0.046	1.553	0.057	1.522
D1	-0.609	-0.692	-0.570	-0.741	-0.557	-0.616
R^2	0.097		0.052		0.105	
	ADEW-4		ADEW-5		ADEW-6	
Ind.V	Coeffi.	T-Stat.	Coeffi.	T-Stat.	Coeffi.	T-Stat.
C	-2.597	-1.398	-1.357	-0.759	-1.640	-1.057
ocRankgood	-0.103	-3.235	-0.112	-2.906	-0.085	-3.336
ocRankbad	0.057	1.492	0.071	1.903	0.059	2.008
D1	0.028	0.032	-0.234	-0.279	-0.563	-0.781
R^2	0.116		0.136		0.124	

5.5. Summary

Our experimental data replicates the findings suggested in the empirical and theoretical literature that overconfidence, in terms of miscalibration score, affects trading behaviour and reduces relative final wealth in the financial market. However, we can not find any support for the conjecture by which there is a gender difference of trading performance. We also test the role of ability rank and overconfidence rank, finding that they are significantly affecting relative final wealth as we expected. This finding suggests that ability enhance trading outcomes and overconfidence worse trading performance, which contributes to the emerging literature of explaining psychological bias and market bahaviours.

Chapter 6. Investigating Gender and Overconfidence bias effects on Trading Activity

6.1. Introduction

It was shown in the previous chapter that overconfidence bias significantly worse relative final wealth in the experimental financial market. The strong association between overconfidence bias and final wealth has been observed in the previous chapter to withstand adjustments in different hypothesised models.

High trading volume is a well-established phenomenon appears in a financial market, thereby leads to lower returns (Barber et al 2009; Barber and Odean 2000). Many studies show that trading activity measured by trading volume will decrease individuals' earnings and performance (Gervais and Odean 2001). Benos (1998) found that investors overestimated the accuracy of their information, leading to increased trading volumes in different markets. Daniel et al. (1998) also conclude that average overconfident behaviour caused by overconfidence in financial markets can cause harmful effects. Thus, this chapter builds on the previous one by expanding the study to empirically analyse the experimental data and attempt to conclude the direct association between overconfidence measures and trading activity measures.

In contrast to the findings of previous chapter, gender effect is significant in explaining active trading behaviours in this section, while direct causality between overconfidence measures and trading volume not being found.

6.2. Regression results 1: overconfidence and trading activity

The most common explanation of active trading behaviours is that people are overconfidence (Odena 1998, DeBondt Thaler 1995), which means that people believe that the accuracy of their estimation about asset values is greater than that of their opponents (odean 1998).

However, there is only a small number of literature analyses the direct relationship between trading volume and overconfidence bias. According to Biais et al (2005) pointed out, there is no significant association between miscalibration based overconfidence bias and trading activity. Furthermore, Glaser and Weber (2007) analyse the relationships between different measurements of overconfidence with measures of trading activity, finding the better-than-average effect to significantly increase trading volume and miscalibration to be not significant. However, Deaves et al 2009 found that misclibration score, as well as better-than-average effect, increases trading volume in an experimental financial market.

Therefore, we next go on investigate the extent to which overconfidence engenders excessive trade.

As Table 17 and Table 18 show, no significant relationship has been found between any overconfidence measures and relative absolute volumes. However, Table 20 does show that ocRankbad is significantly negatively correlated with $m3_{ij}$, which is expressed as share size per order. This indicates that subjects with higher overconfident rank tend to place smaller size orders. While $m2_{ij}$ being negatively correlated with ability, it indicates that a subject with higher ability tend to trade less in terms of total order size.

Table 17. Regressions Of Absolute Volume Onto Miscalibration And Other Controls. *T* Statistics In Parentheses, * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$

	Cross Sectional OLS	Cross-Sec. OLS	Pool OLS	Random Effect GLS	Cross Sectional OLS	Cross-Sec. OLS	Pool OLS	Random Effect GLS
Miscal		-8.15	-8.15	-8.15				
		(-0.69)	(-0.36)	(-0.37)				
ocRankgood					0.02	-0.52*	-0.52	-0.52
					(0.06)	(-1.80)	(-0.95)	(-0.98)
ocRankbad					-0.51	0.03	0.03	0.03
					(-0.93)	(0.15)	(0.08)	(0.08)
bc		-0.11	-0.11	-0.11	-0.35	-1.02	-1.02	-1.02
		(-0.03)	(-0.02)	(-0.02)	(-0.06)	(-0.33)	(-0.18)	(-0.18)
s1		9.94*	9.94	9.94	9.46	9.75*	9.75	9.75
		(1.75)	(0.92)	(0.95)	(0.96)	(1.89)	(1.00)	(1.03)
s2		8.24	8.24	8.24	10.15	10.50*	10.50	10.50
		(1.28)	(0.67)	(0.70)	(0.91)	(1.80)	(0.95)	(0.98)
emp		-20.57**	-20.57	-20.57	-19.50	-18.54**	-18.54	-18.54
		(-2.28)	(-1.20)	(-1.24)	(-1.34)	(-2.45)	(-1.29)	(-1.33)
st		-6.70*	-6.70	-6.70	-6.18	-5.94*	-5.94	-5.94
		(-1.87)	(-0.98)	(-1.02)	(-0.96)	(-1.76)	(-0.93)	(-0.96)
gender		-11.73***	-11.73*	-11.73*	-10.93*	-10.71***	-10.71*	-10.71*
		(-3.34)	(-1.75)	(-1.81)	(-1.72)	(-3.23)	(-1.70)	(-1.76)
age		0.89	0.89	0.89	0.34	0.65	0.65	0.65
		(0.85)	(0.45)	(0.46)	(0.17)	(0.63)	(0.33)	(0.34)
n		-41.60***	-41.60*	-41.60*	-42.48*	-41.04***	-41.04*	-41.04*
		(-3.50)	(-1.84)	(-1.90)	(-1.88)	(-3.48)	(-1.84)	(-1.90)
session=1		0.00		0.00		0.00		0.00
		(.)		(.)		(.)		(.)
session=2		0.08		0.08		-1.48		-1.48
		(0.01)		(0.02)		(-0.29)		(-0.40)
session=3		4.29		4.29		2.27		2.27
		(0.79)		(1.12)		(0.44)		(0.62)
session=4		3.80		3.80		2.16		2.16
		(0.70)		(0.99)		(0.42)		(0.59)
session=5		0.43		0.43		-0.87		-0.87

	(0.08)		(0.11)		(-0.17)		(-0.24)
session=6	2.45		2.45		0.60		0.60
	(0.45)		(0.64)		(0.12)		(0.16)
Constant	44.48	46.32	44.48	63.96	56.12*	56.56	56.12
	(1.59)	(0.88)	(0.87)	(1.16)	(1.94)	(1.04)	(1.07)
R^2	0.035			0.061	0.035		
F	2.44			1.05	2.50		
Observations	948	948	948	173	1038	1038	1038

Table 18. Regressions Of Absolute Volume Onto Other Psychological Variables And Other Controls. *T* Statistics In Parentheses, * $P < 0.10$, ** $P < 0.05$, *** $P < 0.01$

	Cross Sectional OLS	Pool OLS	Random Effect GLS	Random Effect MLE
Dep. Var.:	V_i	V_{ij}	V_{ij}	V_{ij}
ioc	-0.28	-0.83	-0.83	-0.83
	(-0.04)	(-0.22)	(-0.12)	(-0.12)
gender	-10.58*	-10.38***	-10.38*	-10.38*
	(-1.67)	(-3.13)	(-1.65)	(-1.70)
emp	-20.43	-19.45**	-19.45	-19.45
	(-1.41)	(-2.57)	(-1.36)	(-1.40)
svpred	1.10	4.02	3.03	3.02
	(0.51)	(1.32)	(1.05)	(1.06)
gender	-10.40	-4.87	-9.88	-9.75
	(-1.64)	(-1.06)	(-1.34)	(-1.38)
emp	-20.19	-22.59**	-27.36*	-27.25*
	(-1.40)	(-2.29)	(-1.67)	(-1.74)
pderro	1.09	2.21	1.76	1.77
	(0.28)	(1.17)	(1.03)	(1.04)

gender	-10.52*	-11.05***	-10.01	-10.03
	(-1.66)	(-3.07)	(-1.55)	(-1.59)
emp	-20.34	-21.79**	-21.72	-21.71
	(-1.41)	(-2.53)	(-1.48)	(-1.51)
bta	12.21	10.76	10.76	10.76
	(0.67)	(1.12)	(0.59)	(0.61)
gender	-10.60*	-10.37***	-10.37*	-10.37*
	(-1.68)	(-3.13)	(-1.66)	(-1.71)
emp	-21.92	-20.78***	-20.78	-20.78
	(-1.50)	(-2.72)	(-1.44)	(-1.48)

Table 20 Regressions of $m3_{ij}$-shares per order, $m2_{ij}$-total order size onto different psychological variables and other controls. t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE
Dep. Var. :	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$
Miscal	-0.25	-0.27	-0.27							-0.42	-0.47	-0.47
	(-0.43)	(-0.25)	(-0.25)							(-0.85)	(-0.56)	(-0.58)
ocRankgood				0.00	-0.00	-0.00	-0.03**	-0.03	-0.03*			
				(0.03)	(-0.01)	(-0.01)	(-2.49)	(-1.45)	(-1.65)			
ocRankbad				-0.04***	-0.03**	-0.03**	-0.01	-0.01	-0.01			
				(-3.90)	(-2.04)	(-2.03)	(-1.20)	(-0.69)	(-0.70)			
bc	0.39**	0.39	0.39	0.36***	0.36	0.36	0.00	0.01	0.01	-0.04	-0.04	-0.04
	(2.56)	(1.31)	(1.36)	(2.58)	(1.33)	(1.35)	(0.03)	(0.03)	(0.03)	(-0.33)	(-0.16)	(-0.16)
s1	0.33	0.35	0.35	0.05	0.08	0.08	0.39**	0.43	0.44	0.14	0.19	0.19
	(1.14)	(0.62)	(0.69)	(0.19)	(0.15)	(0.17)	(2.04)	(1.29)	(1.25)	(0.71)	(0.56)	(0.49)
s2	0.11	0.13	0.12	-0.03	-0.00	-0.00	0.44*	0.48	0.48	0.08	0.11	0.12
	(0.33)	(0.20)	(0.22)	(-0.10)	(-0.01)	(-0.01)	(1.93)	(1.23)	(1.23)	(0.33)	(0.28)	(0.26)
emp	0.80**	0.76	0.77	0.35	0.31	0.31	0.39	0.33	0.33	0.51	0.45	0.45
	(2.28)	(1.60)	(0.94)	(1.16)	(0.66)	(0.46)	(1.20)	(0.76)	(0.64)	(1.26)	(0.87)	(0.73)
st	0.34*	0.33	0.33	0.39**	0.37	0.37	0.06	0.03	0.03	0.12	0.09	0.09
	(1.90)	(0.89)	(1.02)	(2.35)	(1.13)	(1.26)	(0.43)	(0.12)	(0.12)	(0.87)	(0.35)	(0.37)
gender	-0.91***	-0.93***	-0.93***	-0.83***	-0.86***	-0.86***	0.09	0.04	0.04	0.14	0.09	0.09

