**Herding Behavior in Prediction Markets: Evidence from UK Financial Spread Trading Markets**

Abstract

We contrast the degree (strong *vs.* weak), nature (interaction between more informed (MI) and less informed (LI) traders) and patterns of herding behavior (via their feedback strategies) amongst MI and LI traders and their speed of reaction to shifts in trading by these groups. This is achieved by analyzing individual investment records of 1,943 traders in UK spread-trading markets (2010-2012). We find that herding is far more prevalent than previous studies suggest, particularly amongst LI, herding activity of MI and LI are related and the means used to distinguish MI and LI needs to be considered carefully.

(JEL codes: G12, G14)

**INTRODUCTION**

Prediction markets, which take the form of any market mechanism that provides a single consensus generated by financially motivated participants, has been widely used to predict uncertain events all over the world. The key to the success of prediction markets resides on the efficiency of the market. While the Efficient Market Hypothesis (Fama, 1970) claims that the market price will fully reflect available information in an efficient market, there is evidence that markets might be subject to forces that lead to biased evaluations or even irrational pricing (Shiller, 1981; Shiller, 1999; Malkiel, 2003).

Herding behavior is one of the well-recognized factors that cause market inefficiency and is observed when a sufficient number of traders think in a similar manner (Shiller, 1995). This is likely to result in market prices moving away from valuations based on fundamentals and thereby, creating excess volatility ([Choe et al., 1999](#_ENREF_17)) or even resulting in the destabilization of markets ([Lakonishok et al., 1992](#_ENREF_36)). [Kyle (1985](#_ENREF_35)) 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 et al., 1992](#_ENREF_36); [Kim and Wei, 1999](#_ENREF_33); [Lee et al., 1999](#_ENREF_39); [Nofsinger and Sias, 1999](#_ENREF_46); [Wermers, 1999](#_ENREF_63); [Chang et al., 2000](#_ENREF_13); [Bowe and Domuta, 2003](#_ENREF_8); [Sias, 2004](#_ENREF_58); [Avramov et al., 2006](#_ENREF_2); [Zhou and Lai, 2007](#_ENREF_65); Tan et al., 2008; [Barber et al., 2009](#_ENREF_4); [Chiang and Zheng, 2010](#_ENREF_16); [Jegadeesh and Kim, 2010](#_ENREF_31); Hsieh, 2013; Mobarek et al., 2014; Economou et al., 2015), amongst banks ([Jain and Gupta, 1987](#_ENREF_30)) and amongst bettors in horserace betting markets ([Law and Peel, 2002](#_ENREF_37); Schnytzer and Snir, 2008). However, no previous study has examined herding behavior in financial spread-trading markets.

Spread-trading markets are a particular form of prediction market, and are becoming increasingly significant, with over a million financial spread traders operating in the UK ([Pryor, 2011](#_ENREF_51)). [Brady and Ramyar (2006](#_ENREF_9)) 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 et al., 1999](#_ENREF_14); [Ryoo and Smith, 2004](#_ENREF_52); [Ghysels and Seon, 2005](#_ENREF_26)). 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 less informed 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.

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](#_ENREF_41)), [Muscarella and Piwowar (2001](#_ENREF_45)), [Schnitzlein (2002](#_ENREF_54)), and [Henker and Wang (2006](#_ENREF_28))). In particular, the theory attacks the notion of rational efficiency; proposing that capital markets generate irrationality in valuations due to herding activity by uninformed traders, who trade on random information which they treat as news. It has been suggested that these uninformed traders may be active in financial markets and that their irrationality creates risk which discourages more informed traders from trading against them ([Megginson, 1997](#_ENREF_42)). Furthermore, [Shleifer and Summers (1990](#_ENREF_57)) argue that uninformed 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 less informed 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 in financial spread trading markets.

This study aims to achieve the 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 et al. (1999](#_ENREF_39)). 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 the degree (strong vs. weak), nature (interaction of trades by more and less informed traders) and patterns (via their feedback strategies) of herding activity between more and less informed traders and in terms of the speed with which they react to shocks.

Third, previous studies have generally assumed that more informed traders are those who invest larger amounts ([Easley and O'Hara, 1987](#_ENREF_22); [Barclay and Warner, 1993](#_ENREF_5)). Our data not only allows us distinguish more and less informed 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 informed and less informed 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](#_ENREF_47)), stock markets ([Avramov et al., 2006](#_ENREF_2)), futures ([Cotter, 2005](#_ENREF_18)), bond ([Nyholm, 1999](#_ENREF_48)), option ([Verousis and ap Gwilym, 2011](#_ENREF_60)) and money markets ([Cassola and Morana, 2006](#_ENREF_11))). 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 informed and less informed 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 less informed, are prone to herding activity and that there are differences in the patterns of herding amongst more and less informed traders (in terms of the feedback strategies they employ). 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 (i.e., the degree of self-herding between members of the same group (more *vs*. less informed) or cross-herding between members of different groups. In addition, we find no obvious difference between these two groups in terms of their responses to sudden trading shifts of informed and less informed traders. Finally, our results suggest that the degree and nature of herding varies depending upon the manner in which the more and less informed traders are defined.

