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Insights into irrational financial trading behavior: Evidence from the UK financial spread-trading markets

by

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ABSTRACT

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INSIGHTS INTO IRRATIONAL FINANCIAL TRADING BEHAVIOR: EVIDENCE FROM THE UK FINANCIAL SPREAD-TRADING MAREKTS

By Sarist Gulthawatvichai

Market efficiency forms the basis of modern finance theories and rests on two important pillars: First, all investors are always rational. Second, investors' errors are uncorrelated. In the light of the importance of the role played by market efficiency in many modern financial theories and literature which suggests that the two pillars on which it rests may be suspected, this thesis divided into three papers aims to investigate the two concerns in specific settings and the impact of which on the efficiency of market. In particular, the thesis sets out to explore to what extent and why individual traders' decisions are affected by specific heuristics and biases. This is achieved by focusing on different types of decision made by individuals (e.g., when deciding whether to commit further resources to an existing trade and the manner in which they decide to close a trade) in association with neglected human psychology.

The first paper addresses factors which influence escalation of risk-taking, in terms of the decision of what funds to commit to already existing positions. The paper makes three contributions: First, it identifies the impact of different types of losses on escalation of risk-taking. Second, the impact of previous losses on the degree of escalation of risk-taking by more and less informed traders is examined. Third, this is the first study to examine escalation of risk-taking amongst individual traders in spread-trading markets which are fast growing but have been ignored by the existing literature. The paper employs a dataset associated with individual trading on FTSE 100 index futures and uses a series of linear mixed model regression (degree of escalation of risk-taking as a dependent variable, and events associated with

losing money that are potentially significant to an individual as independent variables). The results suggest that escalation in risk-taking in the form of averaging-in is influenced by previous losses. Overall, the findings demonstrate that the type of irrationality is presented at this type of traders' decision-making.

The second paper examines to what extent traders act in manner consistent with the hedonic editing hypothesis (HEH) when realizing their positions. The paper makes two contributions: First, the paper explains why some previous empirical studies may have found behavior deviated from predictions by the HEH and some found results in line with the HEH. Second, this is the first study to provide insight into the degree to which spread traders are subject to the HEH. Trading data related to FTSE 100 index is analyzed using multilevel logistic regressions (realizing positions partially/fully as a dependent variable, and events associated with gaining/losing money as independent variables). The results demonstrate that traders do not behave in a manner consistent with the HEH, but behave in a manner consistent with the cognitive cost of segregation and cognitive dissonance. To sum up, the research delivers clear evidence of the type of irrationality regarding realizing positons.

The third paper focuses on the extent to which spread traders are subject to herding behavior and it makes four contributions: First, the study overcomes the limitations of previous studies which may underestimate the degree of herding. Second, differences in the degree, nature, and patterns of herding are identified. Third, this is the first paper to examine herding amongst spread traders. Fourth, differences in degree and nature of herding amongst more and less informed traders are investigated. The paper employs high frequency data associated with trades in FTSE 100 index. This is analyzed using Vector Autoregression models. The results indicate that spread traders have a tendency to herding activity and there are differences in the patterns of herding amongst more and less informed traders. In conclusion, the research provides clear evidence of systematic herding.

In conclusion, this thesis investigated two important concerns which can threaten market efficiency: First, investors make irrational decisions, and second, they have a tendency to be subject to correlated errors. This thesis revealed that traders systematically make irrational decisions and the impact of these correlated errors by irrationality is likely to be magnified via herding behavior.

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DECLARATION OF AUTHORSHIP

I, Sarist Gulthawatvichai

declare that this thesis and the work presented in it are my own and has been generated by me as the result of my own original research.

Insights into irrational financial trading behavior: Evidence from the UK financial spread-trading markets

I confirm that:

1. This work was done wholly or mainly while in candidature for a research degree at this University;
2. Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated;
3. Where I have consulted the published work of others, this is always clearly attributed;
4. Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work;
5. I have acknowledged all main sources of help;
6. Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself;
7. None of this work has been published before submission.

Signed:...

Date:..

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Chapter 1: Introduction

Market efficiency forms the basis of many modern financial theories and rests on two important pillars: First, that all investors are always rational. However, Black (1986) states that sometimes individuals trade on noise as if it were information. In other words, traders base their trading decisions on misinformation or information which is not relevant to the valuations of assets. This has been confirmed by subsequent studies (for example see, Schmeling, 2007, Wang, 2010). Second, investors' errors are uncorrelated. However, this has been challenged by studies which show that individuals often commit to similar types of judgement errors. In other words, they tend to deviate from expectations in the same manner by systematically making irrational decisions and this potentially drives asset prices away from fundamental values (for example see, Wermers, 1999, Voronkova and Bohl, 2005). In the light of the importance of the role played by market efficiency in many modern financial theories and the literature which suggests that the two pillars on which it rests may be suspected, this thesis presents research which aims to develop insights concerning the behavior of individuals in financial markets and the implications which may not be fully accounted for by modern finance. In order to achieve this, insights from human psychology which have been neglected are employed in order to enhance the understanding of the behavior and decisions of financial market participants (e.g., cognitive cost of segregation, cognitive dissonance). In particular, the research objective of this thesis is to investigate to what extent and why individual traders' decisions are affected by specific heuristics and biases and the effect these may have on the operation of financial markets. This is achieved by focusing on different types of decision made by individual traders (e.g., when deciding whether to commit further resources to an existing trade and the manner in which they decide to close a trade). The thesis sets out to explore the extent to which the biases displayed may affect the efficiency of markets in specific settings.

The data employed in this thesis is obtained from spread-trading markets. These markets are becoming increasingly significant, with about half a million financial spread traders operating in the UK and this number is expected to reach one million by 2017 (Pryor, 2011, p. xxiii). Brady and

Ramyar (n.d.) indicate that, of the £1.2 trillion traded annually on the London Stock Exchange, 40 per cent is equity derivative related and 25 per cent of this relates to spread-trading (£120 billion). The rapid increase in spread-trading may have potentially important implications for the underlying markets because spread-trading companies hedge their positions in the underlying market, therefore, the behavior of spread traders has a significant impact on the underlying markets. One of the benefits of employing financial spread-trading data is that traders in these markets trade far more frequently than conventional financial market traders. This allows me to gain better understanding of certain trading behavior as suggested by previous studies using high frequency data (Nyholm, 1999, Cotter, 2005, Avramov,Chordia and Goyal, 2006, Cassola and Morana, 2006, Nolte and Nolte, 2011). In particular, this is achieved by examining the data on a trade-by-trade basis and in short time intervals. In addition, the majority of the existing studies investigate trading biases assuming that traders are a homogeneous group. However, one should not assume that all traders would commit to the same trading biases. As a result, the availability of each individual' account profitability in the database enables me to further differentiate more from less informed traders.

The thesis is divided into three separate but inter-related papers based on the types of trading decision investigated. The three sections combined provide a clear picture of the threats to the two important pillars of market efficiency, namely, irrational decisions and correlated errors by traders. A common theme for all the papers is that they develop insights concerning the nature of trading behavior in the financial spread-trading market and to what extent this behavior may be biased because individual traders are subject to certain heuristics.

The first aspect of individual trader decision making considered here, is the decision of whether or not to commit further resources to an existing trade. If this decision is made in an appropriate manner then this can reduce the chances of systematic irrationality spreading throughout financial market systems and may, thus, promote market efficiency. The first paper of this thesis, therefore, seeks to investigate behavioral factors which affect a trader's decision of whether or not to commit further funds to an existing trade and, specifically, focusses on the impact which escalation of commitment may have on this decision. Previous studies associated with financial markets suggest that traders are influenced by prior gains or losses when making investment decisions. However, most of the research focuses simply on the impact of previous gains or losses on an investor's decision to buy or sell. This research has largely neglected the impact of the *size* of the realized and the *size* of unrealized losses and the number of *consecutive* losses the trader has experienced immediately prior to initiating a new trade. Previous research has also neglected to examine the effect of these factors on a trader's decision to escalate their risk-taking, measured in terms of their decision to increase their stake in an existing position. Consequently, to fill this research gap, the first paper explores the extent that the size of realized and unrealized losses and the number of consecutive losses a trader experiences immediately prior to initiating a new trade, influences the degree to which they escalate risk-taking. By doing so, the study aims to provide a clearer understanding of the irrationality which can influence individual traders, particularly, at the stage of initiating new trades. The study also examines the implications of the findings for individual investors, financial institutions, and for market efficiency as a whole.

The second aspect of individual trader decision making considered here, is that associated with their decision to close a trade. Understanding the behavioral factors associated with this aspect of making decision in a systematic manner is crucial to market efficiency. In particular, a large imbalance of selling and purchasing assets could lead to a greater impact on price due to pressure on market maker inventory and/or being realized as private information (Lee *et al.*, 2004). In addition, the behavioral factors influencing the decision to close existing positions may differ between traders and may well be different from the factors which govern the decision of whether or not to commit additional funds to an existing position. One of key influences on the decision of whether to close a position fully or partially may be factors underlying the hedonic edition hypothesis (HEH). There is a substantial literature providing evidence of this phenomenon, but most of this research had been carried out in controlled laboratory conditions (Thaler, 1985, Thaler and Johnson, 1990, Linville and Fischer, 1991). Very few recent empirical studies have explored whether investors in financial markets behave in a manner consistent with the phenomenon, and these studies have produced mixed results (Lim, 2006, Lehenkari, 2009). This is crucial as knowledge of whether investors in financial markets are subject to the HEH may lead to a better understanding of stock prices. The second paper in this thesis is motivated by the belief that the HEH has not fully accounted for some important psychological factors which influence the decisions of investors in real-world environments, namely, the cognitive cost of segregation and cognitive dissonance. Consequently, a hypothesis that investors may not act in a fashion predicted by the HEH was tested in the second paper of the thesis. The methodology of the paper was designed to avoid the erroneous assumption employed in previous empirical studies that the end-of-day profits/losses are known when the segregation/integration decision is made (i.e., traders are making choices with foreseeable outcomes). However, in practice, integration/segregation decisions are made *during* the day when the final profit/loss for that day is unknown, i.e., until the end of day, after the final integration/segregation decision for that day has been made. This paper overcomes the erroneous assumption by examining the data on a trade-by-trade basis which enables the determination of the propensity of a trader to close an entire position (i.e., integrating the profit or loss obtained in that position) or to close just a portion of that position (i.e., segregating the profit or loss associated with that position into a realized portion with a certain outcome and an unrealized portion with an uncertain outcome). Consequently, the paper seeks to develop new insights into the extent to which the HEH affects real-world trading activity.

Emotion is a key behavioral factor which may influence the decisions discussed above, i.e., whether to commit additional funds to an existing position (i.e., whether or not to escalate risk-taking) or whether to close an existing position. In particular, Ackert and Deaves (2010) identify the ability of emotions to be transmitted, in the context of social forces, so that many individuals may feel the same way instantaneously (due to the sharing of similar stimuli or infectious emotion). Consequently, the third paper explores the impact of emotions on markets via an analysis of herding behavior (i.e., the net buying of an asset by a group of trader influences the net buying of other traders). Herding can cause market prices to moving away from valuations based on fundamentals and thereby create excess volatility (Choe,Kho and Stulz, 1999) or may cause destabilization of markets (Lakonishok,Shleifer and Vishny, 1992). Most studies that have investigated herding in conventional markets have used data associated with a variety of securities over a fixed time interval (e.g., Lee,Lin and Liu, 1999). However, this approach may underestimate the degree of herding with respect to a single asset or with respect to different time intervals than that being studied. For example, by considering herding across a portfolio of assets, herding in different directions in different assets could mask the overall degree of herding which takes place. In order to overcome the limitations of previous studies, this paper explores the degree and nature of herding associated with a single asset over a variety of time intervals.

In all three papers, I also examine the manner in which more and less informed traders are subject to the behavioral biases. This aspect is crucial, as considerable cross-sectional variation in individual investment behavior could be masked if we only examine aggregate behavior (Odean, 1999). In addition, disparities in behavior between different groups of investors are important for understanding wider market mechanics and can be applied to the dynamics of asset prices in bubbles or even crashes (Ofek and Richardson, 2003). Importantly, rational agents have an opportunity to exploit and profit from irrational agents who employ ‘non-rational’ heuristics (Barber,Odean and Zhu, 2009b). Consequently, understanding the different degree of the behavior regarding more and less informed traders contributes to the branch of market microstructure theory which focuses on the impact of the information on behavior. In particular, the theory attacks the concept of rational efficiency by suggesting that irrational valuations generated in capital markets occur due to trading activity of less informed traders acting on random information which they perceive as news. Those actions can cause prices to diverge from fundamentals (Shleifer and Summers, 1990). In addition, the irrationality of less informed traders can lead to risks that discourage more informed traders from trading against them (Megginson, 1997, p. 149).

Overall, the three studies are believed to provide valuable insights into investor psychology in general and the factors associated with irrational investor behaviors in a real-world setting. In particular, knowledge of spread traders’ behavior can lead to better hedging decisions by spread-trading firms and may help spread traders adopt more rational trading strategies. In addition, the outcomes may motivate the financial market regulators to devise new regulations to prevent financial markets being damaged by the irrational behavior. The findings also add to the growing market micro structure literature by providing new insights into the manner in which the trading of more and less informed traders are subject to the irrationality, and the interactions between the groups.

In conclusion, there are two essential pillars supporting the efficiency of financial markets: First that decisions-markers are rational and second, that investors' errors are uncorrelated. In the thesis, possible concerns regarding the two pillars are identified in the context of behavioral finance. These are examined from three different angles: First, the thesis examines the impact of behavioral factors on a trader's decision of whether or not to systematically commit additional resources to an existing position; second, it examines the impact of behavioral factors on a trader's decision of whether or not to close a position fully or partially in a systematic manner; third, it examines the impact of emotion which may further influence the irrationality on markets via an analysis of herding behavior. Additionally, the thesis provides the degree to which more and less informed traders are affected by these behavioral factors.

The thesis is structured as follows. In Chapter 2, the first paper is presented, titled "In for a penny, in for a pound": The impact of losses on escalation of risk-taking in financial trading". This paper examines the factors influencing the degree to which traders escalate risk-taking by committing additional funds to existing positions. In Chapter 3, I test the view that real world-traders may be subject to a number of psychological pressures which lead them to behave in a manner inconsistent with the HEH. This work is presented in the chapter titled, "Take it or leave it: Do traders really prefer to segregate their gains and integrate their losses?". The third paper entitled "Insights into herding behavior in financial spread-trading markets" is presented in Chapter 4. This chapter examines the extent and nature of herding in spread-trading markets. In the last chapter, the contributions of each paper are consolidated and conclusions are drawn.

Chapter 2: **"In for a penny, in for a pound":** The impact of losses on escalation of risk-taking in financial trading

Abstract

Prompted by the destabilization of financial markets which occurred during the recent financial crisis, we investigate the degree to which an investor's risk-taking is affected by significant realized and unrealized losses (in terms of size and streaks) to which they are exposed. This is achieved by analyzing 219,575 trades of 792 individual traders from the retail spread-trading market for the period 2010 to 2012. We find that risk-taking escalates following large realized losses and following long streaks of losses and increases even more substantially when the trader faces large unrealized losses. We also shed light on differences in the manner in which less and more informed traders respond to losses. In particular, the former escalate their risk-taking in the face of large losses (both realized and unrealized) and following long losing streaks. However, the latter tend to either not alter their behavior or to reduce the degree of escalation in these circumstances. The results, in addition to providing insights regarding the manner in which individuals react to previous losses, have important implications for those who attempt to regulate and manage risk in financial markets.

2.1 Introduction

Previous studies suggest that an individual's investment decisions are influenced by their prior gains or losses. For example, studies show that there is a general tendency to "sell winners too early and ride losers too long" (Shefrin and Statman, 1985, p. 777). However, the impact on the degree of risk undertaken by individual investors of a range of issues associated with their past performance has remained under-explored. In particular, there are no previous studies which examine the impact of the *number* of *sequential* losses and the *size* of *realized* and *unrealized* losses that investors have experienced on their risk-taking, defined in terms of increasing the size of currently held investments: 'averaging-in behavior'. This is surprising because understanding the degree to which an investor's risk-taking may be affected by the size of previous realized or unrealized losses or the number of their previous sequential losses has important implications for individual financial institutions. For example, there have been a number of high profile cases in recent years where 'rouge traders' have chased their losses, leading to the spectacular collapse of Barings Bank in 1995, the loss of $6.1 billion to Société Générale in 2008 and $2 billion to UBS in 2011. The extent to which traders escalate their risk-taking in the face of losses has important implications for financial market resilience and sustainability and is of particular concern given the collapse of markets during the recent financial crisis.

In domains other than financial market investment (e.g., decisions related to product development, capital investment, and general team management), there is extant research which has investigated the phenomenon of escalation of commitment, whereby individuals tend to maintain a course of action or even increase their commitment (Schulz and Cheng, 2002) in the face of negative information (Brockner, 1992). The general conclusion which has emerged from this stream of literature is that escalation of commitment tends to occur more often when the outcome of a previous action resulted in a loss. The decision to continue with a course of action or even to escalate risk-taking may be motivated by a desire to recover previous losses rather than being based on fundamental information. Consequently, such behavior often leads to further losses. This process can result in a downward spiral, reminiscent of that of the archetypal 'rogue trader' who, having experienced losses, escalates their risk-taking, incurring bigger and bigger losses until their behavior is finally uncovered. We discuss the various psychological theories which explain why individuals might behave in this way in Section 2.2. This seemingly irrational behavior has received far less attention in the financial market literature. Some recent papers have suggested a possible link between escalation of risk-taking and previous portfolio performance (Ding,Charoenwong and Seetoh, 2004, Ben-David and Hirshleifer, 2012, Lehenkari, 2012) but the results are inconclusive.

The dearth of research examining the effect of previous losses on escalation of commitment related to financial investment has motivated us to examine to what extent an investor's escalation of risk-taking may be affected by specific aspects of realized losses (their size and the extent to which they occur in streaks) and by the magnitude of unrealized losses. We expect that realized and unrealized (paper) losses will have different impacts on subsequent risk-taking, as Thaler (1999) suggests that they may have different impacts on perception of the degree of loss. There is some evidence that there are individual differences in susceptibility to escalation of risk-taking, just as there are differences in susceptibility to other biases (Barberis and Thaler, 2003). In this context, we consider whether some individuals (i.e., more *vs.* less informed investors distinguished by a measure based on their individual updated account profitability) may demonstrate more or less escalation of risk-taking in the face of losses.

In order to achieve these objectives, we examine the detailed trading records of 792 individual traders from the retail spread-trading market, where individuals speculate on the movements of a broad range of financial securities (e.g., FX, Indices, Commodities, Interest Rates, Currencies and Equities). The spread-trading market is fast growing, and the number of traders operating in the UK alone is expected to reach one million by 2017 (Pryor, 2011). In fact, it was estimated that about £120 billion of trading on the London Stock Exchange was associated with the spread-trading market (Brady and Ramyar, n.d.). There are a number of reasons why understanding the degree to which traders in these markets escalate their risk-taking in the face of losses is important: First, it may provide valuable insights into investor psychology more generally and the factors associated with irrational behavior. Second, spread-trading brokerage firms hedge into the underlying financial markets and this means that the efficiency of the underlying markets may be significantly impacted by the behavior of spread traders. Third, insights concerning spread traders' behavior can lead to better hedging decisions by spread-trading brokerage firms, resulting in less damaging effects on the efficiency of underlying markets. Fourth, greater awareness of the irrational behaviors which some spread traders display, may help in the process of educating them to adopt more rational trading strategies, leading to better outcomes for the individual traders themselves and less damaging effects on underlying markets.

The chapter offers the following contributions: This is, to our best knowledge, the first attempt to investigate the degree to which different characteristics of losses, including the *numbe*r and *size* of *realized* losses and the *relative magnitude* of *unrealized* losses, affect the escalation of risk-taking by individual investors in financial market studies. Second, we shed light on differences in the escalation of risk-taking by more and less informed traders in the face of previous losses. Third, this is the first study to explore the escalation of risk-taking amongst traders in the fast growing spread-trading markets.

The remainder of the study is organized as follows: In Section 2.2, we briefly examine the literature associated with the escalation of commitment and explain how this helps derive our hypotheses investigating the escalation of risk-taking by traders. In Section 2.3, we describe the data and the procedures employed to test our hypotheses. The results are presented and discussed in Sections 2.4 and 2.5, respectively. We draw conclusions in Section 2.6.

2.2 Escalation of risk-taking: Literature and hypotheses

2.2.1 Financial market studies

Escalation of commitment has largely been examined in terms of management-related decision-making and most studies have been conducted in the laboratory (Conlon and Garland, 1993, Wong and Kwong, 2007, Ku, 2008). Consequently, very few financial market studies related to escalation of commitment have been conducted. Those that have been undertaken only examine escalation of company earnings' forecasts or use escalation of commitment to explain the disposition effect (DE). An example of the former is the study by Beshears and Milkman (2011), which found that financial analysts who make inaccurate forecasts of a firm's quarterly revenue that are significantly different from their peers, tend to escalate their commitment to these outlying forecasts. In particular, they adjust their forecasts for the current year's earnings less than their peers in the direction of unexpected actual values of quarterly earnings. Lehenkari (2012), provides an example using the papers which argue that escalation of commitment could be a factor influencing the disposition effect (DE). The author suggests that traders may try to avoid the anticipated regret which will arise if they sell a stock at a loss, by holding onto losses. It appears that the anticipated regret may be greater for decisions for which one is personally responsible, since Lehenkari's (2012) results confirmed that DE was more pronounced amongst investors making decisions concerning stocks they had purchased rather than those they had inherited or been gifted.

Some papers in the financial domain, whilst not directly addressing escalation, have examined issues related to the influence of previous trading performance on current trading decisions. For example, Ben-David and Hirshleifer (2012) found that investors' future purchases of stocks were affected by the previous gains and losses they had made with those particular stocks. In particular, investors buying and selling behavior followed an asymmetric V-shape, with the probability of a purchase (and a sale) increasing when they made larger profits or losses on these stocks, but with a greater probability of buying (or selling) associated with previous gains (cf. losses).

It has also been found that previous gains and losses associated with pleasant or unpleasant feelings can affect risk-taking behavior. In particular, Seo and Goldfarb (2010) found that individuals in a simulated laboratory-based investment task, tended to be risk-seeking after experiencing losses, where risk was defined as the weighted averaged beta coefficient and degree of diversification in the individual's chosen portfolio. However, the propensity to take more risks after a loss was reduced if immediately after the loss the individual reported affect (pleasant/unpleasant feelings). Additionally, the propensity to avoid risk after experiencing gains vanished or even reversed providing that individuals instantaneously reported experiencing positive affect. The results support the authors' notion that affect can directly influence decision making by bypassing or overpowering cognitive processes. In other words, strong feelings may alter the utility and probability functions.

In a real-world study of risk escalation, Liu *et al.* (2010) found, amongst twenty one market makers on the Taiwan Futures exchange, a tendency to take greater/less than their average risk (in terms of number of orders, trades, contracts per trade and size of orders), in the afternoon after facing morning gains/losses. However, by simply comparing trading behavior in the morning and afternoon, it is not possible to determine the impact of individual gains or losses or sequences of gains or losses. Hsu and Chow (2013) also found that individual traders on the Taiwan Stock Exchange (TSE) took greater risk (measured via the standard deviation of the returns of the stocks purchased) when they had made prior gains, i.e., the so called 'house money effect' (Thaler and Johnson, 1990). The effect was more pronounced following substantial prior gains and the effect tended to decline over time. Huang and Chan (2014) extended the study to examine if different types of investors may be differentially influenced by prior gains and losses. In particular, they found that institutional investors displayed less irrational behavior than active individual investors (i.e., traders with at least 100 trading days experience over the course of the year). In particular, they found that the latter group were more subject to the house money and the break-even effect (i.e., future outcomes may be seen as providing an attractive opportunity to break even, see Thaler and Johnson, 1990), in that their risk-taking was more influenced by prior gains and losses.

None of the limited number of studies which have examined escalation of risk-taking in financial markets have focused explicitly on comparing the effects of realized and unrealized losses nor have they focused on the effect of the number of sequential losses incurred. However, we expect both of these factors could be important in predicting escalation of risk-taking. In particular, the mental accounting literature suggests that equal magnitudes of realized and unrealized (paper) losses may not be perceived identically. Rather, Thaler (1999, p.189) finds that "a realized loss is more painful than a paper loss". Consequently, we believe it is important to investigate the different impacts of these two types of loss. Similarly, the hedonic editing hypothesis literature (Thaler, 1985) proposes that, due to prospect theory's value function (see section 2.2.2), a loss of £500 is not perceived equally to 5 losses of £100 (Kahneman and Tversky, 1979). As such, it possible that the *number* of sequential losses may play a key role over and above the amount lost.

Consequently, we examine the impact of the number of sequential losses and the magnitude of previous realized losses and unrealized losses on the degree to which a trader will subsequently escalate their risk-taking. Furthermore, we examine to what extent these effects differ between more and less informed traders.

To study these effects we believe it is important to employ transactional data, which allows us to examine the immediate impact of previous losses on traders' behavior. The frequent trading activity of spread traders makes this possible. This approach, we believe, has a significant advantage over studies which compare temporally disjoint decisions (e.g., those which examined the effects of profits/losses made in the morning on risk-taking activity in the afternoon (e.g., Liu *et al.*, 2010, Hsu and Chow, 2013, Huang and Chan, 2014)). This is crucial, as traders may not consider or reflect on their activities defined in terms of the time periods used in previous studies (e.g., morning *vs.* afternoon). Consequently, decisions taken in one of these periods (e.g., morning) may not, in practice, influence decisions taken in a different period (e.g., afternoon) as much as trades immediately preceding a given decision. Consequently, by examining behavior on a trade-by-trade basis we believe that we are better able to detect traders' genuine risk-taking preferences.

2.2.2 Causes of escalation and hypotheses

Many theories have been employed to explain why individuals may escalate commitment to a failing course of action (for review see, Slessman *et al.*, 2012). One of the most influential of these is prospect theory (Kahneman and Tversky, 1979). This assumes that changes of wealth from some reference point are crucial to decision makers, in that these changes of wealth affect their risk preferences. In addition, that an individual's subjective value function is concave/convex in the domain of gains/losses, suggesting that decision makers are prone to be risk averse/preferring for gains/losses. Kahneman and Tversky (1984) also found that the value function is steeper in the domain of losses (cf. gains). Consequently, when facing losses, individuals tend to be risk-seeking. As a result, they allocate more resources to reversing the situation, rather than simply accepting the loss (Whyte, 1993).

Self-justification theory (Festinger, 1957, Aronson, 1968) proposes that sunk costs (e.g., previously realized losses) can trigger self-justification pressures. In other words, decision makers may not wish to see themselves as having made a poor decision and, as a result, escalate their commitment to the previously failing course of action (Arkes and Blumer, 1985). Consequently, we might expect that a previously realized loss will result in an escalation of risk-taking in order to recoup that loss. Some authors argue that a combination of prospect theory and self-justification theory are needed to fully explain escalation (e.g., Brockner, 1992).

There is also evidence that events which are *significant* to the decision maker have more impact on their behavior. For example, Barber and Odean (2008) found that individual traders made nearly twice as many purchases as sales of stocks which were associated with *highly significant* trading volume and poor returns. Hsu and Chow's (2013) results suggest that previous outcomes have to be *significant* in *size* in order to influence risk-taking. In addition, Huang and Chan's (2014) results suggest that the impact on risk-taking of different size outcomes may differ between different types of individual trader.

A run of losses may also be viewed as a significant event, as this has been shown to affect decisions made by individuals in real-world gambling situations (Leopard, 1978, Sundali and Croson, 2006) and in laboratory experiments (Johnson,Tellis and Macinnis, 2005). Ball (2012) pointed out that runs in random (or near random) binary events are inevitable but rare and, hence, salient. In addition, due to the characteristics of prospect theory's value function, a run of losses may be perceived to be worse than a single loss of equal magnitude to the combined individual losses (Thaler, 1985). Some evidence supporting these views was provided by Ball (2012) who found that a streak of losses affected the risky choices of gamblers in line with the 'gamblers fallacy'; namely, that a run of losses led them to believe that a change of fortune was now more likely. While this was the most common response, Ball (2012) also found that some individuals will increase their risk-taking following a streak of wins (the 'hot hand effect'), suggesting that there are individual differences in how people respond to streaks of wins and losses. Interestingly, it appears that a run of three wins or three losses appears to be the required amount before people begin to perceive the run as a streak (Carlson and Shu, 2007). This research suggests that the effect of runs of wins and losses on subsequent risk-taking depends on the run length and individual differences.

Based on the literature discussed above, we expect that 'losses' particularly 'significant losses' will drive escalation of risk-taking. The definition of significance is highly subjective, and in the context of investment, it is likely that the significance of a loss to a given individual may depend on whether a loss exceeds their typical return or loss. In addition, it is possible that a particularly salient factor may be how many consecutive losses they have experienced. It is likely that only runs that are greater than three in a row (see Carlson and Shu, 2007) are likely to be significant but beyond nine or ten in row and working memory restrictions could limit effects (Miller, 1956). Furthermore as discussed above, the tendency to escalate risk-taking in these circumstances may be most likely to be exacerbated by the gambler's fallacy, whereby individuals believe that future outcomes are likely to be opposite to those experienced in the past (i.e., negative recency: Altmann and Burns, 2005).

On the one hand, the escalation of commitment literature suggests that if the outcome of previous action is a loss, this is likely to motivate an individual to escalate their risk-taking. On the other hand, normal trading activity, and particularly spread trading, leads to individuals experiencing both gains and losses. Consequently, traders may become desensitised to the impact of *normal* losses and may only react to *significant* losses. We, therefore, test a 'Significant Realized Loss Hypothesis':

A trader will escalate their risk-taking on their next trade if their previous trade resulted in a realized loss which they perceive as significant (in amount or if it is part of a losing streak).

The above hypothesis focuses on realized losses. However, when a trader decides whether or not to increase their position size (i.e., escalate risk), they are also likely to consider the *unrealized* loss or gain associated with their current position. As discussed above, the mental accounting literature suggests that such unrealized losses are perceived differently to realized losses. In particular, paper losses are regarded as less 'painful' than realized losses (Thaler, 1999). On this basis, we might expect paper losses to be less likely than realized losses to promote escalation of risk-taking. However, there are other factors which lead us to believe that unrealized losses may have an important impact on escalation. In particular, at the point of opening a new position, realized losses have already occurred and so will have already elicited some form of regret (i.e., negative utility). Paper losses, on the other hand, point to the *possibility* of a *future realized* (painful) loss (i.e., anticipated regret). From a psychological perspective, the realization of this loss is not certain and could, if market conditions become favorable, lead to a paper profit. This uncertainty is important, as the escalation of commitment literature indicates that uncertain information on decision prospects allows decision makers to focus on positive indicators (Bragger *et al.*, 1998). This may cause investors to increase their position size (escalate risk-taking) on the basis of positive indicators concerning the future returns on their investment. This focus on positive indicators is expected to be particularly powerful if it allows traders to believe that they can eliminate, or at least counteract, the future 'painful' realization of current paper losses. This drive to avoid situations which may involve negative emotions has been shown to be a powerful motivator for escalation of commitment (Conlon and Garland, 1993, Wong and Kwong, 2007, Ku, 2008). Consequently, we expect significant unrealized losses to be a powerful influence on escalation of risk-taking. To examine these speculations, we test a 'Significant Unrealized Loss Hypothesis':

More escalation of risk-taking will occur if an individual is currently incurring significant unrealized losses.