	(-5.49)	(-2.96)	(-2.95)	(-5.36)	(-2.94)	(-2.93)	(0.70)	(0.19)	(0.18)	(1.04)	(0.39)	(0.36)
age	0.07	0.07	0.07	0.06	0.06	0.06	0.01	0.01	0.01	0.01	0.01	0.01
	(1.40)	(0.80)	(0.73)	(1.14)	(0.65)	(0.62)	(0.16)	(0.12)	(0.11)	(0.32)	(0.21)	(0.20)
n	2.01***	1.91***	1.91*	2.11***	2.00***	2.00*	-0.27	-0.46	-0.46	-0.34	-0.53	-0.53
	(4.88)	(5.19)	(1.80)	(5.18)	(5.85)	(1.92)	(-0.61)	(-0.74)	(-0.58)	(-0.75)	(-0.82)	(-0.65)
transcost	1.32***	0.94***	0.94***	0.00	1.03***	1.03***	4.48***	3.70***	3.69***	4.41***	3.63***	3.63***
	(5.06)	(2.81)	(4.12)	(.)	(3.19)	(4.73)	(13.73)	(7.96)	(18.06)	(12.84)	(7.44)	(17.03)
session=2	0.15	0.15	0.15	0.15	0.14	0.14	0.00	0.00	0.00	0.00	0.00	0.00
	(0.60)	(0.87)	(0.86)	(0.62)	(0.87)	(0.86)	(.)	(.)	(.)	(.)	(.)	(.)
session=3	0.11	0.13	0.13	0.13	0.15	0.15	0.02	0.01	0.01	0.09	0.09	0.09
	(0.45)	(0.67)	(0.75)	(0.55)	(0.79)	(0.89)	(0.12)	(0.09)	(0.08)	(0.44)	(0.59)	(0.54)
session=4	0.13	0.13	0.13	0.09	0.09	0.09	0.01	0.04	0.04	0.03	0.06	0.06
	(0.50)	(0.72)	(0.77)	(0.37)	(0.52)	(0.55)	(0.06)	(0.22)	(0.23)	(0.12)	(0.34)	(0.36)
session=5	0.24	0.24	0.24	0.21	0.21	0.21	-0.07	-0.06	-0.06	0.00	0.02	0.02
	(0.98)	(1.30)	(1.41)	(0.89)	(1.16)	(1.27)	(-0.35)	(-0.39)	(-0.41)	(0.01)	(0.09)	(0.10)
session=6	0.06	0.07	0.07	0.10	0.10	0.10	0.09	0.08	0.08	0.12	0.12	0.12
	(0.26)	(0.34)	(0.40)	(0.44)	(0.54)	(0.62)	(0.44)	(0.50)	(0.53)	(0.56)	(0.66)	(0.72)
Constant	2.49*	2.62	2.62	4.25***	4.40*	4.40*	3.41***	3.67**	3.67*	2.62**	2.89	2.89
	(1.84)	(1.08)	(1.05)	(3.05)	(1.71)	(1.73)	(3.32)	(1.96)	(1.88)	(2.54)	(1.60)	(1.53)
R^2	0.108			0.121			0.359			0.342		
F	8.95			10.94			16.23			13.32		
Observations	948	948	948	1038	1038	1038	1038	1038	1038	948	948	948

6.3. Regression results 2: Gender and Trading Activity

Though a significant gender difference in relation to relative final wealth was not found in the previous chapter, there is a widely held perception, built upon theoretical and empirical studies, that gender does impact on trading behaviours. (Agnew et al 2003, Barber and odean 2001; Grinblatt and Keloharju 2009). While there is a lack of empirically or experimentally studies investigating the direct relationship between overconfidence bias measures and trading activity, there is growing number of studies suggesting that males trade more than women, which has been attributed to male are more prone to overconfidence.

In an influential study by Barber and Odean (2001) that used gender as a proxy for overconfidence, they found men to trade more than women, presenting that females trade 55% less than males. Male traders reduce much more returns by making additional trades, when compared to females. One of the explanations for this is that males have been frequently found in different contexts to be more overconfident than female, although this effect does to be task dependent (Lunderberg et al 1994).

Some of the empirical literature studying household trading data suggests that men and women trade differently. Men, for example, are found to be more aggressive and trade excessively, which lowers returns (Barber and Odean 2001). We argue that gender could be one of the proxy variables of overconfidence and that men trade more, leading to lower final wealth. This establishes another accepted explanation of excessive trading puzzle in final market. This chapter also studies the extent to which the role of gender in an experimental market can explain excessive trading, which aims to contribute to the emerging pantheon of literature on this topic.

As can be seen from table 17 to table 20, gender consistently negatively correlates with trading activity measured by either absolute trading volume or average order size. Recall the definition of gender in the regression, it equals to 1 if the subject is female. Therefore a negative coefficient indicates that female subjects trade significantly less than males. As table 22 shows, there is significant gender difference, based on t-test for equality variance, on trading volume, males trade more than female with significant level of 1.26%.

Table 21. Two-sample t test with equal variances of Miscalibration (By Gender)

diff = mean(0) - mean(1) ; Ho: diff=0	
Ha: diff != 0	Pr(|T| > |t|) = 0.0592

Ha: diff < 0	Pr(T < t) = 0.0696
Ha: diff > 0	Pr(T > t) = 0.9704

Table 22 . Two-sample t test with equal variances of Absolute Volume (By Gender)

diff = mean(0) - mean(1) ; Ho: diff=0	
Ha: diff != 0	Pr(|T| > |t|) = 0.0253
Ha: diff < 0	Pr(T < t) = 0.9874
Ha: diff > 0	Pr(T > t) = 0.0126

This gender difference in trading has been attributed to men being more overconfident. Barber and Odean 2001. However, not many studies have systematically tested this interpretation. The purpose of this paper is to experimentally investigate to the extent that gender differences in trading activity are explained by differences in confidence. In particular, a significant gender difference in the relationship between trading activity and psychological bias measurements is expected. However, as can be seen from table 21, the t –test for equality suggests that the underlying gender difference in misclibration is not zero (with a significant level of 5.92%). We can not find systematic difference in overconfidence between men women.

6.4. Summary

This chapter aim to investigate the direct relationship between overconfidence measures and trading volume using the underlying experimental data sets, and in so doing, examine the other evidence for causality and the processes underlying the relationship. However, we have not found any support for the conjecture by which confidence explains active trades. We believe other mechanisms suggested in the literature to promote trading activity might explain the gender differences in relation to trading volume, such as sensation-seeking preferences(Grinblatt and Keloharju 2009), or attitudes towards entertainment or gambling(Dorn and Sengmueller, 2009) Dorn et al 2014)

Chapter 7. Investigating Order Aggressiveness and Trading Performance

7.1 Introduction

My primary goal is to investigate the relationship between psychological bias measures and trading performance in a controlled experimental market. Existing evidence suggests that the linkage between performance and overconfidence bias is likely to be causal, but that many more complicated processes are at play. For the purpose of uncovering the mechanisms how psychological bias affects trading performance, I relate aggressiveness behaviour consequences to the psychological bias measures.

There is no consensus in the emerging literature on what drives the observed behaviour bias and subsequent risk-taking behaviour. This thesis complements previous literature by investigating how behaviour bias affects trading outcome.

7.2. Order aggressiveness

Biais et al (2009a) present the intraday order flows and classify orders in terms of aggressiveness. Investors may suffer from trading loss on their aggressive orders. Apparently, investors demand liquidity and trade aggressively to their detriment. As a results, trading losses was traced to their aggressive trading behaviours. (Barber, et al. 2009b). In a striking constrast, Benos (1998) suggests that aggressive trading may make higher outcomes than rational behaviours.

We next go on to investigate, not only the actual transacted shares, but all the orders being submitted to the market. Thus, we are able to look into the reason that affects order aggressiveness. Our results therefore shed light on the causality relationship of behavioural biases and order submission strategies in limit order markets, which has not been exclusively examined yet, but important in the studies of market behaviours.

7.3. Order aggressiveness determinants:

A number of studies have suggested different explanations of the reasons why investors place aggressive orders, in which assuming investors have rational behaviours. (Parlour 1998 ; Foucault 1999; Handa and Schwartz 1996; Biais et al. 1995). However, we have seen that the psychological bias does affect market outcomes and trader's performance. Thus, we suggest that the underlying psychological bias affects order aggressiveness. To fully analyse the determinants of placing aggressive orders, I consider regression models described as follows:

$$m1_{ij} = \alpha + \beta_1 overconfidence_i + other\ controls_i + session\ dummies + \epsilon_{it},$$

where $m1_{ij}$ is the average order aggressiveness of individual i in session j, $overconfidence_i$ refer to miscalibration score or overconfidence/ability ranks defined in chapter 3; other controls including individual's characteristics are collected in survey experiment; session dummies is a group of 5 dummy variables, in which session i dummy equal to one if session is i is included and session 1dummy is excluded to avoid dummy variable trap.

To assess this association and get robust results, I test the above relationship with different empirical methods.

Table 23 presents multivariate results of order aggressiveness ranks and different overconfident measures with control variables. The table presents coefficients estimators and t-statistics in the parentheses based on the standard errors robust to heteroscedasticity.

The positive relation between Ability rank (ocRankgood) and order aggressiveness is particularly strong and robust under different estimation methods. While miscalibration score(Miscal) and overconfidence rank(ocrRankbad) have no statistically significant relationship with order aggressiveness in this study. The academic background variables (s1 and s2) are weakly positively correlated with order aggressivenss. Surprisingly session dummies for session 5 and 6 are generally significant negatively correlated with order aggressiveness.