The remainder of the paper is organized as follows: The literature exploring herding is examined in Section 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 3. The results are presented and discussed in Section 4 and conclusions are drawn in Section 5.

**2. HERDING: LITERATURE AND HYPOTHESES**

Herding is an important phenomenon in financial markets ([Xia et al., 2009](#_ENREF_64)) 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](#_ENREF_57)) 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](#_ENREF_55)), possibly leading to bubbles ([Zhou and Sornette, 2009](#_ENREF_66)) and even financial crises ([Chiang and Zheng, 2010](#_ENREF_16)). Not surprisingly, therefore, a number of empirical studies have examined herding in stock markets ([Lakonishok et al., 1992](#_ENREF_36); [Kim and Wei, 1999](#_ENREF_33); [Lee et al., 1999](#_ENREF_39); [Nofsinger and Sias, 1999](#_ENREF_46); [Wermers, 1999](#_ENREF_63); [Chang et al., 2000](#_ENREF_13); [Bowe and Domuta, 2003](#_ENREF_8); [Sias, 2004](#_ENREF_58); [Voronkova and Bohl, 2005](#_ENREF_61); [Avramov et al., 2006](#_ENREF_2); [Zhou and Lai, 2007](#_ENREF_65); Tan et al., 2008; [Barber et al., 2009](#_ENREF_4); [Balcilar et al., 2010](#_ENREF_3); [Chiang and Zheng, 2010](#_ENREF_16); [Jegadeesh and Kim, 2010](#_ENREF_31); Hsieh, 2013; Mobarek et al., 2014; Economou et al, 2015). Herding has also been explored in other domains, including commodity ([Adrangi and Chatrath, 2008](#_ENREF_1)), foreign exchange ([Carpenter and Wang, 2007](#_ENREF_10)) and betting markets ([Law and Peel, 2002](#_ENREF_37); Schnytzer and Snir, 2008) and in relation to the lending decisions of banks ([Jain and Gupta, 1987](#_ENREF_30)). Since herding can affect market prices, it is important to understand the nature of herding and its root causes, and we now briefly examine the existing literature which has addressed these issues.

*2.1. The relationship between herding and information*

[Shiller et al. (1984](#_ENREF_56)) 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](#_ENREF_57)) 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](#_ENREF_23))) 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 et al., 1994](#_ENREF_29)) and more informed traders have been found to trade more aggressively than less informed traders on the basis of the information they hold ([Wang, 2010](#_ENREF_62)). 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](#_ENREF_46); [Jeon and Moffett, 2010](#_ENREF_32)). On the other hand, [Bikhchandani and Sharma (2000](#_ENREF_6)) indicate that herding may arise if investors change their investment decisions because they believe that others hold superior information to themselves.

To better understand the mechanisms underlying herding it would be valuable to know if more and less informed 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 ‘negative herding’ as taking place where traders act in a contrary fashion to the trading behavior of others (‘opposing strategy’)[[1]](#footnote-1). Clearly, as shown in Table 1, these definitions can lead to four herding ‘types’: positive self-herding, negative self-herding, positive cross-herding and negative cross-herding. Positive self-herding implies that traders mimic the trading behavior of others in the same group (e.g., more informed traders mimicking themselves) in previous periods while negative self-herding implies that traders act in a contrary manner to other traders in the same group in previous periods. In addition, positive cross-herding implies that traders mimic the trading behavior of others in a different group (e.g., less informed traders mimicking the behavior of more informed traders) in previous periods while negative 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 informed and less informed 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 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* | *Negative Self-herding* | *Positive Cross-herding* | *Negative Cross-herding* |
| Less Informed | *Positive Cross-herding* | *Negative Cross-herding* | *Positive Self-herding* | *Negative Self-herding* |

[Menkhoff and Schmeling (2010](#_ENREF_43)) research suggests that all traders rely on their private information but less informed 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: *More informed traders have a tendency to self-herd in a positive direction and less informed traders have a tendency to cross-herd in a positive direction.* This hypothesis begs the question of how one should effectively distinguish more and less informed traders and we explore this issue in Section 3.

*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](#_ENREF_20)).