Previous studies have shown that individuals with different characteristics display different escalation behavior. For example, Lam and Ozorio's (2013) found that women are more prone to taking greater risks following losses. Furthermore, the propensity toward escalation appears to be greater among Mexican (cf. US) decision makers, due largely to differences in cultural values and contexts (Greer and Stephens, 2001). However, no previous studies have investigated the difference in escalation of risk-taking between more and less informed traders. This is surprising as Chou,Wu and Tu (2014) argue that less informed traders have a tendency to be more motivated by psychological factors rather than economic considerations. Equally, Feng and Seasholes (2005) suggest that informed traders, as a result of their greater sophistication and trading experience, have a tendency to attenuate behavioral biases such as the disposition effect. Therefore, it seems likely that more and less informed traders are likely to respond to the losses differently leading to the different degree of escalation of risk-taking. To explore this possibility we test our 'Informed Trader Hypothesis':

Less informed traders escalate risk-taking to a greater extent than more informed traders following both significant realized and unrealized losses.

2.3 Data and procedures

2.3.1 Data

We test our hypotheses by analyzing 219,575 trades in FTSE 100 index futures of 792 individual traders, the clients of a large spread-trading company in the UK. All the trades were executed between 11 January 2010 and 6 February 2012.

In general, spread-trading firms offer a spread of prices ('bid' and 'ask' prices) on a given financial instrument (e.g., a financial index) and if traders anticipate that the index will rise above or fall below the firm's bid-ask price then they will buy ('long position') or sell ('short position') the index, respectively. The gain or loss they achieve in a long position is determined by multiplying their initial stake by the number of points which the index increases or decreases, respectively, from the price when they opened the trade. Similarly, they gain or lose in a short position if the index decreases or increases, respectively.

We examine trades that are full 'round trips,' whereby each trade has an opening transaction (i.e., the 'buy/sell' portion in a typical 'long/short' position) and an associated closing transaction (i.e., the 'sell/buy' portion in a typical 'long/short' position). We define escalation of risk-taking as the decision to open a new long/short position in the same market as a currently held long/short position. While it is conceivable that escalation could occur through opening new positions in different markets, the degree of escalation in the latter case depends on the correlation between the market prices, or perhaps more accurately, the traders' perception of such correlation. Therefore, to avoid this complexity, we focus only on the escalation of position size in trades associated with FTSE 100 index futures, whilst controlling for realized and unrealized losses in all markets in which a given trader operates.

One of the advantages of employing financial spread-trading data is that individuals in these markets trade far more frequently than conventional financial market traders (e.g. individual investors investing in equities). As a result, in our sample we have, on average, a new transaction from any of the traders every 2 minutes. This allows us to examine the degree of escalation on a trade-by-trade basis. In addition, an important advantage of employing data from the spread-trading market is that trades used to both open and close a position must be made with the same spread-trading brokerage company which is not a requirement in traditional stock markets. Consequently, we have a complete history of an individual's trades associated with a particular investment decision.

Our dataset also allows us to define more and less informed traders using a measure based on their individual updated account profitability. We expect more informed traders to trade in a more sophisticated fashion, often based on more information, and, as a result, to be more successful. Consequently, we define the more/less informed traders as those with total profitability across all their trades prior to the transaction greater/less than zero.

2.3.2 Measuring escalation of risk-taking

Throughout our analysis, we employ a measure of escalation which is analogous to that used in the literature to measure escalation of commitment. In particular, we regard an escalation of risk-taking to have occurred when a trader takes actions which increase the potential variance of the return on their investment. Specifically, trader i is regarded as having escalated their risk-taking at the time of transaction T, if they 'average in', i.e., transaction T increases the size of a previously held position (a long or short position) in the FTSE 100 index futures. Hence we only measure the degree of escalation at the time of transactions used to open positions, since closing transactions can only either reduce the position size or fully close the position. An averaging-in trade was defined as one executed in the same market (FTSE 100 index futures) and in the same direction (i.e., a long or short position) as the trader's current net position. In order to measure the degree of escalation at the time of trade T, we create an 'averaged-in stake' variable (AIS_{iT}). This is defined, as the accumulated size of all the open positions in FTSE 100 index futures by the trader immediately following an 'averaging-in' trade T, by the total size of the initial investment prior to trade T. This enables us to account for accumulation of risk-taking which can occur through successive escalation. If no positions are currently opened when a trade is executed then AIS_{iT} = 0. However, if positions are already open then AIS_{iT} indicates the size of that escalation relative to the original position's stake size. For example, a trader may currently hold a long position in the FTSE 100 index futures at £10 per point (i.e., a notional position value of £65,000 at an index price of 6,500) and they might 'average-in' another £5 a point via a new opening transaction. This action increases their overall position, and therefore risk, in that market to £15 a point (i.e., a notional position value of £97,500) and AIS_{iT} = 15/10 = 1.5. However, if the trader had opened a second position at £10 a point AIS_{iT} = 20/10 = 2, indicating greater escalation of risk-taking in the latter situation.

2.3.3 Examining the causes of escalation of risk-taking

The objective is to examine the degree to which 'averaging-in' behavior is affected by events associated with losing money that are potentially 'significant' to an individual trader. Consequently, we develop a number of independent variables to capture a variety of events which could be significant to trader i associated with their trading activity in the FTSE 100 index futures. In particular, we examine the size of the loss associated with the last closing trade in the FTSE 100 index futures (R) that was executed by trader i prior to trade T, relative to the losses the trader usually experiences. In particular, we create $RLOSS_{iR}$ which take the value of the realized loss from trade R divided by the trader's *current* median loss per trade in FTSE 100 index futures (measured over all their realized losing trades, up to and including the closing of trade R in the FTSE 100 index futures market, and zero otherwise (i.e., if R resulted in a realized gain)).

As discussed in Section 2.2.2, it is possible that events other than the size of the last losing trade may also be important in predicting the degree of averaging-in. In particular, a run of losses may also be important. Consequently, we define three dichotomous variables, $3L_{iR}$, $5L_{iR}$, and $10L_{iR}$ which take the value one if trader i suffered a run of 3-4, 5-9, and 10 or more losses, respectively, on each closing transaction on the FTSE 100 index futures up until the last closing transaction, R, made immediately prior to opening transaction R, and zero otherwise. We examine three or more sequential losses because Carlson and Shu's (2007) study revealed that the third repeat event in a sequence is crucial to the subjective belief that a streak is emerging. We encode streaks longer than ten in a row since, firstly they are likely to be very rare, and secondly because working memory restrictions probably limit any incremental effect beyond a run of ten losses in a row.

We believe, as discussed above, that traders may react differently to realized and unrealized losses. As a result, we introduce a variable $ULOSS_{iT}$ which takes the value of the unrealized loss faced by trader i up to the time of initiating trade T, divided by the trader's current median unrealized loss in FTSE100 index futures (measured over all their unrealized losses at the time of initiating any trade up to the time of initiating trade T in the FTSE 100 index futures market), and zero when the trader is holding an unrealized gain.

In order to test our informed trader hypothesis we include a dichotomous variable MI_{iT} designed to identify those traders who are more successful and are, therefore, more likely to be those who are more informed. In particular, to avoid look-ahead bias, this variable takes the value of one for trader i, if the total returns on all their closing transactions prior to opening transaction T (i.e., up to date profitability), are positive (or breaking even), and zero otherwise. Interaction terms between MI_{iT} and the variables introduced above to capture potentially significant loss-related events are incorporated in the model in order to examine to what extent there are differences in the manner in which more and less informed traders react to these significant events (i.e., variables: $RLOSS_{iR} \times MI_{iT}$, $ULOSS_{iT} \times MI_{iT}$, $3L_{iR} \times MI_{iT}$, $5L_{iR} \times MI_{iT}$, $10L_{iR} \times MI_{iT}$).

A number of control variables are incorporated into the model to ensure that spurious causal relationships are not attributed. In particular, we incorporate variables to capture losses which the trader may have experienced in markets other than the FTSE 100 index futures immediately prior to trade T being executed to open a position. To achieve this we create $ACRLOSS_i$ and $ACULOSS_i$ which take the value one if trader i had, respectively, a total net realized or unrealized loss in all markets other than the FTSE 100 index futures (i.e., other markets provided by the spread-trading platform) at the close of the day prior to the date of transaction T, and zero otherwise.

Ding,Charoenwong and Seetoh (2004) observed that past market conditions affect forecasting errors of analysts. Specifically, they found that analysts' forecasts of stocks listed in the New York Stock Exchange and the American Stock Exchange tended to be more accurate during periods of positive earnings growth but excessively optimistic during periods of negative earnings growth. Consequently, we include the following four control variables that account for the return of the market in various intervals prior to executing trade T: $MKRET$, $MKRET1$, $MKRET2\_5$, and $MKRET6\_20$. Specifically, these intervals relate to periods from (i) the opening of the market on the day transaction T was executed until T is executed, (ii) from the opening to the close of the market on the day prior to transaction T, (iii) from the opening of the market five days prior to the day on which transaction T was executed to the close of the market two days prior to the day on which transaction T was executed and (iv) from the opening of the market twenty days prior to the day on which transaction T was executed to the close of the market six days prior to the day on which transaction T was executed. Risk aversion and market activity have been shown to be linked (Tetlock, 2007). Consequently, to control for market activity, we incorporate the $MKTACT$ variable, which measures the number of individual spread traders in our database operating in the market on the same date and up to the time transaction T was initiated.

Risk-taking has been shown to vary by individual characteristics, such as experience (Menkhoff,Schmidt and Brozynski, 2006, Lam and Ozorio, 2013). As a result, we expect that traders with different levels of experience may react to losses differently and we, therefore, incorporate two variables to capture the trader's level of experience: $TRADE_i$, and $CLTACT_i$. These measure, respectively, up to the time of executing opening transaction T, the number of *trades* (open or close) trader i executed from the start of the dataset (on or after 11 January 2010) and the total number of *days* that trader i had held an account with the spread-trading company from the first trade they executed (on or after 11 January 2010).

2.3.4 Procedures

In order to test our three hypotheses, we estimate a series of linear mixed models (LMM). The main benefit of employing LMMs is their ability to correctly account for the expected correlations across the data that originate from the same individual. As multiple transactions from the same individual cannot be regarded as independent from each other, these correlations would otherwise violate the assumption of independence required for a standard regression model. By employing the LMMs, we can assess the impact of the various fixed effect variables described in section 2.3.3, whilst controlling for the individual differences that might naturally occur between individuals in these effects via random effects variables. In our case, we allow the intercept in the regression model to vary depending on the trader (i.e., by assuming the baseline for each trader). The LMM we employ incorporates the predictor variables, discussed above, which we believe may impact the escalation of risk-taking. In order to reduce positive skew of the dependent variable (see Figure 2-1 for a histogram of averaged-in stake), AIS_{iT}, a log transformation is employed.

We first determine the impact of previous significant realized losses, streaks of losses and unrealized losses on the escalation of risk-taking displayed by trader i when executing trade T, by estimating Model 1:

$$\mathrm{Log}(1 + AIS_{iT}) = b_{0i} + \sum_{k=1}^{14} b_k x_k + \varepsilon_{iT} \qquad (2\text{-}1)$$

where $\varepsilon_{iT} \sim N(0, \sigma^2)$, $b_{0i} = b_0 + u_{0i}$ and $u_{0i} \sim N(0, \tau_{00})$.

This model includes the main fixed effect variables of interest together with relevant control variables discussed above. These LMMs include a random effect factor to control for the individual differences (via the intercept term, b_{0i}). The coefficient b_0 is the mean population intercept and it is assumed that trader i will diverge from this following a random variable, u_{0i}, which is assumed to be normally distributed with mean 0 and variance τ_{00}. The rest of the coefficients b_1 to b_{14} are population average estimates of the fixed effects and are analogous to linear predictors from standard ordinary least square (OLS) regression.[1]

A significant and positive coefficient for $RLOSS_{iR}$, $3L_{iR}$, $5L_{iR}$, $10L_{iR}$, and $ULOSS_{iT}$ would support the view that previous significant realized and unrealized losses elicit an escalation of risk-taking.

In order to investigate the differential effect of significant losses on escalation of risk-taking amongst more and less informed traders, we developed Model 2. This, in addition to the variables included in Model 1, also incorporates six further variables, one to distinguish the trades of more and less informed traders (MI_{iT}) and five interaction terms between the various

[1] Fixed effects and variances of random effects are estimated by minimizing $-2logLik_{ml} = nlog(2\pi) + \log(|V|) + R^t V^{-1} R$, where V is a matrix that depends on the variance components and R is the vector of residuals when the predicted values are based on fixed effects only.

types of losses and the informed trader variable ($RLOSS_{iR} \times MI_{iT}$, $ULOSS_{iT} \times MI_{iT}$, $3L_{iR} \times MI_{iT}$, $5L_{iR} \times MI_{iT}$, and $10L_{iR} \times MI_{iT}$).

A series of planned contrasts are undertaken to examine whether there are significant differences in the escalation of risk-taking by more and less informed traders in response to significant losses and unrealized losses. For example, the marginal impact on less informed traders' propensity to escalate risk-taking when executing trade T, of a greater than median realized loss on the last closing trade, R, executed prior to T, is given by the coefficient of $RLOSS_{iR}$. The equivalent coefficient for more informed traders is given by summing the coefficients for $RLOSS_{iR}$, MI_{iT} and $RLOSS_{iR} \times MI_{iT}$. Significantly greater impacts of losses on the degree of escalation of risk-taking by less (cf. more) informed traders would provide support for the Informed Trader Hypothesis.

2.4 Results

2.4.1 Descriptive statistics

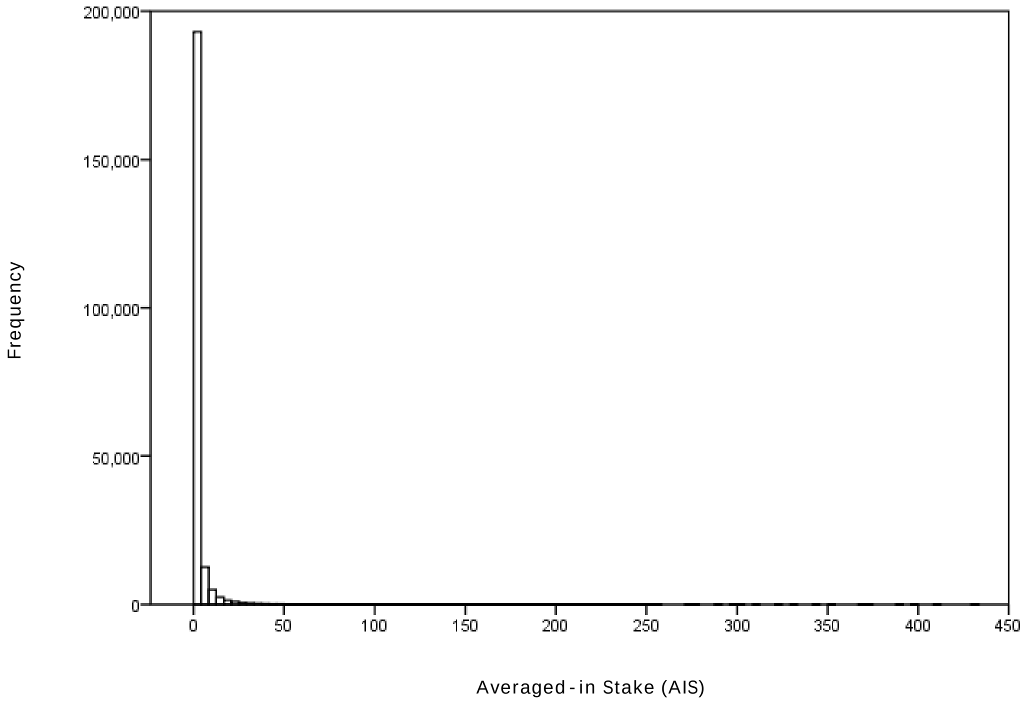
We illustrate the degree of averaging-in across all trades and that following realized and unrealized losses by reporting relevant descriptive statistics in Table 2-1. In particular, we report the mean and the standard deviation of the (non log-transformed) averaging-in variable AIS for all trades associated with the FTSE 100 index futures used to open positions, for those used to open positions immediately following a trade resulting in a realized loss and those trades executed at the time the trader holds an unrealized loss.

Table 2-1 Descriptive statistics associated with 'averaging-in' behavior.

	Averaged-in Stake (AIS)		Averaged-in Stake (AIS) following realized loss		Averaged-in Stake (AIS) following unrealized loss	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.
All transactions	1.86	10.10	2.01	10.16	4.89	15.94
MI	1.64	10.12	1.62	9.01	5.59	18.50
LI	2.06	10.09	2.34	11.02	4.14	12.58
Mean difference (MI vs. LI)[+]	-0.42 (0.04)***		-0.72 (0.04)***		1.45 (-0.21)***	

The table presents means of the variable *AIS*, which captures the degree of averaging-in, for all transactions and for the transactions of more (MI) and less informed traders (LI). The means of *AIS* are also shown for transactions following a realized loss and an unrealized loss. Results of *t*-tests used to compare the difference in 'averaging-in' behavior between more and less informed traders for all transactions and for those following realized losses and unrealized losses are also presented. [+] Prior to undertaking t-tests, the assumption of equality of variances is tested by employing Levene's test.

Figure 2-1 Distribution of averaged-in stake in the sample.



These results suggest that traders tend to escalate their risk-taking (in terms of averaging-in) across all transactions in the FTSE 100 index futures (mean AIS for all transactions is 1.86, which is significantly different from 1 (t=48.09, p<.01)). In addition, based on trades related to the FTSE 100 index futures, a realized loss immediately preceding transaction T and unrealized losses at the time transaction T is executed appear to lead to greater averaging-in, with unrealized losses appearing to have the greatest impact on behavior (2.01 *vs*. 1.86, t=5.58, p<.01; 4.89 *vs*. 1.86, t=28.58, p<.01; 4.89 *vs*. 2.01, t=26.91, p<.01). The results suggest differences in the degree to which more and less informed traders escalate their risk-taking and in the manner they react to realized and unrealized losses. In particular, less informed traders tended to average-in to a greater extent than more informed traders (AIS=2.06 *vs*. 1.64, t=11.65, p<.01). For less informed traders, a realized loss in the FTSE 100 index futures immediately preceding transaction T and unrealized losses at the time transaction T is executed appear to lead to greater averaging-in, with unrealized losses appearing to have the greatest impact on behavior (AIS=2.34 *vs*. 2.06, t=6.90, p<.01 ; 4.14 *vs*. 2.06, t=17.10, p<.01; 4.14 *vs*. 2.34, t=14.61, p<.01). However, a realized loss immediately preceding transaction T had little impact on the degree of averaging-in by a more informed trader (AIS=1.62 *vs*. 1.64, t=-0.58, p>.1) but unrealized losses at the time of transaction T appeared to have a significant impact on the degree to which they averaged-in (AIS=5.59 *vs.* 1.64, t=23.13, p<.01). In fact, when facing unrealized losses, more informed traders averaged in to a greater extent than less informed traders (AIS=5.59 *vs.* 4.14 respectively, t=7.01, p<.01).

2.4.2 Escalation of risk-taking

Estimates of the regression coefficients and their standard errors from LMM regressions for Models 1 and 2, with the log transformed 'averaging-in' stake size (AIS_{iT}) as the dependent variable, are displayed in Table 2-2.

The results of estimating Model 1 indicate that the intercept term is positive and significant, suggesting that traders have a tendency to escalate risk-taking when they make gains. This result is in line with the house money effect (e.g., Hsu and Chow, 2013). The coefficient for $RLOSS_{iR}$is significant and positive, suggesting, in line with the Significant Realized Loss Hypothesis that escalation of risk-taking is more likely to occur following a significant realized loss. The coefficients for $3L_{iR}$ and $5L_{iR}$ are negative, the former being significant and the latter insignificant, suggesting that a run of three or 4 losses can decrease the degree of escalation and 5-9 losses in a row have no effect on escalation. However, the coefficient of $10L_{iR}$ is positive and significant, suggesting that a streak of 10 or more losses is likely to lead to an escalation of risk-taking (cf. when gains are made). The large size of the coefficient for losing streaks of more than 10 losses suggests that long losing streaks have a large effect on the escalation of risk-taking, leading to almost double the degree of escalation over that which occurs when gains are made. The coefficient of $ULOSS_{iT}$ is also positive and significant, suggesting that significant unrealized losses lead traders to escalate their risk. This is consistent with the Significant Unrealized Loss Hypothesis indicating that large unrealized losses lead to an increase in risk-taking. Interestingly, the coefficients of $ULOSS_{iT}$ and $RLOSS_{iR}$ suggest that realized losses have less of an effect than equivalent-sized unrealized losses ($ULOSS_{iT}$-$RLOSS_{iR}$=0.029, z=15.42, p<0.01).

Overall, the results of estimating Model 1 provide support for the view that both realized and unrealized losses lead to an escalation of risk-taking but a streak of losses has to be sufficiently 'significant' to the trader (10 losses or over) in order to influence the degree of escalation in their risk-taking. In addition, the results suggest that realized and unrealized losses may have different psychological impacts on traders, as they differ in the extent to which they cause traders to escalate risk-taking. This seems to be in line with Thaler (1999) suggesting that realized and unrealized losses are perceived differently.

Following the estimation of Model 2, a series of planned contrasts are undertaken to examine whether there are significant differences in the escalation of risk-taking by more and less informed traders in response to significant losses. The coefficient of MI_{iT} in Model 2 is negative and significant, suggesting that more informed traders escalate risk-taking to a significantly less extent than less informed traders. In addition, the coefficient of $RLOSS_{iR}$ is significant and positive, suggesting that less informed traders are likely to escalate risk-taking following realized losses, particularly when those losses are large. However, a planned contrast suggests that more informed traders significantly *reduce* their escalation of risk-taking in the face of realized losses, particularly large realized losses ($RLOSS_{iR}+MI_{iT}+RLOSS_{iR}\times MI_{iT}$ = -0.051 ; z= -8.265, p<.01).

Table 2-2 Estimation results for Model 1, and Model 2 with averaged-in stake (AIS) as dependent variable.

Variable	Model			
	(1)	(1)ⱡ	(2)	(2)ⱡ
Intercept	0.2119***	0.2159***	0.2399***	0.2443***
	(0.0197)	(0.0198)	(0.0198)	(0.0199)
RLOSS	0.0055***	0.0055***	0.0042***	0.0042***
	(0.0007)	(0.0007)	(0.0009)	(0.0009)
ULOSS	0.0341***	0.0342***	0.0217***	0.0217***
	(0.0017)	(0.0017)	(0.0023)	(0.0023)
3L	-0.0187***	-0.0188***	0.0192***	0.0191***
	(0.0049)	(0.0049)	(0.0067)	(0.0067)
5L	-0.0011	-0.0011	0.0230***	0.0229***
	(0.0050)	(0.0050)	(0.0067)	(0.0067)
10L	0.1840***	0.1839***	0.2669***	0.2669***
	(0.0058)	(0.0058)	(0.0073)	(0.0073)
MI			-0.0577***	-0.0579***
			(0.0062)	(0.0062)
RLOSS×MI			0.0025*	0.0025*
			(0.0013)	(0.0013)
ULOSS×MI			0.0276***	0.0276***
			(0.0035)	(0.0035)
3L×MI			-0.0837***	-0.0835***
			(0.0098)	(0.0098)
5L×MI			-0.0534***	-0.0532***
			(0.0098)	(0.0098)
10L×MI			-0.2139***	-0.2142***
			(0.0108)	(0.0108)
ACRLOSS	-0.0419***	-0.0419***	-0.0373***	-0.0373***
	(0.0043)	(0.0043)	(0.0043)	(0.0043)
ACULOSS	0.1455***	0.1448***	0.1365***	0.1358***
	(0.0057)	(0.0058)	(0.0057)	(0.0057)
MKRET	-0.0195	0.0386	-0.0096	0.0519
	(0.1383)	(0.1390)	(0.1381)	(0.1387)
MKRET1	-0.2664**	-0.2830**	-0.2295**	-0.2469**
	(0.1048)	(0.1048)	(0.1046)	(0.1046)
MKRET2_5	-0.2078***	-0.1990***	-0.1979***	-0.1887***
	(0.0645)	(0.0646)	(0.0644)	(0.0644)
MKRET6_20	-0.1907***	-0.1840***	-0.1247***	-0.1175***
	(0.0406)	(0.0406)	(0.0406)	(0.0406)
MKACT	-0.0003***	-0.0003***	-0.0003***	-0.0003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
TRADE	-0.000002***	-0.000002***	-0.000003***	-0.000003***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
CLTACT	0.0003	0.0003	0.0004	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
DAY		-0.0178***		-0.0188***
		(0.0042)		(0.0042)
-2LL	490,890.4	490,872.6	489,974.2	489,954.2
AIC	490,924.4	490,908.6	489,974.2	490,002.2
Random effects (Individual differences)				
Variance	0.1187	0.1187	0.1152	0.1152
SD	0.3445	0.3446	0.3394	0.3394

* p<0.1, ** p<0.05 , *** p<0.01. Standard errors for estimates are shown in parentheses. Model 1ⱡ,2ⱡ: Model 1 and 2 were estimated again with the same data and controlled for weekend effect.

The coefficients for $3L_{iR}$, $5L_{iR}$, and $10L_{iR}$ in Model 2 are significant and positive, suggesting that less informed traders are likely to escalate their risk-taking following streaks of more than three losses. In addition, the coefficient for $10L_{iR}$ (0.2669) is significantly greater than those for $3L_{iR}$ (0.019) and $5L_{iR}$ (0.023) (0.248, z=29.09, p<.01; 0.2340, z=29.94, p<.01, respectively), indicating that a run of more than ten losses leads to particularly large increases in risk-taking by less informed traders. However, planned contrasts suggest that more informed traders *do not* escalate risk-taking following streaks of more than 3 losses ($3L_{iR}+MI_{iT}+3L_{iR}\times MI_{iT}$=-0.122, z=-14.61, p<.01; $5L_{iR}+MI_{iT}+5L_{iR}\times MI_{iT}$=-0.088, z=-10.65, p<.01; $10L_{iR}+MI_{iT}+10L_{iR}\times MI_{iT}$=

-0.005, z=-0.505, p>.1). Rather, streaks of 3 or 4 losses and 5 to 9 losses significantly decrease their risk-taking, and streaks of 10 or more losses has no effect on their risk-taking.

The coefficient of $ULOSS_{iT}$ in Model 2 is significant and positive, indicating that less informed traders escalate their risk-taking following an unrealized loss. However, a planned contrast suggests that more informed traders *do not* escalate their risk in the face of unrealized loss, rather unrealized losses have no effect in the their degree of risk escalation in the face of unrealized losses, particularly large unrealized losses ($ULOSS_{iT}+MI_{iT}+ULOSS_{iT}\times MI_{iT}=-0.008$, z=-1.285, p >.1).

Overall, the results of estimating Model 2 provide support for the view that more and less informed react to realized and unrealized losses differently. In particular by taking the control variables into consideration, the less informed tend to *escalate* and the more informed significantly *reduce* their escalation of risk-taking in the face of realized losses, particularly large realized losses. In the case of unrealized losses, particularly large unrealized losses, less informed tend to *escalate* their escalation of risk-taking. However this has no effect on the more informed traders regarding their escalation of risk-taking. In addition, less informed traders increase their escalation of risk-taking in the face of streaks of losses, particularly longer streaks of losses. However, more informed traders reduce their escalation of risk-taking in the face of shorter streaks of losses (3- 4, and 5-9 losses), and more than 10 consecutive losses has no effect on the extent to which they escalate risk-taking.

The coefficients of the control variables employed when estimating Models 1 and 2 have consistent signs and levels of significance in Models 1 and 2 (see Table 2-2). In particular, the coefficients of $ACRLOSS_i$ and $ACULOSS_i$ are negative and positive, respectively, and all are significant. This implies that accumulated realized/unrealized losses across all markets in which the trader holds positions at the close of the day prior to the date of initiating a FTSE 100 index futures trade lead to less/greater escalation of risk-taking on the FTSE 100 index futures trade. The different reaction of traders to accumulated realized and unrealized losses across all markets supports Thaler (1999) view that realized and unrealized (paper) losses may not be perceived in the same manner. We believe that this is evidence of individuals attempting to recoup, as yet, unrealized (but anticipated) losses before they become crystalized and therefore 'painful'.

The coefficient of the recent market return periods ($MKRET$) is negative but not significant. However, the coefficients for market returns ($MKRET1$, $MKRET2\_5$, and $MKRET6\_20$) are all negative and significant, suggesting that high market returns in these earlier periods have a dampening effect on risk-taking on trade T. The coefficient of $TRADE_i$ is negative and significant, suggesting that the more trades an individual places the less they are inclined to escalate their risk-taking. However $CLTACT_i$ is not significant, suggesting that the period a trader holds a spread-trading account does not affect the extent to which they escalate their risk-taking. Viewed together, the coefficients relating to $TRADE_i$ and $CLTACT_i$ may suggest that traders learn to improve their trading discipline by placing a larger number of trades rather than simply by time spent in the market. It is possible that those traders who reduce their escalation of risk-taking through trading experience are those who are best able to continue trading for a large number of trades, in which case one might suspect some element of survivorship bias in these results. However, the fact that the number of days a trader holds an account has no effect on their escalation of risk-taking reduces this concern.

We also conducted tests to confirm the robustness of the results which support the hypotheses. In particular, we replicated the analysis by adding the weekend effect into consideration. These analyses yielded similar results to those presented above.

2.5 Discussion

Previous studies suggest that, as a result of the 'house-money' effect, past gains are likely to lead to an escalation of risk-taking by financial traders (Liu *et al.*, 2010, Hsu and Chow, 2013). Our finding that the intercept term in Model 1 is positive suggests that this is certainly the case. However, based on the escalation of commitment literature, we hypothesized that we would observe greater escalation of risk-taking in response to losses and that the significance of the loss to the trader (i.e., in terms of size, and whether the losses occurred in streaks) and the nature of the loss (realized *vs*. unrealized) may play important roles in this effect. In particular, we argued that both realized and unrealized losses would induce an escalation of risk-taking and that the more significant the losses to the investor the more this may increase their degree of escalation.

Our results reveal that escalation of risk-taking, as measured by averaging-in, is indeed affected by loss and that the characteristics of the loss play an important role. This perhaps is not surprising given that averaging-in is a similar form of escalation to that examined in traditional escalation of commitment studies, which have shown that decision makers increase their commitment of resources to a chosen course of action after facing negative consequences (Staw, 1976). Similarly, by averaging-in, traders escalate the risk they face by committing more resources to the outcome of an uncertain event (i.e., the direction in which the market will move) which had formed the basis of their earlier decision to invest. In other words, averaging-in is different from other types of risk-taking which do not take the commitment of resources to a chosen course of action into account. Consequently, previous studies examining risk-taking in the face of losses may not be explained as well in the context of escalation of commitment. Rather, those results may be better explained with other concepts, such as the house money effect or the break-even effect (Liu *et al.*, 2010, Hsu and Chow, 2013, Huang and Chan, 2014).