Table 23. Regressions of order aggressiveness onto different psychological variables and other controls t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Panel A	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE
Dep. Var.:	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$	$m1_{ij}$
ocRankgood	0.03^{***}	0.03^{**}	0.03^{**}						
	(4.71)	(2.34)	(2.36)						
ocRankbad	0.01	0.01	0.01						
	(1.34)	(0.66)	(0.62)						
Miscal				-0.05	-0.07	-0.07			
				(-0.20)	(-0.13)	(-0.13)			

bc	-0.13*	-0.13	-0.13	-0.12	-0.12	-0.12	-0.13*	-0.13	-0.13
	(-1.90)	(-0.93)	(-0.94)	(-1.58)	(-0.75)	(-0.75)	(-1.87)	(-0.90)	(-0.92)
s1	0.42***	0.44**	0.44*	0.41***	0.42*	0.42	0.38***	0.39	0.39
	(4.32)	(2.31)	(1.81)	(3.70)	(1.94)	(1.51)	(3.10)	(1.55)	(1.59)
s2	0.43***	0.44**	0.44	0.52***	0.53**	0.53*	0.44***	0.45	0.45
	(3.67)	(1.98)	(1.61)	(3.81)	(1.98)	(1.68)	(3.17)	(1.58)	(1.61)
emp	-0.19	-0.21	-0.21	0.03	0.01	0.01	-0.11	-0.13	-0.13
	(-1.21)	(-0.77)	(-0.58)	(0.15)	(0.02)	(0.02)	(-0.60)	(-0.34)	(-0.35)
st	-0.05	-0.05	-0.05	-0.11	-0.13	-0.13	-0.09	-0.09	-0.09
	(-0.56)	(-0.34)	(-0.34)	(-1.28)	(-0.71)	(-0.72)	(-1.07)	(-0.56)	(-0.58)
gender	0.01	-0.00	-0.00	0.02	-0.00	-0.00	-0.01	-0.03	-0.02
	(0.12)	(-0.03)	(-0.03)	(0.18)	(-0.02)	(-0.02)	(-0.15)	(-0.15)	(-0.16)
age	0.06***	0.06	0.06	0.03	0.03	0.03	0.03	0.04	0.04
	(2.65)	(1.55)	(1.29)	(1.29)	(0.73)	(0.63)	(1.44)	(0.71)	(0.73)
n	0.02	-0.04	-0.04	0.06	-0.02	-0.01	0.04	-0.01	-0.01
	(0.06)	(-0.17)	(-0.07)	(0.19)	(-0.06)	(-0.02)	(0.15)	(-0.02)	(-0.02)
transcost	1.17***	0.93***	0.93***	1.19***	0.89***	0.89***	1.15***	0.92***	0.92***
	(8.47)	(6.65)	(9.14)	(7.99)	(6.03)	(8.38)	(9.61)	(9.00)	(9.06)
session=2	-0.00	-0.01	-0.01	0.01	0.01	0.01	-0.00	-0.01	-0.01
	(-0.02)	(-0.09)	(-0.09)	(0.09)	(0.11)	(0.11)	(-0.03)	(-0.09)	(-0.09)
session=3	-0.02	-0.01	-0.01	0.02	0.04	0.04	-0.02	-0.01	-0.01
	(-0.14)	(-0.11)	(-0.13)	(0.17)	(0.38)	(0.45)	(-0.13)	(-0.13)	(-0.13)
session=4	-0.08	-0.08	-0.08	-0.05	-0.05	-0.05	-0.08	-0.08	-0.08
	(-0.70)	(-1.06)	(-1.10)	(-0.42)	(-0.60)	(-0.64)	(-0.69)	(-1.10)	(-1.10)
session=5	-0.19	-0.19**	-0.19**	-0.16	-0.16*	-0.16**	-0.19	-0.19**	-0.19**
	(-1.62)	(-2.18)	(-2.54)	(-1.25)	(-1.71)	(-2.00)	(-1.54)	(-2.54)	(-2.55)
session=6	-0.25**	-0.25***	-0.25***	-0.21*	-0.21**	-0.21***	-0.25**	-0.25***	-0.25***
	(-2.22)	(-3.07)	(-3.34)	(-1.73)	(-2.41)	(-2.66)	(-2.04)	(-3.33)	(-3.34)
Constant	-0.74	-0.66	-0.66	1.06	1.16	1.16	1.05*	1.12	1.12
	(-1.19)	(-0.62)	(-0.49)	(1.63)	(0.97)	(0.85)	(1.78)	(0.92)	(0.94)
R^2	0.142			0.114			0.111		
F	10.94			7.97			9.10		
Observations	1038	1038	1038	948	948	948	1038	1038	1038
Panel B									
BGLM test									
χ^2			656.5						

p-value	0.00

The panel B of Breush-Pagan LM test results suggests that the variance is systematic different from zero and random effect model is appropriate.

It is clear that ability rank increase order aggressiveness with coefficient of 0.03 in random effect GLS model, while weaker academic background in financial economics (s1=1, IEBF students) also engender higher aggressive orders with coefficient of 0.44. The reported standard deviations of ability, s1 are 0.121 and 0.0068. Though they all have positive associations with the order aggressiveness and coefficient of s1 is even higher, the standardized coefficients indicate a different story. The standardized coefficients suggest that a change of one standard deviation in ability rank leads in a $\frac{0.03}{0.0068} = 4.41$ standard deviations increase in the order aggressiveness, which is higher than that in s1. The significance of session dummies equal to session 5 or session 6 suggests that the last two sessions' order aggressiveness are significantly less than previous sessions.

The results show that ocRankgood as a measure of ability increases order aggressiveness, while IEBF students do behave more aggressive comparing to FE and Finance students.

7.4 Order book information and final wealth:

Table 24 reports results for regressing relative final wealth onto miscalibration and overconfident/ability ranks, in which controlling for individuals' characteristics. As can be seen from the first row of coefficients across different regression specifications, order aggressive is statistically and significantly correlated with relative final wealth. Subjects who place higher aggressive orders have higher relative final wealth. This finding is in contrast to the literature of aggressiveness is harmful to one's wealth (Barber, et al. 2009b). However, there is emerging literature that suggests aggressive trader can survive in the market by generating higher performance comparing to more rational trader (Benos, 1998).

Table 24. Regressions of total order size onto different psychological variables and other controls t statistics in parentheses, * p < 0.10, ** p < 0.05, *** p < 0.01

	Pool OLS	RE-GLS	REMLE	Pool OLS	REGLS	REMLE	Pool OLS	RE-GLS	RE-MLE
Dep. Var. :	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$	$m2_{ij}$
Miscal				-0.42	-0.47	-0.47			
				(-0.85)	(-0.56)	(-0.58)			
ocRankgood	-0.03**	-0.03	-0.03*						
	(-2.49)	(-1.45)	(-1.65)						
ocRankbad	-0.01	-0.01	-0.01						
	(-1.20)	(-0.69)	(-0.70)						
bc	0.00	0.01	0.01	-0.04	-0.04	-0.04	-0.00	0.00	0.00
	(0.03)	(0.03)	(0.03)	(-0.33)	(-0.16)	(-0.16)	(-0.00)	(0.01)	(0.01)
s1	0.39**	0.43	0.44	0.14	0.19	0.19	0.44**	0.49	0.49
	(2.04)	(1.29)	(1.25)	(0.71)	(0.56)	(0.49)	(2.21)	(1.41)	(1.40)
s2	0.44*	0.48	0.48	0.08	0.11	0.12	0.44*	0.49	0.49
	(1.93)	(1.23)	(1.23)	(0.33)	(0.28)	(0.26)	(1.95)	(1.23)	(1.22)
emp	0.39	0.33	0.33	0.51	0.45	0.45	0.31	0.24	0.24
	(1.20)	(0.76)	(0.64)	(1.26)	(0.87)	(0.73)	(1.04)	(0.46)	(0.45)
st	0.06	0.03	0.03	0.12	0.09	0.09	0.10	0.07	0.07
	(0.43)	(0.12)	(0.12)	(0.87)	(0.35)	(0.37)	(0.73)	(0.31)	(0.30)
gender	0.09	0.04	0.04	0.14	0.09	0.09	0.11	0.06	0.06
	(0.70)	(0.19)	(0.18)	(1.04)	(0.39)	(0.36)	(0.82)	(0.26)	(0.26)
age	0.01	0.01	0.01	0.01	0.01	0.01	0.04	0.04	0.04
	(0.16)	(0.12)	(0.11)	(0.32)	(0.21)	(0.20)	(0.97)	(0.60)	(0.59)
n	-0.27	-0.46	-0.46	-0.34	-0.53	-0.53	-0.31	-0.51	-0.51
	(-0.61)	(-0.74)	(-0.58)	(-0.75)	(-0.82)	(-0.65)	(-0.67)	(-0.63)	(-0.63)
transcost	4.48***	3.70***	3.69***	4.41***	3.63***	3.63***	4.51***	3.70***	3.68***
	(13.73)	(7.96)	(18.06)	(12.84)	(7.44)	(17.03)	(22.93)	(18.33)	(18.00)
session=2	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.01	0.01
	(.)	(.)	(.)	(.)	(.)	(.)	(0.12)	(0.08)	(0.08)

session=3	0.02	0.01	0.01	0.09	0.09	0.09	0.01	0.04	0.04
	(0.12)	(0.09)	(0.08)	(0.44)	(0.59)	(0.54)	(0.06)	(0.23)	(0.23)
session=4	0.01	0.04	0.04	0.03	0.06	0.06	-0.07	-0.06	-0.06
	(0.06)	(0.22)	(0.23)	(0.12)	(0.34)	(0.36)	(-0.35)	(-0.41)	(-0.41)
session=5	-0.07	-0.06	-0.06	0.00	0.02	0.02	0.09	0.08	0.08
	(-0.35)	(-0.39)	(-0.41)	(0.01)	(0.09)	(0.10)	(0.43)	(0.53)	(0.53)
session=6	0.09	0.08	0.08	0.12	0.12	0.12	0.01	0.01	0.01
	(0.44)	(0.50)	(0.53)	(0.56)	(0.66)	(0.72)	(0.04)	(0.06)	(0.06)
Constant	3.41***	3.67**	3.67*	2.62**	2.89	2.89	1.38	1.59	1.60
	(3.32)	(0.95)	(1.88)	(2.54)	(1.96)	(1.60)	(1.41)	(1.53)	(0.95)
R^2	0.359			0.342			0.350		
F	16.23			13.32			39.33		
Observations	1038	1038	1038	948	948	948	1038	1038	1038

Trading activity (total order size):

Table 25 and 26 , ability rank is weakly significant, negatively correlated with $m2_{ij}$

Table 27 and 28, overconfidence rank is significantly negatively correlated with $m3_{ij}$

However, no obvious associations have been found between $m2_{ij}$, $m3_{ij}$ and relative final wealth.

VWAP and price:

According to the definition of $m4_{ij}$, the higher the value the lower the strategy performance.

Table 25. Regressions of shares per order onto different psychological variables and other controls *t* statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE
Dep. Var. :	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$	$m3_{ij}$