It has been suggested that individual traders’ herding behavior is likely to be related to feedback strategies ([Patel et al., 1991](#_ENREF_50); [Odean, 1998](#_ENREF_49); [Sirri and Tufano, 1998](#_ENREF_59)). In fact, [Nofsinger and Sias (1999](#_ENREF_46)) 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. [Kim and Wei (1999](#_ENREF_33)) 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](#_ENREF_53))) 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: *More informed individual traders in spread trading markets employ positive feedback strategies while less informed traders employ negative feedback strategies.*

*2.3. Effect of herding*

Previous research has suggested that more informed traders tend to react more quickly to market shocks. For example, [Lee et al. (1999](#_ENREF_39)), 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 et al. (2010](#_ENREF_38)) find that abnormal trading volumes of less informed 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 less informed traders responds relatively slowly compared to that of more informed traders. In the context of herding, we explore reactions to a sudden change of trading by more and less informed traders. In particular, we test the following shocks-response hypothesis: *More informed traders generally respond more quickly to a sudden change in trading by more or less informed traders than do less informed traders.*

1. **DATA AND PROCEDURES**
	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 or sell 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 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 et al. (2005](#_ENREF_19)) 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 et al. (2005](#_ENREF_19)).

In the following section, we discuss the definitions we employ to distinguish informed and less informed traders.

**Table 2.** *Descriptive statistics associated with the investments of spread traders captured in the data*

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | Min | 1st Quartile | Median | Mean | 3rd Quartile | Max |
| Stake size associated with trades | StakeNatural logarithm of Stake | £0.087-2.440 | £10 | £10 | £5.0961.628 | £31.099 | £57108.65 |
| Trader account balances |  | -£25410 | -£1418 | -£267.8 | -£1993 | -£8.475 | £5008 |
| The final point\* profits/losses associated an individual trade  |  | -5733 | -8.5 | 2.8 | -5.883 | 12.8 | 5733 |

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

*3.1.1 Stake size*

Existing studies generally assume that traders who invest larger sums have greater access to information. For example, [Easley and O'Hara (1987](#_ENREF_22)) and [Barclay and Warner (1993](#_ENREF_5)) suggest, respectively, that more informed 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 et al. (1999](#_ENREF_39)); [Chakravarty (2001](#_ENREF_12)); foreign exchange markets: [Bjønnes and Rime (2005](#_ENREF_7)); [Moore and Payne (2009](#_ENREF_44))). Consequently, we follow this approach and define more and less informed 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 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 more (mean = £9.92 and SD = £47.03 of stake size) and less informed 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 1a for a histogram of stake sizes associated with opening trades). We find no significant difference in mean profit/loss between the more and less informed traders defined in this way (less-informed = -£6.03, informed = -£3.16, *t* = -1.275, *p* =0.203). This leads us to question the use of the stake size approach for distinguishing more and less informed traders and prompted us to examine alternative approaches.

*3.1.2 Overall account profitability*

Our dataset allows us to classify more and less informed traders using a more direct measure based on overall account profitability. In particular, we expect more informed traders to be more profitable in the long run. Consequently, we define more informed traders as those with positive account balances over their trading history and less informed 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 less informed, respectively, and these groups are associated with 11,269 and 37,301 opening trades, respectively (See Table 2 and Figure 1b for further descriptive statistics associated with these groups).

*3.1.3 Profitability of each opened position*

While the previous approach for distinguishing more and less informed traders is focused on the overall account profitability, it is possible that different traders may be more informed 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 less informed 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 less informed 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 more informed and 24,381 trades being identified as less informed. (See Table 2 and Figure 1c for further descriptive statistics related to the final point/profit loss).

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



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



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



**1c.** *Histogram of the final point profit/loss associated with each trade. The median distinguishing threshold between the more and less informed 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.*

* 1. *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 et al., 1992](#_ENREF_25)). 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 et al. (2010](#_ENREF_15)) 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](#_ENREF_65)), and in trading associated with all firms’ shares in the Taiwan Stock Exchange (TSE) over a 15-minute interval ([Lee et al., 1999](#_ENREF_39)).

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. 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 might be offset by herding in another direction in a different asset, 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 FTSE100 index) over *a variety* ofshorttime intervals (intervals less than 1 day are examined as most spread trades are opened and closed within a day ([Pryor, 2011](#_ENREF_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 less informed 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 et al. (1999](#_ENREF_39)) and [Jain and Gupta (1987](#_ENREF_30)), the Vector Autoregression (VAR) model and causality tests to test our hypotheses.

*3.2.1 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.

*3.2.2 VAR model*

We examine the dynamic interactions between more and less informed traders in order to test the first hypothesis, namely, more informed traders have a tendency to self-herd (intra-group) in a positive direction while less informed traders tend to cross-herd (inter-group) in a positive direction. In these analyses, we distinguish more and less informed 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:

 (eq. 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 less informed 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 *nt* for the equations up to time interval *t* are estimated by Hannan-Quinn criterion (HQC). 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](#_ENREF_40)).