We observe that traders have a higher tendency to average-in (whether they have recently experienced realized losses or they face unrealized losses), which accords with the findings of the escalation of commitment literature, that decision makers escalate their commitment to a failing course of action (Festinger, 1957, Aronson, 1968, Staw, 1976, Whyte, 1993). We find, support of our 'Significant Realized Losses' hypothesis. In particular, after controlling for market conditions and factors related to the trader's experience, there is tendency to escalate risk-taking to a greater extent following previous large, realized losses. In addition, we find that long streaks of losses (i.e., greater than 10 losses) lead to very large increases in the degree at which traders escalate their risk-taking. However, shorter streaks of losses (5-9) have no effect on escalation of risk-taking and very short streaks of 3 or 4 losses, can even lead to a reduction in the degree of escalation. These results suggest that spread traders are aware of the inherent uncertainty of spread trading and understand that streaks of losses are common. Short streaks may signal to traders that their current strategy is flawed in relation to current trading conditions, thus resulting in a reduction in the degree of escalation. As the streak increases in length the probability of this arising by chance appears to reach a point where the trader feels that their 'luck' must turn (i.e., the gambler's fallacy comes into play) and , as a result their degree of escalation increases significantly. These findings, chime with previous literature which suggests that events which are perceived as significantly different to the norm have a greater impact on individuals' risk-taking behavior (Barber and Odean, 2008, Hsu and Chow, 2013).

The results suggest, in line with our 'Significant Unrealized Loss Hypothesis', that if a trader is facing a large unrealized loss at the time of opening a new trade, then this is likely to increase their propensity to average-in. In fact, we find that what are deemed large unrealized losses lead to a more than six fold increase in the degree of escalation in risk-taking compared to large realized losses. That there are differences in the effects of realized and unrealized losses is consistent with the mental accounting literature, which suggest that these two types of loss losses are perceived differently (Thaler, 1999). However, Thaler (1999) suggested that paper losses are perceived as less 'painful' than realized losses, implying that realized losses might be perceived as more 'significant' to the trader, leading to greater escalation of risk-taking following realized (*vs.* unrealized) losses. Our results, on the other hand, give more credence to the observations of Conlon and Garland (1993), that retrospective factors (realized losses) may be dominated by prospective factors (future gains/losses from current unrealized losses). In particular, they found that the effect of the retrospective factors might be a goal substitution effect whereas prospective factors become a new goal. Consequently, traders may focus on the new goal of recouping their unrealized losses in order to avoid the anticipated pain, at least more so than acting in response to those losses that have already been felt. In addition, Lehenkari (2012) suggests that intensification of regret occurs when a negative outcome is the product of a decision to act as opposed to a decision not to act. In other words, when facing unrealized losses, traders perceive that their regret at making a loss following a deliberate act to close their position may be greater than if they fail to act (i.e., do not close their position), especially as this may give them the opportunity to focus on the possibility that the market may turn and the unrealized loss may result in a realized profit.

We examine the extent to which more and less informed traders differ in the degree to which their escalation of risk-taking is affected by previous losses of various types by estimating Model 2. Overall, the results add to the growing literature which points to differences in trading behavior among various types of traders (e.g., Genesove and Mayer, 2001, Shapira and Venezia, 2001, Dhar and Zhu, 2006). We find that less informed traders increase their escalation of risk-taking in the face of large realized and unrealized losses. They also increase their degree of escalation of risk-taking following streaks of more than three losses, with longer losing streaks causing a greater increase in risk-taking. By contrast, we find that more informed traders either do not alter their risk-taking behavior or reduce their degree of risk escalation in the face of realized or unrealized losses, particularly if these are large. They also do not alter their risk-taking behavior or reduce their degree of risk escalation when experiencing streaks of losses. Overall, therefore, our results provide strong support for our 'Informed Trader Hypothesis'.

The very different reaction of more (*vs.* less) informed traders to significant realized and unrealized losses and to streaks of losses may derive from Personality systems interactions theory (PSI). Mcelroy and Dowd (2007) explain that action-oriented individuals (i.e., those who tend to devote more cognitive resources to a given task and are relatively better at focusing their attention) are able to overcome negative experiences and to manage negative affect more effectively than state-oriented individuals (i.e., those who tend to dwell upon negative aspects of an event and have difficulty controlling negative affect.). In addition, Molden and Hui (2011) suggest that people who think less about preventing loss and more about achieving gains may reduce their commitment to previous mistakes. Since we define more informed traders as those who are generally more profitable, it may well be that these individuals have more experience of achieving success and are thus more focussed on achieving gains rather than avoiding losses. In addition, those traders who make greater returns are likely to be those who use information most appropriately and who devote more cognitive resources to the trading task. Consequently, it is likely that these are more akin to the action-orientated individuals and the less informed more aligned with the stated-orientated individuals. It is not surprising, therefore, that the more informed do not escalate risk-taking following significant realized and unrealized losses and following streaks of losses. In fact, they often scale back on their escalation when facing significant losses. This may arise because they use the significant losses as signals that their trading behavior is not currently in tune with market conditions. This would fit with the view that they accord more to the action-orientated individuals identified by Mcelroy and Dowd (2007), who are those best able to reduce their commitment to previous mistakes.

The insights we develop concerning the factors which affect the degree of escalation of risk-taking are made possible by the nature of data we employ. In particular, the high frequency nature of the data allows us to examine the degree of escalation on a trade-by-trade basis, thus enabling us to explore the effects of different types of losses. In addition, our data allows us to attribute specific trades to particular traders and this enables us, via the use of linear mixed models, to account for individual differences in their approaches to averaging-in. This also allows us to attribute the decision to escalate to previous decisions made by the same individual. Previous real-world studies in the financial and management domains have not been able to ensure that the same individual who makes subsequent decisions to escalate risk-taking, made the original decision on which the escalation is based. In management contexts, decisions are often made by individuals on behalf of others, and they are likely to have less personal attachment to the resulting outcomes. We believe, therefore, that previous studies which have simply *assumed* that individuals made the original decision on which their escalation is based are likely to have under-estimated the degree of escalation. Our dataset does not suffer the same limitation since it contains transactions of individual investor accounts rather than the transactions of an organization or financial institution. We believe, therefore, that our results provide an accurate assessment of the degree to which escalation of risk-taking occurs.

2.6 Conclusion

We conclude that risk-taking escalates following previous gains (i.e., the hot-hand effect) and losses (i.e., the gamblers fallacy effect) but is particularly influenced by losses that are perceived to be significant to the individual concerned. We are able to reach this conclusion having examined the impact of losses on individuals' propensity to average-in to previous investments.

Due to the unique features of spread-trading data, we are able to provide clear evidence regarding the effects of loss on risk-taking behavior. Importantly, we uniquely examine the impact of different *types* of loss on escalation of risk-taking, specifically single large realized and unrealized losses as well as different lengths of streaks of consecutive losses. We find that paper losses and realized losses lead traders to escalate the risk they take but the effect of an unrealized loss is significantly greater than that of a realized loss. In addition, we find that long consecutive losing runs (i.e., ten or more losses in a row) lead to a significant increase in the degree of escalation.

We also discover important differences in the manner in which more and less informed individuals respond to losses; the less informed generally escalating risk-taking following a large realized and unrealized losses and after streaks of losses, but more informed traders tend to reduce or do not react to their escalation in these circumstances. This is consistent with the view that some individuals tend to be more susceptible to some cognitive biases than others and tend to make more decisions based on emotional responses rather than using more logical decision rules (Stanovich and West, 2000).

The insights the chapter offers are important in terms of understanding the manner in which individuals may respond to losses in a variety of domains. However, they are particularly important for those who operate and regulate financial markets because spread-trading markets are growing rapidly and the actions of traders in these markets, via the hedging activities of the spread-trading companies, can have a significant impact on the underlying financial markets. The tendency to increase risk-taking in the face of losses in these markets might, therefore, have a de-stabilizing effect on underlying markets, particularly, during periods of financial crisis, when losses are more likely to be experienced. This is of particular concern because the low barriers to entry and the highly geared nature of spread trading opens up the possibility of speculative trading to those with little or no previous experience; these are the very individuals who are more likely to fit the characteristics of 'less informed' traders, those we have shown are most susceptible to escalation in the face of losses. Consequently, understanding the factors which are most likely to cause of escalation of risk-taking can inform responsible hedging operations of spread-trading companies. In addition, regulators may use the insights developed here to develop strategies/regulations designed to maintain calm, ordered markets. For example, we find that less informed traders are those most susceptible to escalating of risk-taking in the face of losses and regulators may attempt to develop strategies/regulations to discourage less informed traders from participating in these markets or they may require them to undertake training/education designed to discourage risk escalation. In particular, we find that those traders who have placed more trades are less inclined to escalate their risk-taking.

Interestingly, some companies offer the opportunity for prospective clients to first trade using dummy accounts before trading with real money. A logical step, might be for regulators to insist that prior to full participation in these markets, traders must operate simulated accounts and place a certain number of 'dummy' trades, enabling them to see the effects of their actions on their own accounts without risking any money and without affecting the real markets. However, our research suggests that it is the *significance* of loss that is important and Lehenkari's (2012) showed that gifted or inherited positions are not as likely to result in escalation of risk-taking. As such, we do not expect to observe as significant a degree of escalation of risk-taking in dummy trades. Therefore we would expect traders to receive fairly limited valuable feedback from dummy trade activity which could improve their subsequent real-money trades.

A more radical, but perhaps more fruitful, approach might be to examine whether changes in the design of the trading platforms (i.e., web-based user interfaces) could help to reduce some of these behavioral biases. However, such design changes must be made very carefully since the manner in which risk information is presented to individuals can have dramatic effects on their risk-taking and these effects even depends on the cultural background and experience of the user (Fraser-Mackenzie,Sung and Johnson, 2014).

Having observed the impacts of different types of a loss in a spread-trading environment, it would be valuable for future studies to check the robustness of these findings in different trading and decision-making situations. In addition, future controlled laboratory-based studies are needed to further explore the underlying reasons for the differences we observe in reactions to different types of loss and for the different responses of more and less informed traders. Insights concerning the factors driving these differences may help target education programmes to prevent individuals, particularly traders in financial markets, from inappropriate escalation of risk-taking in the face of losses. It may also help financial market regulators in targeting policies to minimize the damaging effect that this sort of behavior might have on market stability. Thus we hope that our study might be a first helpful step towards finding ways to educate decision makers that ‘in for a penny in for a pound’ is not a good maxim when it comes to financial decision making.

Chapter 3: Take it or leave it: Do traders really prefer to segregate their gains and integrate their losses?

Abstract

The hedonic editing hypothesis (HEH), proposes that individuals prefer to segregate gains and to integrate losses. Evidence from laboratory studies supports this view. However, we suggest that real-world traders may be subject to psychological pressures not experienced by subjects in experimental studies and as a result they may not act in a fashion predicted by the HEH. We test this view by analyzing 237,641 investments of 2,969 spread traders between 2004 and 2013. We find that these traders do not behave in a manner which is consistent with the HEH. Rather, their general tendency is to integrate positions and where they do segregate this tends to be associated with losing positions. In addition, we find that there are significant differences in the manner that more and less informed traders treat losses and gains. We explain our results by cognitive dissonance and by the cognitive cost of segregation to which traders may be subject.

3.1 Introduction

The hedonic editing hypothesis (HEH) proposes that individuals prefer to combine, or 'integrate', many small losses into one large loss but to spread or 'segregate' gains over time (Thaler, 1985, Thaler, 1999). This view arises from the notion that individuals engage in mental accounting when attempting to maximize the happiness that they expect to derive as a result of a forthcoming decision. In particular, Thaler (1985) points out that the value function proposed in prospect theory (Kahneman and Tversky, 1979), which is concave/convex for perceived gains/losses, means that happiness is maximized if one segregates gains and integrates losses.

The majority of studies demonstrating the existence of the HEH have been conducted in the laboratory (Thaler, 1985, Jones, 2007, Falsetta,Rupert and Wright, 2012). However, recent empirical studies (Lim, 2006, Lehenkari, 2009) examining whether investors in financial markets behave in a manner consistent with the HEH have produced mixed results. Due to this inconsistency between the laboratory and real-world results, the extent to which the HEH truly predicts the behavior of financial market investors is still in doubt. This is important, because knowledge of whether the phenomenon exists amongst investors in financial markets may lead to a better understanding of the stock prices. In particular, Lee *et al.* (2004) suggest that large imbalance of selling/purchasing asset could lead to a greater impact on price due to pressure on market marker inventory and/or being realized as private information. In addition, the existence of the phenomenon would suggest that uneven selling of investors' winning and losing investments could result in asymmetry in the market (Lim, 2006).

The motivation for this study is our belief that the HEH has not fully accounted for some important psychological factors (i.e., cognitive cost of segregation, cognitive dissonance) which influence the decisions of investors in real-world environments. As a result, we expect the behavior of real-world traders to deviate from the predictions of the HEH. In particular, we identify a cognitive cost associated with segregating positions, which real-world traders would prefer to avoid (i.e., based on 'bounded rationality' (Simon, 1972, March, 1978)). We suggest that this cognitive cost of segregation is likely to be particularly powerful in real-world environments where the profit/loss involved is likely to be of economic significance to the investor. In addition, as Levitt and List (2007, p. 170) point out, "*choices that individuals make depend not just on financial implications, but also on the nature and degree of others' scrutiny, the particular context in which a decision is embedded, and the manner in which participants are selected to participate*", and as such, "*experiments may not always yield results that are readily generalizable*" (Levitt and List, 2007, p. 170). Therefore, we believe that we are likely to observe different results to those derived from the HEH laboratory experiments. In particular, we test our proposition, based on the notion of cognitive cost of segregation, that most positions, whether in profit or loss, will be integrated rather than segregated.

In addition, we argue that in real-world markets a greater proportion of investments showing paper losses (cf. gains) are likely to be segregated, a conclusion which runs counter to the HEH. This proposition arises because the unrealized profits of real-world traders are not certain whereas a premise underlying the HEH (and incorporated into related experimental designs) is that there is no uncertainty regarding future potential gains. We show why the uncertainty of unrealized *gains* is likely to lead to greater integration of profitable positions of real-world traders than the HEH predicts. On the other hand, we suggest that when traders are facing unrealized *losses* they are subject to opposing psychological motives (based on 'motivated reasoning' (e.g., 'inside *vs.* outside forecasts') (Brownstein, 2003) and 'timid actions' (Kahneman and Lovallo, 1993)) which produces two distinct motives, one driving them towards wanting to hold losing positions but another, a counter motive, driving them towards wanting to realize the losing position. This, we argue, leads to cognitive dissonance, a psychological conflict, the discomfort of which investors may alleviate by segregating their position, i.e., to appease both motives. If the desire to alleviate the cognitive dissonance outweighs the cognitive cost of segregation together with the utility advantages of integrating losses (derived from the concave nature of prospect theory's value function for losses), then more segregation of losses will occur. Consequently, we test the hypothesis, that a greater proportion of investments showing paper losses are segregated than those showing paper gains.

Clearly, whether an individual is holding a position showing paper profits or losses has no economic significance regarding the future direction of the financial asset in which the position was invested. However, the decisions that individuals make when facing paper profits or losses have been shown to be affected by a number of psychological biases (Dhar and Zhu, 2006, Lehenkari, 2012). Less informed traders have been shown to be more motivated by psychological considerations than more informed traders, the latter being better able to supress these psychological biases and make decisions based on economic motives (e.g., Shapira and Venezia, 2001, Feng and Seasholes, 2005). Despite this, previous studies examining the HEH have not examined differences in the degree to which less and more informed individuals segregate or integrate losses and gains. We argue that particular psychological factors are likely to influence the integration/segregation decisions of less informed traders to an even greater extent in real-world financial markets than would the case in experimental studies. Consequently, we test our hypothesis that integration/segregation decisions of less (*vs.* more) informed traders will be more influenced by whether or not a position is in profit or loss. Consequently, whilst we expect similar proportions of positions which are in profit or loss to be segregated by more informed traders, we expect a greater difference in these proportions for less informed traders.

In summary, we believe that a range of psychological factors may be involved in the decision to segregate or integrate returns in a real-world trading environment. As a result, we suggest that such motives could result in investors acting in a different manner to that predicted by the HEH. In particular, we anticipate that most positions will be integrated and where segregation does occur it is more likely for losing positions. We develop hypotheses based on these views and test them using data related to over 200,000 trades of nearly 3,000 individual retail spread traders. A series of multilevel logistic regression is employed to ensure that individual differences in the probability of individual traders integrating/segregating are taken into account.

Our study offers a new approach to testing the predictions of HEH. This approach, we believe, provides a clearer view of the degree of integration/segregation adopted by traders. Previous empirical studies (Lim, 2006, Lehenkari, 2009) have assumed an (arbitrary) integration period of one day. This required an erroneous assumption that the end-of-day profits/losses are known when the segregation/integration decision is made (i.e., traders are making choices with foreseeable outcomes). We avoid this assumption by examining traders' decisions to integrate or segregate on a trade-by-trade basis. In particular, we determine the propensity of a trader to close an entire position (i.e., integrating the profit or loss obtained in that position) or to close just a portion of that position (i.e., segregating the profit or loss associated with that position into a realized portion with a certain outcome and an unrealized portion with an uncertain outcome).

Our data also allows us to distinguish more and less informed traders, defined in terms of their long run trading profit. This allows us, in contrast to previous studies, to distinguish the degree to which different groups of traders may be more inclined to segregate or integrate gains or losses. This has potentially important implications for market microstructure theory, since, as Megginson (1997, p. 149) points out, irrationality by uninformed traders may create risk and this discourages the informed from trading against the less informed and may cause prices to deviate from fundamentals (Shleifer and Summers, 1990).

This is the first study to provide an insight into the degree to which individuals in the fast growing spread-trading market are subject to the HEH. It is surprising that no previous study of the HEH has been undertaken in this market, as it is growing rapidly. In particular, Brady and Ramyar (n.d.) estimate that of the £1.2 trillion traded annually on the London Stock Exchange, 40 percent is equity derivative related and 25 percent of this is associated with spread trading (£120 billion). In fact, the number of financial market spread traders operating in the UK is expected to double from 0.5 million in 2011 to 1 million in 2017 (Pryor, 2011, p. xxiii). Furthermore, spread-trading firms hedge into the underlying markets, and, consequently, the behavior of spread traders has a significant impact on the underlying markets.

The results suggest that traders in real world financial markets behave in a manner more consistent with our expectations rather than that predicted by the HEH. In particular, traders are most likely to integrate positions, in general, whether these are in profit or loss. Importantly, the relatively few positions that are segregated, again in contrast to the HEH, tend to be those in loss. We also find that it is the less informed investors that show a greater disparity in their segregation rates between gains and losses, suggesting that cognitive bias is the likely cause of the greater segregation of losses (cf. gains).

The remainder of the chapter is organized as follows: The literature associated with the HEH and other psychological concepts which might affect the decision to integrate/segregate is examined in Section 3.2, and this is employed to develop our hypotheses. The data and procedures employed to test the hypotheses are described in Section 3.3. The results are presented and discussed in Sections 3.4 and 3.5, respectively. Conclusions are drawn in Section 3.6.

3.2 The hedonic editing hypothesis

3.2.1 Prospect theory and the HEH

Prospect theory offers a means of describing and predicting decision-making behavior (Kahneman and Tversky, 1979) and suggests that individuals make choices which enable them to maximize over a value function $v(.)$, defined in terms of gain and loss relative to a reference point. The value function is S-shaped, concave for gains, and convex for losses, and is steeper for losses than for gains.

This value function is defined over single outcomes. However, Thaler (1985) extends this idea to incorporate multiple outcomes. He characterizes decision makers as value maximizers and hypothesizes that they attempt to code outcomes in a manner to make themselves as happy as possible. In particular, he suggests that individuals segregate or integrate outcomes in a manner which is more desirable. For a joint outcome (x, y), individuals prefer to integrate rather than segregate the outcomes when integration yields a higher value than segregation (i.e., $v(x+y)>v(x)+v(y)$) and they prefer to segregate providing segregation yields higher value than integration (i.e., $v(x+y)<v(x)+v(y)$). Consequently, Thaler (1985) develops the hedonic editing hypothesis, which predicts that individuals will integrate losses and segregate gains because the value function, which is concave/convex in the domain of gains/losses, results in a series of small losses/gains bringing a greater reduction/increase in value than one equivalent larger loss/gain. In the case of mixed outcomes (i.e., mixed gains and losses), integration or segregation occurs based on the magnitude of the gains and losses. Due to loss aversion (i.e., where a loss is treated as more psychologically significant than an equivalent gain), larger gains are likely to be combined with smaller losses. Due to diminishing sensitivity of the value function in the region of higher gains or losses, it is also preferable to segregate small gains from larger losses as a 'silver lining' (Thaler, 1985, Jarnebrant,Toubia and Johnson, 2009) (i.e., one can protect a small silver lining by realizing it separately from a larger loss).

3.2.2 Laboratory-based studies examining the HEH

Most of the evidence for the HEH has been drawn from experimental studies. In the first investigation, Thaler (1985) asked subjects to choose between combinations of scenarios, framed in terms of certain gains or loss. Thaler (1985) found, in line with the HEH, that subjects preferred to integrate scenarios framed as losses and to segregate scenarios framed as gains.

Subsequently, experimental studies have largely been conducted on the basis of *temporal spacing*, introduced by Thaler and Johnson (1990), namely that an individual's integration/segregation preferences should be reflected in their choice about the timing of the events. In particular, the process of segregating/integrating events is achieved by allowing the events to occur in different/the same time periods (e.g., one day). Consequently, Thaler and Johnson (1990) developed a set of experiments in which subjects were asked whether they preferred particular financial events involving gains/losses (e.g., lottery win, tax bill) to occur on the same day or to be separated by a week or two. The results only partially supported the HEH, in that subjects segregated gains, but they did not integrate losses. Linville and Fischer (1991) examined to what extent the HEH was supported when the events of interest had impacts related to quality/feelings (e.g., receiving two manuscript acceptance/rejection letters on one day or separated in time) rather than related to quantity (e.g., in terms of gains/losses in money). In this case they found that subjects tended to segregate negative and positive events. Schaffner *et al.* (2013) extended this work by comparing the degree of integration/segregation of gains/losses amongst individuals who base their decisions on accuracy and those who base their decisions on feelings. They found a greater propensity to segregate gains when valuations were based on feelings (*vs.* accuracy) but an equally strong preference for integration of losses for both types of valuation.

Recent studies have examined the applicability of the HEH in wider areas. For example, Jones (2007) found that the predictions of the HEH principles were consistent with health behavior decisions, in that subjects preferred to receive/evaluate multiple positive events (e.g., successful weight loss) in a segregated form and to receive/evaluate multiple negative events (e.g., dental treatment) in an integrated manner. Falsetta,Rupert and Wright (2012), came to similar conclusions regarding decisions related to taxation. They found, in an experimental study, that subjects showed a greater preference for incremental (cf. aggregated) reductions in capital gains tax (i.e., they prefer to segregate gains) but a greater preference for aggregated (cf. incremental) increases in the tax (i.e., they prefer to integrate losses).

3.2.3 Empirical studies examining the HEH

There have, to our best knowledge, only been two studies which have examined the extent to which the HEH is revealed in real-world financial decisions. Lim (2006) employed data from a large U.S. discount brokerage firm and found, in line with the HEH, that traders attempt to integrate their losses on the same day. A subsequent study of domestic investors on the Helsinki Exchange investigated different integration periods for the sale of stocks (i.e., 0, 3, 5, and 10 consecutive days) (Lehenkari, 2009). Clearly, over these periods, traders are able to choose to segregate or integrate gains or losses or to mix these together in a way that enables them to maximize their perceived values. However, the findings did not fully support the HEH as different integration period yielded different results. In particular, shorter integration periods were associated with increased integration rate of losses. Lehenkari (2009, p. 17) concluded that "the application of prospect theory to financial settings is not as straightforward a task as it may seem". We agree with this statement but we also believe that there are problems associated with using a single predefined integration period. Given that financial markets are a meeting place for a broad range of different types of investor there may be large differences between individuals in their trading time horizons. For example, high frequency traders trade for a matter of seconds or minutes, day traders trade for hours and days whereas longer-term investors trade for days, months and years. Clearly one single integration period will not fit all these different types of individuals and therefore in our study we employ a different approach which does not rely on any predefined integration period.

In summary, the results of laboratory-based studies are largely supportive of the HEH but empirical studies have yielded mixed results. We argue below that this may be explained by the fact that the HEH neglects some crucial psychological phenomena that are more likely to apply to real-world traders than to subjects in experiments.

3.2.4 Factors that may influence decisions to integrate/segregate

3.2.4.1 Motives which drive towards the integration of gains and losses

Individuals are likely to view an investment made at a particular time (e.g., a tranche of 100 shares) as a single entity even if it is part of a larger portfolio, because the whole investment was probably based on the same set of specific analysis or private information, reflecting the investor's beliefs concerning its prospects (Coval,Hirshleifer and Shumway, 2005). Once a trader has opened such a position they will incur a cost to their limited cognitive resources of monitoring the state (e.g., performance, relevant news) of that position. This cost is eliminated once that position is fully closed. Segregating a position into several transactions is cognitively (and administratively) more taxing than simply realizing the entire position together since it requires a judgement concerning the portion to close and some continued monitoring of the state of the remaining portion. We know that, as a result of bounded rationality, individuals tend to simplify complex decision tasks (Simon, 1972). A desire to minimize cognitive effort (Fiske and Taylor, 1984) would thus drive individuals towards realizing their gain/loss from this investment at a single point in time (i.e., integration). Only if the subjective utility of segregation outweighs the negative utility associated with the cognitive effort required to decide on the proportion to close and that required to keep track of the segregated positions (*cognitive cost of segregation*) would we expect segregation. This applies to all investments whether in profit or loss and may be greater in real-world environments, where other demands on cognitive effort lead investors to have low tolerance for the cognitive effort of segregation. The HEH does not account for the *cognitive cost of segregation* cost in its subjective utility calculations. This may in part explain why evidence confirming the HEH has not consistently been observed in empirical studies.

3.2.4.2 Motives which drive decision-makers towards resisting the segregation of gains

The concave value function of prospect theory for gains implies that more segregation of gains (cf. losses) should be observed. However, as discussed above, the cognitive cost of segregation may modulate this effect. In addition, paper gains in real-world trading are not certain until the point of realization. However, the HEH is based on the assumption that the segregated gains are certain. In the original conception, it was suggested that individuals would prefer to win $50 and $25 on two separate occasions, rather than $75 on one occasion due to the shape of the value function. This idea is supported in results from laboratory studies. However, in real-world investment, the segregation of gains is more complex. For example, segregating a 75 share position into two (say 50 and 25 share) positions involves two sequential trades at two different times. If the investor sells 50 shares to realize the first 'segregated gain' then the return on the remaining portion is not certain due to potential market fluctuations. In fact, it is possible that this remaining portion could even return a loss given sufficient market volatility. Prospect theory predicts that individuals are risk averse in the domain of gains. Consequently, they ought to avoid behavior that induces uncertainty related to the gain associated with the original 75 share position. In other words, if the act of segregation itself results in uncertainty of gains then there should be a tendency for it to be avoided. In addition, investors with paper profits may set those profits as a new reference point, any reduction from this point being perceived as a loss. Consequently, the convex nature of the value function for 'perceived losses' would lead them to be averse to segregating gains, in case the remaining portion of paper gains loses value.

Overall, therefore, whilst the concave value function of prospect theory for gains implies that more segregation of (certain) gains (cf. losses) should be observed, in real-world trading, where returns are uncertain, there are powerful forces facing an investor with paper profits which drive them towards integration. It is not surprising that previous experimental studies produced evidence of segregation of gains (Thaler, 1985, Thaler and Johnson, 1990) because the gains arising from particular scenarios were certain. In addition, the manner in which the experiments were designed resulted in no additional cognitive load associated with segregation. Consequently, the concave nature of prospect theory's value function would lead to segregation of gains. Clearly, this is not the case for real-world investment, where gains are only certain once they are realized and the gains/losses are of significant consequence to the decision maker.

3.2.4.3 Motives which drive decision-makers towards segregating losses

When faced by potential losses, investors may be subject to opposing motives, some leading them towards holding, and others leading them towards realizing, their losses. As a result, we believe that they may experience *cognitive dissonance*. In order to deal with the discomfort of these opposing forces, traders may opt to segregate their losing position to satisfy both motives. We explore these ideas below.

3.2.4.3.1 Factors driving decision-makers towards holding losing positions

It has been found that individuals engage in '*Motivated Reasoning'*, whereby information is processed in a biased fashion to align with hopes and expectations for the future (Kunda, 1990, Brownstein, 2003). Moreover, it has been established that individuals have a tendency to be overconfident and to make unrealistic forecasts (Kahneman and Lovallo, 1993). Consequently, when real-world traders face paper losses, motivated reasoning may lead them to assess available information in a biased fashion; i.e., they may be motivated to reason that markets will turn and they can escape making a loss, protecting both their ego and their account balance. This phenomenon is likely to be exacerbated by the tendency toward *inside* rather than *outside forecasts* (Kahneman and Lovallo, 1993). By taking an "inside" view individuals tend to rely more on information related to the details of the situation, such as spurious patterns in price movements, convincing them that prices are more likely to move in their favor. This contrasts with an "outside" view that avoids the details of the decision itself and instead considers more general information such as the statistical likelihood that any trade which is making paper losses will result in a realized loss. This focus on inside rather than outside forecasts, combined with the phenomena of overconfidence and motivated reasoning could explain a resistance to realize a losing position (i.e., the disposition effect; see (Shefrin and Statman, 1985)). These phenomena are unlikely to have played a part in the HEH studies conducted in the laboratory, because in those cases the losses and gains offered were certain.

3.2.4.3.2 Factors driving decision-makers towards realizing losses

Kahneman and Lovallo (1993) observed that decision makers choices are often timid when compared to their predictions of success. Indeed, attitudes and behavior do not always entirely correlate (for review see, Ajzen and Fishbein, 2005). Thus, an individual when facing a paper loss may have a positive *evaluation* of the future outcome (i.e., expecting the market to turn in their direction), suggesting they should hold onto their position. However, they may *act* more timidly than their bold forecasts, realizing just a portion of their position and holding the rest.

Additionally, investors in real-world markets use the term 'discipline' to indicate strategies that aim to avoid holding onto losses (Locke and Mann, 2005). Indeed, as stated by John Mack, Morgan Stanley's CEO: "*One of the critical criteria I use in judging my traders is their ability to take a loss. If they can't take a loss, they can't trade*" (Locke and Mann, 2005, p.403). The importance of being well disciplined in order to avoid one's natural instincts to hold onto losses is well known, particularly, by good traders.

Consequently, traders who face unrealized losses are subject to opposing motives, some of which (mainly emotional in nature) are telling the investor to hold onto their losses, and others (mainly rational in nature) are telling the investor to close their losses. This conflict between the "heart and the mind" could lead to *cognitive dissonance*, a psychological conflict within in the investor's mind which needs to be alleviated. We believe they may try to resolve this by segregating their position in an attempt to appease both motives.