ocRankgood				0.00	-0.00	-0.00			
				(0.03)	(-0.01)	(-0.01)			
ocRankbad				-0.04***	-0.03**	-0.03**			
				(-3.90)	(-2.04)	(-2.03)			
Miscal	-0.25	-0.27	-0.27						
	(-0.43)	(-0.25)	(-0.25)						
bc	0.39**	0.39	0.39	0.36***	0.36	0.36	0.32**	0.32	0.32
	(2.56)	(1.31)	(1.36)	(2.58)	(1.33)	(1.35)	(2.24)	(1.15)	(1.18)
s1	0.33	0.35	0.35	0.05	0.08	0.08	0.16	0.18	0.18
	(1.14)	(0.62)	(0.69)	(0.19)	(0.15)	(0.17)	(0.65)	(0.39)	(0.40)
s2	0.11	0.13	0.12	-0.03	-0.00	-0.00	0.08	0.10	0.10
	(0.33)	(0.20)	(0.22)	(-0.10)	(-0.01)	(-0.01)	(0.29)	(0.20)	(0.20)
emp	0.80**	0.76	0.77	0.35	0.31	0.31	0.24	0.20	0.20
	(2.28)	(1.60)	(0.94)	(1.16)	(0.66)	(0.46)	(0.69)	(0.29)	(0.30)
st	0.34*	0.33	0.33	0.39**	0.37	0.37	0.41***	0.40	0.40
	(1.90)	(0.89)	(1.02)	(2.35)	(1.13)	(1.26)	(2.60)	(1.28)	(1.31)
gender	-0.91***	-0.93***	-0.93***	-0.83***	-0.86***	-0.86***	-0.84***	-0.87***	-0.87***
	(-5.49)	(-2.96)	(-2.95)	(-5.36)	(-2.94)	(-2.93)	(-5.42)	(-2.87)	(-2.94)
age	0.07	0.07	0.07	0.06	0.06	0.06	0.11**	0.11	0.11
	(1.40)	(0.80)	(0.73)	(1.14)	(0.65)	(0.62)	(2.30)	(1.20)	(1.22)
n	2.01***	1.91***	1.91*	2.11***	2.00***	2.00*	1.99***	1.88*	1.88*
	(4.88)	(5.19)	(1.80)	(5.18)	(5.85)	(1.92)	(3.59)	(1.74)	(1.78)
transcost	1.32***	0.94***	0.94***	0.00	1.03***	1.03***	1.49***	1.03***	1.03***
	(5.06)	(2.81)	(4.12)	(.)	(3.19)	(4.73)	(6.34)	(4.68)	(4.72)
session=2	0.15	0.15	0.15	0.15	0.14	0.14	0.15	0.14	0.14
	(0.60)	(0.87)	(0.86)	(0.62)	(0.87)	(0.86)	(0.61)	(0.86)	(0.86)
session=3	0.11	0.13	0.13	0.13	0.15	0.15	0.13	0.15	0.15
	(0.45)	(0.67)	(0.75)	(0.55)	(0.79)	(0.89)	(0.55)	(0.89)	(0.89)
session=4	0.13	0.13	0.13	0.09	0.09	0.09	0.09	0.09	0.09
	(0.50)	(0.72)	(0.77)	(0.37)	(0.52)	(0.55)	(0.36)	(0.54)	(0.55)
session=5	0.24	0.24	0.24	0.21	0.21	0.21	0.21	0.21	0.21

	(0.98)	(1.30)	(1.41)	(0.89)	(1.16)	(1.27)	(0.87)	(1.26)	(1.27)
session=6	0.06	0.07	0.07	0.10	0.10	0.10	0.10	0.10	0.10
	(0.26)	(0.34)	(0.40)	(0.44)	(0.54)	(0.62)	(0.42)	(0.62)	(0.62)
Constant	2.49*	2.62	2.62	4.25***	4.40*	4.40*	1.41	1.54	1.53
	(1.84)	(0.70)	(1.05)	(3.05)	(1.08)	(1.71)	(1.21)	(1.73)	(0.68)
R^2	0.108			0.121			0.105		
F	8.95			10.94			8.59		
Observations	948	948	948	1038	1038	1038	1038	1038	1038

Table 26. Regressions of the performance of VWAP strategy onto different psychological variables and other controls. t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE
Dep. Var.:	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$	$m4_{ij}$
Miscal	-0.03	-0.02	-0.02						
	(-1.27)	(-0.86)	(-1.18)						
ocRankbad				-0.00	-0.00	-0.00			
				(-0.40)	(-0.27)	(-0.37)			
ocRankgood							-0.00***	-0.00***	-0.00***
							(-3.36)	(-2.60)	(-3.04)
bc	-0.01*	-0.01	-0.01	-0.01*	-0.01	-0.01	-0.01*	-0.01	-0.01
	(-1.76)	(-1.22)	(-1.16)	(-1.95)	(-1.52)	(-1.50)	(-1.87)	(-1.38)	(-1.41)
s1	0.01**	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(2.28)	(1.61)	(0.70)	(1.42)	(0.90)	(0.70)	(1.16)	(0.84)	(0.86)
s2	0.01	0.01	0.01	0.01***	0.01**	0.01	0.01*	0.01	0.01
	(1.62)	(1.16)	(0.78)	(2.62)	(2.02)	(1.36)	(1.65)	(1.20)	(1.24)
emp	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-0.41)	(-0.25)	(-0.84)	(-0.27)	(-0.17)	(-0.44)	(-0.90)	(-0.64)	(-0.66)
st	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(0.17)	(0.17)	(0.13)	(0.19)	(0.17)	(0.13)	(0.54)	(0.41)	(0.42)
gender	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.17)	(-0.06)	(-0.08)	(-0.62)	(-0.42)	(-0.51)	(-0.45)	(-0.31)	(-0.32)
age	0.00	0.00	0.00	-0.00	-0.00	-0.00	0.00	0.00	0.00
	(0.69)	(0.48)	(0.63)	(-0.00)	(-0.00)	(-0.00)	(0.79)	(0.58)	(0.60)
n	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
	(0.68)	(0.59)	(0.62)	(0.71)	(0.57)	(0.60)	(0.68)	(0.53)	(0.55)
transcost	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***	-0.03***
	(-5.80)	(-2.62)	(-3.78)	(-5.50)	(-3.30)	(-3.64)	(-4.10)	(-3.41)	(-3.47)

session=2	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.91)	(-1.07)	(-1.10)	(-0.16)	(-0.17)	(-0.22)	(-0.20)	(-0.21)	(-0.21)
session=3	-0.01**	-0.01**	-0.01**	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.04)	(-2.27)	(-2.39)	(-0.76)	(-0.80)	(-1.00)	(-0.91)	(-1.01)	(-1.01)
session=4	-0.01	-0.01	-0.01	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00
	(-0.86)	(-0.99)	(-1.19)	(-0.33)	(-0.36)	(-0.48)	(-0.43)	(-0.48)	(-0.48)
session=5	-0.01**	-0.01**	-0.01**	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.02)	(-2.07)	(-2.17)	(-1.08)	(-1.08)	(-1.39)	(-1.27)	(-1.38)	(-1.39)
session=6	-0.01	-0.01*	-0.01**	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-1.59)	(-1.84)	(-2.19)	(-0.66)	(-0.73)	(-0.96)	(-0.87)	(-0.95)	(-0.96)
Constant	0.03	0.03	0.03	0.08**	0.08*	0.08	0.00	0.00	0.00
	(0.75)			(2.45)			(0.05)		
R^2	0.045			0.048			0.028		
F	2.95			3.41			2.12		
Observations	948	948	948	1038	1038	1038	1038	1038	1038
				(0.49)	(0.51)	(1.81)		(1.47)	(0.02)
				(0.02)					

Table 27. Regressions of the relative final wealth onto $m1_{ij}$ and different psychological variables and other controls. t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Pool OLS	Random Effect GLS	Random effect ML	Pool OLS	Random Effect GLS	Random effect ML	HT (m1 is endogenous)	Pool OLS	Random Effect GLS	Random effect ML	HT (m1 is endogenous)
Dep. Var.:	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}
m1	0.16***	0.18***	0.18***	0.16**	0.17*	0.17**	0.19*	0.15**	0.16*	0.16**	0.19*
	(2.80)	(2.62)	(2.65)	(2.11)	(1.79)	(2.44)	(1.83)	(2.05)	(1.85)	(2.44)	(1.94)
Miscal				-1.31**	-1.28**	-1.28*	-1.37*				
				(-2.49)	(-2.09)	(-1.84)	(-1.93)				
ocRankgood								0.05***	0.05***	0.05***	0.05***
								(3.60)	(2.74)	(2.92)	(2.75)
ocRankbad								-0.03***	-0.03***	-0.03***	-0.03***
								(-3.60)	(-2.80)	(-2.99)	(-3.08)

bc	-0.03	-0.02	-0.02	0.03	0.03	0.03	0.03	0.02	0.03	0.03	0.03
	(-0.18)	(-0.11)	(-0.11)	(0.21)	(0.18)	(0.18)	(0.16)	(0.14)	(0.16)	(0.16)	(0.15)
s1	-0.31	-0.30	-0.30	-0.19	-0.19	-0.19	-0.23	-0.36*	-0.35	-0.35	-0.40
	(-1.33)	(-0.99)	(-1.01)	(-0.79)	(-0.58)	(-0.56)	(-0.67)	(-1.66)	(-1.39)	(-1.22)	(-1.34)
s2	-0.22	-0.21	-0.21	-0.13	-0.12	-0.12	-0.16	-0.35	-0.35	-0.35	-0.39
	(-0.85)	(-0.61)	(-0.63)	(-0.45)	(-0.31)	(-0.32)	(-0.42)	(-1.38)	(-1.13)	(-1.05)	(-1.16)
emp	-0.05	-0.02	-0.02	0.16	0.20	0.20	0.23	-0.04	-0.01	-0.02	0.01
	(-0.13)	(-0.03)	(-0.04)	(0.31)	(0.28)	(0.37)	(0.42)	(-0.11)	(-0.03)	(-0.04)	(0.02)
st	0.14	0.15	0.15	0.05	0.06	0.06	0.05	0.17	0.18	0.18	0.17
	(0.91)	(0.73)	(0.75)	(0.30)	(0.27)	(0.29)	(0.24)	(1.11)	(0.86)	(0.94)	(0.88)
gender	-0.10	-0.10	-0.10	0.03	0.02	0.02	0.02	-0.05	-0.06	-0.06	-0.07
	(-0.64)	(-0.52)	(-0.53)	(0.15)	(0.08)	(0.09)	(0.08)	(-0.34)	(-0.28)	(-0.31)	(-0.35)
age	-0.06	-0.07	-0.07	-0.08	-0.09	-0.09	-0.10	-0.08*	-0.09	-0.09	-0.10*
	(-1.20)	(-1.07)	(-1.09)	(-1.53)	(-1.28)	(-1.35)	(-1.51)	(-1.67)	(-1.38)	(-1.44)	(-1.66)
n	0.50	0.52	0.52	0.56	0.59	0.59	0.58	0.61	0.62	0.62	0.62
	(0.92)	(0.73)	(0.75)	(0.99)	(1.19)	(0.83)	(0.81)	(1.08)	(1.24)	(0.93)	(0.92)
transcost	-0.24	-0.20	-0.20	-0.28	-0.21	-0.22	-0.24	-0.19	-0.17	-0.17	-0.20
	(-0.96)	(-0.74)	(-0.76)	(-1.08)	(-0.83)	(-0.76)	(-0.78)	(-0.78)	(-0.73)	(-0.65)	(-0.73)
session=2	-0.06	-0.07	-0.07	-0.09	-0.11	-0.11		-0.05	-0.07	-0.07	
	(-0.24)	(-0.34)	(-0.34)	(-0.41)	(-0.56)	(-0.50)		(-0.24)	(-0.36)	(-0.32)	
session=3	0.04	0.01	0.02	0.04	0.01	0.02		0.04	0.02	0.02	
	(0.16)	(0.07)	(0.07)	(0.17)	(0.06)	(0.07)		(0.17)	(0.08)	(0.08)	
session=4	-0.03	-0.05	-0.05	-0.07	-0.09	-0.09		-0.03	-0.05	-0.05	
	(-0.13)	(-0.24)	(-0.23)	(-0.27)	(-0.37)	(-0.39)		(-0.12)	(-0.21)	(-0.22)	
session=5	-0.08	-0.09	-0.09	-0.20	-0.21	-0.21		-0.08	-0.09	-0.09	
	(-0.34)	(-0.41)	(-0.41)	(-0.86)	(-1.00)	(-0.91)		(-0.38)	(-0.45)	(-0.42)	
session=6	0.23	0.21	0.21	0.16	0.14	0.14		0.23	0.21	0.21	
	(0.99)	(0.97)	(0.98)	(0.72)	(0.63)	(0.61)		(1.08)	(1.01)	(0.98)	