Regression results from the VAR model are employed to detect herding and feedback strategies via correlated trades ([Lee et al., 1999](#_ENREF_39)). 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 negative herding where a group of traders act in a contrary fashion to trading patterns of the same group of traders in previous periods (negative self-herding) or act in a contrary fashion to the behavior of a different group of traders (negative cross-herding). Specifically, in order to seek evidence of herding, we examine the sign of the coefficients of the more or less informed traders net buying positions (*ai, bi, di, ei*) 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 *ai* or *ei* are positive or negative and significant this suggests evidence of positive or negative self-herding amongst more and less informed traders, respectively. Similarly, if *bi* or *di* are positive or negative and significant this suggests evidence of positive or negative cross-herding amongst more and less informed 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 ($c\_{i}$, $f\_{i}$) for the VAR regression results for $M\_{t }and L\_{t}$. If *ci* and *fi* are positive and significant this suggests that positive feedback strategies are being employed by more and less informed traders, respectively. Similarly, if *ci*and *fi* are negative and significant this suggests that negative feedback strategies are being employed by more and less informed 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 strategies 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 HQC).

We then examine the significance and sign of the coefficients within each time interval and lagged time period. 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 less informed 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 less informed 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 amongst a particular group of traders we combine the two types of herding results discussed above. Specifically, we examine the results for herding across all the four time intervals for that group of traders and for all lagged time periods (across each of the time intervals).

*3.2.3 Causality tests*

Causality tests examine whether more and less informed traders’ investments are correlated. However, in order to test further whether the trading of more informed traders influences the trading of less informed traders (cross-herding), we employ Granger causality ([Granger, 1969](#_ENREF_27)), in a similar manner to that adopted by [Jain and Gupta (1987](#_ENREF_30)) for detecting herding regarding the lending decisions of US banks. In particular, to test the second part of herding hypothesis, namely, that less informed traders tend to cross-herd in a positive direction with informed traders, we examined how much of the current net buying positions of less informed traders ($L\_{t}$) can be explained by the past net buying positions of more informed traders ($M\_{t-i}$). In particular, we test this by exploring whether the coefficients of previous trading activity ($d\_{1}to d\_{n}$) of more informed traders are able to help explain $L\_{t}$ (i.e., all of the coefficients are not equal to zero). Providing that they are able to be employed to help explain $L\_{t}$ (i.e., they are not equal to zero), it can be said that less informed traders are likely to herd on the previous behavior of more informed traders.

*3.2.4 Impulse response analysis*

In order to test the shocks-response hypothesis, namely, that more informed traders respond to a sudden change in trading more quickly than less informed 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 et al. (1996](#_ENREF_34)). 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 less informed 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](#_ENREF_21)) in order to show the uncertainty surrounding point estimates .

1. **RESULTS AND DISCUSSION**

4.1 *Stationarity*

In this section, we show the unit root results relating to the three means of distinguishing more and less informed traders discussed above (stake size, profitability of account, and successful trade, respectively). Table 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 less informed traders and the FTSE 100 index returns.

The results demonstrate that using all three criteria (stake size, profitability of account and successful trade) employed for defining more and less informed traders, 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 less informed traders).[[2]](#footnote-2) Consequently, for all three of the definitions of more and less informed traders we employ, the vast majority of variables appear to be stationary.

*4.2 Herding and feedback strategies*

*4.2.1 Informed/less informed traders categorized on the basis of stake size*

Tables 4 and 5 report, respectively, the VAR regression results associated with the equations in which the net buying positions of more and less informed 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 less informed traders we examine the results across all time intervals together.

In order to test the first part of the herding hypothesis, namely that more informed traders self-herd in a positive direction, we examine the coefficients ($a\_{i}$) of the lagged net buying positions of more informed traders in the equation with the net buying position of informed 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). Overall, these results suggest that across all the time intervals examined there is strong evidence that informed traders herd on the behavior of other informed traders in preceding periods. However, this herding involves taking up contrary positions to those taken by informed traders in previous time periods. We find that at lag 1 the coefficients of the net buying position of informed 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 *a5* and *a6* 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 more informed traders self-herd but, contrary to our expectations, they appear to herd in a negative rather than positive manner.