Consequently, although prospect theory's convex value function for losses and the cognitive cost of segregation are factors which may drive traders towards integration of losses, there may also be forces which lead them towards segregation. The relative strength of these factors in a given situation will determine the segregation/integration outcome.

Overall, as outlined above, there are many factors in real-world trading environments which lead investors towards the integration and segregation of both gains and losses. Despite this, we believe that the cognitive cost of segregation of both gains and losses for real-world investors is likely to dominate. Consequently, we test Hypothesis 1:

Investors have a propensity to integrate (i.e., realize the entirety of a given position whether in profit or loss) rather than to segregate.

There will be times when investors decide to segregate gains and others when they decide to segregate losses, the relative strength of the various psychological factors discussed above in a given situation determining the eventual outcome. However, as indicated above, there are a number of factors which suggest that traders are likely to integrate gains. In addition, cognitive dissonance is a powerful psychological factor which we have suggested may lead investors to segregate losses in some circumstances. Consequently, we expect more cases where investors segregate losses than gains, the reverse of that predicted by the HEH. We therefore test Hypothesis 2:

A greater proportion of investments showing paper losses are segregated than those showing paper gains.

3.2.5 Individual factors: More vs. less informed

Previous studies have not examined whether the behavior of more and less informed traders is more consistent with the HEH. This question is important as considerable cross-sectional variation in individual investment behavior could be masked if we only examine aggregate behavior (Odean, 1999). In addition, disparities in behavior between different groups of investors are important for understanding wider market mechanics and can be applied to the dynamics of asset prices in bubbles or even crashes (Ofek and Richardson, 2003). Importantly, rational agents have an opportunity to exploit and profit from irrational agents who employ ‘non-rational’ heuristics (Barber,Odean and Zhu, 2009b). Consequently, understanding the differential application of segregation/integration of gains and losses by more and less informed traders contributes to the branch of market microstructure theory which focuses on the impact of the information on behavior. In particular, the theory attacks the concept of rational efficiency by suggesting that irrational valuations generated in capital markets occur due to trading activity of less informed traders acting on random information which they perceive as news. Those actions can cause prices to diverge from fundamentals (Shleifer and Summers, 1990). In addition, the irrationality of less informed traders can lead to risks that discourage more informed traders from trading against them (Megginson, 1997, p. 149).

It is surprising that no studies have examined the degree to which the behavior of different types of trader are consistent with the predictions of the HEH since it has been found that other heuristic-based behaviors related to prospect theory do vary between more and less informed individuals. For example, Genesove and Mayer (2001) found that more informed real estate investors exhibit less loss aversion than less informed (i.e., owner occupants) investors. In addition, Shapira and Venezia (2001) and Dhar and Zhu (2006) found that less informed investors (i.e., independent investors) tended to exhibit the disposition effect to a greater extent than more informed traders (i.e., professional investors). In general this literature points to less informed traders being more motivated by psychological rather than economic considerations, and as a result more susceptible to bias. Consequently, we would expect those psychological factors discussed above, which may lead to greater difference in segregation rates between gains and losses to have most effect on less informed traders. Consequently, we test Hypothesis 3:

The integration/segregation decisions of less (cf. more) informed traders are more influenced by whether or not a position is in profit or loss, leading to a greater proportion of losses (cf. gains) being segregated by less informed traders.

3.3 Data and procedures

3.3.1 Data

We test our hypotheses by analyzing the trades of the spread-trading clients of a large financial services company. To provide a clearer picture of the factors which influence their decisions to segregate or integrate gains/losses we restrict our analysis to those 5,407 clients who only trade on the FTSE 100 index. All the trades were executed between 16 November 2004 and 28 March 2013.

In order to make sure that traders have the choice of segregating or integrating their gains/losses, transactions which had an initial investment equal to the minimum investment (i.e., £1), were removed before conducting our analysis. This resulted in 237,641 trades (from 919,889 trades) and 2,969 traders being available for analysis.

3.3.2 Method

Our data enables us to adopt a methodology which has five key advantages over previous enquiries:

First, the limited number of real-world empirical studies which test the HEH (Lim, 2006, Lehenkari, 2009) have assumed an (arbitrary) integration period of one day. In other words, these studies assume that investors decide, on a *daily* basis, whether to integrate or segregate their losses/gains. This involves the erroneous assumption that the end-of-day profits/losses are known when the segregation/integration decision is made (i.e., traders are making choices with foreseeable outcomes). However, in practice, integration/segregation decisions are made *during* the day when the final profit/loss for that day is unknown, i.e., until the end of day, after the final integration/segregation decision for that day has been made. Consequently, these procedures may not appropriately measure the degree to which investors integrate or segregate their gains and losses. By contrast, in Thaler's (1985) experimental study, the profits and losses are *known* prior to the decision to integrate or segregate. In other words, the subjects in the study have some control over when significant events occur. These conditions more strictly match those required to enable prospect theory to provide guidance on subjects' preferences for integration or segregation (i.e., subjects given choices with foreseeable outcomes and their decisions reflected their preferences for segregation or integration). Additionally, we disagree with the idea that a single integration period will be suitable for all individuals who may differ dramatically in their trading time horizons. Consequently, we believe that, in order to test the HEH in an equally appropriate fashion to that adopted by Thaler (1985), but in a real world trading environment, it requires examination of the segregation/integration decisions of investors on a trade-by-trade basis without any predefined integration period.

Consider an investor who has opened a position in the FTSE 100 earlier in the day and is about to close all of that position. They will know their current paper profit/loss on this position and, will, therefore, know with near certainty what their realized profit/loss for that trade will be if they close the entire position at that point in time. An investor could decide to realize the whole position (an *integration* decision) or they could sell a portion of their position at that time (*segregation*). In the latter case, the investor would know precisely what their realized profit/loss would be for the portion they close, the profit/loss for the remaining portion being unknown. This trade-by-trade methodology avoids the erroneous assumption that the end-of-day portfolio of payoffs are known when the segregation/integration decision is made.

Second, our data enables us to employ a methodology which overcomes the criticisms levelled at some HEH experimental studies, that they relied on temporal spacing of outcomes when measuring segregation/integration (Thaler and Johnson, 1990, Linville and Fischer, 1991, Schaffner *et al.*, 2013).

By contrast, our data allows us to test the hypotheses based on traders' preferences about the framing of events without assuming temporal spacing. This means that we do not need to restrict our analysis to a specified time interval (e.g., integration of gains/losses across a day). This is important because the time interval selected (based on potentially flawed experimenter guesswork) may not reflect the way in which traders actually make their decisions. As a result, we believe we are better able to detect traders' genuine integration/segregation preferences.

A third advantage of our data is that because of its real-world context, we are able to examine traders' segregation/integration decisions associated with gains/losses which impact, and are significant to, the traders.

A fourth advantage is that we are able to investigate the effect of the size of unrealized gains/losses on the degree of the integration/segregation. It is surprising that this has not been examined in previous studies, since the size of unrealized gains/losses may be perceived differently among individual traders, as found in relation to other aspects of behavior, such as risk-taking (Huang and Chan, 2014). In addition, the integration/segregation decisions we examine are associated with a wide range of values of gains and losses. This is an important improvement on Thaler's (1985) experiment which only considered integration/segregation decisions associated with one set of values, the size of which may or may not be important to real-world decision makers. By contrast, our data enables us to examine to what extent the predictions of the HEH are confirmed across a wide sets of values.

The fifth key advantage of our data is that traders in spread-trading markets can liquidate their positions at the time of *their choosing* (as the spread-trading firms act as the counter party to the trade). However, the traders featured in empirical studies conducted in stock markets (Lim, 2006, Lehenkari, 2009) do not always have this opportunity. In particular, their ability to liquidate relies on there being another individual in the underlying market who is prepared to buy/sell their position. Furthermore, previous empirical studies of the HEH in financial markets have employed the weighted average purchase price as the reference point, calculated by using the average price of a particular stock within a portfolio built up by purchases at different times. It is certainly questionable whether an investor uses the weighted average purchase price as their point of reference. By contrast our data allows us to know precisely the price at which all trades are conducted and the current prices. This enables us to determine *unrealized (paper)* profit/loss a trader faces at any given time and the *actual realized* profit/loss obtained by an individual trader on a given trade.

3.3.3 Variables

Spread traders often execute several trades in a day. A trade with an investment size, S, may either be a transaction to open or close a (long or short) position. At the time of closing a position the trader has the option of closing all or part of that position. We create an integration variable (INT_{iT}) which takes the value 1 if the closing transaction, T, fully closes a previously opened position (integration) and zero if it only partially closes that position (segregation) by trader i. We also define the psychological factor, $LOSS_{iT}$ as a dichotomous variable, which takes a value of 1 if T resulted in a loss and 0 otherwise.

We employed a set of control variables which have been found in previous studies to influence the trading behavior of investors (e.g., Lim, 2006, Lehenkari, 2009). In particular, we incorporated: the trader's 'current stake balance' (CSB_{iT}), that is the total amount she had invested in a particular position at the time she executed a closing trade T related to that position, and the unrealized gain (UG_{iT}) and absolute unrealized loss ($|UL_{iT}|$) associated with a given position at the time of closing trade T. We also incorporated a variety of variables to capture aspects of the trader's short and long run experience: the number of transactions the trader used to open (NOT_i) or fully or partially close (NCT_i) positions on the same day, but prior to, transaction T; the number of trades (to open or fully or partially close) a particular trader had executed from 16th November 2004 (the first trading day in our data) up to the time of executing trade T ($TRADE_i$); the total number of days that a particular trader had continued to hold an account with the spread-trading company from the first trade they executed on or after 16th November 2004, up to closing transaction T ($CLTACT_i$).

Ding,Charoenwong and Seetoh (2004) observed that past market conditions affected forecasting errors of analysts. In order to ensure that our results were not unduly influenced by previous market conditions, we employed four additional variables to control for market returns (i.e., the difference between the level of the FTSE 100 at the beginning and end of the period), covering various periods prior to the execution of closing trade T: the period from the opening of the market on the day trade T was executed up to the time that trade T was initiated ($MKTRET$), the day prior to trade T being initiated ($MKETRET1$), the period two to five days prior to the day on which trade T was initiated ($MKTRET2\_5$) and the period six to twenty days before trade T was initiated ($MKTRET6\_20$).[2] Finally, we included a variable to provide a proxy for spread-trading market activity. In particular, we incorporated the number of clients of the spread-trading company who executed trades on the FTSE 100 on the same day, up to the time of trade T ($MKTACT$).

In order to examine to what extent segregation and integration differs between more and less informed traders we incorporated a dummy variable (MI_{iT}), which takes the value 1 and 0 for more and less informed traders, respectively. We defined more informed traders as those with a return (profitability per £1 invested) across all their trades prior to transaction T, greater than the median for that of all traders in the dataset (i.e., the variable is time-varying or not depending on each particular trader's profitability account). In particular, MI_{iT} was designed in such a way to identify those traders who are more successful and are, therefore, more likely to be those who are more informed. We examined the robustness of our findings to this definition. To achieve this, we explored whether the results differed if we defined more/less informed traders as those whose returns across all their trades were in the (i) top/bottom thirty, and (ii) top/bottom twenty percentile, for all traders.

We examined to what extent more and less informed traders differed in their reaction to a paper loss at the time of closing a position by including an interaction term between the variable used to distinguish positions showing a paper loss and the MI_{iT} variable ($MI_{iT} \times LOSS_{iT}$). In addition, we controlled for other aspects of the segregation/integration decision associated with closing trade T which may differ between more and less informed traders by incorporating a number of interaction terms. In particular, we controlled for differences in the manner in which more and less informed traders might react

[2] The market return intervals do not overlap to each other and are within 20 trading days prior to the transaction. Previous periods beyond this point (i.e., more than 20 days) appear to have little impact on trading decisions as suggested by Grinblatt and Keloharju (2001).

to the current stake balance at the time of closing a position ($MI_{iT} \times CSB_{iT}$) and the size of any unrealized gain or loss associated with T, ($MI_{iT} \times UG_{iT}$), and ($MI_{iT} \times |UL_{iT}|$), respectively.

3.3.4 Procedures

In order to test our hypotheses, we estimated two multilevel logistic regression models with probability that an individual trader i decides to fully (integrate) or partially close (segregate) a position, as the dependent variable. We employed multilevel logistic regression as it accounts for the fact that there may be individual differences associated with the probability of a trader choosing to integrate/segregate a position. Consequently, Model 1 is developed to include a random intercept (i.e., the intercept captures the extent to which different individuals vary in their choice of integration/segregation, u_{0i}), the $LOSS_{iT}$ variable as an independent variable and the control variables discussed above (included in order to account for the fact that the decision to integrate/segregate a currently open position may be affected by characteristics of the trader (CSB_{iT}, UG_{iT}, $|UL_{iT}|$, NCT_i, NOT_i, $TRADE_i$, and $CLTACT_i$) and the market ($MKTRET$, $MKTRET2\_5$, $MKRET6\_20$, and $MKTACT$). Model 1, therefore, takes the following form:

Level 1: For a trader, the probability of observing $INT_{iT} = 1$ is

$$\Pr(INT_{iT} = 1) = \Lambda(b_{0i} + \textstyle\sum_{k=1}^{n} b_k x_k + \varepsilon_{iT}) \tag{3-1}$$

Level 2: For the trader, the second-level equation is

$$b_{0i} = b_0 + u_{0i} \tag{3-2}$$

where $\Lambda(\cdot)$ is the logistic cumulative distribution function, b_0 is the random intercept term, b_k are the coefficients of the independent variables and the control variables, $u_{0i} \sim N(0, \tau_{00})$, u_{0i} is the individual level residual, which is assumed to be normally distributed with mean 0 and variance τ_{00}, and ε_{iT} is the error term.

Our first hypothesis, that investors have a propensity to integrate rather than to segregate when closing positions, would be supported if we observed a greater propensity to integrate whether or not the position was associated with an unrealized loss or gain. The second hypothesis, that a greater proportion of investments showing paper losses are segregated, would be supported if we found that there was a significantly higher probability of a position being segregated if it were associated with unrealized losses.

We also estimated Model 2, which, in addition to the independent and control variables in Model 1 also includes a variable to distinguish more and less informed traders (MI_{iT}), and the interaction terms ($MI_{iT} \times LOSS_{iT}$, $MI_{iT} \times CSB_{iT}$, $MI_{iT} \times UG_{iT}$, and $MI_{iT} \times |UL_{iT}|$) discussed above, which control for differences in the manner in which more and less informed traders might react to the current stake balance, and whether a position was associated with an unrealized gain or loss.

Our third hypothesis would be supported if we observed that less informed traders segregated a greater proportion of positions showing a paper loss than positons showing a paper gain and the difference in these rates of segregation was significantly larger than that for more informed traders.

3.4 Results

3.4.1 Descriptive statistics

In Table 3-1 we report the means and standard deviations of the profit/loss (£), and the stake size (£) associated with positions which were (a) partially closed (i.e., segregated) and (b) completely closed (i.e., integrated) by all traders and, separately, for those defined as more and less informed. For those positions which were partially closed, the table reports the investment (stake) size[3] and the profit/loss for that part of the position which was closed (e.g., if the stake size associated with a trade to open a position was £100 and 60% of the position was closed then the stake size associated with this closed position is designated as £60). The remaining portion of a partially closed position was treated as a new position. We also report the mean differences in the profits (£) and stake sizes (£) between the positions which were partially and completely

[3] Since positions are highly leveraged, the stake size does not indicate the total amount at risk. Trading a £100 per point stake in the FTSE 100 which has a 0.4% margin means that the trader must have 0.4% of the notional size (calculated as the stake times price) of the trade in their account to cover the trade, i.e., £100 × 6500 = £65,000 trade size of which £2,600 (0.4% × £65,000) is risked by the client. In other words, the client risks around 26 times their stake on each trade.

closed. Table 3-1 reports these statistics for all closing trades and, separately, for those closing trades which resulted in a loss and those that resulted in a profit.

The statistics shown in Panel A of Table 3-1 reveal three interesting findings: First, of the 237,641 transactions examined, only 5.28 percent (12,552 positions) were partially realized, suggesting a strong preference for integration (94.72% *vs.* 5.28%; z=616.58, p<.01). On average, positions which were partially closed (segregated) earned £0.083 and these were associated with a mean stake of £4.445 (a return of about 1.9%), whilst positions that were closed in a single transaction (integrated) had a mean stake of £9.000 and resulted in a mean loss of −£0.622 (a loss of 6.9%). However, the difference in percentage returns was not found to be significant (t=0.28, p>.1). Second, we find that for positions showing a paper profit and for those showing a paper loss there is a significantly greater tendency to integrate (paper profits: 4.90% *vs.* 95.10%, z=496.17, p<.01; paper losses: 5.94% *vs.* 94.06%, z=366.11, p<.01). Third we find a significantly higher degree of segregation for positions showing a paper loss than for positions showing paper gains (5.94% *vs.* 4.90%; z=10.92, p<.01).

Turning to the results related to more and less informed traders shown in panel B and C of Table 3-1, we find a similar pattern to that revealed for all traders. In particular, for both more and less informed traders there is a significantly lower propensity to segregate than integrate their positions, although the probability of segregating is higher for more informed traders (MI: 5.39% *vs.* LI 4.97%; z=3.97, p<.01). Interestingly, we find that around 75 percent (178,591) of trades are associated with those traders we define as more informed, suggesting that these traders initiate a greater number of trades than the less informed. For the more informed group, the positions which were partially closed achieved a mean profit of £19.003 and were associated with a mean stake of £4.738 (a return of 4.01), while positions which were closed in their entirety were associated with a mean stake size of £9.655 and gained £11.107 (a return of 1.15). The difference in these returns was significant at the 99% level (t=12.80, p<.01). For the less informed group, the positions which were partially closed resulted in a loss of −£61.995 and were associated with a mean stake of £3.486 (a return of -17.78), while positions which were closed in their entirety resulted in a loss of −£35.937

and were associated with a mean stake size of £7.029 (a return of – 5.11). For these less informed traders, the returns for segregated positions were significantly less than those associated with integrated positions (-17.78 *vs.* -5.11; t=11.94, p<.01).

The results displayed in panels B and C in Table 3-1 suggest that the less informed and more informed traders had different segregation rates for positions showing paper losses (6.49% *vs.* 5.69%; z=4.63, p<.01). In addition, the more informed group had significantly higher segregation rates for positions showing a paper gain (5.23% *vs.* 3.64%, z=11.68, p<.01). Importantly, in relation to hypothesis 3, the results demonstrate that the differences in segregation rates for positions in gain and for those in loss appear to be greater for less informed traders (2.85%: 3.64% cf. 6.49%, z=15.90, p<.01) than for more informed traders (0.46%: 5.23% cf. 5.69%, z=3.99, p<.01).

Overall the results clearly suggest that neither the more nor the less informed groups of traders behave in accordance with the HEH. In particular, whether a position is showing a paper profit or loss, individuals are more likely to realize their entire position rather than to segregate that position. In addition, contrary to the HEH, individuals are more likely to segregate positions currently showing a loss (cf. gain) and this applies to both the more and less informed groups.

Table 3-1 Descriptive statistics.

	Partially realized positions (segregated)		Fully realized positions (integrated)				
	Mean(£)	St. Dev.(£)	Mean(£)	St. Dev.(£)	Mean Difference(£)	95% CI Lower	95% CI Upper
Panel A All traders	N = 12,552 (5.28%)		N = 225,089 (94.72%)				
Profit/loss	0.083	206.789	-0.622	442.645	-0.705	-4.758	3.349
Stake size[1]	4.445	8.446	9.000	19.331	4.555***	4.387	4.723
Positions in profit	N = 7,420 (4.90%)		N = 143,896 (95.10%)				
Profit	49.347	205.550	72.758	360.403	23.411***	18.377	28.446
Stake size[1]	5.099	9.460	8.724	17.912	3.625***	3.391	3.859
Positions in loss	N = 5,132 (5.94%)		N= 81,193 (94.06%)				
Loss	-71.145	186.881	-130.671	535.284	-59.526***	-65.828	-53.225
Stake size[1]	3.501	6.601	9.490	21.609	5.990***	5.756	6.223
Panel B More informed traders	N = 9,620 (5.39%)		N = 168,971 (94.61%)				
Profit/loss	19.003	203.981	11.107	429.529	-7.896***	-12.458	-3.334
Stake size[1]	4.738	9.359	9.655	20.764	4.917***	4.706	5.129
Positions in profit	N = 6,268 (5.23%)		N = 113,418 (94.76%)				
Profit	51.437	218.885	73.834	333.191	22.397***	16.641	28.153
Stake size[1]	5.367	10.100	9.113	18.776	3.746***	3.473	4.019
Positions in loss	N = 3,352 (5.69%)		N= 55,553 (94.31%)				
Loss	-41.647	155.522	-116.958	556.850	-75.310***	-82.323	-68.298
Stake size[1]	3.561	7.651	10.761	24.287	7.200***	6.872	7.529
Panel C Less informed traders	N = 2,932 (4.97%)		N = 56,118 (95.03%)				
Profit/loss	-61.995	203.793	-35.937	478.247	26.058***	8.664	43.451
Stake size[1]	3.486	4.098	7.029	13.978	3.542***	3.354	3.730
Positions in profit	N = 1,152 (3.64%)		N= 30,478 (96.36%)				
Profit	37.973	106.388	68.755	447.340	30.78***	22.844	38.720
Stake size[1]	3.639	4.351	7.274	14.149	3.635***	3.338	3.932
Positions in loss	N = 1,780 (6.49%)		N= 25,640 (93.51%)				
Loss	-126.693	224.595	-160.383	483.960	-33.690***	-45.693	-21.688
Stake size[1]	3.388	3.923	6.738	13.768	3.350***	3.101	3.598

This table reports the results of t-tests undertaken to ascertain whether there are significant differences between integrated and segregated closing trades, in terms of mean profit/loss (£) and the mean stake size(£). These tests are performed for (a) all closing trades and for those closing trades which were associated with unrealized (b) profit and (c) loss.

[1] The stake values used in these calculations represent the full stake values for investments which were fully closed (integrated) and the proportion of the original stake corresponding to the proportion of the position which was closed, for investments which were partially closed (segregated).

* p<0.1, ** p<0.05, *** p<0.01.

3.4.2 Multilevel logistic regression results

Models 1 and 2 were estimated and the resulting maximum likelihood estimates of the regression coefficients and their standard errors are displayed in Table 3-2.

The results of estimating Model 1 were employed to test the first two hypotheses. The first observation is that all the variables used to capture characteristics of traders (CSB_{iT}, UG_{iT}, $|UL_{iT}|$, NCT_i, NOT_i, $TRADE_i$, and $CLTACT_i$) and the market ($MKRET$, $MKRET1$, $MKRET2\_5$, $MKRET6\_20$, and $MKTACT$) were highly significant. This confirms our suspicion that these all have a significant influence on the propensity to fully or partially close a position, justifying their inclusion in the model. In particular, the total amount invested in the position (CSB_{iT}), the size of unrealized gain (UG_{iT}), the absolute size of unrealized losses ($|UL_{iT}|$), the number of transactions opened on the same day (NOT_i) and the long-run experience of the trader measured by the total number days the individual has been trading ($CLTACT_i$), are all negatively related to the propensity to integrate. However, the number of transactions the trader used to fully or partially close positions on the same day, but prior to, transaction T (NCT_i) and the traders long run experience, as measured by their total number of trades ($TRADE_i$), are positively related to the propensity to close a position in its entirety. We find that most of the variables related to market returns across different periods are negatively related to the probability of selling an entire position. However, the period of 20 to 6 days before the day on which the position is realized ($MKRET6\_20$) is positively related to the propensity to close a position in its entirety. In addition, the coefficient of $MKTACT$ is positive and significant suggesting a positive relationship between the market activity and the probability of integration.

Having controlled for the various individual and market related characteristics, the intercept for Model 1 is positive and significant (5.518) confirming the descriptive results, which suggest that trades resulting in a gain tend to be integrated. In addition, the $LOSS_{iT}$ coefficient is negative and significant (-0.350), suggesting that significantly less integration occurs for trades which result in a loss. However, a planned contrast confirms that even trades resulting in a loss are more likely to be integrated than segregated, since the combined coefficients ($Intercept+LOSS_{iT}=5.168$) are significantly greater than zero ($z=44.62$, $p<.01$). This suggests that traders tend to integrate their positions and segregation is a rare occurrence. The finding confirms our first hypothesis that in general, investors have a tendency to integrate rather than to segregate. However, in those rare instances where a position is segregated it is more likely that the position will be showing a paper loss. This supports our second hypothesis, namely a greater proportion of investments showing paper losses are segregated than those showing paper gains.

Table 3-2 Multilevel logistic regression results.

Variable	Model			
	(1)	(2)	(2)ɫ	(2)ɫɫ
Intercept	5.5180	6.2520	7.1920	6.5340
	(0.1157)***	(0.1758)***	(0.2935)***	(0.2366)***
LOSS	-0.3496	-0.6560	-0.7869	-0.7706
	(0.0232)***	(0.0485)***	(0.1023)***	(0.0825)***
CSB	-0.0100	-0.0302	-0.0716	-0.0372
	(0.0008)***	(0.0028)***	(0.0058)***	(0.0034)***
UG	-0.0001	-0.0001	-0.0003	-0.0004
	(0.0000)**	(0.0001)	(0.0002)*	(0.0001)***
IULI	-0.0001	-0.0002	-0.00024	0.00002
	(0.0000)***	(0.0001)***	(0.0001)**	(0.0001)
NCT	0.0003	0.0003	0.0003	0.0003
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
NOT	-0.0003	-0.0003	-0.0003	-0.0003
	(0.0000)***	(0.0000)***	(0.0000)***	(0.0000)***
TRADE	0.0003	0.0004	0.0010	0.0007
	(0.0000)***	(0.0000)***	(0.0001)***	(0.0000)***
CLTACT	-0.0050	-0.0083	-0.0158	-0.0096
	(0.0013)***	(0.0015)***	(0.0030)***	(0.0021)***
MKRET	-5.3630	-3.5690	-4.9980	-4.7570
	(0.8045)***	(0.7964)***	(1.3480)***	(0.9932)***
MKRET1	-18.7900	-16.6200	-18.6300	-22.8500
	(0.6656)***	(0.6554)***	(1.1650)***	(0.8041)***
MKRET2_5	-4.4860	-3.4030	1.1440	-5.9250
	(0.4092)***	(0.4070)***	(0.7677)	(0.5135)***
MKRET6_20	11.9000	11.9300	3.0480	10.5900
	(0.2510)***	(0.2517)***	(0.4268)***	(0.3155)***
MKTACT	0.0099	0.0105	-0.0070	0.0006
	(0.0009)***	(0.0009)***	(0.0016)***	(0.0013)
MI		-0.2013	-0.6972	-0.5786
		(0.2184)	(0.3536)**	(0.2821)**
MI×LOSS		0.4129	0.4613	0.5316
		(0.0555)***	(0.1081)***	(0.5316)***
MI*CSB		0.0225	0.0596	0.0267
		(0.0029)***	(0.0059)***	(0.0036)***
MI×UG		0.000004	0.0003	0.0004
		(0.0001)	(0.0002)	(0.0002)***
MI×IULI		0.0002	0.0001	-0.0001
		(0.0001)**	(0.0001)	(0.0001)
-2LL	66682.39	66503.59	34034.06	45984.86
AIC	66712.39	66543.59	34074.06	45944.86
Random effects (Individual differences)				
Variance	8.535	11.52	8.754	9.258
SD	2.921	3.394	2.959	3.043

* p<0.05, ** p<0.01, *** p<0.001. Standard errors for estimates are shown in parentheses. Model 2ɫ, Model 2ɫɫ: Model 2 was estimated again with the same data but where the more and less informed traders were defined as those individual with the highest and lowest 20 and 30 percent of total average point profits, respectively.

Having estimated Model 2, we found that the coefficient related to the variable that takes the value 1 if the trader is regarded as more informed and zero otherwise (MI_{iT}), is not significant. This suggests that the rate of segregation for positions showing a paper profit are similar for more and less informed traders. A planned contrast also suggests that there is no significant difference in rates of segregation for positions showing a paper loss among the more and less informed groups, $((MI_{iT} \times LOSS_{iT} + MI_{iT} + LOSS_{iT}) - (LOSS_{iT}) = 0.212$; $z = 0.973$, $p > 0.1$). However, the $MI_{iT} \times LOSS_{iT}$ term is significant, suggesting that, in support of hypothesis 3, there are significant differences between the more and less informed traders in how they respond to gains and losses. In particular, we calculate the probabilities with which less informed traders integrate a winning and a losing trade directly from Model 2, with inputs $intercept$ (6.252) and $intercept$ plus $LOSS_{iT}$ (-0.656). This enables us to determine that the probability of less informed traders is 1.923 more likely to segregate losses than gains. However, employing a similar approach, we find that the probability of more informed traders is only 1.274 more likely to segregate losses than gains. This finding is consistent with hypothesis 3, that whilst all traders have a greater tendency to segregate positions showing a paper loss (cf. those positions showing a paper gain), the difference in these segregation rates is most marked amongst less informed traders.

In summary, we find a main effect between whether or not a position is in gain or loss and trader group (more *vs*. less informed) in terms of segregation rates, which confirms hypothesis 3. However, we did not detect significant differences in segregation rates between more and less informed traders when analyzing positions in gain or loss separately. This may have arisen because of the reduced statistical power of the tests caused by analyzing the effects of gains and losses separately.

We also conducted tests to confirm the robustness of the results which support the third hypothesis using different thresholds of profitability for distinguishing more and less informed traders. In particular, we replicated the analysis defining more/less informed traders as those with a return (profitability per £1 invested) across all their trades in the top/bottom twenty and thirty percentile. These analyses yielded similar results to those presented above.

3.5 Discussion

The picture which emerges from our results is that spread traders' preferences associated with closing positions are not as straightforward as the HEH suggests. Our results confirm Lehenkari's (2009) view that preferences beyond those accounted for by prospect theory need to be considered when explaining the decision of investors to integrate or segregate their gains and losses. In particular, our results suggest that the traders are more likely to integrate their positions in general. We believe that this is explained by the *cognitive cost of segregation*. As indicated in section 3.2, segregating positions into many portions is cognitively more taxing than simply realizing an entire position. As a result, most traders chose the cognitively simpler option of realizing their entire position. This is supported by the ideas of *bounded rationality* (March, 1978) which suggest that individuals are likely to simplify decision problems to reduce cognitive load.