Constant	1.24	1.42	1.41	2.59**	2.72	2.71	3.07*	2.01	2.16	2.15	2.67
	(1.07)	(0.94)	(0.96)	(1.99)	(1.61)	(1.63)	(1.74)	(1.52)	(1.25)	(1.30)	(1.54)
R^2	0.015			0.020				0.034			
F	1.03			1.07				1.74			1.79
Observations	1016	1016	1016	927	927	927	927	1016	1016	1016	1016

Tabe 28. Regressions of the relative final wealth onto $m2_{ij}$ – total order side, and different psychological variables and other controls. t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Pool OLS	Random Effect GLS	Random effect ML	Pool OLS	Random Effect GLS	Random effect ML	HT(m2 is endogenous)	Pool OLS	Random Effect GLS	Random effect ML	HT(m2 is endogenous)
Dep. Var. :	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}
m2	0.01	0.03	0.03	0.00	0.03	0.02	0.06	0.02	0.03	0.03	0.06
	(0.25)	(0.67)	(0.66)	(0.07)	(0.69)	(0.60)	(1.27)	(0.44)	(0.85)	(0.75)	(1.19)
Miscal				-1.31**	-1.27**	-1.28*	-1.37*				
				(-2.48)	(-2.05)	(-1.82)	(-1.91)				
ocRankgood								0.05***	0.05***	0.05***	0.05***
								(3.95)	(2.95)	(3.30)	(3.24)
ocRankbad								-0.03***	-0.03***	-0.03***	-0.03***
								(-3.49)	(-2.66)	(-2.87)	(-2.95)
bc	-0.05	-0.04	-0.04	0.01	0.02	0.02	0.01	0.00	0.01	0.01	0.00

	(-0.34)	(-0.24)	(-0.24)	(0.08)	(0.09)	(0.09)	(0.05)	(0.01)	(0.04)	(0.03)	(0.00)
s1	-0.24	-0.24	-0.24	-0.12	-0.11	-0.11	-0.16	-0.30	-0.29	-0.29	-0.34
	(-1.04)	(-0.78)	(-0.80)	(-0.50)	(-0.36)	(-0.34)	(-0.45)	(-1.37)	(-1.13)	(-1.00)	(-1.14)
s2	-0.15	-0.14	-0.14	-0.04	-0.02	-0.02	-0.07	-0.29	-0.28	-0.28	-0.33
	(-0.56)	(-0.39)	(-0.40)	(-0.13)	(-0.06)	(-0.06)	(-0.17)	(-1.14)	(-0.91)	(-0.85)	(-0.98)
emp	-0.06	-0.04	-0.04	0.17	0.20	0.19	0.21	-0.07	-0.05	-0.05	-0.04
	(-0.18)	(-0.09)	(-0.09)	(0.32)	(0.26)	(0.36)	(0.38)	(-0.19)	(-0.09)	(-0.13)	(-0.09)
st	0.12	0.13	0.13	0.03	0.04	0.04	0.02	0.16	0.17	0.17	0.16
	(0.82)	(0.64)	(0.66)	(0.20)	(0.17)	(0.19)	(0.10)	(1.07)	(0.80)	(0.89)	(0.81)
gender	-0.10	-0.11	-0.11	0.03	0.02	0.02	0.01	-0.06	-0.06	-0.06	-0.07
	(-0.66)	(-0.54)	(-0.55)	(0.16)	(0.07)	(0.08)	(0.04)	(-0.35)	(-0.29)	(-0.32)	(-0.39)
age	-0.05	-0.06	-0.06	-0.07	-0.08	-0.08	-0.10	-0.07	-0.08	-0.08	-0.10
	(-1.08)	(-0.97)	(-0.98)	(-1.45)	(-1.21)	(-1.25)	(-1.48)	(-1.49)	(-1.23)	(-1.26)	(-1.54)
n	0.51	0.53	0.53	0.58	0.61	0.60	0.61	0.62	0.63	0.63	0.64
	(0.94)	(0.75)	(0.76)	(1.03)	(1.18)	(0.85)	(0.84)	(1.11)	(1.20)	(0.94)	(0.94)
transcost	-0.08	-0.12	-0.12	-0.09	-0.13	-0.13		-0.09	-0.12	-0.12	
	(-0.28)	(-0.38)	(-0.38)	(-0.29)	(-0.43)	(-0.39)		(-0.29)	(-0.41)	(-0.38)	
session=2	-0.06	-0.07	-0.07	-0.09	-0.12	-0.11		-0.05	-0.07	-0.07	
	(-0.24)	(-0.35)	(-0.35)	(-0.40)	(-0.57)	(-0.51)		(-0.24)	(-0.37)	(-0.33)	

session=3	0.03	0.01	0.01	0.04	0.01	0.01		0.03	0.01	0.01	
	(0.13)	(0.02)	(0.03)	(0.17)	(0.05)	(0.05)		(0.14)	(0.04)	(0.04)	
session=4	-0.04	-0.07	-0.06	-0.08	-0.10	-0.10		-0.04	-0.06	-0.06	
	(-0.19)	(-0.30)	(-0.30)	(-0.30)	(-0.42)	(-0.44)		(-0.16)	(-0.26)	(-0.28)	
session=5	-0.11	-0.12	-0.12	-0.22	-0.24	-0.24		-0.11	-0.12	-0.12	
	(-0.48)	(-0.58)	(-0.58)	(-0.97)	(-1.16)	(-1.04)		(-0.52)	(-0.62)	(-0.58)	
session=6	0.19	0.16	0.16	0.13	0.10	0.10		0.19	0.17	0.17	
	(0.81)	(0.76)	(0.77)	(0.57)	(0.47)	(0.44)		(0.91)	(0.82)	(0.78)	
				2.73							
	(1.07)			(2.11)							
R^2	0.015			0.013							
F	1.03			0.85			0.75			0.75***	1.57
Observations	1016	1016	1016	927	927	927	927			(8.20)	1016
Constant	1.24	1.42	1.41	**	2.81*	2.81*	3.23*	1.83	1.92	1.92	2.47
		(0.94)	(0.96)		(1.67)	(1.66)	(1.80)	(1.40)	(1.11)	(1.15)	(1.40)

As can be seen from Table 29 and Table 30, ocRankgood is significantly negatively correlated with $m4_{ij}$; $m4_{ij}$ is negatively significantly correlated with relative final wealth.

Table 29. Regressions of the relative final wealth onto $m3_{ij}$ and different psychological variables and other controls. t statistics in parentheses, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	Pool OLS	Random Effect GLS	Random effect ML	Pool OLS	Random Effect GLS	Random effect ML	HT(m3)	Pool OLS	Random Effect GLS	Random effect ML	HT(m3)
Dep. Var. :	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}
m3	0.05*	0.05	0.05	0.04	0.05	0.04	0.05	0.04	0.05	0.05	0.05
	(1.68)	(1.58)	(1.60)	(1.26)	(1.19)	(1.29)	(1.02)	(1.40)	(1.33)	(1.43)	(1.18)

Miscal				-1.31**	-1.27**	-1.27*	-1.39*				
				(-2.45)	(-2.04)	(-1.82)	(-1.96)				
ocRankgood								0.05***	0.05***	0.05***	0.05***
								(3.93)	(2.91)	(3.27)	(3.16)
ocRankbad								-0.03***	-0.03**	-0.03***	-0.03***
								(-3.28)	(-2.50)	(-2.73)	(-2.83)
bc	-0.06	-0.06	-0.06	-0.00	-0.00	-0.00	-0.01	-0.01	-0.01	-0.01	-0.02
	(-0.46)	(-0.33)	(-0.34)	(-0.03)	(-0.01)	(-0.01)	(-0.06)	(-0.11)	(-0.06)	(-0.06)	(-0.11)
s1	-0.24	-0.23	-0.24	-0.13	-0.12	-0.12	-0.16	-0.29	-0.28	-0.28	-0.32
	(-1.06)	(-0.77)	(-0.79)	(-0.55)	(-0.39)	(-0.37)	(-0.48)	(-1.34)	(-1.10)	(-0.97)	(-1.09)
s2	-0.15	-0.13	-0.13	-0.04	-0.03	-0.03	-0.07	-0.28	-0.27	-0.27	-0.30
	(-0.56)	(-0.38)	(-0.39)	(-0.15)	(-0.07)	(-0.07)	(-0.18)	(-1.10)	(-0.86)	(-0.82)	(-0.92)
emp	-0.07	-0.04	-0.05	0.13	0.17	0.17	0.22	-0.08	-0.06	-0.06	-0.03
	(-0.22)	(-0.10)	(-0.10)	(0.25)	(0.23)	(0.32)	(0.39)	(-0.21)	(-0.10)	(-0.13)	(-0.06)
st	0.10	0.11	0.11	0.02	0.03	0.03	0.01	0.15	0.15	0.15	0.14
	(0.69)	(0.55)	(0.56)	(0.11)	(0.12)	(0.13)	(0.05)	(0.96)	(0.71)	(0.81)	(0.72)
gender	-0.06	-0.06	-0.06	0.06	0.06	0.06	0.06	-0.02	-0.02	-0.02	-0.03
	(-0.36)	(-0.30)	(-0.31)	(0.38)	(0.26)	(0.29)	(0.28)	(-0.11)	(-0.09)	(-0.10)	(-0.14)
age	-0.06	-0.06	-0.06	-0.07	-0.08	-0.08	-0.10	-0.07	-0.08	-0.08	-0.10
	(-1.20)	(-1.05)	(-1.07)	(-1.50)	(-1.26)	(-1.30)	(-1.55)	(-1.54)	(-1.26)	(-1.31)	(-1.61)

n	0.40	0.41	0.41	0.49	0.50	0.50	0.48	0.52	0.52	0.52	0.50
	(0.73)	(0.57)	(0.59)	(0.87)	(0.98)	(0.70)	(0.67)	(0.93)	(1.00)	(0.77)	(0.73)
transcost	-0.12	-0.08	-0.08	-0.14	-0.08	-0.08	-0.08	-0.08	-0.05	-0.05	-0.06
	(-0.50)	(-0.30)	(-0.31)	(-0.56)	(-0.30)	(-0.29)	(-0.29)	(-0.33)	(-0.23)	(-0.21)	(-0.24)
session=2	-0.06	-0.08	-0.08	-0.10	-0.12	-0.12		-0.06	-0.08	-0.08	
	(-0.27)	(-0.38)	(-0.38)	(-0.43)	(-0.59)	(-0.52)		(-0.27)	(-0.40)	(-0.36)	
session=3	0.02	-0.00	0.00	0.03	0.01	0.01		0.03	0.00	0.01	
	(0.10)	(-0.00)	(0.00)	(0.14)	(0.04)	(0.04)		(0.12)	(0.02)	(0.03)	
session=4	-0.05	-0.07	-0.07	-0.08	-0.11	-0.10		-0.04	-0.07	-0.06	
	(-0.21)	(-0.33)	(-0.33)	(-0.31)	(-0.44)	(-0.46)		(-0.17)	(-0.29)	(-0.30)	
session=5	-0.12	-0.13	-0.13	-0.23	-0.25	-0.24		-0.12	-0.13	-0.13	
	(-0.52)	(-0.62)	(-0.62)	(-1.01)	(-1.20)	(-1.08)		(-0.55)	(-0.66)	(-0.61)	
session=6	0.18	0.16	0.16	0.12	0.10	0.10		0.19	0.16	0.16	
	(0.78)	(0.73)	(0.74)	(0.56)	(0.45)	(0.43)		(0.89)	(0.80)	(0.76)	
								1.71			
	(1.16)			(2.02)				(1.28)			
R^2	0.010			0.015				0.030			
F	0.69			1.06			0.71	1.70			1.59
Observations	1016	1016	1016	927	927	927	927	1016	1016	1016	1016
Constant	1.35	1.52	1.51	2.64**	2.77	2.76	3.31*		1.82	1.81	2.45
		(1.01)	(1.02)		(1.63)	(1.64)	(1.87)		(1.03)	(1.09)	(1.40)