**Table 3.** *Unit root test results (on HQ criterion) for more/less informed traders categorized by stake size, account profitability and successful trade for time intervals 5, 15, 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* |
| Stakesize | 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 |
| Profitabilityof 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 |
| Successfultrade | 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 |

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

**Table 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 |
|  | *a0* | 0.406 | 1.340 | 3.196 | 3.753 |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | (0.525) | (0.582) | (0.722) | (0.672) |  |  |  |  |  |  |  |  |  |  |  |  |
| Lagged period  |  *More informed trader coefficients* |  |  *Less-informed trader coefficients* |  |  *Return coefficients* |
| 1 | *a1* | -0.311\*\* | -0.341\*\* | -0.372\*\* | -0.096\*\* |  | *b1* | 1.515\*\* | 1.757\* | 2.820\*\* | 6.345\*\* |  | *c1* | -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 | *a2* | -0.091\*\* | -0.126\*\* | -0.167\*\* | -0.021 |  | *b2* | 0.291 | 1.656\* | 3.558\*\* | -1.517 |  | *c2* | -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 | *a3* | -0.058\*\* | -0.080\*\* | -0.084\*\* | 0.011 |  | *b3* | 0.206 | 1.171 | 4.027\*\* | 1.957 |  | *c3* | -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 | *a4* | -0.028\*\* | -0.0490\*\* | -0.040\*\* | -0.014 |  | *b4* | 0.833\* | 2.308\*\* | 1.400 | -0.090 |  | *c4* | -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 | *a5* | -0.008 | -0.051\*\* | -0.007 | -0.068\*\* |  | *b5* | 1.156\*\* | 2.087\*\* | 0.502 | 0.487 |  | *c5* | -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 | *a6* | -0.010\* | -0.024\*\* | 0.002 | 0.009 |  | *b6* | 0.118 | 1.691\* | -0.173 | 4.811\*\* |  | *c6* | 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 | *a7* | -0.011\* |  | -0.002 |  |  | *b7* | -0.141 |  | 0.038 |  |  | *c7* | -353.25 |  | -714.645 |  |
|  |  | (-2.347) |  | (-0.139) |  |  |  | (-0.366) |  | (0.037) |  |  |  | (-0.469) |  | (-0.398) |  |
| 8 | *a8* | -0.009 |  | -0.021 |  |  | *b8* | 0.236 |  | -0.009 |  |  | *c8* | -828.598 |  | 1592.9 |  |
|  |  | (-1.925) |  | (-1.780) |  |  |  | (0.614) |  | (-0.009) |  |  |  | (-1.099) |  | (0.886) |  |
| 9 | *a9* | -0.022\*\* |  | -0.020 |  |  | *b9* | 1.460\*\* |  | 1.331 |  |  | *c9* | -1383.4 |  | -696.845 |  |
|  |  | (-4.919) |  | (-1.744) |  |  |  | (3.805) |  | (1.299) |  |  |  | (-1.837) |  | (-0.388) |  |
| 10 | *a10* | -0.021\*\* |  | -0.022 |  |  | *b10* | 0.421 |  | 1.894 |  |  | *c10* | -371.948 |  | 264.569 |  |
|  |  | (-4.695) |  | (-1.928) |  |  |  | (1.100) |  | (1.846) |  |  |  | (-0.500) |  | (0.147) |  |
| 11 | *a11* |  |  | -0.027\* |  |  | *b11* |  |  | -0.156 |  |  | *c11* |  |  | -1270.6 |  |
|  |  |  |  | (-2.304) |  |  |  |  |  | (-0.152) |  |  |  |  |  | (-0.708) |  |
| 12 | *a12* |  |  | -0.015 |  |  | *b12* |  |  | 3.162\*\* |  |  | *c12* |  |  | 1719.9 |  |
|  |  |  |  | (-1.289) |  |  |  |  |  | (3.083) |  |  |  |  |  | (0.958) |  |
| 13 | *a13* |  |  | -0.020 |  |  | *b13* |  |  | 2.545\* |  |  | *c13* |  |  | -1662.5 |  |
|  |  |  |  | (-1.794) |  |  |  |  |  | (2.490) |  |  |  |  |  | (-0.926) |  |
| 14 | *a14* |  |  | -0.027\* |  |  | *b14* |  |  | 0.807 |  |  | *c14* |  |  | 2.017 |  |
|  |  |  |  | (-2.501) |  |  |  |  |  | (0.801) |  |  |  |  |  | (0.001) |  |
|  Herding evidence |   | strong (-) | strong (-) | strong (-) | strong (-) |   |   | strong (+) | strong (+) | strong (+) | strong (+) |   |   | strong (-) | strong (-) | strong (-) | strong (-) |