The HEH suggests that individuals should segregate gains. However, our results, based on the real world financial market data, suggest that on the rare occasions that traders do segregate, they are more likely to do so when the position is in loss (cf. gain). This can be explained by the factors which may cause traders to avoid segregating gains and by those that motivate them to segregate losses. In particular, we outline in section 3.2 two reasons why traders may be averse to segregating gains, namely, the cognitive cost of segregation and the uncertainty of returns on segregated positions. Prospect theory suggests that individuals are risk averse for gains and, as a result, traders who have positions showing paper profits may wish to avoid the uncertainty of returns, which would arise should they keep a portion of the position open. Equally, we identified in section 3.2, that cognitive dissonance may explain why traders may be motivated to segregate losses. The cognitive dissonance is caused by opposing motives that simultaneously drive traders towards realizing and holding losing positions. In particular, motivated reasoning or wishful thinking (Kunda, 1990, Brownstein, 2003) and a tendency towards relying on 'inside' rather than 'outside' forecasts (Kahneman and Lovallo, 1993) may motivate a desire to hold onto losses. On the other hand, individuals often make 'timid' choices when compared to their bold forecasts (Kahneman and Lovallo, 1993). In addition, the importance of being well disciplined with respect to closing losses is widely shared amongst traders (Locke and Mann, 2005). Both these factors may motivate a desire to close losing position. In section 3.2, we suggested that these opposing psychological forces, which motivate traders to both close and keep open losing positions, may lead to cognitive dissonance. In order to resolve the psychological conflict between these opposing motives, traders may attempt to appease both by partially closing losing positions (i.e., segregating).

Our finding, that traders prefer to segregate losses more than gains contradicts the laboratory results of Thaler (1985) and the empirical findings of Lim (2006). However, our results are in line with some of Lehenkari's (2009) findings; specifically, that investors tend to segregate their losses more than their gains in longer integration periods. The contrast between our results and those of Thaler (1985) and Lim (2006) can be explained by the methodologies employed by these earlier studies. In particular, in Thaler's (1985) study, segregation/integration decisions were related to choices involving *certain* outcomes, whereas traders in our study face uncertain gains and losses should they decide to segregate. We outline above the psychological reasons why this uncertainty may influence the decision to segregate. Lim (2006) *did* employ empirical data which involved some uncertainty. However, she assumed an *arbitrary* integration period of one day, implying that investors decide, on a *daily* basis, whether to integrate or segregate their losses/gains. This involves the erroneous assumption that the end-of-day profits/losses are known when the segregation/integration decision is made. Consequently, the study makes unlikely assumptions about the nature of integration and segregation decisions and ignores the important role that uncertainty plays in such decisions.

By contrast, the approach we adopted is more similar to Thaler's (1985) initial conceptualization of integration and segregation. Our approach analyzes decisions on a trade-by-trade basis. This ensures that we are aware of the circumstances facing the trader at the time of their integration/segregation decision. Additionally, earlier empirical studies which examined HEH amongst stock market investors (e.g., Lim, 2006, Lehenkari, 2009), have tried to account for the number of stocks in an individual's portfolio (i.e., to control for the possibility that the greater the portfolio size the greater the likelihood of segregation). However, the number of shares in the portfolio may well change during a given day (as shares are bought/sold), and this is not accounted for in the subsequent decisions of the investor during that day. By contrast, because we are examining individual trades associated with a given position held by an individual, we are able to examine directly whether the position size affects the likelihood of segregation rather integration. In fact, we find that the bigger the unrealized gain or the unrealized loss on a given position the greater is the chance that this position will be segregated, confirming that there are reasons other than a position being in profit or loss which affects the integration/segregation decision. Finding that the sizes of unrealized gains and losses both influence the decision to segregate/integrate is important because Thaler's (1985) seminal study only examined segregation/integration decisions associated with a fixed amount of money.

Previous studies have shown mixed results with respect to the degree to which not in line with the predictions of HEH. However, it is important to note that this does not necessarily invalidate HEH as a theory since the effects are clearly observed in specific decision tasks; particularly, it seems, in those segregation/integration decisions involving certain outcomes. Indeed, it is certainly possible that HEH does play a small part in the decision of whether to close an entire position or segregate that position into smaller parts but, if this is the case, these effects are weak when compared to the other factors considered in the decision (e.g., cognitive cost of segregation, motivated reasoning and trading discipline).

Linville and Fischer (1991) suggested that there may be individual differences in the decision rules that guide people's integration/segregation preferences. We tested this view by examining the extent to which more and less informed traders differed in their segregation of positions in gain and loss. Consistent with hypothesis 3, we observed a significant interaction between the trader group (more *vs*. less informed) and the profit status of the position (gain *vs*. loss) in terms of the probability of a position being segregated (i.e., the $MI_{iT} \times LOSS_{iT}$ term was significant in Model 2). Notably, the degree of segregation of losses was around 1.9 and 1.3 that of gains for the less and more informed traders, respectively. The differential in the degree of segregation of losses for less and more informed traders is consistent with the idea that the trading decisions of the former will be less driven by fundamental information about the prospects of the investment and more by unrelated, psychologically based, information such as whether a position is showing paper profit or loss.

We found that more informed individuals tended to segregate positions, particularly those in gain, at a higher rate than the less informed individuals (albeit still less than those positions in loss). It is possible that the house money effect (Thaler and Johnson, 1990) is playing a role here. In particular, well informed (and generally profitable) traders with positions showing paper profits might actually tend to be more risk seeking in relation to these positions than less informed (generally unprofitable) traders who rarely make such profits. As discussed in the introduction, the segregation of gains increases the uncertainty of the final returns for that position and this uncertainty may be attractive to a more informed/profitable trader who has every expectation of securing a large profit. In addition, we found that less informed traders tended to segregate their losses more often than more informed traders. This is consistent with the idea that good traders are likely to avoid holding onto even partial losses in an effort to maintain good trading discipline, as suggested by Locke and Mann (2005).

Our results echo the findings of studies examining individual differences in the prevalence of other behavioral biases, such as the disposition effect; namely that these biases are more pronounced among less informed individuals (Genesove and Mayer, 2001, Shapira and Venezia, 2001, Dhar and Zhu, 2006). Our findings also contribute to the growing market micro structure literature (e.g., Shleifer and Summers, 1990, De Long *et al.*, 1991). In this regard, understanding the behavior of less informed traders is important since their irrationally-driven trading behavior can introduce noise into markets, thereby creating risk which can discourage the more informed investors from trading (Shleifer and Summers, 1990).

3.6 Conclusion

Previous studies confirming the HEH have been largely conducted in the laboratory (Thaler, 1985, Thaler and Johnson, 1990, Linville and Fischer, 1991, Jones, 2007, Falsetta,Rupert and Wright, 2012). Mixed results have been obtained from the very limited number of empirical studies to address the HEH (Lim, 2006, Lehenkari, 2009). This chapter attempts to provide explanations for the failure of empirical studies to find consistent results supporting the HEH predictions.

We argue that traders in real-world environments are likely to generally prefer to integrate (cf. segregate) positions because there is a *cognitive cost of segregation* and traders are likely to choose the cognitively simpler option of realizing entire positions rather than partially closing positions. Our results provide evidence to support this notion since, on average both gains and losses were rarely segregated, suggesting that there is a strong aversion to segregating any position.

However, we find that those positions which are segregated are more likely to be in loss (cf. gain); the opposite of what would be expected given the HEH. We believe there are psychological factors that may be involved in this motivation to segregate losses. In particular, we outline a number of factors which motivate a desire to hold onto a loss (i.e., inside forecasts, motivated reasoning) and others motivating a desire to close out the loss (i.e., timid choices and trading discipline). We propose that these competing motives may cause psychological distress to the trader in the form of cognitive dissonance and that this may be resolved by closing some of the loss and holding the remaining portion. In the event that the discomfort associated with cognitive dissonance outweighs the cognitive cost of segregation, then we predict that segregation of losses will occur.

Importantly, the notion that individuals might segregate losses more than gains is based on the premise that they are employing suboptimal reasoning techniques associated with paper losses, such as motivated reasoning, wishful thinking and inside rather than outside forecasts. Accordingly, if this is the case, then individuals that have a greater tendency to employ such suboptimal reasoning strategies should most clearly show a disparity between their rates of segregation for positions in loss and those in gain. Our results indicate that this is indeed the case. Those traders we defined as being less informed tending to segregate losses around twice as much as gains whereas the more informed traders (i.e., those we expect to employ more rational reasoning strategies), tended to segregate losses and gains at a more similar rate.

In conclusion, the data and the new methods we employed to examine segregation/integration (e.g., by examining decisions on a trade-by-trade basis), enabled us to develop new insights into the degree to individuals tend to prefer to integrate or segregate gains and losses. The results suggest that traders in real world financial markets behave in a manner which is inconsistent with the HEH. We suggest that this behavior can be explained by psychological concepts, such as the cognitive cost of segregation and cognitive dissonance. Additionally, we find that less informed individuals appear to be most susceptible to these psychological biases. While our findings do not necessarily invalidate HEH for other decisions in other domains (particularly those with certain outcomes), and even other decisions by traders in financial markets, we find little evidence that HEH is predictive of individuals' decisions to segregate a position rather than to close it entirely. It must be noted that one reason why we find different results to previous studies is that we examine the decision to fully *vs.* partially close a position. By contrast, other studies examine the closure of multiple positions in either a similar period of time (e.g., on the same day) or in different periods of time (e.g. on different days), known as the integration period. Our motivation for choosing this different methodology is that it overcomes the difficulties in choosing the optimum integration period with which to detect the HEH, bearing in mind that individuals in financial markets can differ dramatically in their respective trading time horizons. We believe our methodology, which does not rely on temporal spacing, but rather examines segregation on a trade-by-trade basis, makes fewer assumptions than previous enquiries and is a more effective way of testing the HEH. We encourage future work investigating the HEH in other financial markets and work considering alternative approaches to the temporal spacing methodology used prior to this study.

Chapter 4: Insights into herding behavior in financial spread-trading markets

Abstract

We contrast herding behavior amongst more (MI) and less informed (LI) traders. Specifically, we examine differences in the degree (strong *vs.* weak), the pattern (via feedback strategies) and the nature (reaction to the herding of more and LI traders) of these two groups of traders. We also contrast their speed of reaction to shifts in trading by the other group. This is achieved by analyzing individual investment records of 1,943 traders in UK spread-trading markets (2010-2012). We conclude that herding is far more prevalent than previous studies suggest, particularly amongst LI and that the herding activity of more and LI are related. We also conclude that the means used to distinguish more and LI in previous studies may have serious limitations.

4.1 Introduction

The branch of market microstructure theory that addresses the manner in which information is incorporated in market prices through herding activity has been extensively studied (e.g., Madhavan, 2000, Muscarella and Piwowar, 2001, Schnitzlein, 2002, Henker and Wang, 2006). In particular, the theory attacks the notion of rational efficiency; proposing that capital markets generate irrationality in valuations due to herding activity by less informed (LI) traders, who trade on random information which they treat as news. It has been suggested that these LI traders may be active in financial markets and that their irrationality creates risk which discourages more informed (MI) traders from trading against them (Megginson, 1997, p. 149). Furthermore, Shleifer and Summers (1990) argue that LI traders can cause prices to diverge from fundamentals. Given the importance of this debate, we seek to develop a greater understanding of the interaction between the trading activity of more and LI traders in terms of the degree and nature of their herding and the speed with which their trading behavior reacts to sudden shifts in the trading activity of different groups of traders.

Herding behavior is observed when a sufficient number of traders follow each other's decisions. This is likely to result in market prices moving away from valuations based on fundamentals and thereby, creating excess volatility (Choe,Kho and Stulz, 1999) or even resulting in the destabilization of markets (Lakonishok,Shleifer and Vishny, 1992). Kyle (1985) was one of the first to demonstrate how inefficiencies such as these can be exploited by informed traders. Subsequently, empirical research exploring such herding behavior has been conducted in a range of domains associated with decisions by traders, analysts in stock markets and managers of pension funds (Lakonishok,Shleifer and Vishny, 1992, Kim and Wei, 1999, Lee,Lin and Liu, 1999, Nofsinger and Sias, 1999, Wermers, 1999, Chang,Cheng and Khorana, 2000, Bowe and Domuta, 2003, Sias, 2004, Avramov,Chordia and Goyal, 2006, Zhou and Lai, 2007, Barber,Odean and Zhu, 2009a, Chiang and Zheng, 2010, Jegadeesh and Kim, 2010), amongst banks (Jain and Gupta, 1987, Nakagawa and Uchida, 2011) and amongst bettors in horserace betting markets (Law and Peel, 2002). However, no previous study has examined herding behavior in financial spread-trading markets.

Spread-trading is becoming increasingly significant, with about half a million financial spread traders operating in the UK and this number is expected to reach one million by 2017 (Pryor, 2011, p. xxiii). Brady and Ramyar (n.d.) indicate that, of the £1.2 trillion traded annually on the London Stock Exchange, 40 per cent is equity derivative related and 25 per cent of this relates to spread-trading (£120 billion). The rapid increase in spread-trading may have potentially important implications for the underlying markets because spread-trading companies often hedge their positions in the underlying market (e.g., in stock or foreign exchange markets). Consequently, movements of funds from spread-trading markets to the underlying markets may impact market prices, as has been found with the movement of funds from futures markets to underlying markets (Chang,Cheng and Pinegar, 1999, Ryoo and Smith, 2004, Ghysels and Seon, 2005). In fact, spread-trading has opened up financial market investment and speculation to a far wider cross-section of society, as spread-trading offers the general public a convenient, low barrier means of participating in financial markets. In particular, the simplicity and convenience of spread-trading (e.g., low barriers to entry) may encourage more inexperienced and LI traders to participate in the markets. Clearly, spread-trading may provide valuable liquidity to underlying markets (via hedging activities of spread-trading firms) but, it may also expose the underlying markets to greater fluctuations, particularly if spread traders are more prone to herding than traditional investors. Consequently, it is important to understand the degree, nature and patterns of herding amongst spread traders.

This study aims to achieve these objectives and in doing so to make an important contribution to four aspects of the market microstructure literature: First, most studies that have investigated herding and feedback strategies in conventional markets have used data associated with a variety of securities over a fixed time interval (e.g., Lee,Lin and Liu, 1999). However, this approach may under-estimate herding by a particular group of investors who follow the actions of other investors with respect to a *single asset* or over a *different time interval* than that being studied. In addition, by examining multiple assets, herding in one asset could be masked or nullified by herding in the opposite direction in another asset. The data we employ enables us to overcome these concerns by examining herding in a single asset (the FTSE100 index) across a variety of time intervals.

Second, the individual trader level data we employ enables us to discern differences in herding activity of more and LI traders. Specifically, we examine differences in the degree (strong vs. weak), nature (reaction to the trades by more and LI traders) and patterns (via their feedback strategies) of herding activity between more and LI traders and in terms of the speed with which they react to shocks.

Third, previous studies have generally assumed that MI traders are those who invest larger amounts (Easley and O'hara, 1987, Barclay and Warner, 1993). Our data not only allows us to distinguish more and LI traders in this manner but also to use more direct approaches (i.e., based on account profitability). This has not been possible in studies using conventional stock market data, especially as there is no clear end point in these markets when all uncertainty is resolved. In fact, our findings cast some doubt on the efficacy of employing investment size as a means of separating more and LI traders.

Fourth, high frequency data has been shown to improve understanding of reactions to price movements when studying behavior in conventional financial markets (e.g., in foreign exchange (Nolte and Nolte, 2011), stock markets (Avramov,Chordia and Goyal, 2006), futures (Cotter, 2005), bond (Nyholm, 1999), option (Verousis and Ap Gwilym, 2011) and money markets (Cassola and Morana, 2006)). We are able to capitalize on the benefits of high frequency data, such as enhancing our understanding of trading behavior in short time intervals, by linking intraday trading patterns and intraday index returns.

In summary, the data we employ enable us to provide new insights into the prevalence and the nature of herding by more and LI traders and enables us to examine, for the first time, herding amongst traders in the fast growing spread-trading market. We find that spread traders, particularly the LI, are prone to herding activity and that there are differences in the patterns of herding amongst more and LI traders (in terms of the feedback strategies they employ). There are also differences in the manner in which more and LI traders react to the herding of other more or LI traders (i.e., the degree of self-herding between members of the same group (MI *vs.* LI) or cross-herding between members of different groups. However, we find no obvious difference between these two groups in terms of their responses to sudden trading shifts of more and LI traders. Finally, our results suggest that the degree and nature of herding varies depending upon the manner in which the more and LI traders are defined.

The remainder of the chapter is organized as follows: The literature exploring herding is examined in Section 4.2, and this is used to develop our hypotheses. The data employed in our study are described and the procedures used to test the hypotheses are explained in Section 4.3. The results are presented and discussed in Section 4.4 and conclusions are drawn in Section 4.5.

4.2 Herding: Literature and hypotheses

Herding is an important phenomenon in financial markets (Xia,Gao and Jiang, 2009) and is observed when the net buying of an asset by a number of traders influences the net buying of other traders. Herding may disrupt efficient price discovery in financial markets. For example, Shleifer and Summers (1990) suggest that herding by liquidity traders can cause prices to diverge from fundamental valuations and rational traders may be unwilling to engage in arbitrage due to fundamental risk and the unpredictability of future prices. Consequently, when sufficient investors mimic the trading behavior of other investors, this can result in market movements that are unjustified in scale (Shiller, 2005, p. 157), possibly leading to bubbles (Zhou and Sornette, 2009) and even financial crises (Chiang and Zheng, 2010). Not surprisingly, therefore, a number of empirical studies have examined herding in stock markets (Lakonishok,Shleifer and Vishny, 1992, Kim and Wei, 1999, Lee,Lin and Liu, 1999, Nofsinger and Sias, 1999, Wermers, 1999, Chang,Cheng and Khorana, 2000, Bowe and Domuta, 2003, Sias, 2004, Voronkova and Bohl, 2005, Avramov,Chordia and Goyal, 2006, Zhou and Lai, 2007, Barber,Odean and Zhu, 2009a, Balcilar,Demirer and Hammoudeh, 2010, Chiang and Zheng, 2010, Jegadeesh and Kim, 2010). Herding has also been explored in other domains, including commodity (Adrangi and Chatrath, 2008), foreign exchange (Carpenter and Wang, 2007) and betting markets (Law and Peel, 2002) and in relation to the lending decisions of banks (Jain and Gupta, 1987, Nakagawa and Uchida, 2011). Since herding can affect market prices, it is important to understand the nature of herding and its root causes. Previous literature has identified three broad types of herding, namely, irrational herding (psychology-driven), rational herding (information-driven, reputation-driven, and compensation-driven), and event-related herding (for review, Bikhchandani and Sharma, 2000, Demirer,Kutan and Chen, 2010). The next section focuses on the information-based herding literature and this is used to develop our hypotheses.

4.2.1 The relationship between herding and information

Shiller,Fischer and Friedman (1984) suggests that social activities (i.e., discussion, reading and/or gossiping about investments) can result in investors reacting to the same set of information by making similar decisions simultaneously. Similarly, Shleifer and Summers (1990) suggest that individual traders may employ common trading strategies on the basis of advice provided by financial brokers and gurus, thereby leading to an over-reaction to recent news.

There has been a tendency in the herding literature to examine groups of traders who are expected to act on similar sets of information (e.g., Eguíluz and Zimmermann, 2000) and it has indeed been shown that trading patterns do vary between groups of investors based on the nature of their information sources. For example, investors who receive information early have been found to trade differently from those that receive information late (Hirshleifer,Subrahmanyam and Titman, 1994) and MI traders have been found to trade more aggressively than LI traders on the basis of the information they hold (Wang, 2010). Similarly, institutional (and foreign) investors have been demonstrated to trade together in the same direction as a result of them receiving similar information and analyzing similar price factors (Nofsinger and Sias, 1999, Jeon and Moffett, 2010).

Bikhchandani and Sharma (2000) indicate that herding may arise if investors change their investment decisions because they believe that others hold superior information to themselves. However, traders may show the reverse bias and 'contrary-herd' (Naujoks *et al.*, 2009). This can occur if they trade in a manner designed to avoid the consensus and if they overemphasize the value of their private information.

To better understand the mechanisms underlying herding it would be valuable to know if more and LI traders differ in terms of the degree, nature and patterns of their herding activity. To examine these issues we distinguish different types of herding behavior. In particular, we define 'self-herding' to occur where a group of traders react to the trading patterns of the same group of traders (intra-group) in previous periods. We define 'cross-herding' to occur when a group of traders react to the trading patterns of another group of traders (inter-group) in previous periods. In addition, we define 'positive herding' as taking place where traders mimic the trading behavior of others, and 'contrary-herding' as taking place where traders act in a contrary fashion to the trading behavior of others ('opposing strategy')[4]. Clearly, as shown in Table 4-1, these definitions can lead to four herding 'types': Positive-self-herding, contrary-self-herding, positive-cross-herding and contrary-cross-herding. Positive-self-herding implies that traders mimic the trading behavior of others in the same group (e.g., MI traders mimicking themselves) in previous periods while contrary-self-herding implies that traders act in a contrary manner to other traders in the same group in previous periods. In

[4] An 'opposing strategy' is one where traders act in a contrary fashion to the trading behavior of others. This should not be confused with a contrarian strategy, where traders act against prevailing market trends.

addition, positive-cross-herding implies that traders mimic the trading behavior of others in a different group (e.g., LI mimicking the behavior of MI traders) in previous periods while contrary-cross-herding implies that traders act in a contrary manner to other traders in the same group in previous periods.

Developing insights into the degree, nature and patterns of self- and cross-herding amongst more and LI traders will enable us to better understand the manner in which herding is likely to occur in any given market, allowing a more informed view of its causes and the means by which it might be controlled. In addition, this knowledge can help to predict market movements, and this may enable spread trading firms to manage their cost more effectively via effective hedging.

Table 4-1 Herding behavior of groups of traders based on the nature of their interactions.

	Followed by:			
	More informed		Less informed	
Direction of trading	Same	Contrary	Same	Contrary
More informed	*Positive-Self-herding*	*Contrary-Self-herding*	*Positive-Cross-herding*	*Contrary-Cross-herding*
Less informed	*Positive-Cross-herding*	*Contrary-Cross-herding*	*Positive-Self-herding*	*Contrary-Self-herding*

Menkhoff and Schmeling (2010) research suggests that all traders rely on their private information but LI traders have a tendency to react strongly to the trading of those they perceive to be better-informed. Consequently, this motivates our self-/cross-herding hypothesis, namely, that:

MI traders have a tendency to self-herd in a positive direction and LI traders have a tendency to cross-herd in a positive direction.

This hypothesis begs the question of how one should effectively distinguish more and LI traders and we explore this issue in Section 4.3.2.

4.2.2 Herding and feedback strategies

Traders can be distinguished by the manner in which they respond to changes in security prices. In particular, they may follow a positive feedback strategy, whereby they buy or sell following, respectively, an increase or decrease in the price of a security. Equally, traders may follow a negative feedback strategy, whereby they sell or buy following, respectively, an increase or decrease in the price of a security (De Long *et al.*, 1990).

It has been suggested that individual traders' herding behavior is likely to be related to their feedback strategies (Patel,Zeckhauser and Hendricks, 1991, Odean, 1998, Sirri and Tufano, 1998). In fact, Nofsinger and Sias (1999) suggest that feedback strategies can be viewed as one type of herding and occur when lag returns, or variables associated with lag returns (e.g., decisions of other traders, earning momentum, and changes in firms' characteristics) are viewed as common information signals.[5] Kim and Wei (1999) study the trading behavior of foreign portfolio investors in Korea and find that the feedback strategies they employ depend on the characteristics of traders. In particular, they find that institutions (that are likely to be better informed than individual traders (Schmeling, 2007)) tend to employ positive feedback strategies whereas individual traders tend to engage in negative feedback strategies.

We are interested in examining to what extent the pattern observed by Kim and Wei (1999) is observable amongst European individual traders, by testing the following feedback strategy hypothesis:

MI individual traders in spread-trading markets employ positive feedback strategies while LI traders employ negative feedback strategies.

4.2.3 Effect of herding

Previous research has suggested that MI traders tend to react more quickly to market shocks. For example, Lee,Lin and Liu (1999), employing impulse response analysis in the Taiwan Stock Exchange (TSE), find that institutional and large stake individual traders tended to respond more quickly to shocks (fast learners) than smaller stake individual investors (slow learners). Lee,Li and Wang (2010) find that abnormal trading volumes of LI traders following firm specific disclosures, drop more slowly and remain significantly positive for longer than those of informed traders. Consequently, the consensus from previous literature is that the trading activity of LI traders responds relatively slowly compared to that of MI traders. In the context of herding, we explore

[5] This particular type of herding is one where herding is affected by previous market trends. This should not be confused with the herding between groups of traders presented earlier.

reactions to a sudden change of trading by more and LI traders. In particular, we test the following shocks-response hypothesis:

MI traders generally respond more quickly to a sudden change in trading by more or LI traders than LI traders.

4.3 Data and procedures

4.3.1 Data

Spread-trading companies offer a spread of prices on, for example, a given index. If a trader believes that the index will rise above or fall below the firm's bid-ask price they will buy ('long position') or sell ('short position') the index. If the trader's investment is successful or unsuccessful, they will, respectively, win or lose their initial stake multiplied by the number of points by which the market has fallen or risen. We explore herding behavior in spread-trading markets by analyzing the trades of 1,943 individual clients of a spread-trading company, all the trades being executed between 20 January 2010 and 7 February 2012. The stake sizes of an individual's trades were converted to GBP using the daily average currency rate prevailing for the day in which the trade was conducted. We examine 48,570 trades associated with the FTSE 100, and supplement details of the investors' trades with information concerning the underlying market. In particular, we use tick data of FTSE 100 returns supplied by a financial data provider, *Tick Data*, to assess movements in the index.

In our analysis, we focus on the opening positions of traders because, as Coval,Hirshleifer and Shumway (2005) point out, closing positions are often not strongly driven by specific analysis or private information. In fact, closing positions can often arise from liquidity needs or from traders revising their position to limit risk exposure. On the other hand, opening a position on a stock index (purchasing or selling) is regarded as a relatively clear sign that the investor believes the market is likely to rise or fall (Coval,Hirshleifer and Shumway, 2005).

In the following section, we discuss the definitions we employ to distinguish more and LI traders.

4.3.2 More and less informed traders

4.3.2.1 Stake size

Existing studies generally assume that traders who invest larger sums have greater access to information. For example, Easley and O'hara (1987) and Barclay and Warner (1993) suggest, respectively, that MI investors trade in larger lot sizes at any given price and achieve larger share positions through multiple medium-size trades (500-9,900 shares). Similar approaches have been adopted in a range of markets (e.g., stock markets (Lee,Lin and Liu, 1999, Chakravarty, 2001); foreign exchange markets (Bjønnes and Rime, 2005, Moore and Payne, 2009)). Consequently, we follow this approach and define more and LI traders as those whose median stakes across all trades is, respectively, more and less (or equal) than the overall median stake (£1/point) for all trades in the database (see descriptive statistics of stake sizes in Table 4-2). There are 820 and 1,123 traders in these groups who open 21,480 and 27,090 positions, respectively. Median (cf. mean) stake is used to differentiate MI (mean=£9.92 and SD=£47.03 of stake size) and LI traders (mean=£1.27, SD=£1.00 of stake size) because the distribution of stakes is highly skewed (Jarque-Bera=977000000000, Probability=0.00) and we want to reduce the impact of a few very large stakes (see Figure 4-1a for a histogram of stake sizes associated with opening trades). We find no significant difference in mean profit/loss between the more and LI traders defined in this way (LI=-£6.03, MI=-£3.16, t=-1.275, p=0.203). This leads us to question the use of the stake size approach for distinguishing more and LI traders and prompted us to examine alternative approaches.

Table 4-2 Descriptive statistics associated with the investment of spread traders captured in the data.

		Min	1st Quartile	Median	Mean	3rd Quartile	Max
Stake size associated with trades	Stake	£0.087	£1	£1	£5.096	£3	£5,710
	Natural logarithm of Stake	-2.440	0	0	1.628	1.099	8.65
Trader account balances		-£25,410	-£1,418	-£267.8	-£1,993	-£8.475	£5,008
The final point* profits/losses associated an individual trade		-5,733	-8.5	2.8	-5.883	12.8	5,733

* a point stands for value of profit/loss of each trade divided by stake size

Figure 4-1 Distributions of stake size and profitability of accounts of spread traders in the sample and final point profit/loss associated with each trade.

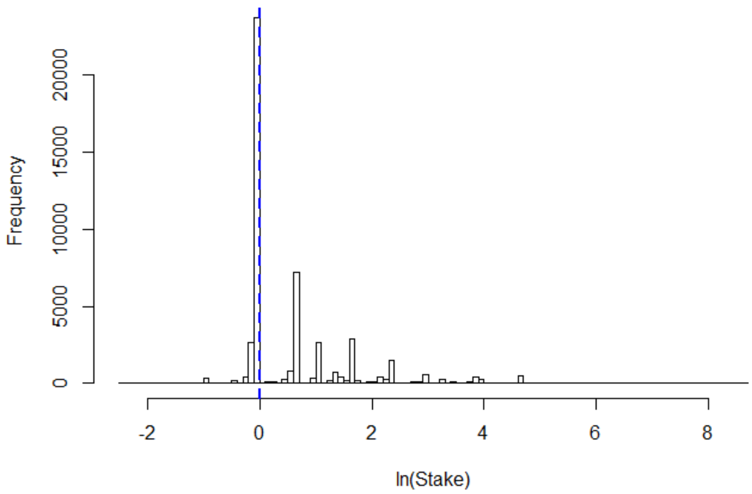


Figure 4-1a Histogram of the natural log of the stake (£) associated with each trade. The distinguishing threshold for the more and LI traders is shown by the dashed line.

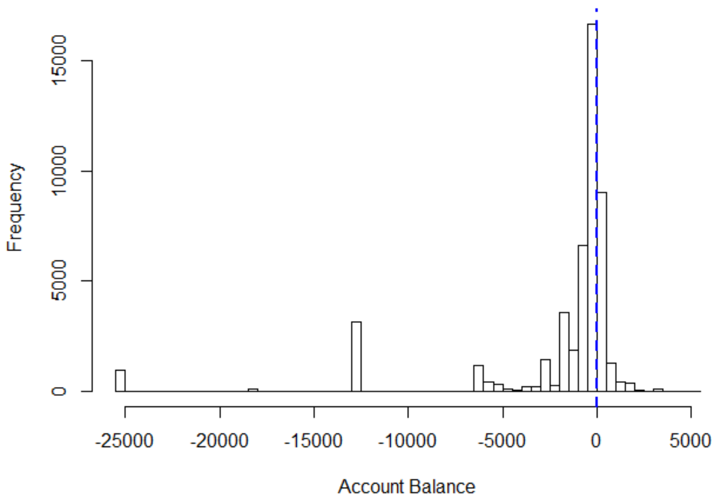


Figure 4-1b Histogram of traders' account balances (£). The distinguishing threshold for accounts with positive and negative (break-even) accounts is shown by the dashed line.

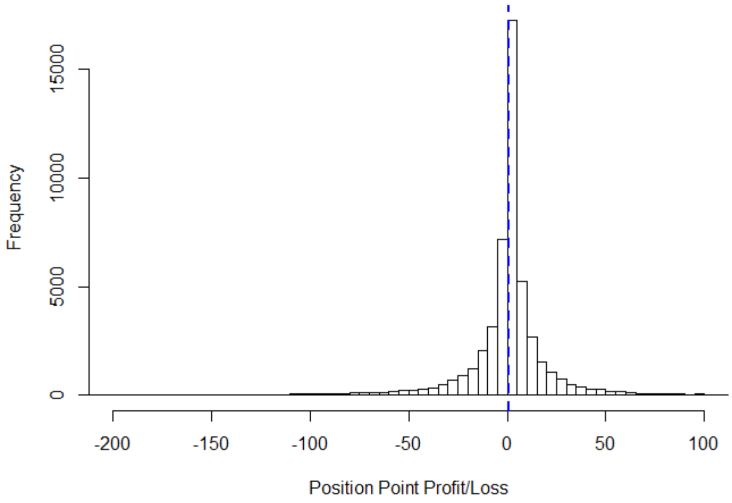


Figure 4-1c Histogram of the final point profit/loss associated with each trade. The median distinguishing threshold between the more and LI group is shown by a dashed line. The x axis is only defined for values between -200 and 100 to more clearly depict the main bulk of the data points.