Table 30. Regressions of the relative final wealth onto $m4_{ij}$ and different psychological variables and other controls. t statistics in parentheses, $^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

	Pool OLS	RE-GLS	RE-MLE	Pool OLS	RE-GLS	RE-MLE	HT(m4)	Pool OLS	RE-GLS	RE-MLE	HT(m4)
Dep. Var. :	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}	W_{ij}
m4	-3.01***	-2.47**	-2.47**	-3.77***	-2.96*	-2.97**	-1.35	-2.74**	-2.35*	-2.35**	-1.50
	(-3.09)	(-2.51)	(-2.52)	(-2.85)	(-1.80)	(-2.48)	(-0.99)	(-2.35)	(-1.74)	(-2.40)	(-1.36)
Miscal				-1.42***	-1.38**	-1.38**	-1.43**				
				(-2.74)	(-2.37)	(-2.00)	(-2.03)				
ocRankgood								0.05***	0.05***	0.05***	0.05***
								(3.60)	(2.77)	(3.05)	(3.03)
ocRankbad								-0.03***	-0.03***	-0.03***	-0.03***
								(-3.62)	(-2.85)	(-2.97)	(-3.05)
bc	-0.07	-0.06	-0.06	-0.01	-0.01	-0.01	-0.00	-0.02	-0.01	-0.01	-0.01
	(-0.53)	(-0.36)	(-0.37)	(-0.10)	(-0.03)	(-0.03)	(-0.01)	(-0.17)	(-0.08)	(-0.09)	(-0.07)
s1	-0.21	-0.21	-0.21	-0.09	-0.09	-0.09	-0.13	-0.27	-0.27	-0.27	-0.30
	(-0.92)	(-0.70)	(-0.70)	(-0.39)	(-0.28)	(-0.27)	(-0.40)	(-1.26)	(-1.04)	(-0.93)	(-1.04)
s2	-0.10	-0.09	-0.09	-0.00	0.01	0.01	-0.05	-0.24	-0.24	-0.24	-0.28
	(-0.39)	(-0.27)	(-0.28)	(-0.01)	(0.02)	(0.02)	(-0.12)	(-0.95)	(-0.77)	(-0.72)	(-0.85)
emp	-0.09	-0.07	-0.07	0.10	0.14	0.14	0.22	-0.09	-0.07	-0.07	-0.03
	(-0.27)	(-0.16)	(-0.16)	(0.22)	(0.24)	(0.27)	(0.41)	(-0.24)	(-0.14)	(-0.16)	(-0.06)
st	0.13	0.14	0.14	0.03	0.04	0.04	0.03	0.17	0.17	0.17	0.16
	(0.88)	(0.70)	(0.71)	(0.21)	(0.19)	(0.20)	(0.13)	(1.09)	(0.82)	(0.91)	(0.84)
gender	-0.10	-0.11	-0.11	0.03	0.02	0.02	0.02	-0.06	-0.06	-0.06	-0.07
	(-0.69)	(-0.57)	(-0.57)	(0.15)	(0.09)	(0.10)	(0.08)	(-0.39)	(-0.32)	(-0.35)	(-0.39)
age	-0.05	-0.06	-0.06	-0.07	-0.07	-0.07	-0.09	-0.07	-0.08	-0.08	-0.10
	(-0.99)	(-0.92)	(-0.92)	(-1.34)	(-1.16)	(-1.20)	(-1.44)	(-1.47)	(-1.21)	(-1.27)	(-1.53)
n	0.54	0.55	0.55	0.62	0.63	0.63	0.60	0.65	0.65	0.65	0.64
	(1.00)	(0.79)	(0.80)	(1.08)	(1.16)	(0.90)	(0.85)	(1.14)	(1.18)	(0.98)	(0.95)

transcost	-0.14	-0.09	-0.09	-0.22	-0.13	-0.13	-0.07	-0.11	-0.07	-0.07	-0.04
	(-0.59)	(-0.35)	(-0.35)	(-0.89)	(-0.55)	(-0.49)	(-0.25)	(-0.45)	(-0.31)	(-0.27)	(-0.15)
session=2	-0.06	-0.08	-0.08	-0.12	-0.13	-0.13		-0.06	-0.07	-0.07	
	(-0.26)	(-0.36)	(-0.36)	(-0.51)	(-0.64)	(-0.58)		(-0.26)	(-0.38)	(-0.34)	
session=3	0.01	-0.01	-0.01	-0.02	-0.03	-0.03		0.01	-0.01	-0.01	
	(0.04)	(-0.05)	(-0.05)	(-0.07)	(-0.13)	(-0.13)		(0.06)	(-0.03)	(-0.03)	
session=4	-0.05	-0.07	-0.07	-0.10	-0.12	-0.12		-0.05	-0.07	-0.07	
	(-0.23)	(-0.34)	(-0.35)	(-0.40)	(-0.50)	(-0.53)		(-0.20)	(-0.31)	(-0.32)	
session=5	-0.14	-0.15	-0.15	-0.27	-0.27	-0.27		-0.14	-0.14	-0.14	
	(-0.60)	(-0.67)	(-0.68)	(-1.20)	(-1.33)	(-1.20)		(-0.63)	(-0.72)	(-0.67)	
session=6	0.17	0.15	0.15	0.08	0.06	0.06		0.17	0.15	0.15	
	(0.73)	(0.69)	(0.70)	(0.36)	(0.29)	(0.27)		(0.84)	(0.74)	(0.72)	
Constant	1.40	1.58	1.58	2.83^{**}	2.95^{*}	2.95^{*}	3.37^{*}	2.09	2.21	2.21	2.71
	(1.20)	(1.07)	(1.08)	(2.19)	(1.77)	(1.79)	(1.93)	(1.60)	(1.29)	(1.34)	(1.57)
R^2	0.017			0.024				0.036			
F	1.14			1.61			0.71	1.97			1.65
Observations	1016	1016	1016	927	927	927	927	1016	1016	1016	1016

7.4.1 Robustness check with Hausman and Taylor Model

As can been seen from the results presented in this chapter, each regression models were revisited with different estimation methods. The pool OLS regression assumes there is no unobserved effect, the systematic variance is zero. However, according to Table 31 BGLM suggests that the null hypothesis of OLS regression is rejected in all the regressions with alternative overconfidence or aggressiveness measures. Though the OLS results shows statistical significance, it may not be efficient and unbiased. We are suggested that order book information were collected to reflect psychological bias, so if we adding order book information into the basic relation of overconfidence measures and relative final wealth, we expect that order book information as additional regressors may be correlated with overconfidence measures or unobserved individual effect. Endogenous variables are a common problem in OLS regression, and can lead to violation of the assumptions of OLS regression and random effect GLS models. Hausman and Taylor regression model introduced in chapter 4 could present efficient and consistent estimators when the model is suffering endogeneity problem. Recall the conclusion section in chapter 6 suggests that there are some other psychological bias not observed and potentially correlated with trading behaviour, which indicating that the individual effects may be correlated with the regressors of order book information. In this case, the OLS or Random effect GLS are biased upward.

As mentioned in chapter 4, the fixed effect estimator can provide generally consistent estimator. However, in this thesis, the coefficients of psychological measures can not be estimated by a fixed effect model. In addition, the fixed effect estimates may not be fully efficient.

Hausman and Taylor regression model is presented to address the issues. As can be seen from Table 24, consider the Hausman and Taylor estimator given in the seventh column. The coefficient on $m1_{ij}$ is estimated to be 0.19, which is higher than OLS, GLS and MLE estimate results. In addition, a Hausman test results of the difference between fixed effect estimators and Hausman and Taylor estimaors is shown in Table 31. The test statistics is $\chi^2 = 0.87$, with p-value of 0.6476. Therefore, the null hypothesis of there is not systematic different in efficiency between fixed effect estimator and HT estimator can not be rejected, which indicate that the instruments used in HT model are valid. In general, the HT estimators resemble the Pool OLS and random effect estimators across estimation results in this chapter.

Table 31. Hausman Test Fixed And HT Estimator ($m1_{ij}$ Is Endogenous)

	χ^2	p-value
Mical	0.87	0.6476
goodbad	1.26	0.5323
bta	1.28	0.5276

pderro	1.26	0.5336
svpred	2.41	0.491

7.6. Discussion

To sum up, I examine the relationships between order aggressiveness, overconfidence or ability measures and relative final wealth. I found that subjects with higher ability rank tend to place higher aggressive orders and end up by higher relative wealth. This may be one of the channel that explains the mechanism how psychological bias affect final wealth in the financial market. Another finding is that ability improve order performance ($m4_{ij}$), through which improves relative final wealth. The results presented in this chapter elucidate the mechanisms and causal pathways operating in the complex relationship and allow conclusions to be made separately by different possible psychological bias measurements.

Chapter 8. Discussions and Conclusions

8.1. Findings

This thesis studies the overconfidence effect on heterogeneous behaviours in an experimental financial market. In order to document miscalibration score and other relevant psychological bias measures, we used the miscalibration test suggested by psychological literature. We collected a survey data set that encompassing the participants of this experimental research that contains both psychological measures and their demographic variables for the purposes of this study. We also gathered two panel data sets about experimental financial market trading details from both stand-alone and network trading games. The data sets span six-session trading periods and contain various trading information, which support the empirical analysis of experimental trading market.

The results reported across this thesis consistently show that overconfidence rank and ability rank, which are newly defined by this study, significantly and simultaneously affect relative final wealth. More precisely, ability rank significantly increases relative final wealth, while overconfidence rank reduces relative final wealth. Unsurprisingly, misclibration score has been found to negatively correlate with trading performance in this study, which is consistent with the existing literature. Gender effect has been found to help explain excessive trading volume but not relative final wealth. For the process of discovering the channel through which psychological bias affects financial market performance, we have found that ability rank significantly enhances order aggressiveness and improves trading performance. This indicates that people placing more aggressive orders were willing to take more risk with price volatility. Such risktaking behaviour, alongside higher ability rank, can enhance trading performance. This also explains why sometimes aggressive traders can survive in the current financial market.