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

**Table 5.** *VAR regression 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 |
|  | *d0* | -0.007 | -0.020 | -0.044 | -0.085 |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | (-0.769) | (-0.794) | (-0.949) | (-1.058) |  |  |  |  |  |  |  |  |  |  |  |  |
| Lagged period |  *More informed trader coefficients* |  |  *Less-informed trader coefficients* |  |  *Return coefficients* |
| 1 | *d1* | 0.0002\*\* | 0.0002\*\* | 0.0003\*\* | 0.001\*\* |  | *e1* | -0.060\*\* | -0.083\*\* | -0.163\*\* | -0.214\*\* |  | *f1* | -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 | *d2* | 0.0001\* | 0.0003\*\* | 0.0002 | 0.0002 |  | *e2* | -0.053\*\* | -0.072\*\* | -0.097\*\* | -0.063\*\* |  | *f2* | -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 | *d3* | 0.0000 | 0.0003\*\* | 0.0001 | 0.0002 |  | *e3* | -0.035\*\* | -0.105\*\* | -0.044\*\* | 0.006 |  | *f3* | -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 | *d4* | 0.0001 | 0.0001 | -0.0000 | 0.0001 |  | *e4* | -0.020\*\* | -0.017\* | -0.034\*\* | -0.009 |  | *f4* | -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 | *d5* | 0.0002\*\* | -0.0001 | 0.0002 | 0.0001 |  | *e5* | -0.002 | -0.053\*\* | -0.023\* | -0.071\*\* |  | *f5* | -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 | *d6* | 0.0002\*\* | 0.0001 | 0.0003\* | 0.001\* |  | *e6* | -0.034\*\* | -0.021\*\* | 0.015 | -0.091\*\* |  | *f6* | 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 | *d7* | 0.0001 |  | 0.0000 |  |  | *e7* | -0.027\*\* |  | 0.004 |  |  | *f7* | -12.380 |  | 9.704 |  |
|  |  | (1.553) |  | (0.285) |  |  |  | (-6.255) |  | (0.327) |  |  |  | (-1.444) |  | (0.512) |  |
| 8 | *d8* | 0.0000 |  | -0.0000 |  |  | *e8* | -0.042\*\* |  | -0.006 |  |  | *f8* | -20.525\*\* |  | 2.636 |  |
|  |  | (0.519) |  | (-1.174) |  |  |  | (-9.648) |  | (-0.586) |  |  |  | (-2.394) |  | (0.139) |  |
| 9 | *d9* | 0.0000 |  | 0.0001 |  |  | *e9* | -0.031\*\* |  | -0.037\*\* |  |  | *f9* | -9.991 |  | 13.870 |  |
|  |  | (0.334) |  | (0.989) |  |  |  | (-7.134) |  | (-3.656) |  |  |  | (-1.166) |  | (0.732) |  |
| 10 | *d10* | 0.0002\*\* |  | 0.0001 |  |  | *e10* | -0.021\*\* |  | -0.015 |  |  | *f10* | -7.105 |  | -6.839 |  |
|  |  | (3.075) |  | (0.424) |  |  |  | (-4.847) |  | (-1.426) |  |  |  | (-0.840) |  | (-0.361) |  |
| 11 | *d11* |  |  | 0.0002 |  |  | *e11* |  |  | -0.053\*\* |  |  | *f11* |  |  | 23.638 |  |
|  |  |  |  | (1.367) |  |  |  |  |  | (-4.850) |  |  |  |  |  | (1.247) |  |
| 12 | *d12* |  |  | 0.0001 |  |  | *e12* |  |  | -0.038\*\* |  |  | *f12* |  |  | 0.642 |  |
|  |  |  |  | (0.525) |  |  |  |  |  | (-3.475) |  |  |  |  |  | (0.034) |  |
| 13 | *d13* |  |  | 0.0000 |  |  | *e13* |  |  | -0.036\*\* |  |  | *f13* |  |  | 21.322 |  |
|  |  |  |  | (0.413) |  |  |  |  |  | (-3.293) |  |  |  |  |  | (1.125) |  |
| 14 | *d14* |  |  | 0.0001 |  |  | *e14* |  |  | 0.079\*\* |  |  | *f14* |  |  | 5.625 |  |
|  |  |  |  | (1.297) |  |  |  |  |  | (7.454) |  |  |  |  |  | (0.300) |  |
|  Herding evidence |   | strong (+) | strong (+) | strong (+) | strong (+) |   |   | strong (-) | strong (-) | strong (-) | strong (-) |   |   | strong (-) | strong (-) | strong (-) | strong (-) |

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

We then tested the second part of the herding hypothesis, namely that less informed traders cross-herd with more informed traders in a positive direction. To achieve this, we examine the coefficients of the lagged net buying positions of more informed traders, ($d\_{1}$ to $d\_{6}$) in the equation with the net buying position of less informed traders as the dependent variable (*Lt*) (see Table 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, the 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 less informed traders are likely to follow the actions of informed traders in the preceding periods (particularly with a lag of 1, 2 and 6 periods).