4.3.2.2 Overall account profitability

Our dataset allows us to classify more and LI traders using a more direct measure based on overall account profitability. In particular, we expect MI traders to be more profitable in the long run. Consequently, we define MI traders as those with positive account balances over their trading history and LI traders as those with negative or zero account balances over their trading history. This results in us defining 805 and 1,138 traders as more and LI, respectively, and these groups are associated with 11,269 and 37,301 opening trades, respectively (see Table 4-2 and Figure 4-1b for further descriptive statistics associated with these groups).

4.3.2.3 Profitability of each opened position

While the previous approach for distinguishing more and LI traders is focused on the overall account profitability, it is possible that different traders may be MI at different times. On those occasions they are more ‘informed’, one might expect them to profit from any information they hold. Consequently, we employ an alternative approach to distinguishing more and LI trades by grouping opened positions on the basis of the degree to which they *turn out* to be profitable. Clearly, in a rising market, for example, it might be possible for even LI traders to make a profit on a given trade, but our aim is to discern those trades which contained more information than the norm. Consequently, we separated those trades that produced a final profit more or less (or equal) than the median point per trade profit of +2.8 points. This resulted in 24,189 trades being identified as MI and 24,381 trades being identified as LI (see Table 4-2 and Figure 4-1c for further descriptive statistics related to the final point profit/loss).

4.3.3 Procedures

The literature suggests that herding tends to occur over short time horizons as traders focus on limited rather than diverse sources of information, particularly when they focus on the information held by others rather than that related to fundamentals (Froot,Scharfstein and Stein, 1992). By contrast, across longer time horizons, it is more likely that diverse sources of information will be employed and markets will reach equilibrium. Consequently, most existing herding studies select a fixed, short time interval (e.g., daily, 30 minutes, 15 minutes) and examine herding across various securities over this fixed interval. For example, Chiang,Li and Tan (2010) explore herding in stock prices for all listed firms in the NYSE and AMEX and in the Shanghai (SHSE) and Shenzhen Stock Exchanges (SZSE) over a one day period. Others have examined herding in property firms' shares in the Hong Kong stock market over a 30-minute interval (Zhou and Lai, 2007), and in trading associated with all firms' shares in the Taiwan Stock Exchange (TSE) over a 15-minute interval (Lee,Lin and Liu, 1999).

However, we believe that the methods employed in previous studies may have underestimated the degree of herding in the market. In particular, by focusing on only one time interval, herding in alternative time intervals may have been under-estimated. As financial markets are a meeting place for a broad type of investors, there may be significant differences between their trading time horizons. Clearly, one fixed time interval may not capture the behavioral pattern of all types of trader. In addition, by exploring combined trading across a variety of assets it is possible that herding associated with individual assets may have been over-looked. For example, herding in one direction in one asset (e.g., positive herding) might be offset by herding in another direction in a different asset (e.g., contrary herding), so that a study which simply looked at trading in the two assets combined would detect no herding. Consequently, we analyze trading in a *single* asset (the FTSE 100 index) over *a variety* of short time intervals (intervals less than 1 day are examined as most spread trades are opened and closed within a day (Pryor, 2011, p. 51)). Our approach, by focusing on one asset, enables us to determine the actual herding which took in that asset and by examining trades in the FTSE 100 index, we are able to examine herding related to a significant market.

As indicated above, our data also allows us to distinguish more and LI traders and we are able to explore the degree and direction of herding by these two groups in order to test our hypotheses. In particular, we employ, in a similar fashion to Lee,Lin and Liu (1999) and Jain and Gupta (1987), the Vector Autoregression (VAR) model and causality tests to test our hypotheses.

4.3.3.1 Unit roots

To employ the VAR method, we first test for stationarity of the trading data, using the standard tests employed in many studies, namely, the Augmented Dickey-Fuller (ADF), the Phillips-Perron (PP) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests.

4.3.3.2 VAR model

We examine the dynamic interactions between more and LI traders in order to test the first hypothesis, namely, MI traders have a tendency to self-herd (intra-group) in a positive direction while LI traders tend to cross-herd (inter-group) in a positive direction. In these analyses, we distinguish more and LI traders and trades in the three ways discussed above, namely via median stake size, the profitability of a trader's account, and the profitability of a given trade. We develop VAR models for a variety of time intervals (5, 15, 30, and 60 minutes) from the opening of the FTSE market on a given day until its close. The equations employed to represent the interactions between the traders are as follows:

$$M_T = a_0 + \sum_{k=1}^{n} a_k M_{T-k} + \sum_{k=1}^{n} b_k L_{T-k} + \sum_{k=1}^{n} c_k R_{T-k} + u_{1T}$$

$$L_T = d_0 + \sum_{k=1}^{n} d_k M_{T-k} + \sum_{k=1}^{n} e_k L_{T-k} + \sum_{k=1}^{n} f_k R_{T-k} + u_{2T} \qquad (4\text{-}1)$$

where, M_T and L_T represent the net buy stakes (i.e., the difference between the total buy and sell stakes) of more and LI traders respectively, in specific time intervals T (i.e., 5, 15, 30 and 60 minutes). In both of the equations, R_T, represents the return on the FTSE 100 index in time interval T. In both equations R_T is treated as an exogenous variable in order to control for possible trend effects and to control for learning about fundamental asset values from publicly available past index returns. We also adopt this approach because we believe that the trades of spread traders do not affect the index directly. The u's in the equations represent the stochastic error terms while the number of lags n_T for the equations up to time interval T are estimated by Hannan-Quinn information criterion (HQIC). This criterion is shown to out-perform the other criteria (Akaike's information criterion (AIC) and Schwarz information criterion (SIC) in terms of giving the correct number of lags when sample sizes are large (Liew, 2004)).

Regression results from the VAR model are employed to detect herding and feedback strategies via correlated trades (Lee,Lin and Liu, 1999). We identify positive herding where a group of traders mimic trading patterns of the same group of traders in previous periods (positive-self-herding) or mimic the behavior of a different group of traders (positive-cross-herding). Similarly, we identify contrary-herding where a group of traders act in a contrary fashion to trading patterns of the same group of traders in previous periods (contrary-self-herding) or act in a contrary fashion to the behavior of a different group of traders (contrary-cross-herding). Specifically, in order to seek evidence of herding, we examine the sign of the coefficients of the more or LI traders net buying positions (a_k, b_k, d_k, e_k) in the VAR regression results (M_T/L_T), to see if they are positive or negative and significantly different to zero. For instance, if the coefficients a_k or e_k are positive or negative and significant this suggests evidence of positive or contrary-self-herding amongst more and LI traders, respectively. Similarly, if b_k or d_k are positive or negative and significant this suggests evidence of positive- or contrary-cross-herding amongst more and LI traders, respectively.

We also identify positive feedback strategies where a group of traders buy or sell following a rise or fall in the index, respectively, and negative feedback strategies where a group of traders buy or sell following a fall or rise in the index, respectively. To examine this, we look at the sign of the return coefficients (c_k, f_k) for the VAR regression results for M_T and L_T. If c_k and f_k are positive and significant this suggests that positive feedback strategies are being employed by more and LI traders, respectively. Similarly, if c_k and f_k are negative and significant this suggests that negative feedback strategies are being employed by more and LI traders, respectively.

In order to ensure that our results are sufficiently robust, we re-estimate the VAR model by varying the time interval T (5, 15 minute, 30 minute, and 1 hour). We also examine the extent to which herding/feedback strategy are employed in a given number of lagged time *periods* from the initial trade. For the purposes of exposition we make a clear distinction here between the time *intervals* we explore (i.e., 5, 15, 30 and 60 minutes) and the lagged time *periods* (i.e., 1, 2, 3…up to n_T lagged periods associated with each time interval, where n_T is determined by HQIC).

We then examine the significance and sign of the coefficients within each time interval and lagged time period. For example, the overall degree and direction of herding in each time interval and in each lagged time period is assessed by examining the sign and level of significance of the coefficients relating to the net buy stakes of the more or LI traders in that time interval or lag period. In particular, we define 'strong' evidence of herding for each time interval or for a given lagged time period when the majority of the coefficients relating to the net buy stakes of the more or LI traders in this time interval or lagged time period are statistically significant and are consistently of the same sign. Similarly, we define 'weak' evidence of, say, positive herding in a given time interval when some of the coefficients are significant and have mixed signs, but the majority of these are positive.

To make an overall assessment of the degree and direction of herding/feedback strategy amongst a particular group of traders we combine the two types of herding/feedback strategy results discussed above. Specifically, we examine the results for herding/feedback strategy across all the four time intervals for that group of traders and for all lagged time periods (across each of the time intervals).

4.3.3.3 Causality tests

Causality tests examine whether more and LI traders' investments are correlated. However, in order to test further whether the trading of MI traders influences the trading of LI traders (cross-herding), we employ Granger causality (Granger, 1969), in a similar manner to that adopted by Jain and Gupta (1987) for detecting herding regarding the lending decisions of US banks. In particular, to test the second part of the herding hypothesis, namely, that LI traders tend to cross-herd in a positive direction with informed traders, we examined how much of the current net buying positions of LI traders (L_T) can be explained by the past net buying positions of MI traders (M_{T-k}). In particular, we test this by exploring whether the coefficients of previous trading activity (d_1 to d_n) of MI traders are able to help explain L_T (i.e., the coefficient is not equal to zero). Providing they are able to be employed to help explain L_T, it can be said that LI traders are likely to positive-herd/contrary-herd on the previous behavior of MI traders.

4.3.3.4 Impulse response analysis

In order to test the shocks-response hypothesis, namely, that MI traders respond to a sudden change in trading more quickly than LI traders, we employ generalized (*vs.* orthogonalized) impulse response analysis. This analysis has been shown to be indifferent to the ordering of the variables in the VAR, while the ordering of the variables may have an effect on the results when employing orthogonalized impulse response functions (Koop,Pesaran and Potter, 1996). The generalized impulse response functions are plotted to measure the relative contribution that past shocks in each variable have on the volatility of the two dependent variables (i.e., the net buying positions of more and LI traders). The rapidity of the decay of these responses represents the speed with which a particular trader group responds to shocks. An important assumption associated with the use of VAR models is the normality of residuals. This appears to be a particularly important assumption when modeling with high frequently data. Consequently, when judging the actual responses, we not only report the point estimates of the impulse response coefficients, but we also employ the bootstrap procedure by Dees *et al.* (2007) in order to show the uncertainty surrounding point estimates.

4.4 Results and discussion

4.4.1 Stationarity

In this section, we show the unit root results relating to the three means of distinguishing more and LI traders discussed above (stake size, profitability of account, and successful trade, respectively). Table 4-3 presents the ADF, PP, and KPSS unit root test results for each time interval (5, 15, 30 and 60 minutes) for the more and LI traders and the FTSE 100 index returns.

The results demonstrate that using all three criteria for defining more and LI traders (stake size, profitability of account and successful trade), the ADF and PP unit roots tests for all variables indicate a rejection of the null hypothesis of a unit root at the 1 per cent level of significance. In addition, the KPSS unit root test does not reject the null hypothesis of level and trend stationarity (for the vast majority of the time intervals, whatever means is used to define more and LI traders)[6]. Consequently, for all three of the definitions of more and LI traders we employ, the vast majority of variables appear to be stationary.

[6] We detect that some series are not stationary around deterministic trends which may possibly lead to spurious regression. However, we focus on the majority of the results which are largely stationary.

Table 4-3 Unit root test results (on HQIC) for more/less informed traders categorized by stake size, account profitability and successful trade for time intervals 5, 15, 30 and 60 minutes.

MI/LI+ categorized by:		ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS	ADF	PP	KPSS
Time intervals			*5-minute*			*15-minute*			*30-minute*			*1-hour*	
Stake size	MI	-76.230**	-346.354**	0.033	-63.573**	-202.954**	0.033	-56.993**	-144.642**	0.032	-33.581**	-76.084**	0.032
	LI	-65.684**	-266.383**	0.027	-53.469**	-150.905**	0.023	-27.169**	-117.471**	0.028	-21.159**	-89.008**	0.031
	Return	-111.303**	-197.001**	0.050	-116.084**	-116.468**	0.046	-81.399**	-81.825**	0.045	-59.111**	-59.406**	0.046
Profitability of account	MI	-229.507**	-229.509**	0.340**	-80.610**	-135.276**	0.113	-69.812**	-98.297**	0.048	-32.772**	-77.417**	0.027
	LI	-115.614**	-214.119**	0.114	-40.815**	-140.596**	0.040	-25.791**	-100.063**	0.030	-23.298**	-75.597**	0.031
	Return	-111.414**	-197.106**	0.049	-116.137**	-116.520**	0.045	-81.434**	-81.860**	0.044	-59.266**	-59.563**	0.045
Successful trade	MI	-80.106**	-226.006**	0.785	-86.366**	-128.557**	0.479	-20.859**	-93.555**	0.253	-15.778**	-67.496**	0.161*
	LI	-75.814**	-212.276**	0.219	-81.764**	-127.965**	0.178	-68.563**	-94.868**	0.189*	-69.116**	-69.143**	0.147*
	Return	-111.421**	-197.181**	0.049	-116.198**	-116.582**	0.046	-81.469**	-81.894**	0.045	-59.266**	-59.563**	0.045

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, + MI: more informed traders; LI: less informed traders

4.4.2 Herding and feedback strategies

4.4.2.1 More and less informed traders categorized on the basis of stake size

Tables 4-4 and 4-5 report, respectively, the VAR regression results associated with the equations in which the net buying positions of more and LI traders (M_T, and L_T), differentiated on the basis of stake size, are the dependent variables. The results for all the four time intervals (5, 15, 30 and 60 minutes) are displayed in these tables. To develop a clear picture of the overall persistence and degree of herding amongst more and LI traders we examine the results across all time intervals together.

In order to test the first part of the herding hypothesis, namely that MI traders self-herd in a positive direction, we examine the coefficients (a_k) of the lagged net buying positions of MI traders in the equation with the net buying position of MI traders as the dependent variable (M_T). We find that there are significant coefficients for each time interval and in all cases these are negative (see Table 4-4). Overall, these results suggest that across all the time intervals examined there is strong evidence that MI traders contrary-herd on the behavior of other MI traders in preceding periods. In particular, this contrary-herding involves taking up contrary positions to those taken by MI traders in previous time periods. We find that at lag 1 the coefficients of the net buying position of MI traders (a_1) for all time intervals are negative and statistically significant. At lags 2, 3, and 4, the coefficients a_2 to a_4 are statistically significant and negative for 3 of the 4 time intervals (only the coefficient for 60 minute time interval is not significant). Similarly, at lags 5, and 6, the coefficients a_5 and a_6 are statistically significant and negative for 2 of the 4 time intervals. In summary, these results confirm the view expressed in the herding hypothesis that MI traders self-herd but, contrary to our expectations, they appear to contrary-herd rather than positive-herd.

We then test the second part of the herding hypothesis, namely that LI traders cross-herd with MI traders in a positive direction. To achieve this, we examine the coefficients of the lagged net buying positions of MI traders, (d_1 to d_6) in the equation with the net buying position of LI traders as the dependent variable (L_T) (see Table 4-5). We find that for all time intervals examined there are significant coefficients and all these significant coefficients are positive. In particular, we find that at lag 1 the coefficients of the net buying position of informed traders (d_1) for all time intervals are positive and statistically significant. At lag 2, the coefficients of two of the time intervals (d_2), are positive and statistically significant and at lag 6, coefficients of three of the time intervals are positive and statistically significant. Overall, these results provide support for the herding hypothesis, in that they suggest that LI traders are likely to follow the actions of MI traders in the preceding periods (particularly with a lag of 1, 2 and 6 periods).

In summary, when defining more and LI traders on the basis of stake size, we find evidence to support the herding hypothesis, of cross-herding among LI traders. In other words, they mimic the behavior of MI traders in previous periods, across a variety of time intervals. In addition, we confirm that MI traders do not follow the actions of MI traders in previous periods, but contrary to our expectations, they appear to contrary-herd, namely they choose an opposite course of action to that adopted by MI traders in previous periods. These results are to some extent confirmed by the causality tests (results displayed in Table 4-10a). These show significant results for all time intervals, suggesting that MI traders are likely to influence LI traders.

We now test the feedback strategy hypothesis, namely that more and LI traders adopt positive and negative feedback strategies, respectively. To achieve this, we examine the coefficients associated with the lagged returns (c_k , f_k) in the equations with the net buying position of more and LI traders as the dependent variables (M_T / L_T), respectively (shown in Table 4-4 and 4-5, respectively). The results confirm that LI traders follow negative feedback strategies, as all of the significant coefficients for all time intervals (f_k) are negative. This is particularly the case for a one period lag return, these coefficients are negative and significant for all the time intervals considered. However, the results do not support the feedback strategy hypothesis in relation to MI traders. In fact, the significant coefficients of lagged returns in the equation with the net buying position of MI traders (c_k), are negative. This is particularly the case for a one period lag return, for which the coefficient (c_1) is significant and negative for all time intervals considered. The results, suggest, therefore, that MI traders also follow a negative feedback strategy.

Consequently, when more and LI traders are distinguished in terms of stake size we find that both groups appear to follow negative feedback strategies. This result confirms the feedback strategy hypothesis in terms of the actions of LI traders but not in relation to the trading behavior of MI traders.

Table 4-4 VAR regression results across time intervals (more informed trader equations) for traders categorized by stake size.

Potential herding time interval		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr
	a_0	0.406	1.340	3.196	3.753										
		(0.525)	(0.582)	(0.722)	(0.672)										
Lagged period		*MI trader coefficients*					*LI trader coefficients*					*Return coefficients*			
1	a_1	-0.311**	-0.341**	-0.372**	-0.096**	b_1	1.515**	1.757*	2.820**	6.345**	c_1	-2693.1**	-7736.9**	-4049.7*	-5824.5**
		(-71.556)	(-45.266)	(-34.880)	(-6.591)		(3.954)	(2.498)	(2.801)	(6.280)		(-3.621)	(-5.9907)	(-2.279)	(-3.512)
2	a_2	-0.091**	-0.126**	-0.167**	-0.021	b_2	0.291	1.656*	3.558**	-1.517	c_2	-1508.5*	-690.6081	-4923.2**	359.070
		(-20.013)	(-15.824)	(-14.674)	(-1.447)		(0.757)	(2.350)	(3.487)	(-1.465)		(-2.004)	(-0.5294)	(-2.739)	(0.214)
3	a_3	-0.058**	-0.080**	-0.084**	0.011	b_3	0.206	1.171	4.027**	1.957	c_3	-959.301	-1340.3	-987.322	2994.4
		(-12.742)	(-9.954)	(-7.269)	(0.719)		(0.536)	(1.656)	(3.930)	(1.886)		(-1.273)	(-1.0275)	(-0.549)	(1.785)
4	a_4	-0.028**	-0.0490**	-0.040**	-0.014	b_4	0.833*	2.308**	1.400	-0.090	c_4	-1856.7*	-3253.8*	-311.210	-721.066
		(-6.117)	(-6.093)	(-3.426)	(-0.955)		(2.168)	(3.267)	(1.366)	(-0.087)		(-2.464)	(-2.4936)	(-0.173)	(-0.430)
5	a_5	-0.008	-0.051**	-0.007	-0.068**	b_5	1.156**	2.087**	0.502	0.487	c_5	-4152.4**	-1882.7	-708.070	-1136.5
		(-1.778)	(-6.367)	(-0.598)	(-4.649)		(3.010)	(2.962)	(0.490)	(0.470)		(-5.509)	(-1.4428)	(-0.394)	(-0.678)
6	a_6	-0.010*	-0.024**	0.002	0.009	b_6	0.118	1.691*	-0.173	4.811**	c_6	986.975	-1498.1	1602	-50.700
		(-2.004)	(-3.235)	(0.192)	(0.649)		(0.307)	(2.406)	(-0.169)	(4.745)		(1.309)	(-1.1583)	(0.892)	(-0.031)
7	a_7	-0.011*		-0.002		b_7	-0.141		0.038		c_7	-353.25		-714.645	
		(-2.347)		(-0.139)			(-0.366)		(0.037)			(-0.469)		(-0.398)	
8	a_8	-0.009		-0.021		b_8	0.236		-0.009		c_8	-828.598		1592.9	
		(-1.925)		(-1.780)			(0.614)		(-0.009)			(-1.099)		(0.886)	
9	a_9	-0.022**		-0.020		b_9	1.460**		1.331		c_9	-1383.4		-696.845	
		(-4.919)		(-1.744)			(3.805)		(1.299)			(-1.837)		(-0.388)	
10	a_{10}	-0.021**		-0.022		b_{10}	0.421		1.894		c_{10}	-371.948		264.569	
		(-4.695)		(-1.928)			(1.100)		(1.846)			(-0.500)		(0.147)	
11	a_{11}			-0.027*		b_{11}			-0.156		c_{11}			-1270.6	
				(-2.304)					(-0.152)					(-0.708)	
12	a_{12}			-0.015		b_{12}			3.162**		c_{12}			1719.9	
				(-1.289)					(3.083)					(0.958)	
13	a_{13}			-0.020		b_{13}			2.545*		c_{13}			-1662.5	
				(-1.794)					(2.490)					(-0.926)	
14	a_{14}			-0.027*		b_{14}			0.807		c_{14}			2.017	
				(-2.501)					(0.801)					(0.001)	
Herding evidence		strong (-)	strong (-)	strong (-)	strong (-)		strong (+)	strong (+)	strong (+)	strong (+)		strong (-)	strong (-)	strong (-)	strong (-)

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, ✕ no evidence of herding

Table 4-5 VAR regresssion results across time intervals (less informed trader equations) for traders categorized by stake size.

Potential herding time interval		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr
	d_0	-0.007	-0.020	-0.044	-0.085										
		(-0.769)	(-0.794)	(-0.949)	(-1.058)										
Lagged period		*MI trader coefficients*					*LI trader coefficients*					*Return coefficients*			
1	d_1	0.0002**	0.0002**	0.0003**	0.001**	e_1	-0.060**	-0.083**	-0.163**	-0.214**	f_1	-24.596**	-47.400**	-87.007**	-55.573*
		(3.454)	(2.612)	(3.049)	(2.735)		(-13.654)	(-11.053)	(-15.340)	(-14.706)		(-2.908)	(-3.426)	(-4.639)	(-2.332)
2	d_2	0.0001*	0.0003**	0.0002	0.0002	e_2	-0.053**	-0.072**	-0.097**	-0.063**	f_2	-28.492**	-17.023	-0.574	-30.749
		(1.986)	(3.357)	(1.823)	(0.972)		(-12.023)	(-9.556)	(-8.964)	(-4.238)		(-3.328)	(-1.218)	(-0.030)	(-1.276)
3	d_3	0.0000	0.0003**	0.0001	0.0002	e_3	-0.035**	-0.105**	-0.044**	0.006	f_3	-12.484	-53.191**	0.617	31.168
		(0.718)	(3.124)	(0.943)	(1.060)		(-8.105)	(-13.799)	(-4.026)	(0.432)		(-1.457)	(-3.806)	(0.033)	(1.293)
4	d_4	0.0001	0.0001	-0.0000	0.0001	e_4	-0.020**	-0.017*	-0.034**	-0.009	f_4	-30.292**	9.743	-23.119	-2.299
		(1.241)	(0.631)	(-0.241)	(0.453)		(-4.623)	(-2.213)	(-3.171)	(-0.570)		(-3.534)	(0.697)	(-1.218)	(-0.095)
5	d_5	0.0002**	-0.0001	0.0002	0.0001	e_5	-0.002	-0.053**	-0.023*	-0.071**	f_5	-16.598	-15.143	-33.674	31.433
		(3.196)	(-0.061)	(1.595)	(0.506)		(-0.436)	(-7.019)	(-2.134)	(-4.758)		(-1.936)	(-1.083)	(-1.775)	(1.304)
6	d_6	0.0002**	0.0001	0.0003*	0.001*	e_6	-0.034**	-0.021**	0.015	-0.091**	f_6	10.980	19.443	22.76	6.431
		(2.949)	(1.718)	(2.195)	(2.382)		(-7.846)	(-2.723)	(1.408)	(-6.231)		(1.280)	(1.403)	(1.200)	(0.270)
7	d_7	0.0001		0.0000		e_7	-0.027**		0.004		f_7	-12.380		9.704	
		(1.553)		(0.285)			(-6.255)		(0.327)			(-1.444)		(0.512)	
8	d_8	0.0000		-0.0000		e_8	-0.042**		-0.006		f_8	-20.525**		2.636	
		(0.519)		(-1.174)			(-9.648)		(-0.586)			(-2.394)		(0.139)	
9	d_9	0.0000		0.0001		e_9	-0.031**		-0.037**		f_9	-9.991		13.870	
		(0.334)		(0.989)			(-7.134)		(-3.656)			(-1.166)		(0.732)	
10	d_{10}	0.0002**		0.0001		e_{10}	-0.021**		-0.015		f_{10}	-7.105		-6.839	
		(3.075)		(0.424)			(-4.847)		(-1.426)			(-0.840)		(-0.361)	
11	d_{11}			0.0002		e_{11}			-0.053**		f_{11}			23.638	
				(1.367)					(-4.850)					(1.247)	
12	d_{12}			0.0001		e_{12}			-0.038**		f_{12}			0.642	
				(0.525)					(-3.475)					(0.034)	
13	d_{13}			0.0000		e_{13}			-0.036**		f_{13}			21.322	
				(0.413)					(-3.293)					(1.125)	
14	d_{14}			0.0001		e_{14}			0.079**		f_{14}			5.625	
				(1.297)					(7.454)					(0.300)	
Herding evidence		strong (+)	strong (+)	strong (+)	strong (+)		strong (-)	strong (-)	strong (-)	strong (-)		strong (-)	strong (-)	strong (-)	strong (-)

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, ✕ no evidence of herding

4.4.2.2 More and less traders categorized on the basis of account profitability

Table 4-6, and 4-7 report the VAR regression results associated with, respectively, the equations in which the net buying positions of more and LI traders (M_T, and L_T), differentiated on the basis of account profitability, are the dependent variables. Results for all the four time intervals (5, 15, 30 and 60 minutes) are reported in these tables. In three of the four time intervals, the significant coefficients of the lagged net buying positions of MI traders (a_k), in the equation with the net buying position of MI traders as the dependent variable (M_T), are all negative. In particular, the coefficients for a one period lag are significant and negative for three of the four time intervals, the remaining coefficient for a 5 minute time interval being non-significant. These results provide evidence of contrary-self-herding amongst MI traders, in contrast to the herding hypothesis. Particularly, the negative sign of the significant coefficients suggests that informed traders act in a contrary fashion to informed traders in previous periods.

There is only weak evidence to support the second part of the herding hypothesis, namely that LI traders cross-herd with MI traders. In fact, few of the coefficients of the lagged net buying positions of MI traders (d_k) are significant across the four time intervals considered in the equation with the net buying position of LI traders as the dependent variable (L_T) (see Table 4-7). Only the 60-minute time interval produces significant coefficients; these are positive for a lag of one period and negative for a lag of four periods. The causality results, displayed in the Table 4-10b, suggest that MI traders are likely to influence LI traders only in the 60-minute time interval.

We now test the feedback strategy hypothesis, namely that more and LI traders adopt positive and negative feedback strategies, respectively. To achieve this, we examine the coefficients associated with the lagged returns (c_k and f_k) in the equations with the net buying position of more and LI traders as the dependent variable (M_T/L_T), respectively (shown in Table 4-6 and 4-7). The results do not support the hypothesis, as the few coefficients of lagged returns (c_k) which are significant in the equation with the net buying position of MI traders as dependent variable, are negative (Table 4-6). In fact, for two of the four time intervals (for the 15- and 60- minute intervals) the one period lag return coefficients are significant and negative; suggesting that if informed traders follow feedback strategies at all, then they are more inclined to follow a negative feedback strategy. In addition, few of the lag return coefficients (f_k) are significant for any of the time intervals in the equation with the net buying position of LI traders as the dependent variable (Table 4-7), for any of the time intervals. The only two significant lag return coefficients, relating to the 15-minute (six period lag) and 30- minute time intervals (three period lag), are positive, suggesting that if LI traders follow a feedback strategy at all it is likely to be a positive feedback strategy.

Overall, it is clear that when categorizing traders into more and LI on the basis of account profitability, the herding results, whilst providing less conclusive evidence, tend to be in line with the herding results obtained when dividing traders based on the stake size.

Table 4-6 VAR regression results across time intervals (more informed trader equations) for trader categorized by account profitability.

Potential herding time interval		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr
	a_0	-4.483**	-8.842**	-10.998**	-8.217										
		(-7.798)	(-4.807)	(-3.050)	(-1.716)										
Lagged period			*MI trader coefficients*					*LI trader coefficients*						*Return coefficients*	
1	a_1	0.001	-0.016*	-0.041**	-0.119**	b_1	0.040	0.077*	0.285**	0.157**	c_1	-786.625	-2770.600**	-271.812	-6472.700**
		(0.247)	(-2.137)	(-3.877)	(-8.173)		(1.526)	(2.130)	-5.929	(3.812)		(-1.441)	(-2.713)	(-0.189)	(-4.579)
2	a_2		-0.002	-0.027*	-0.014	b_2		0.171**	-0.022	0.053	c_2		1835.100	-2596.200	1269.300
			(-0.316)	(-2.537)	(-0.953)			(4.758)	(-0.453)	(1.286)			(1.781)	(-1.785)	(0.8867)
3	a_3		-0.043**	-0.007	0.021	b_3		0.062	0.096*	-0.004	c_3		-1357.300	-74.798	1580.800
			(-5.724)	(-0.665)	(1.457)			(1.732)	(2.001)	(-0.086)			(-1.317)	(-0.051)	(1.104)
4	a_4		-0.008	-0.001	0.012	b_4		-0.035	0.056	0.009	c_4		-1346.700	159.502	-262.764
			(-1.065)	(-0.046)	(0.810)			(-0.978)	(1.160)	(0.213)			(-1.306)	(0.110)	(-0.184)
5	a_5		-0.019*	0.009	-0.063**	b_5		-0.004	-0.089	0.087*	c_5		222.101	-666.238	-2567.600
			(-2.448)	(0.821)	(-4.315)			(-0.110)	(-1.857)	(2.120)			(0.215)	(-0.463)	(-1.814)
6	a_6		0.003			b_6		0.038			c_6		-1377.000		
			(0.355)					(1.062)					(-1.336)		
7	a_7		-0.0004			b_7		0.026			c_7		266.353		
			(-0.057)					(0.715)					(0.258)		
8	a_8		0.002			b_8		0.018			c_8		123.311		
			(0.222)					(0.485)					(0.120)		
9	a_9		-0.002			b_9		-0.010			c_9		-104.184		
			(-0.215)					(-0.282)					(-0.101)		
10	a_{10}		0.001			b_{10}		0.022			c_{10}		-750.837		
			(0.111)					(0.594)					(-0.728)		
11	a_{11}		0.004			b_{11}		0.020			c_{11}		624.834		
			(-0.463)					(0.548)					(0.606)		
12	a_{12}		0.004			b_{12}		0.050			c_{12}		644.778		
			(0.588)					(1.390)					(0.626)		
13	a_{13}		0.007			b_{13}		-0.006			c_{13}		356.067		
			(0.887)					(-0.171)					(0.349)		
14	a_{14}					b_{14}					c_{14}				
Herding evidence		×	strong (-)	strong (-)	strong (-)		×	strong (+)	strong (+)	strong (+)		×	strong (-)	×	strong (-)

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, × no evidence of herding

Table 4-7 VAR regression results across time intervals (less informed trader equations) for traders categorized by account profitability.