8.2. Criticisms

Criticisms have emerged despite the volume of findings investigating and improving overconfidence measurements having proliferated in recent years. Criticisms that have been raised against all types of overconfidence are usually directed either at research methodology and experimental design or the underlying concept itself. For example, the overuse of the term "overconfidence" may generate statistical and economic bias (Olsson, 2014). Fellner and Krugel (2012) indicate that overconfidence and miscalibration are unrelated, even though miscalibration has frequently been measured as the overprecision of knowledge. The list of psychological researchers who have questioned the reality of overconfidence or the research design includes Juslin (1994); Gigerenzer (1991); Marsh and Merton (1986); Gigerenzer, Hoffrage and Kleinbolting (1991); Erev, Wallsten & Budescu (1999); Kleidon 1986). Researchers should be able to document the validity and reliability of the measures adopted in their research to reconcile these doubts and concerns about overconfidence itself and its measurement.

8.3. Limitations and Further Research

The thesis adopts an experimental approach in testing overconfidence and its interaction with gender and ability. Several measures of overconfidence are proposed and used in regression analysis to test for potential relationship between overconfidence of trading performance and activity. Although the use of different measures of overconfidence and ability provide a wealth of information of measuring the different aspects of psychological bias, most of the measures are ad hoc and can be problematic. We have not, for example, systematically distinct the differences between all these measures. Furthermore, one of the limitation of this thesis is that the loss of generality. We were not able to get a sample of participants with different age, occupations, trading experiences and levels of educations.

However, the restricted sample still tells us some stories about overconfidence. With the similar age, education and trading experiences, students still behaved very differently, not only in the overconfidence measurement tests(misclibration questionnaire surveys), but also trading performance. With controlling age, education and trading experience, we can discover the direct relationships between proxies of overconfidence and trading behaviours. Another limitation is that the noncash incentive may not be the proper incentive and encourages participant to trade seriously. Higher incentive dose improve performance often, typically judgment tasks that are responseive to better effort. Incentives also reduce"presentation" effects(eg generosity and risk -seeking). However, table 5 and 6 with lagged dependent variable as regressors suggest that there is significant improvement in terms of relative final wealth or trading activity between two consecutive sessions. This finding somehow implies that participant were trading seriously and were learning to behave better as well.

In view of the criticisms and limitations, further research is needed to address the relevant issues. The financial market experiments in this research were designed based on assuming no feedback effect. In other words, each participant is assumed to have a constant overconfidence level and that there are no dynamics in the analytical model. However, Gervais and Odean (2001) proposed a theoretical overconfidence model incorporating learning process, suggesting that overconfidence changes over the time if there is learning through feedback. Empirically, Griffin et al (2007) suggest that past earning success as a proxy variable of psychological bias can significantly affect investor's belief and trading activity. If the assumption of giving feedback to participants after each session is released, dividend prediction may be a more appropriate proxy of overconfidence, which is not found to be significant in this study.

If we allow feedback effect in an experimental study, we could expect a time fixed effect on the data. A heterogeneous panel model with time-specific factors can be estimated. However, this assumption may also cause an endogeneity problem, with some of the regressors on the righthand side of the regression potentially correlating with the error term. Precisely, feedback effect induces the impact of last period's outcome on this period dividend prediction and possible onto this period performance. Therefore, a dynamic panel model may be considered and GMM estimation method could be applied with valid instruments.

A risk averse investor tend to sell stock promptly or by placing a limit order at a more favourable price. We use order book information to measure order aggressiveness to interpret the attitude towards risk. However, a more formal theoretical model should be investigated to contribute the volume of literature of studying risk attitude and behaviour bias.

Appendix A.

OLS Solution of Kyle (1985) model:

$$\min E[(\tilde{v} - P(y))^2] = E[\tilde{v} - \mu - \lambda(\alpha + \beta\tilde{v} + \tilde{u})]^2$$

$$= E[\tilde{v}(1 - \lambda\beta) - \lambda\tilde{u} - \mu - \lambda\alpha]^2$$

Recall the assumptions: $E[\tilde{v}] = p_0; E[(\tilde{v} - p_0)^2] = \Sigma_0, E[u] = 0; E[u^2] = \sigma_u^2, E[uv] = 0$

Objective function becomes:

$$\min[(1 - \lambda\beta)^2(\Sigma_0 + p_0^2) + (\mu + \lambda\alpha)^2 + \lambda^2\sigma_u^2 - 2(\mu + \lambda\alpha)(1 - \lambda\beta)p_0]$$

First order condition with respect to μ, λ:

$$\mu = -\lambda\alpha + p_0(1 - \lambda\beta)$$

$$-2\beta(1 - \lambda\beta)(\Sigma_0 + p_0^2) + 2\alpha(\mu + \lambda\alpha) + 2\lambda\sigma_u^2 - 2p_0[-\beta(\mu + \lambda\alpha) + \alpha(1 - \lambda\beta)] = 0$$

Hence:

$$\lambda = \frac{\beta\Sigma_0}{\beta^2\Sigma_0 + \sigma_u^2}$$

Appendix B.

Trading Game Instructions

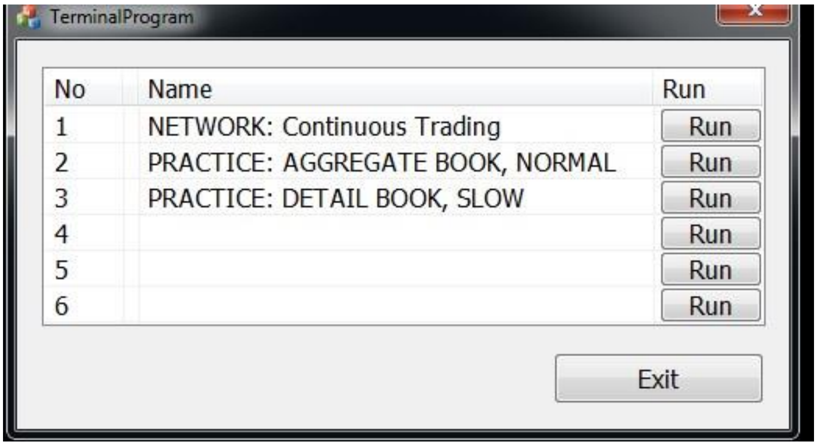
1. General instructions

Please read these simple instructions carefully.

This is an assessed exercise (part 1 of Coursework 1) of using TRETS. For more details of TRETS, please study Lecture handout of E-Trading. This trading exercise tutorial will last for approximately 1 hour, including instructions, practice, and post-exercise questionnaires. There will be a sequence of 6 assessed trading sessions each of which lasts 5 minutes in the tutorial. The session will be closed after 5 minutes. YOU CAN NOT TRADE any shares after the session closed.

2. Using the software

<u>To find the software, go to 'Learning Central---Tutorial Question Sheets/Answers---T04-E trading', Download TRETS_1.3 Client.bat (Right Click—Click 'Save target as ', to save the software to the desktop)</u>



You may practice by clicking 'Run' of 'PRCTICE: AGGREGATE BOOK, NORMAL' OR 'PRACTICE: DETAIL BOOK, SLOW'. Then you can click START button on the bottom left corner to start practice.

3. The Market:

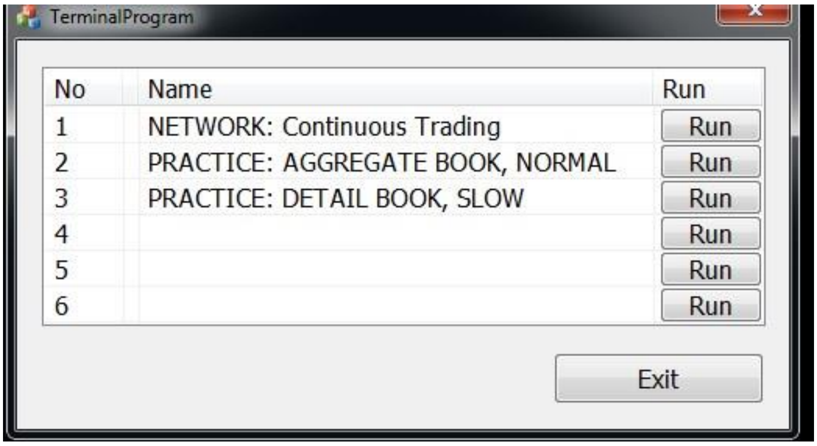
At the beginning of each session, you will be endowed with 300 cash and 50 shares. In a nextwork exercise, 8 traders will participant in each market. After the session starts, you may buy and sell any numbers of shares subject to your available fund and positions. Each session lasts for 5 minutes and will be repeated for 6 times. Your inventories of cash and share will not carry over from one session to the next one.

Before each session starts, you will receive a private signal about true dividend value shown in the "NEWS" panel on your screen. You have to predict the true dividend value before the session ends and write it down in the paper provided by the experimenter.

Your performance in the market will be equal to the total dividend value you receive on the shares you are holding plus the end of session cash you have.

4. <u>Assessed trading exercise procedure</u>

Before assessed trading exercise starts, you will be instructed to click ‘run’ of NETWORK: Continuous Trading, then click ‘Connect’ on the bottom left corner.



The market as described above will be repeated for 6 times. Before session starts, you will receive a dividend signal shown in the NEWS panel. After the beginning of each session, subject to sufficient amount of cash and number of shares, you may sell part of your shares or purchase more shares using your cash. Pay attention with the transaction cost of each trade. It will be deducted from your profits.

At the end of each market, the shares of ‘position’(In Account Balance panel) will pay a dividend. The dividend value is unknown. You can speculate the true dividend value according to the dividend signal, limit order book and price path. After dividends are paid, the stock is worth nothing. Then your portfolio wealth will be calculated based on :

Cash + true dividend* Position

For more details of calculating portfolio wealth and marking scheme of your coursework 1, please read lecture handout L04-E Trading.ppt

5. After each trading sessions, you need to provide a prediction (guess) of the true dividend and write down the number on the paper provided.