In summary, when defining less and more informed traders on the basis of stake size, we find evidence to support the herding hypothesis, of cross-herding among less informed traders, in other words, they mimic the behavior of more informed traders in previous periods, across a variety of time intervals. In addition, we confirm that more informed traders self-herd, that is they follow the actions of more informed traders in previous periods, but contrary to expectations, they appear to herd in a negative, rather than positive direction. These results are to some extent confirmed by the causality tests (results displayed in Table 10a). These show significant results for all time intervals for less informed following more informed traders and more informed traders following less informed traders (i.e., this implies that they act in a contrary manner to more informed traders in previous periods).

We now test the feedback strategy hypothesis, namely that more and less informed traders adopt positive and negative feedback strategies, respectively. To achieve this, we examine the coefficients associated with the lagged returns ($c\_{i} , f\_{i}$) in the equations with the net buying position of more and less informed traders as the dependent variables ($M\_{t}/L\_{t}$), respectively (shown in Tables 4 and 5, respectively). The results confirm that less informed traders follow negative feedback strategies, as all of the significant coefficients for all time intervals ($f\_{j}$) 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 more informed traders. In fact, those coefficients of lagged returns in the equation with the net buying position of more informed traders ($c\_{j}$) which are significant 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 more informed traders also follow a negative feedback strategy.

Consequently, when more and less informed 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 less informed traders but not in relation to the trading behavior of more informed traders.

*4.2.2 More and less informed traders categorized on the basis of account profitability*

Tables 6 and 7 report the VAR regression results associated with, respectively, the equations in which the net buying positions of more and less informed 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 more informed traders ($a\_{i}$), in the equation with the net buying position of more informed 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 self-herding amongst more informed traders, confirming the herding hypothesis. However, in contrast to the prediction of the herding hypothesis, 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 less informed traders cross-herd with more informed traders. In fact, few of the coefficients of the lagged net buying positions of more informed traders ($d\_{i}$) are significant across the four time intervals considered in the equation with the net buying position of less informed traders as the dependent variable (*Lt*) (see Table 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 10b, confirm that less-informed traders are unlikely to follow more informed traders except in the 60-minute time interval.

We now test the feedback strategy hypothesis, namely that more and less informed traders adopt positive and negative feedback strategies, respectively. To achieve this, we examine the coefficients associated with the lagged returns ($c\_{i} $and $f\_{i}$) in the equations with the net buying position of more and less informed traders as the dependent variable ($M\_{t}$/$L\_{t}$), respectively (shown in Tables 6 and 7). The results do not support the hypothesis, as the few coefficients of lagged returns which are significant in the equation with the net buying position of more informed traders as dependent variable, are negative (Table 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 are significant for any of the time intervals in the equation with the net buying position of less informed traders as the dependent variable (Table 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 less informed traders follow feedback strategy at all it is likely to be a positive feedback strategy.

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

**Table 6.** *VAR regression results across time intervals (more 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 |
|  | *a0* | -4.483\*\* | -8.842\*\* | -10.998\*\* | -8.217 |  |  |  |  |  |  |  |  |  |  |  |  |
|  |  | (-7.798) | (-4.807) | (-3.050) | (-1.716) |  |  |  |  |  |  |  |  |  |  |  |  |
| Lagged period |  *More informed trader coefficients* |  |  *Less-informed trader coefficients* |  |  *Return coefficients* |
| 1 | *a1* | 0.001 | -0.016\* | -0.041\*\* | -0.119\*\* |  | *b1* | 0.040 | 0.077\* | 0.285\*\* | 0.157\*\* |  | *c1* | -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 | *a2* |  | -0.002 | -0.027\* | -0.014 |  | *b2* |  | 0.171\*\* | -0.022 | 0.053 |  | *c2* |  | 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 | *a3* |  | -0.043\*\* | -0.007 | 0.021 |  | *b3* |  | 0.062 | 0.096\* | -0.004 |  | *c3* |  | -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 | *a4* |  | -0.008 | -0.001 | 0.012 |  | *b4* |  | -0.035 | 0.056 | 0.009 |  | *c4* |  | -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 | *a5* |  | -0.019\* | 0.009 | -0.063\*\* |  | *b5* |  | -0.004 | -0.089 | 0.087\* |  | *c5* |  | 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 | *a6* |  | 0.003 |  |  |  | *b6* |  | 0.038 |  |  |  | *c6* |  | -1377.000 |  |  |
|  |  |  | (0.355) |  |  |  |  |  | (1.062) |  |  |  |  |  | (-1.336) |  |  |
| 7 | *a7* |  | -0.0004 |  |  |  | *b7* |  | 0.026 |  |  |  | *c7* |  | 266.353 |  |  |
|  |  |  | (-0.057) |  |  |  |  |  | (0.715) |  |  |  |  |  | (0.258) |  |  |
| 8 | *a8* |  | 0.002 |  |  |  | *b8* |  | 0.018 |  |  |  | *c8* |  | 123.311 |  |  |
|  |  |  | (0.222) |  |  |  |  |  | (0.485) |  |  |  |  |  | (0.120) |  |  |
| 9 | *a9* |  | -0.002 |  |  |  | *b9* |  | -0.010 |  |  |  | *c9* |  | -104.184 |  |  |
|  |  |  | (-0.215) |  |  |  |  |  | (-0.282) |  |  |  |  |  | (-0.101) |  |  |
| 10 | *a10* |  | 0.001 |  |  |  | *b10* |  | 0.022 |  |  |  | *c10* |  | -750.837 |  |  |
|  |  |  | (0.111) |  |  |  |  |  | (0.594) |  |  |  |  |  | (-0.728) |  |  |
| 11 | *a11* |  | 0.004 |  |  |  | *b11* |  | 0.020 |  |  |  | *c11* |  | 624.834 |  |  |
|  |  |  | (-0.463) |  |  |  |  |  | (0.548) |  |  |  |  |  | (0.606) |  |  |
| 12 | *a12* |  | 0.004 |  |  |  | *b12* |  | 0.050 |  |  |  | *c12* |  | 644.778 |  |  |
|  |  |  | (0.588) |  |  |  |  |  | (1.390) |  |  |  |  |  | (0.626) |  |  |
| 13 | *a13* |  | 0.007 |  |  |  | *b13* |  | -0.006 |  |  |  | *c13* |  | 356.067 |  |  |
|  |  |  | (0.887) |  |  |  |  |  | (-0.171) |  |  |  |  |  | (0.349) |  |  |
| 14 | *a14* |  |  |  |  |  | *b14* |  |  |  |  |  | *c14* |  |  |  |  |
| Herding evidence  |   | ✕ | strong (-) | strong (-) | strong (-) |   |   | ✕ | strong (+) | strong (+) | strong (+) |   |   | ✕ | strong (-) | ✕ | strong (-) |