Potential herding time interval		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr
	d_0	-0.150	-0.818*	-1.113	0.289										
		(-1.589)	(-2.129)	(-1.408)	(0.171)										
Lagged period		*MI trader coefficients*					*LI trader coefficients*					*Return coefficients*			
1	d_1	0.001	0.002	0.003	0.0116*	e_1	0.069**	-0.061**	0.009	-0.054**	f_1	-12.151	-300.217	-309.995	178.064
		(0.663)	(1.078)	(1.355)	(2.255)		(15.837)	(-8.149)	(0.857)	(-3.675)		(-0.136)	(-1.407)	(-0.983)	(0.356)
2	d_2		0.0000	0.004	0.006	e_2		0.006	-0.028**	0.006	f_2		-265.442	-331.601	-282.412
			(0.0004)	(1.628)	(1.059)			(0.801)	(-2.607)	(0.398)			(-1.233)	(-1.040)	(-0.558)
3	d_3		0.003	0.002	0.004	e_3		0.085*	-0.020	-0.091**	f_3		189.774	748.492*	794.434
			(1.784)	(0.796)	(0.751)			(11.243)	(-1.849)	(-6.256)			(0.881)	(2.347)	(1.570)
4	d_4		0.0004	0.002	-0.022**	e_4		0.051**	-0.010	-0.037*	f_4		-243.963	-338.979	299.093
			(0.285)	(1.007)	(-4.238)			(6.703)	(-0.934)	(-2.516)			(-1.133)	(-1.063)	(0.591)
5	d_5		0.0002	0.002	0.007	e_5		-0.038**	-0.125**	-0.039**	f_5		103.220	-160.802	586.551
			(0.107)	(0.820)	(1.430)			(-4.959)	(-11.814)	(-2.659)			(0.479)	(-0.510)	(1.173)
6	d_6		0.001			e_6		0.008			f_6		633.348**		
			(0.705)					(1.066)					(2.941)		
7	d_7		0.0000			e_7		0.008			f_7		20.551		
			(0.004)					(1.044)					(0.095)		
8	d_8		0.0002			e_8		0.024**			f_8		27.637		
			(0.126)					(3.208)					(0.1283)		
9	d_9		0.003			e_9		-0.009			f_9		-100.659		
			(1.828)					(-1.213)					(-0.467)		
10	d_{10}		0.001			e_{10}		-0.049**			f_{10}		-111.255		
			(0.606)					(-6.489)					(-0.517)		
11	d_{11}		-0.001			e_{11}		-0.021**			f_{11}		-142.801		
			(-0.521)					(-2.840)					(-0.663)		
12	d_{12}		0.001			e_{12}		-0.001			f_{12}		227.110		
			(0.332)					(-0.158)					(1.055)		
13	d_{13}		0.001			e_{13}		-0.078**			f_{13}		372.308		
			(0.644)					(-10.387)					(1.744)		
14	d_{14}					e_{14}					f_{14}				
Herding evidence		×	×	×	weak (+,-)		strong (+)	weak (-)	strong (-)	strong (-)		×	strong (+)	strong (+)	×

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, × no evidence of herding

4.4.2.3 More and less informed trades categorized on the basis of their success

Tables 4-8 and 4-9 report the VAR regression results associated with the equations in which, respectively, the net buying positions of more and LI trades (M_T, and L_T), differentiated on the basis of their success, are the dependent variables. Results are presented for all the four time intervals (5, 15, 30 and 60 minutes). The results in relation to the equation with MI trades as the dependent variable (M_T) (shown in Table 4-8) provide strong support for the first part of herding hypothesis, namely that informed trades follow the direction of informed trades in previous periods (i.e., positive-self-herding). Across all time periods many of the coefficients of the lagged net buying positions of informed trades (a_k) are significant and all bar one of these are positive.

The results presented in Table 4-9 provide some evidence that LI trades are correlated with MI trades in previous periods, as for all the time intervals many of the coefficients of the lagged net buying positions of informed trades (d_k) are significant. In fact, the evidence points to a negative relationship between the net buying positions of LI and MI trades. In particular, for two of the time intervals (5- and 15- minutes) the significant coefficients of the lagged net buying positions of MI trades are all negative, for the 30-minute time interval the majority are negative and for the 60-minute time interval there is an equal number of negative and positive coefficients. Overall these results suggest that LI trades do not follow MI trades from previous periods, but act in a contrary direction. In addition, we can see from the causality tests presented in Table 4-10c that the LI trades tend to be influenced by the MI trades in the 30- and 60-minute time intervals.

In order to test the feedback strategy hypothesis, namely that more and LI traders adopt positive and negative feedback strategies, respectively, we examine, the coefficients associated with the lagged returns (c_k and f_k) in the equations with the net buying position of more and LI traders as the dependent variables, respectively (M_T/L_T). The results are displayed in Tables 4-8 and 4-9. There is some evidence of MI traders employing negative feedback strategies, as all bar one of the significant coefficients of the lag return variables in the informed trade equation are negative and for each of the five time intervals examined the majority of the significant coefficients are negative (see Table 4-8). In particular, the coefficients of the one period lag return variables are significant and negative for each of the time intervals. By contrast, there is little evidence that LI traders follow feedback strategies. Across all four time intervals only one of the lag return variables in the equation with LI trader net buying position as the dependent variable is significant (lag 10 for the 30-minute time interval: see Table 4-9).

Table 4-8 VAR regression results across time intervals (more informed trade equations) for traders categorized by successful trades.

Potential herding time interval		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr		5-min	15-min	30-min	1-hr
	a_0	-2.571**	-6.634**	-7.989**	-10.132**										
		(-9.352)	(-7.698)	(-4.223)	(-2.669)										
Lagged period		*MI trader coefficients*					*LI trader coefficients*					*Return coefficients*			
1	a_1	0.033**	0.047**	0.008	-0.004	b_1	-0.025**	-0.041**	-0.118**	-0.147**	c_1	-1083.60**	-2565.90**	-2386.30**	-2584.00*
		(7.587)	(6.188)	(0.761)	(-0.234)		(-4.568)	(-5.427)	(-11.968)	(-11.801)		(-4.148)	(-5.355)	(-3.202)	(-2.306)
2	a_2	0.031**	0.038**	-0.023*	0.013	b_2	0.004	-0.010	-0.080**	-0.011	c_2	-373.504	-725.505	-2008.20**	-745.506
		(7.030)	(4.960)	(-2.120)	(0.853)		(0.708)	(-1.273)	(-8.101)	(-0.888)		(-1.413)	(-1.500)	(-2.666)	(-0.658)
3	a_3	0.012**	-0.014	0.011	0.048**	b_3	-0.015**	-0.130**	-0.031**	0.005	c_3	-468.501	-801.940	671.544	1097.1
		(2.848)	(-1.815)	(1.032)	(3.170)		(-2.728)	(-17.407)	(-3.130)	(0.367)		(-1.770)	(-1.657)	(0.891)	(0.968)
4	a_4	0.006	0.014	0.015	0.032*	b_4	0.002	-0.026**	-0.004	-0.017	c_4	-765.905**	-587.422	37.243	-459.186
		(1.355)	(1.811)	(1.380)	(2.086)		(0.272)	(-3.437)	(-0.425)	(-1.328)		(-2.894)	(-1.214)	(0.050)	(-0.405)
5	a_5	0.040**	-0.010	0.019	0.036*	b_5	-0.001	-0.054**	-0.006	-0.007	c_5	-239.481	-869.248	-51.918	19.876
		(9.075)	(-1.379)	(1.728)	(2.360)		(-0.111)	(-7.148)	(-0.589)	(-0.518)		(-0.905)	(-1.813)	(-0.069)	(0.018)
6	a_6	0.009*		0.021*	0.035*	b_6	0.005		0.014	0.007	c_6	-538.719*		814.608	979.368
		(2.111)		(1.963)	(2.310)		(0.815)		(1.420)	(0.516)		(-2.035)		(1.081)	(0.8641)
7	a_7	0.011*		0.025*	0.005	b_7	-0.003		-0.004	-0.002	c_7	114.181		-133.426	484.462
		(2.460)		(2.301)	(0.353)		(-0.540)		(-0.362)	(-0.188)		(0.431)		(-0.177)	(0.428)
8	a_8	-0.002		0.036**	-0.020	b_8	0.012*		-0.016	0.0002	c_8	-72.680		386.401	33.083
		(-0.449)		(3.345)	(-1.338)		(2.125)		(-1.607)	(0.014)		(-0.275)		(0.513)	(0.030)
9	a_9	-0.005		0.012		b_9	-0.096**		0.004		c_9	-443.094		-316.224	
		(-1.210)		(1.077)			(-17.417)		(0.375)			(-1.674)		(-0.420)	
10	a_{10}	-0.003		0.014		b_{10}	0.009		0.001		c_{10}	-179.885		-174.712	
		(-0.706)		(1.256)			(1.660)		(0.094)			(-0.680)		(-0.232)	
11	a_{11}	0.017**		-0.0004		b_{11}	-0.057**		-0.002		c_{11}	-181.022		-36.691	
		(3.881)		(-0.035)			(-10.301)		(-0.231)			(-0.684)		(-0.049)	
12	a_{12}	-0.0003		0.037**		b_{12}	0.007		-0.002		c_{12}	-270.808		1415.1	
		(-0.068)		(3.342)			(1.181)		(-0.171)			(-1.023)		(1.879)	
13	a_{13}	-0.0004		-0.009		b_{13}	0.006		-0.014		c_{13}	87.882		-916.665	
		(-0.092)		(-0.811)			(1.056)		(-1.429)			(0.332)		(-1.217)	
14	a_{14}	-0.002		0.045**		b_{14}	-0.055**		-0.027**		c_{14}	-76.743		1534.900*	
		(-0.470)		(4.173)			(-9.966)		(-2.721)			(-0.294)		(2.060)	
Herding evidence		strong (+)	strong (+)	weak (+)	strong (+)		weak (-)	strong (-)	strong (-)	strong (-)		strong (-)	strong (-)	weak (-)	strong (-)

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, ✕ no evidence of herding

Table 4-9 VAR regression results across time intervals (less informed trade equations) for traders categorized by successful trades.

Potential herding time interval		5 min	15 min	30 min	1 hr		5 min	15 min	30 min	1 hr		5 min	15 min	30 min	1 hr
	d_{0}	0.469*	1.606	2.436	3.132										
		(2.165)	(1.849)	(1.162)	(0.685)										
Lagged period		*MI trader coefficients*					*LI trader coefficients*					*Return coefficients*			
1	d_{1}	-0.010**	0.005	-0.018	-0.005	e_{1}	0.078**	0.044**	-0.006	0.004	f_{1}	-35.275	-943.574	-975.680	-2469.000
		(-2.960)	(0.686)	(-1.488)	(-0.248)		(17.906)	(5.800)	(-0.553)	(0.292)		(-0.171)	(-1.954)	(-1.181)	(-1.828)
2	d_{2}	0.004	-0.016*	0.005	0.011	e_{2}	-0.007	0.030**	-0.027*	-0.017	f_{2}	-32.986	246.465	145.723	2649.4
		(1.021)	(-2.070)	(0.442)	(0.608)		(-1.543)	-3.907	(-2.443)	(-1.143)		(-0.158)	(0.505)	(0.175)	(1.940)
3	d_{3}	-0.005	-0.005	0.022	-0.037*	e_{3}	0.013**	-0.097**	-0.0001	0.024	f_{3}	109.415	-471.172	512.119	1319.1
		(-1.531)	(-0.705)	(1.794)	(-2.004)		(3.037)	(-12.843)	(-0.011)	(1.580)		(0.525)	(-0.966)	(0.613)	(0.966)
4	d_{4}	-0.0002	-0.002	-0.015	-0.031	e_{4}	0.003	0.006	0.001	-0.022	f_{4}	-336.233	-62.053	644.671	-197.690
		(-0.068)	(-0.204)	(-1.213)	(-1.691)		(0.585)	(0.822)	(0.109)	(-1.460)		(-1.612)	(-0.127)	(0.772)	(-0.145)
5	d_{5}	-0.002	-0.006	-0.021	-0.120**	e_{5}	0.002	-0.014	-0.0031	-0.021	f_{5}	-113.645	914.552	42.885	-2257.5
		(-0.563)	(-0.758)	(-1.703)	(-6.561)		(0.555)	(-1.803)	(-0.287)	(-1.355)		(-0.545)	(1.892)	(0.051)	(-1.653)
6	d_{6}	0.002		-0.006	0.042*	e_{6}	0.002		-0.003	-0.012	f_{6}	321.513		948.393	-550.293
		(0.461)		(-0.494)	(2.273)		(0.482)		(-0.295)	(-0.772)		(1.541)		(1.136)	(-0.403)
7	d_{7}	-0.004		-0.001	-0.023	e_{7}	0.004		-0.008	0.011	f_{7}	-97.559		644.762	-545.493
		(-1.222)		(-0.091)	(-1.226)		(0.832)		(-0.716)	(0.750)		(-0.468)		(0.772)	(-0.394)
8	d_{8}	-0.002		-0.041**	0.063**	e_{8}	0.011*		-0.008	-0.056**	f_{8}	-9.335		707.302	2398.7
		(-0.453)		(-3.420)	(3.462)		(2.428)		(-0.739)	(-3.713)		(-0.045)		(0.847)	(1.776)
9	d_{9}	-0.007*		-0.005		e_{9}	-0.095**		-0.004		f_{9}	120.008		57.393	
		(-2.084)		(-0.417)			(-21.885)		(-0.361)			(0.575)		(0.069)	
10	d_{10}	0.006		-0.023		e_{10}	0.019**		-0.008		f_{10}	-132.844		189.657	
		(1.801)		(-1.904)			(4.414)		(-0.688)			(-0.637)		(0.227)	
11	d_{11}	-0.002		-0.097**		e_{11}	-0.003		-0.026*		f_{11}	191.435		-2023.600*	
		(-0.472)		(-7.985)			(-0.606)		(-2.379)			(0.918)		(-2.424)	
12	d_{12}	-0.0003		0.049**		e_{12}	0.001		-0.019		f_{12}	29.082		451.735	
		(-0.093)		(4.020)			(0.290)		(-1.735)			(0.139)		(0.541)	
13	d_{13}	-0.0008		-0.018		e_{13}	0.005		-0.013		f_{13}	-72.837		-942.150	
		(-0.238)		(-1.514)			(1.126)		(-1.149)			(-0.350)		(-1.129)	
14	d_{14}	0.003		0.007		e_{14}	-0.0000		-0.001		f_{14}	258.526		-351.931	
		(0.959)		(0.563)			(-0.009)		(-0.058)			(1.257)		(-0.426)	
Herding evidence		strong (-)	strong (-)	weak (-)	weak (+,-)		weak (+)	weak (+)	strong (-)	strong (-)		×	×	strong (-)	×

* Statistically significant at the 5 percent level, ** Statistically significant at the 1 percent level, × no evidence of herding

Table 4-10 Results of causality tests, in terms of the herding strategies of more/less informed traders, categorized by stake size, account profitability and successful trade, for time intervals 5, 15, 30 and 60 minutes.

a. Outcome of Causality Test *(MI/LI traders defined by stake size)*					
Time interval	No. of lag	(1) LI influence MI	(2) MI influence LI	(3) LI influence MI/MI influence LI	(4) No clear influences
5 min	10			**/**	
15 min	6			**/**	
30 min	14			**/*	
1 hour	6			**/*	
b. Outcome of Causality Test *(MI/LI traders defined by account profitability)*					
Time interval	No. of lag	(1) LI influence MI	(2) MI influence LI	(3) LI influence MI/MI influence LI	(4) No clear influences
5 min	1				●
15 min	13	**			
30 min	5	**			
1 hour	5			**/**	
c. Outcome of Causality Test *(MI/LI trades defined by successful trade)*					
Time interval	No. of lag	(1) LI influence MI	(2) MI influence LI	(3) LI influence MI/MI influence LI	(4) No clear influences
5 min	14	**			
15 min	5	**			
30 min	14			**/**	
1 hour	8			**/**	

* indicates significant at 5 percent level,** indicates significant at 1 percent level, ● not significant, MI – MI traders, LI – LI traders

4.4.3 Overall results on behavior and information

In summary, the results of examining herding behavior amongst more and LI traders, defined in various ways, are consistent in several respects, but they do contain some important differences. The picture to emerge is, as we expected, of positive self-herding amongst MI traders. However, it is only when we equate informed trades with successful trades that we find that informed trades mimic informed trades in preceding periods. When we distinguish MI traders on the basis of stake size or the profitability of their account we find evidence of contrary-self-herding.

We find some evidence that LI traders positive-cross-herd with MI traders when we distinguish MI traders on the basis of their median stake size and to a lesser extent when they are distinguished by account profitability. However, there is evidence that they act in a contrary fashion to MI traders when we equate MI traders with successful trades.

Whichever means we employ to distinguish more and LI traders, we find evidence that MI traders follow negative feedback strategies, although this evidence is weak when we distinguish traders on the basis of account profitability. On the other hand, we find little evidence that LI traders follow feedback strategies, other than when we distinguish LI traders on the basis of the median stake size (when we find evidence that they follow negative feedback strategies).

What is clear from these results is that to fully understand the herding behavior of more and LI traders it is important to select the most appropriate means of distinguishing these groups of traders. We suggest that separating traders based on account profitability and on the basis of successful trades are the most likely to appropriately separate more and LI traders, even though previous studies largely rely on size of investment. This is highlighted by the fact that there is no significant difference in the mean account profitability of traders defined as more and LI on the basis of their median stake size. Using account profitability and/or the success of a trade as a basis for distinguishing more and LI traders we find consistent evidence for MI traders following negative feedback strategies but no evidence that LI traders follow feedback strategies. We also find strong evidence that MI traders engage in self-herding (although the direction of this herding depends upon the criteria employed for distinguishing more and LI traders). Furthermore there is evidence that LI traders herd on the basis of the actions of MI traders in earlier periods, although this evidence is much stronger when we distinguish MI traders on the basis of the success of a given trade.

One consistent finding that emerges is that herding is far more commonplace amongst more and LI spread traders than might have been thought to be the case based on previous studies. This might be explained by the recent growth of electronic trading and the expansion of internet-based, trader bulletin boards, which enable traders to readily share information. Falkenstein (1996) argues that herding by investors in mutual funds may happen due to preference towards specific types of stock. This is also likely to occur in our case, especially as we focus only on trading in the FTSE 100. In addition, Lakonishok,Shleifer and Vishny (1992) and Wermers (1999) argue that herding is most likely to occur in short-term trading strategies and these are the very strategies employed by most spread traders.

Our finding that MI traders follow the actions of other MI traders from previous periods (and in the same direction, if we distinguish more and LI traders on the basis of a successful/unsuccessful trade) is consistent with the findings of Nofsinger and Sias (1999) and Jeon and Moffett (2010). Our findings also support Menkhoff and Schmeling (2010) suggestion that LI traders are likely to react to the trading of those they perceive to be better-informed. However, based on what we regard as the most reliable means of classifying more and LI traders (i.e., based on a successful trade), we find that they act in a contrary fashion to the actions of MI traders in previous periods.

Our results do not support Kim and Wei (1999) conclusion that informed traders employ positive feedback strategies. In fact, we found that MI traders, categorized by any of the three criteria we employed, tend to employ negative feedback strategies. Our results also lead us to conclude that LI traders do not employ any form of feedback strategy. This conclusion emerges because we only find evidence of them employing feedback strategies when we categorize LI on what we regard as an unreliable basis (i.e., stake size).

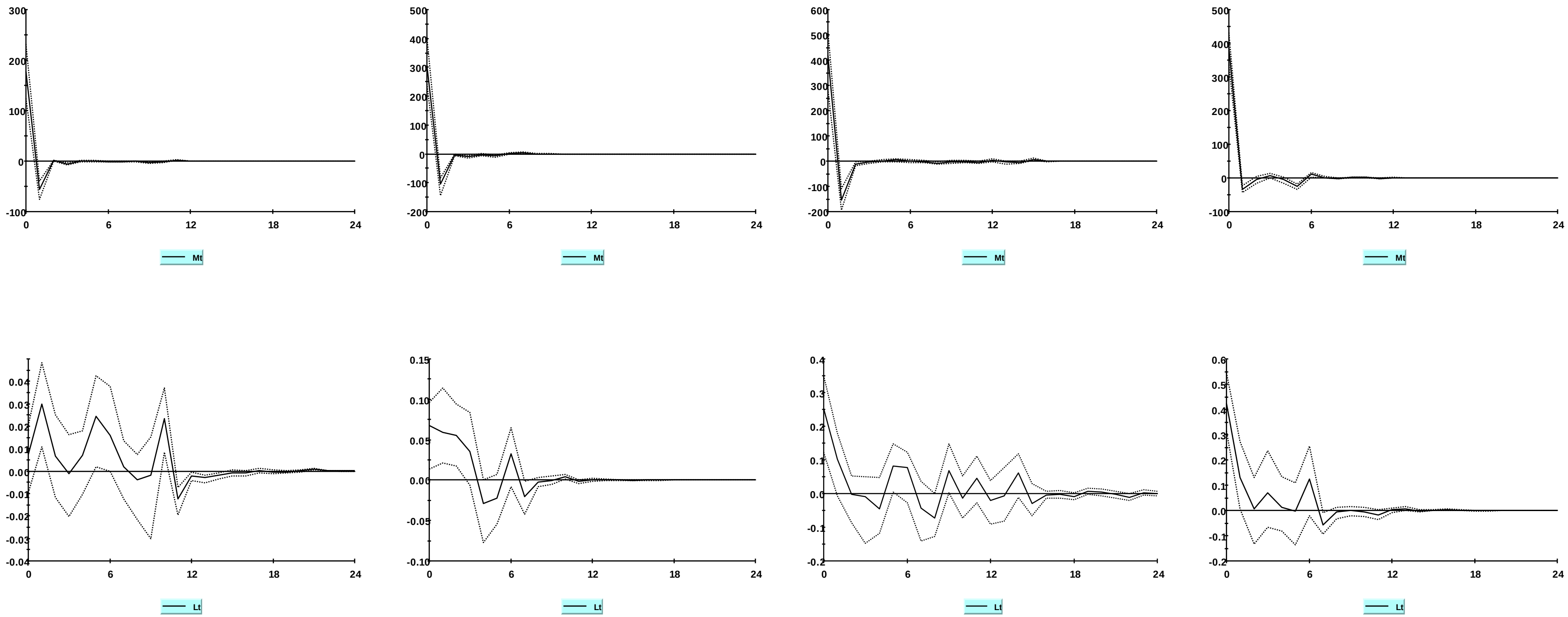
Overall, we find that spread traders engage in more herding than that anticipated based on previous studies conducted in traditional financial markets. In addition, the manner in which more and LI spread traders herd is not always in line with what previous research in traditional markets would suggest. We are tempted to conclude that this might be explained in terms of the more appropriate means of distinguishing more and LI traders, which our data enables us to employ. Worryingly, our results suggest that spread traders may act in a manner very different to those normally operating in traditional financial markets. Given the close connection between the fast growing spread trading markets and the markets on which they are based (via the hedging decisions of spread trading companies), it is important that regulators and market participants are aware of the impact the actions of spread traders may have on these underlying markets.

4.4.4 Differential speed of adjustments to sudden shifts in trading by more and less informed traders

We next test the shocks response hypothesis, namely, that MI traders generally respond quicker than LI traders to a sudden change in trading by more or LI traders. We achieve this by conducting impulse response analysis and examining the generalized impulse response functions. We present the generalized impulse response functions for MI traders' net buying positions and LI traders' net buying positions resulting from a one-standard deviation shift in, respectively, the more and the LI traders' net buying positions, for different time intervals. These generalized impulse response functions for more and LI traders, distinguished by the three criteria employed earlier (i.e., stake size, account profitability and success of a trade), are displayed in Figure 4-2, 4-3, and 4-4, respectively.

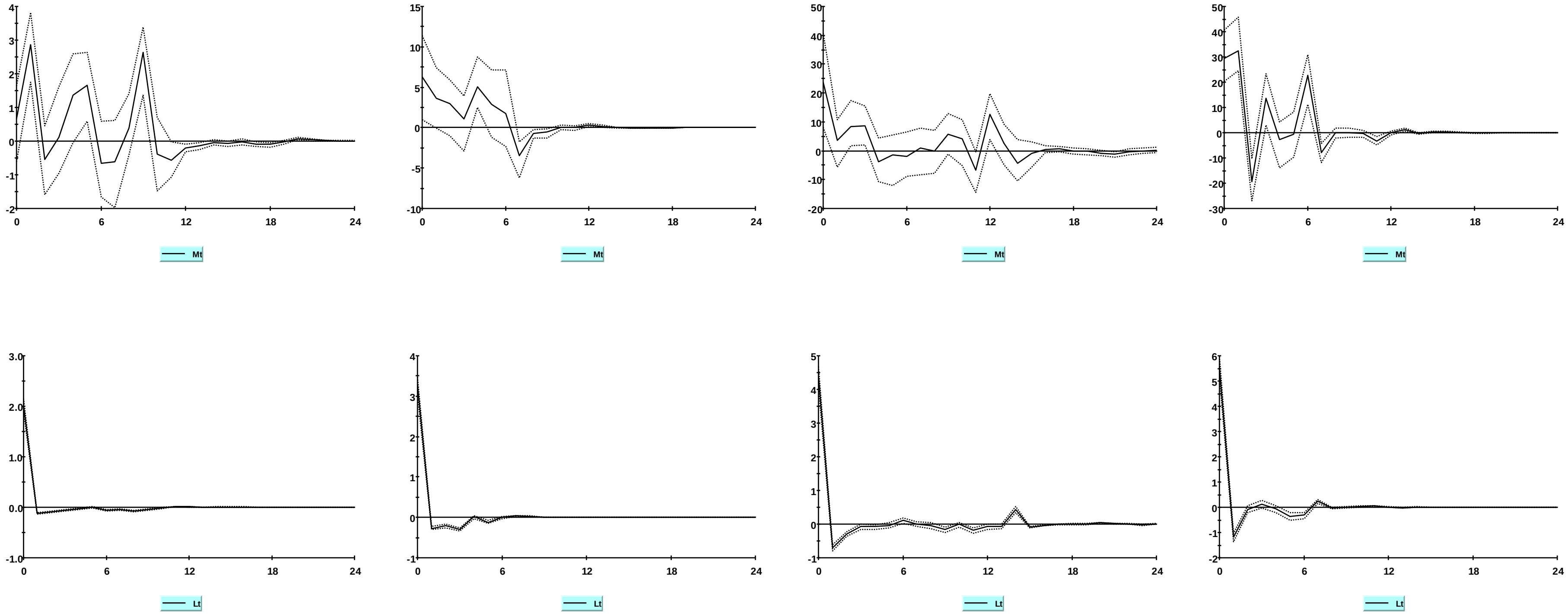
Figure 4-2a and 4-2b show how the net buying of more and LI traders (distinguished by stake size), in a specified time interval (i.e., 5, 15, 30 and 60 minutes), respond to a one-standard deviation shock to the net buying of, respectively, the more and LI traders. The unbroken lines in these graphs represent the net buying positions of LI/MI traders while the dotted lines show the bootstrap error bounds (i.e., a 95 percent confidence interval). It is not clear from Figure 4-2a and 4-2b that MI traders respond more quickly (than LI traders) to sudden shifts in the net buying of more or LI traders, across the time intervals examined. A similar conclusion is reached when examining Figure 4-3 and 4-4. In other words, whichever of the three means we employ to distinguish more and LI traders, our results lead us to conclude that there is no obvious difference in terms of the response of more and LI traders to shifts in trading. Our findings, across a wider range of time intervals and using a variety of means of distinguishing MI/LI traders, contradict those of Lee,Lin and Liu (1999) and Lee,Li and Wang (2010) that a sudden change of trading is responded to more slowly by LI traders.

Figure 4-2 Impulse response from shocks induced by shifts in the net buying of more and less informed traders distinguished by stake size (solid lines on graph) with 95% bootstrap error bounds (dashed lines), at 5-minute, 15-minute, 30-minute, and 60-minute time intervals.



5 min 15 min 30 min 60 min

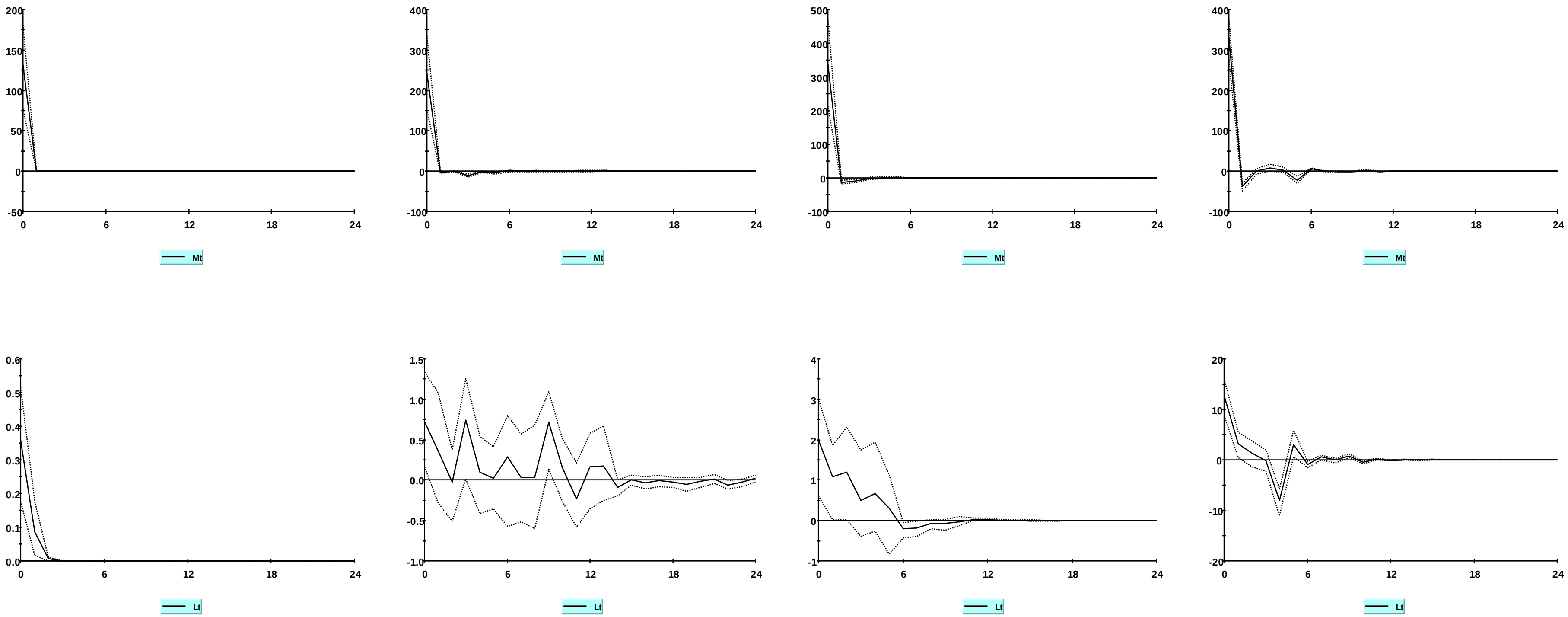
Figure 4-2a Impulse response from a shock induced by shifts in the net buying of MI traders.