6. After all the trading sessions, you need to fill a post experimental questionnaire.

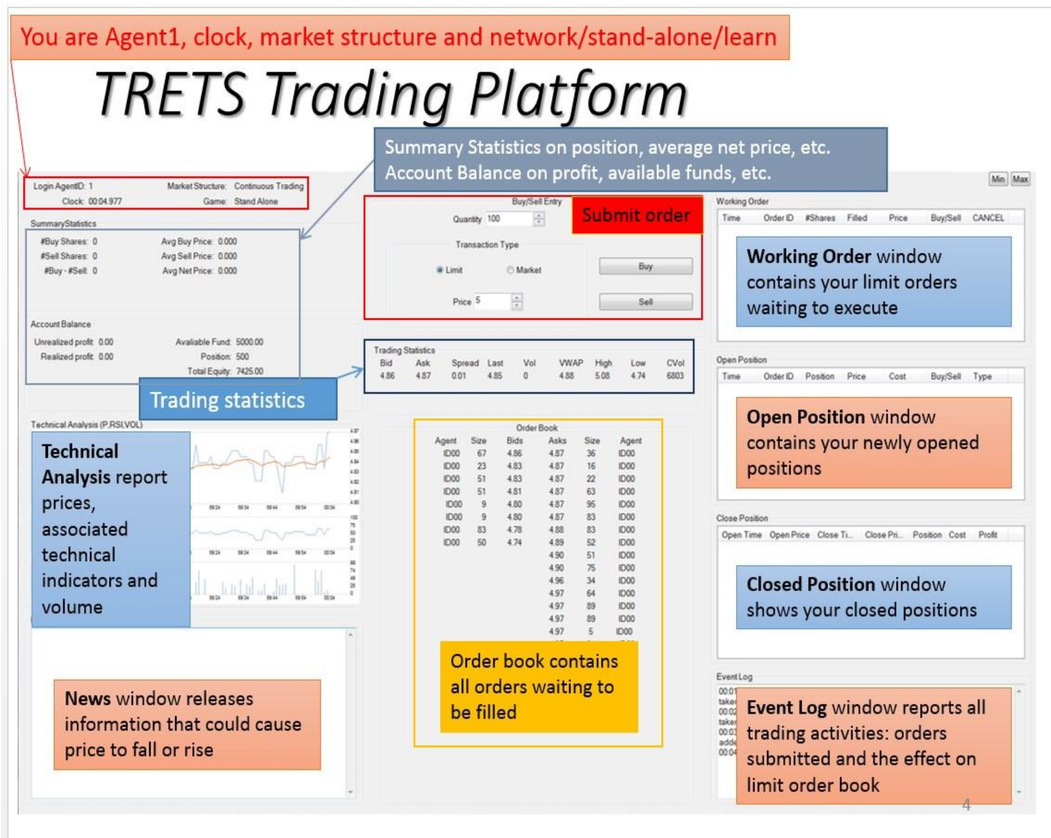
7 Marking scheme

Subject to successful completion of 6 trading sessions, your marks will be rewarded as follows (account for 10% of module mark):

1. 6% for participating each of 6 trading sessions in week 5 and 6.

2. Maximum 4% extra bonus based on your portfolio wealth in your trading group at the end of each game.

Software For Trading Experiments



Documents for Experimental Research

Letter to students

Dear Students,

Please be informed that we would like to make use of the outcomes of your two tutorial session activities in BST277 (Investment and Electronic Trading) for experimental research. The participation in the above experiment will not be linked in any way with the performance in any module, including BST277. Your tutorial exercise results will be treated with strict anonymity and confidentiality.

You will be asked to fill in a questionnaire if you choose to participate in the experiment. All information provided in the questionnaire will be held anonymously so that it will not be possible to trace information or comments back to individual contributors.

Information will be stored in accordance with the current Data Protection Act. Participants may opt to omit any questions of the questionnaire that they do not want to answer.

You may withdraw from the participation of the experiment without providing a reason at any stage of the exercise. Your withdrawal will neither affect your performance in the module nor your right as a student of Cardiff Business School. In the event that you withdraw from the experiment, your trading outcomes will be deleted.

If you would like the outcomes of your tutorial sessions to be used for research, please kindly sign the accompanied Informed Consent Declaration form.

Yours sincerely

Dr Woon Wong & Ms Xinran Zhao Informed Consent Declaration – For Research Participants

This study is being conducted by Xinran Zhao, an Economics PhD student of the Cardiff Business School under the supervision of Dr Woon Wong (email: WongWK3@cardiff.ac.uk).

Participation in the study is entirely voluntary and participants can withdraw from the study at any time without giving a reason. Participants may also ask questions at any time and discuss any concerns with either the researcher Xinran Zhao, ZhaoX8@cf.ac.uk or her supervisor as listed above.

The findings of the study will form part of my research assignment.

All information provided in the questionnaire will be held anonymously so that it will not be possible to trace information or comments back to individual contributors. Information will be stored in accordance with the current Data Protection Act. Participants may opt to omit any questions of the questionnaire that they do not want to answer.

Participation in the experiment will not be linked in any way with the performance in any modules. Participants can request information and feedback about the purpose and results of the study by applying directly to the researcher Xinran Zhao (ZhaoX8@cf.ac.uk)

If you would like the outcomes of your trading exercise to be used for research, please select 'Yes I consent' and kindly fill in your student ID and your University Email address; If you do not consent, please select 'No I do not consent' and no other information is required.

Yes, I consent

Student ID: ____________________

University Email: _________________________

No, I do not Consent

Researcher – Xinran Zhao

Cardiff Business School

Cardiff University

CF10 3EU

01/01/2017

Questionnaire 1: Individual's characteristics
Student Number:______________ University Email Address:_________________

(Please circle the right answer, and provide details as required)

1. Are you male or female?

   Male Female

2. What is your age? ___________

3. What is your nationality? __________

4. What is your BSc grade

   First-class honours Upper second Lower second Others

   If others, please provide details: ______________

5. What is your program of study (IEBF, FE, or others)?

   ____

6. Were you employed in trading or investment related area before?

   Yes No

   If yes, Please provide details of your job. _________________________
   ____

7. Do you have any self-investment or Online-trading experience? (If no, please skip question 8,9)

Yes No

8. How long is your investment experience?

Up to 6 months 6 months to 1 year more than 1 year

9. How would you rate your performance of investing in financial market?

Very poor Poor Average Good Very good

For the following questions, please estimate your performance in the trading exercises.

1—Totally agree to 5—completely disagree

10. I will not earn positive profits in the trading games

1 2 3 4 5

11. I may buy stocks that will underperform in the future

1 2 3 4 5

12. I am not able to identify stocks with above average performance in the future.

1 2 3 4 5

13. Buying stocks is like buying lottery tickets. Above-average performance seems to me to be more a matter of chance.

1 2 3 4 5

14. My forecasts of future prices are always wrong.

1 2 3 4 5

Questionnaire 2: General Knowledge questions for Miscalibration Score

Student Number________________ Gender Female/Male

For the following questions, please provide two estimates each, Lower Bound and Upper Bound. You believe that the true answers to the questions: should not fall short of the Lower Bound with 95% probability; should not exceed the Upper Bound with 95% probability. In another word, you are 90% certain that the true answers are in between Lower and Upper Bounds.

*Example Question: What was the population of Great Britain in 1997 (**in millions**)?*

Answer: (If you are 90% certain that the population of Great Britain in 1997 was between 47000000 and 80000000) you write:

Lower Bound :47

Upper Bound: 80

Questions	Lower Bound	Upper Bound
1. Princess Diana (Princess of Wales) 's age at death		
2. Length of River Thames (**in km**)		
3. Number of countries that are members of United Nations		

4. Air distance from New York to London (**<u>in km</u>**)		
5. Deepest point in the Ocean (**<u>in meters</u>**)		
6. What was the population in UK in year 2012(**<u>in millions</u>**)		
7. Number of calories in a piece of white toast		
8. Heights of the highest principal mountain of the world (**<u>in meters</u>**)		
9. Largest continent in area of the world (**<u>in km</u>**^{2})		
10. Year in which Newton discovered universal gravitation		
11. Percentage of total area in world covered by water (**<u>%)</u>**		
12. Number of joints in human body		
13. GDP per capita in UK (**<u>in US$)</u>** in year 2008		
14. Birth rate (birth/1000 population) in world in 2005		

Please turnover

15. How many cities in UK		
16. What was the price of a US dollar in GBP yesterday		

17. How many companies are listed in London Stock Exchange		
18. Suppose the expected return on stock ABC is 14%. Suppose risk-free interest rate =3%, E(Rm)=10% and ABC's BETA =1.45. Then the alpha(excess return) on ABC is		
19. There is a 7% semi-annual coupon bond with exactly 2.5 years to maturity and a yield to maturity of 8.75%, if face value(par)=100, what is the price(value) of the bond?		
20. The price of a stock today is 100. Next year, the stock price will be either 120 or 90. The risk free rate is 3% per year . What is the price of put option with strike price(exercise price) 98.		
21. A company has just paid a £2 dividend. If the company's current growth rate of 4% is expected to continue indefinitely, and shareholders require a rate of return of 10% per annum, what ought to be the price of the company's shares.(Price of a constant growth stock).		
22. If the spot rate for one-year lending is 12 %, and the spot rate for two-year loans is 11% , the one- year implied forward rate is		

Final question: Look back at your answers. Without changing any of the stated intervals, estimate how many of these intervals you believe contain the true value. In other words, how many correct answers do you think you had in those intervals?

Answer: _______correct answers.

Questionnaire 3 Post- Experimental Questionnaire

Participants were asked:

"After the trading experiment, do you think what percentage of students doing this exercise will end up generating higher portfolio wealth than you?"____

Events in the Financial Market Experiment

Figure 2. Sequence of Events in Financial Market Experiment

Appendix C.

Hausman and Taylor step by step estimation

1. Obtain consistent estimates of β_1 and β_2 using differences from "temporal mean-LSDV method

$$(y_{it} - \bar{y}_i) = (x_{1it} - \bar{x}_{1i})'\beta_1 + (x_{2it} - \bar{x}_{2i})'\beta_2 + (\epsilon_{it} - \bar{\epsilon}_i)$$

2. (a) From step 1, use the residuals to compute the intra-group temporal mean of the residuals,

$\bar{e}_i = \frac{\sum_{t=1}^{T} e_{it}}{T}$, and stack them into vector $\bar{e}' = ((\bar{e}_1, \bar{e}_1, \dots, \bar{e}_1)^T, \dots,$

(b) Do a regression of z_{2i}, the invariant effects correlated with u_i, on z_{1i} and x_{1it} (c) Use the predicted values $\hat{z}_{2i}$ from (b) in the big matrix $Z = (Z_1^*, \hat{Z}_2^*)$, where matrices Z_k are formed using the z_{ki} for each group i.

Estimate of σ_ϵ^2 : Use the estimate from LSDV regression in step 1 (d) Regress vector $\bar{e}$ on Z to get estimates of $(\hat{\alpha}_1, \hat{\alpha}_2)$

(e) Note, we just did a 2SLS regression

1. Estimate of σ_u^2: As in the RE model, use the estimate of σ_{*2} from the 2SLS regression in Step2. Since:

$$\sigma^{*2} = \sigma_u^2 + \frac{\sigma_\epsilon^2}{T}$$

Then an estimate of σ_u is

$$\sigma_u^2 = \sigma^2 - \frac{\sigma_\epsilon^2}{T}$$

2. We need weights $*$ to compute the FGLS. Let $\theta = \sqrt{\frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + T\sigma_u^2}}$, then, for each group I, let

$$W = [x_{1it}, x_{2it}, z_{1i}, z_{2i}] - \hat{\theta}[x_{1it}, x_{2it}, z_{1i}, z_{2i}]$$

$$y^* = y_{it} - \theta y_{it}$$

$$v_{it}' = [(x_{1it} - x_{1i})', (x_{2it} - x_{2i})', z_1'{}_i, \bar{x}_1'{}_i]$$

Be the new weighted data and V the matrix of instruments, then do a 2SLS regression of $*$ $*$ y on W with instruments V:

a) Regression W_* on V, the generate the predicted values $\hat{W}_*$

b) Regress y_* on the predicted values $\hat{W}_*$ to get $(\beta', \hat{\alpha}')'$

3. To get the variance of $(\beta', \hat{\alpha}')'$, one should not use the residuals of the 2SLS regression, because it is not convergent. See Greene Ch8 eq (8.8)

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