5 min 15 min 30 min 60 min

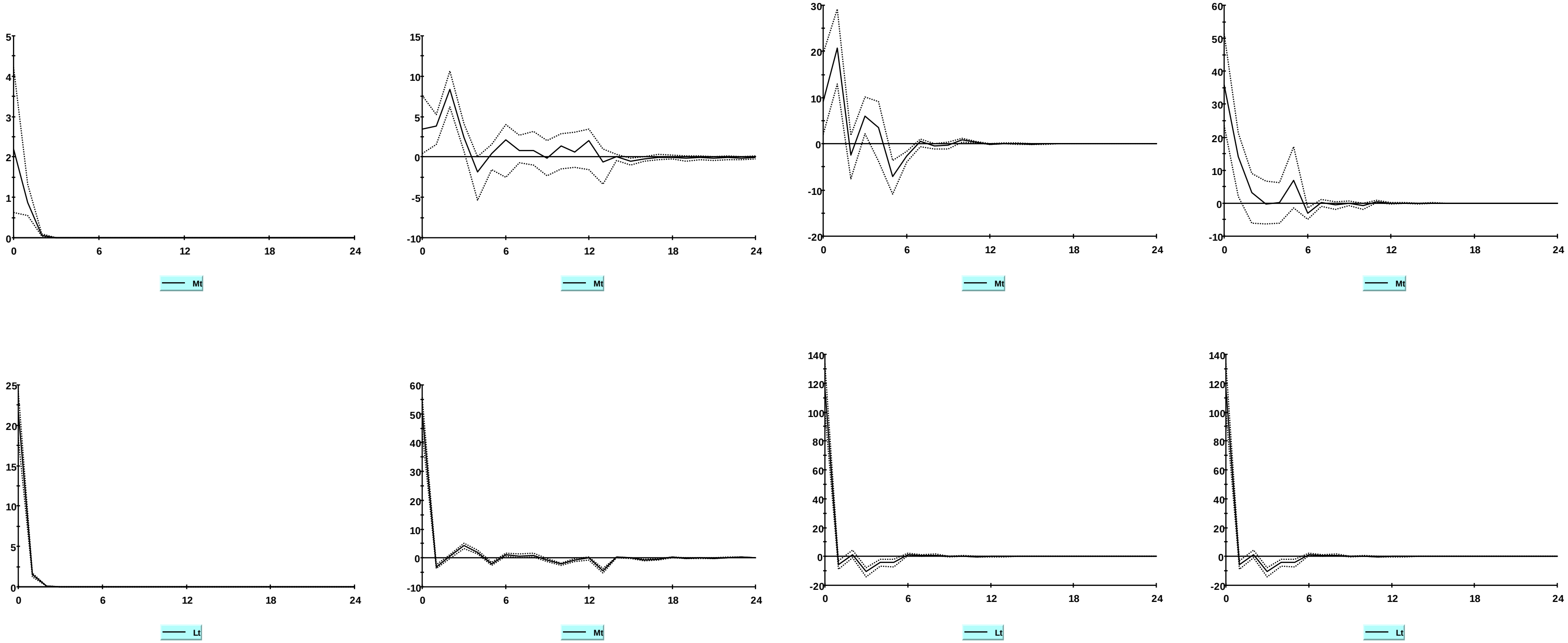
Figure 4-2b Impulse response from a shock induced by shifts in the net buying of LI traders.

Figure 4-3 Impulse response from shocks induced by shifts in the net buying of more and less informed traders, distinguished by account profitability (solid lines on graph) with 95% bootstrap error bounds (dashed lines), at 5-minute, 15-minute, 30-minute, and 60-minute time intervals.



5 min 15 min 30 min 60 min

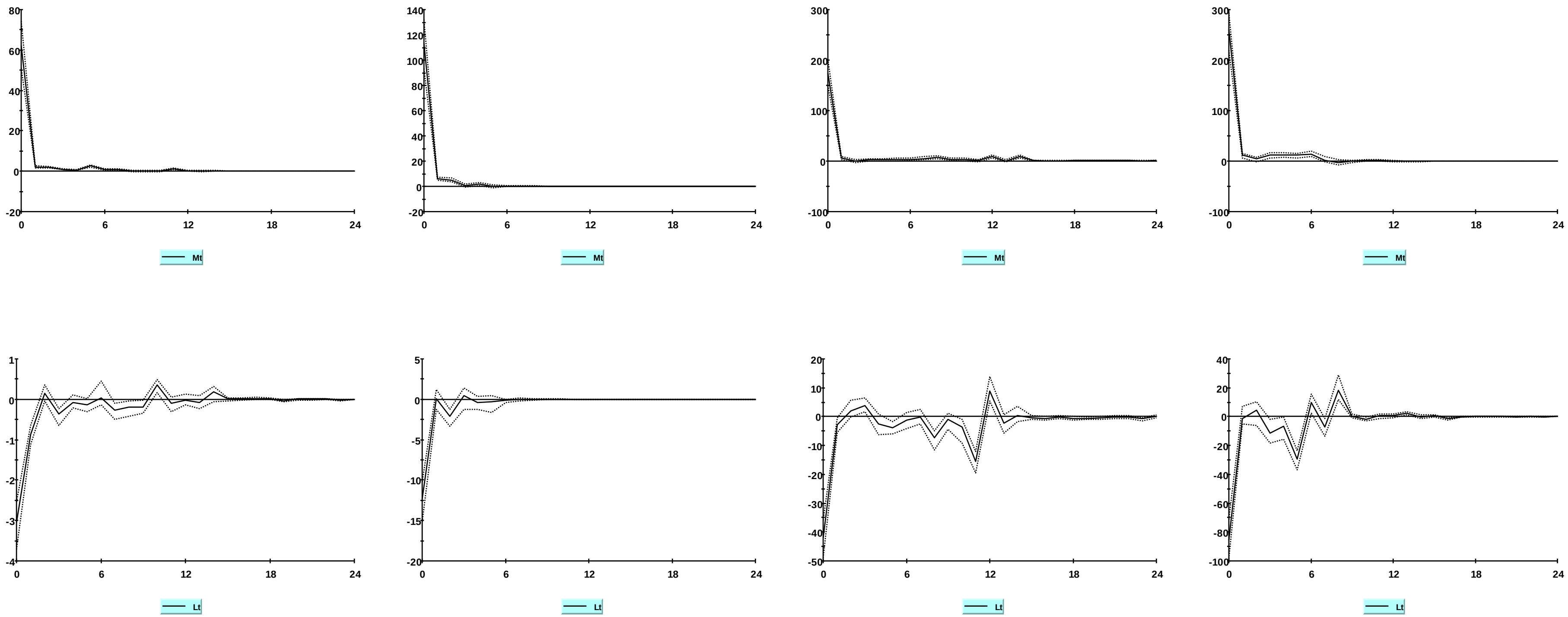
Figure 4-3a Impulse response from a shock induced by shifts in the net buying of MI traders.



5 min 15 min 30 min 60 min

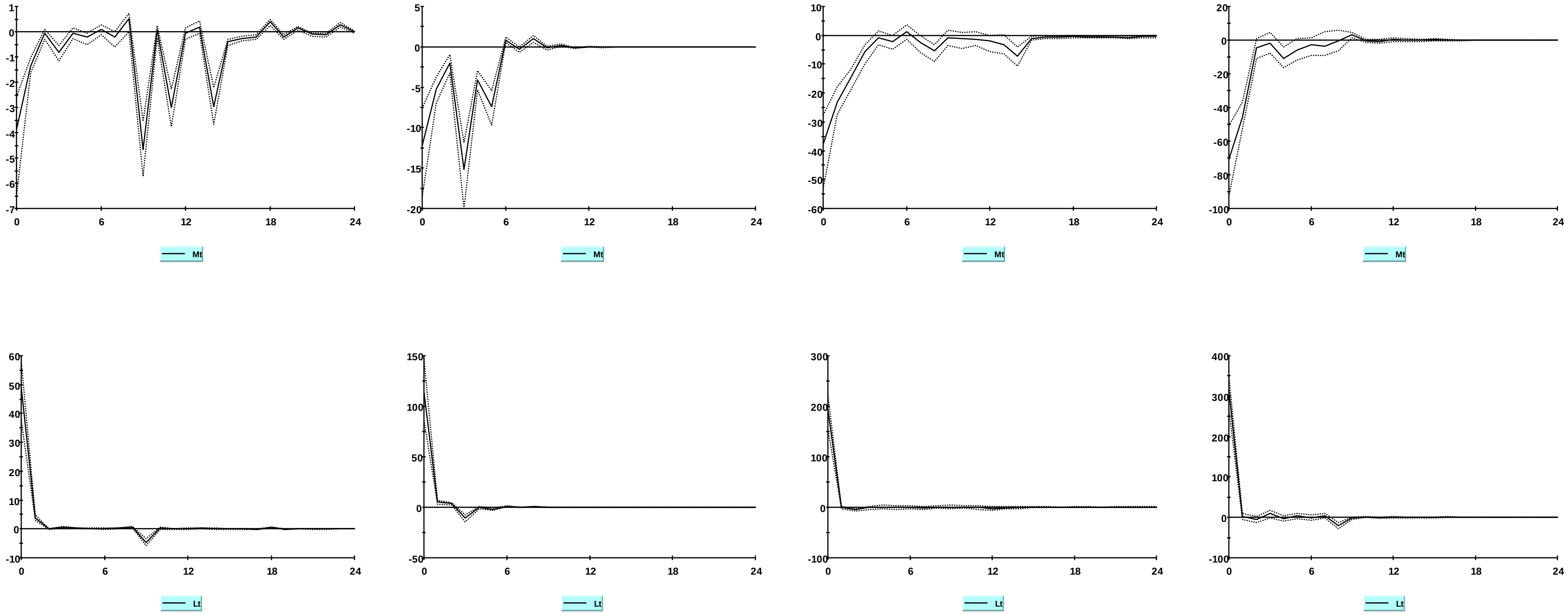
Figure 4-3b Impulse response from a shock induced by shifts in the net buying of LI traders.

Figure 4-4 Impulse response from shocks induced by shifts in the net buying of more and less informed traders, distinguished by a successful trade (solid lines on graph) with 95% bootstrap error bounds (dashed lines), at 5-minute, 15-minute, 30-minute, and 60-minute time intervals.



5 min 15 min 30 min 60 min

Figure 4-4a Impulse response from a shock induced by shifts in the net buying of MI traders.



5 min 15 min 30 min 60 min

Figure 4-4b Impulse response from a shock induced by shifts in the net buying of LI traders.

4.5 Conclusion

This chapter investigates herding and feedback strategies during different short time intervals in a financial spread-trading market. The motivation for the study lies in the growing interest in market microstructure theory, high frequency data analysis, and in behavior in speculative financial markets (particularly, the degree, nature, and patterns of herding within the rapidly growing spread trading markets). Spread trading markets are inextricably linked to the underlying stock and currency markets via the hedging activities of spread-trading companies. Consequently, behavior within spread trading markets can spill over into the underlying markets. In addition, spread trading markets open up trading to a wider cross section of the public and traders in these markets generally speculate over short time horizons. As a result it is possible that they may be more prone to herding than investors in traditional markets have been in the past. This is likely to have an increasing effect on the underlying markets as spread trading markets gain in popularity.

Our results suggest that herding is a prevalent phenomenon in spread trading markets amongst both more and LI traders. We unearth more evidence of herding than that expected on the basis of studies conducted in traditional financial markets. This may have arisen because there is simply more herding amongst spread traders than those who are active in traditional financial markets. However, we suspect that herding in more traditional markets may have been under-estimated. In particular, most existing studies exploring herding behavior focus on trading activity in a fixed time interval across different products (Chang,Cheng and Khorana, 2000, Zhou and Lai, 2007). We believe that the degree of herding which occurs in the market may be masked by only examining one time interval and our results confirm this view. For example, from Table 4-6 we can see that by only examining the degree of herding by MI traders (defined by their account profitability) on the actions of MI traders in the previous 5-minute time intervals, we would conclude that no such self-herding was taking place. However, for all the other time intervals we have examined (15-, 30- and 60-minutes) there is clear evidence of self-herding. In addition, we believe that by examining herding across a number of different assets, previous studies may have underestimated the degree of herding which takes place in a single asset. In particular, where these studies find no evidence of herding, this may have a risen as result of herding in a positive direction for several assets and herding in an opposite direction for other assets. As a result, when examining herding across all of these assets together the true effects of herding may be masked.

Our findings also add to the growing market micro structure literature (e.g., De Long *et al.*, 1990, Shleifer and Summers, 1990) by providing new insights into the manner in which the trading of more and LI traders interacts and the manner in which these groups employ feedback strategies. As expected, we find evidence of self-herding amongst MI traders. However, it is only when we equate informed trades with successful trades that informed trades are demonstrated to mimic (rather than to take a contrary position to) informed trades in preceding periods. We also find evidence that LI traders cross-herd with MI traders. However, the manner in which they cross-herd (i.e., mimic or act in a contrary fashion) depends on the manner in which we distinguish more and LI traders. We find strong evidence that MI traders follow negative feedback strategies, although this evidence is weak when we distinguish traders on the basis of account profitability. By contrast, we find little evidence that LI traders follow feedback strategies. We also find no obvious differences in the responses of more and LI traders to shocks generated by shifts in the net buying activities of more and LI traders.

It is clear from our results that to fully understand the herding behavior of more and LI traders it is important to select the most appropriate means of distinguishing these groups of traders. Previous research exploring the differential trading activities of more and LI traders has employed the size of investment as a criterion to distinguish these two groups of investors. This approach has been applied in studies examining a range of financial markets (Lee,Lin and Liu, 1999, Moore and Payne, 2009). However, our results suggest that this approach may not be appropriate, at least for the market we investigate. This can be seen from the fact that there is no significant difference between the profitability of the accounts of traders in the more and LI groups when these are distinguished by stake size. One would expect MI traders to be able to capitalize on their enhanced knowledge/ability to earn higher profits. In addition, it is likely that more and LI traders employ different feedback strategies, yet we find no difference in their feedback strategies if we simply distinguish them by the size of their stakes. Consequently, we come to the view that distinguishing more and LI traders on the basis of their stake size may fail to adequately explain the inter-play of their trading activities and the manner in which they herd, at least in the spread-trading market.

In conclusion, the results of this study provide clear evidence of the systematic herding which takes place in spread trading markets. Given the size and rapid growth of these markets and their links (via the hedging activities of spread trading companies) to the underlying markets, these findings have potentially important implications concerning the future efficiency of the underlying financial markets. In addition, we believe the findings also have value for informing the manner in which herding studies are conducted in wider financial markets. In particular, we believe that our study suggests that herding may be found to be more prevalent in these markets amongst individual assets and more herding may be unearthed if a variety of time intervals were examined. In addition, our study highlights how important it is to consider carefully the manner in which more and LI traders are distinguished.

We hope that future studies in wider financial markets will examine herding and feedback strategies taking into account the concerns expressed above. Further studies are encouraged to check the robustness of our findings in other trading platforms. Whilst we focus on the intraday trading patterns, these may be different across daily or longer time periods. It is our belief that if further research is conducted in this manner, it may be found that herding is far more widespread than has previously been thought and we may come to a deeper understanding of the manner in which trading takes place in financial markets.

Chapter 5: Conclusion

This chapter briefly summarizes the major findings of each of the three papers in this thesis, and identifies the contributions and implications of each. In addition, the links between the papers are established, and the overall research contribution is highlighted.

The research objective of this body of work was to investigate to what extent and why individual traders' decisions are affected by specific heuristics and biases and the effect these may have on the operation of financial markets. This is achieved by focusing on different types of decision made by individual traders. The thesis sets out to explore the extent to which the biases displayed may affect the efficiency of markets in specific settings.

The first paper of the thesis focused on examining the extent to which behavioral factors influence the escalation of risk-taking, in terms of the decision of what funds to commit to already existing positions. Previous financial market studies have narrowly focused on the impact of past decisions regarding the size of previous losses or gains on future decisions. However, this paper makes three important contributions: First, it identifies the impact of different types of losses on escalation of risk-taking, specifically, the size of previous realized and unrealized losses and the number of consecutive losses experienced. Second, the impact of previous losses on the degree of escalation of risk-taking by more and less informed traders is examined. Third, this is the first study to examine escalation of risk-taking amongst traders in rapidly growing spread-trading markets. The paper uses a unique dataset of decisions associated with trading on FTSE 100 index futures by individual traders and employs a series of linear mixed model regressions to take account of individual differences in behavior which might exist. The results suggest that escalation in risk-taking in the form of averaging-in is indeed influenced by past losses. In particular, both realized and unrealized losses lead traders to escalate their risk-taking and the larger these losses the greater the effect. In addition, unrealized losses have a greater impact on the escalation of risk-taking. It is apparent that realized losses which are perceived as significant to the trader are those which cause the escalation because, for example, it is only large individual losses or *long* (cf. short) losing streaks which lead to this escalation. In addition, I find that that more and less informed traders respond differently to previous losses. In particular, less informed traders escalate their risk-taking to a greater extent than more informed traders following all types of significant losses. Consequently, these findings demonstrate that irrationality is present at this stage of traders' decision-making and this irrationality may be seen as threat to financial market efficiency and stability.

The second paper of this thesis focuses on examining to what extent traders act in a manner consistent with the hedonic editing hypothesis when realizing their positions. The paper makes two major contributions: First, the study attempts to explain why some previous empirical studies may have found behavior which deviated from that predicted by the HEH and others found results in line with the HEH. This was achieved by suggesting that crucial psychological factors, namely, the cognitive cost of segregation and cognitive dissonance, need to be considered when examining the behavior of real world traders. Second, this is the first study to provide an insight into the degree to which individuals in the fast growing spread-trading market are subject to the HEH. Trading data related to the FTSE 100 index is analyzed using multilevel logistic regressions. The data is analyzed on a trade-by-trade basis, which ensures that the circumstances facing the traders at the time of their integration/segregation decision are the only ones considered. The results demonstrate that traders do not behave in a manner consistent with the HEH, rather they behave in a manner which is consistent with them being affected by the cognitive cost of segregation and cognitive dissonance. In addition, the results make it clear that less (cf. more) informed traders are those most susceptible of these psychological biases. In summary, the research delivers clear evidence of irrationality (in terms of being subject to psychological factors related to the cognitive cost of segregation and cognitive dissonance) on the part of real world traders, particularly less informed traders, at the stage of realizing positions.

The third paper of the thesis focuses on the extent to which spread traders are subject to herding behavior and it makes four important contributions: First, the study overcomes the limitations of earlier studies which may have led to the degree of herding being under-estimated or masked. This is achieved by examining herding in a single asset across a variety of time intervals. Second, differences in the degree, nature, and patterns of herding are identified. Third, this is the first paper to examine herding amongst traders in the fast growing spread-trading market. Fourth, I determine differences in the degree and nature of herding amongst more and less informed traders and contrast the results when these groups are distinguished in the manner usually employed with, what I regard, as a more appropriate means of distinguishing these two groups. The paper employs high frequency spread-trading data associated with trades in FTSE 100 index. This is analyzed using Vector Autoregression model. The results indicate that spread traders, in particular the less informed, have a tendency to herding activity and that there are differences in the patterns of herding amongst more and less informed traders and in the manner in which more and less informed traders react to the herding of other more or less informed traders. There are also differences in the manner in which more and less informed traders react to the herding of other more or less informed traders. Additionally, the findings show no obvious difference between these two groups in terms of their responses to sudden trading shifts of informed and less informed traders. Finally, the results suggest that selecting the appropriate means of distinguishing the more and less informed groups of traders is crucial as the results reveal that the degree and nature of herding varies depending upon the definitions. In summary, the research provides clear evidence of systematic herding which could pose a serious threat to market efficiency.

Overall, the results of the three studies presented here provide valuable insights into investor psychology in general and the factors associated with irrational investor behaviors in a real-world setting. In addition, knowledge of spread traders' behavior can lead to better hedging decisions by spread-trading brokerage firms and, in addition, via education, may help spread traders adopt more rational trading strategies. The findings may also motivate the financial market regulators to devise new regulations to prevent financial markets being damaged by the irrational behavior identified here. In addition, by finding contrasting findings to those observed in laboratory based studies, this work may help stimulate further empirical research in the environments where the real decisions are made. Finally, the findings also add to the growing market micro structure literature by providing new insights into the manner in which the trading of more and less informed traders are subjected to the irrationalities, and the interactions between the groups.

In conclusion, this thesis has investigated the two important concerns which can threaten market efficiency: First, that investors make irrational decisions, and second that they have a tendency to be subjected to correlated errors. Exploring three different aspects of traders' decision making, this thesis has revealed that traders systematically make irrational decisions. In particular, they escalate their risk-taking in the face of significant losses and that their decisions are influenced by psychological factors (e.g., cognitive cost of segregation and cognitive dissonance). In addition, the results of this work suggest that the impact of these correlated errors caused by irrationality is likely to be magnified via herding behavior. Finally, in the hope that a deeper understanding of trading decisions/patterns in wider financial markets can be developed, future studies are encouraged to investigate the robustness of the studies presented this thesis in wider financial markets.

Appendix: VAR lag order selection criteria

VAR lag order selection criteria for more/less informed traders categorized by stake size.

5 minute time interval

Lag	AIC	SIC	HQIC
0	17.54477	17.54511	17.54487
1	17.45727	17.45828	17.45759
2	17.44990	17.45158	17.45043
3	17.44670	17.44906	17.44744
4	17.44594	17.44898	17.44689
5	17.44580	17.44950	17.44695
6	17.44496	17.44934	17.44633
7	17.44453	17.44958	17.44611
8	17.44317	17.44890	17.44496
9	17.44192	17.44833	17.44392
10	17.44102	17.44810*	17.44323*
11	17.44098	17.44874	17.44341
12	17.44102	17.44945	17.44365
13	17.44095	17.45005	17.44379
14	17.44073	17.45050	17.44378
15	17.44065*	17.45110	17.44392

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

15 minute time interval

Lag	AIC	SIC	HQIC
0	19.63448	19.63536	19.63477
1	19.53599	19.53863	19.53686
2	19.52356	19.52797	19.52501
3	19.51047	19.51664	19.51250
4	19.50944	19.51737	19.51205
5	19.50520	19.51490*	19.50839
6	19.50414	19.51560	19.50791*
7	19.50387	19.51710	19.50822
8	19.50372*	19.51871	19.50865
9	19.50401	19.52077	19.50953
10	19.50413	19.52265	19.51023
11	19.50437	19.52465	19.51104
12	19.50377	19.52582	19.51103
13	19.50395	19.52776	19.51179
14	19.50414	19.52972	19.51256
15	19.50451	19.53185	19.51351

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

Appendix

30 minute time interval

Lag	AIC	SIC	HQIC
0	20.88251	20.88410	20.88305
1	20.75786	20.76265	20.75949
2	20.73284	20.74082	20.73556
3	20.72643	20.73759*	20.73023
4	20.72506	20.73942	20.72995
5	20.72500	20.74255	20.73097
6	20.72494	20.74569	20.73201
7	20.72569	20.74962	20.73384
8	20.72599	20.75311	20.73522
9	20.72552	20.75583	20.73584
10	20.72600	20.75950	20.73741
11	20.72424	20.76094	20.73674
12	20.72273	20.76262	20.73631
13	20.72052	20.76360	20.73519
14	20.71397	20.76024	20.72973*
15	20.71390*	20.76336	20.73074

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

60 minute time interval

Lag	AIC	SIC	HQIC
0	21.09468	21.09739	21.09563
1	21.03763	21.04577*	21.04049
2	21.03431	21.04787	21.03907
3	21.03482	21.05381	21.04149
4	21.03629	21.06070	21.04487
5	21.03134	21.06118	21.04182
6	21.01782	21.05308	21.03021*
7	21.01771	21.05841	21.03201
8	21.01692	21.06304	21.03312
9	21.01724	21.06878	21.03534
10	21.01774	21.07470	21.03775
11	21.01614	21.07854	21.03806
12	21.01453	21.08235	21.03836
13	21.01022	21.08347	21.03596
14	21.00601	21.08468	21.03365
15	21.00487*	21.08897	21.03442

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

VAR lag order selection criteria for more/less informed traders categorized by account profitability.

5 minute time interval

Lag	AIC	SIC	HQIC
0	21.59636	21.59703	21.59657
1	21.59173	21.59307*	21.59215*
2	21.59170	21.59372	21.59233
3	21.59169	21.59439	21.59254
4	21.59151	21.59487	21.59256
5	21.59133	21.59536	21.59259
6	21.59140	21.59611	21.59287
7	21.59138	21.59676	21.59306
8	21.59137	21.59742	21.59326
9	21.59101*	21.59774	21.59311
10	21.59109	21.59849	21.59340
11	21.59116	21.59924	21.59369
12	21.59129	21.60004	21.59403
13	21.59143	21.60085	21.59437
14	21.59149	21.60159	21.59465
15	21.59163	21.60240	21.59500

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

15 minute time interval

Lag	AIC	SIC	HQIC
0	24.52858	24.53122	24.52945
1	24.52522	24.52963	24.52667
2	24.52448	24.53064	24.52651
3	24.51559	24.52351	24.51820
4	24.51291	24.52260*	24.51610
5	24.51171	24.52315	24.51547
6	24.51203	24.52524	24.51638
7	24.51245	24.52742	24.51738
8	24.51221	24.52894	24.51772
9	24.51242	24.53091	24.51851
10	24.50986	24.53011	24.51652
11	24.50974	24.53175	24.51698
12	24.51004	24.53381	24.51786
13	24.50436*	24.52989	24.51276*
14	24.50456	24.53185	24.51354
15	24.50474	24.53380	24.51431

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

Appendix

30 minute time interval

Lag	AIC	SIC	HQIC
0	25.97384	25.97544	25.97439
1	25.96918	25.97396	25.97081
2	25.96862	25.97659	25.97134
3	25.96867	25.97982	25.97246
4	25.96927	25.98361	25.97415
5	25.95426	25.97178*	25.96022*
6	25.95346	25.97417	25.96051
7	25.95319	25.97709	25.96133
8	25.95337	25.98046	25.96259
9	25.95295	25.98322	25.96326
10	25.95300	25.98645	25.96439
11	25.95315	25.98979	25.96562
12	25.95329	25.99312	25.96685
13	25.95341	25.99642	25.96805
14	25.95130	25.99750	25.96703
15	25.95120*	26.00058	25.96801

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

60 minute time interval

Lag	AIC	SIC	HQIC
0	26.83861	26.84132	26.83957
1	26.82073	26.82886*	26.82359
2	26.82151	26.83506	26.82627
3	26.81442	26.83338	26.82108
4	26.80872	26.83310	26.81729
5	26.80394	26.83373	26.81441*
6	26.80514	26.84035	26.81751
7	26.80359	26.84422	26.81786
8	26.80064	26.84669	26.81682
9	26.79890	26.85036	26.81698
10	26.79728	26.85416	26.81726
11	26.79760	26.85990	26.81948
12	26.79481	26.86253	26.81860
13	26.79524	26.86837	26.82093
14	26.79445	26.87300	26.82204
15	26.79347*	26.87744	26.82297

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

VAR lag order selection criteria for more/less informed traders categorized by successful trades.

5 minute time interval

Lag	AIC	SIC	HQIC
0	21.75449	21.75483	21.75459
1	21.74700	21.74801	21.74732
2	21.74566	21.74734	21.74619
3	21.74515	21.74750	21.74588
4	21.74523	21.74826	21.74617
5	21.74339	21.74709	21.74455
6	21.74340	21.74777	21.74476
7	21.74338	21.74842	21.74495
8	21.74350	21.74922	21.74529
9	21.72823	21.73462	21.73023
10	21.72795	21.73501	21.73016
11	21.72563	21.73337*	21.72805
12	21.72575	21.73416	21.72838
13	21.72587	21.73496	21.72871
14	21.72413*	21.73389	21.72718*
15	21.72423	21.73466	21.72749

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

15 minute time interval

Lag	AIC	SIC	HQIC
0	24.65578	24.65666	24.65606
1	24.64897	24.65161	24.64984
2	24.64560	24.65000	24.64705
3	24.61642	24.62259*	24.61845
4	24.61578	24.62370	24.61839
5	24.61293	24.62261	24.61611*
6	24.61260	24.62404	24.61636
7	24.61239	24.62559	24.61673
8	24.61249	24.62745	24.61741
9	24.61263	24.62936	24.61814
10	24.61285	24.63134	24.61894
11	24.61253	24.63278	24.61919
12	24.61190	24.63391	24.61914
13	24.61150	24.63527	24.61933
14	24.61135	24.63688	24.61976
15	24.60980*	24.63709	24.61878

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

Appendix

30 minute time interval

Lag	AIC	SIC	HQIC
0	26.53865	26.54024	26.53919
1	26.51931	26.52409	26.52094
2	26.51166	26.51962*	26.51437
3	26.51036	26.52151	26.51415
4	26.51064	26.52498	26.51552
5	26.51062	26.52814	26.51658
6	26.51058	26.53128	26.51763
7	26.51041	26.53430	26.51854
8	26.50828	26.53536	26.51750
9	26.50896	26.53922	26.51926
10	26.50938	26.54283	26.52077
11	26.50400	26.54063	26.51647
12	26.49938	26.53920	26.51294
13	26.49969	26.54270	26.51433
14	26.49677*	26.54297	26.51250*
15	26.49750	26.54688	26.51432

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

60 minute time interval

Lag	AIC	SIC	HQIC
0	28.28729	28.29000	28.28824
1	28.25369	28.26182*	28.25655
2	28.25412	28.26766	28.25888
3	28.25195	28.27091	28.25861
4	28.25106	28.27544	28.25963
5	28.24458	28.27437	28.25504
6	28.24272	28.27793	28.25508
7	28.24413	28.28476	28.25840
8	28.23859	28.28464	28.25477*
9	28.23909	28.29055	28.25717
10	28.23941	28.29629	28.25939
11	28.24064	28.30294	28.26253
12	28.24197	28.30968	28.26576
13	28.23369	28.30682	28.25938
14	28.23094	28.30949	28.25853
15	28.22837*	28.31234	28.25787

* Indicate lag order selected by the criterion, AIC: Akaike information criterion, SIC: Schwarz information criterion, HQIC: Hannan-Quinn information criterion.

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