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

**Table 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 |
|   | *d0* | -0.150 | -0.818\* | -1.113 | 0.289 |   |   |   |   |   |   |   |   |   |   |   |   |
|   |   | (-1.589) | (-2.129) | (-1.408) | (0.171) |   |   |   |   |   |   |   |   |   |   |   |   |
| Lagged period |  *More informed trader coefficients* |  |  *Less-informed trader coefficients* |  |  *Return coefficients* |
| 1 | *d1* | 0.001 | 0.002 | 0.003 | 0.0116\* |  | *e1* | 0.069\*\* | -0.061\*\* | 0.009 | -0.054\*\* |  | *f1* | -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 | *d2* |  | 0.0000 | 0.004 | 0.006 |  | *e2* |  | 0.006 | -0.028\*\* | 0.006 |  | *f2* |  | -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 | *d3* |  | 0.003 | 0.002 | 0.004 |  | *e3* |  | 0.085\* | -0.020 | -0.091\*\* |  | *f3* |  | 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 | *d4* |  | 0.0004 | 0.002 | -0.022\*\* |  | *e4* |  | 0.051\*\* | -0.010 | -0.037\* |  | *f4* |  | -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 | *d5* |  | 0.0002 | 0.002 | 0.007 |  | *e5* |  | -0.038\*\* | -0.125\*\* | -0.039\*\* |  | *f5* |  | 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 | *d6* |  | 0.001 |  |  |  | *e6* |  | 0.008 |  |  |  | *f6* |  | 633.348\*\* |  |  |
|  |  |  | (0.705) |  |  |  |  |  | (1.066) |  |  |  |  |  | (2.941) |  |  |
| 7 | *d7* |  | 0.0000 |  |  |  | *e7* |  | 0.008 |  |  |  | *f7* |  | 20.551 |  |  |
|  |  |  | (0.004) |  |  |  |  |  | (1.044) |  |  |  |  |  | (0.095) |  |  |
| 8 | *d8* |  | 0.0002 |  |  |  | *e8* |  | 0.024\*\* |  |  |  | *f8* |  | 27.637 |  |  |
|  |  |  | (0.126) |  |  |  |  |  | (3.208) |  |  |  |  |  | (0.1283) |  |  |
| 9 | *d9* |  | 0.003 |  |  |  | *e9* |  | -0.009 |  |  |  | *f9* |  | -100.659 |  |  |
|  |  |  | (1.828) |  |  |  |  |  | (-1.213) |  |  |  |  |  | (-0.467) |  |  |
| 10 | *d10* |  | 0.001 |  |  |  | *e10* |  | -0.049\*\* |  |  |  | *f10* |  | -111.255 |  |  |
|  |  |  | (0.606) |  |  |  |  |  | (-6.489) |  |  |  |  |  | (-0.517) |  |  |
| 11 | *d11* |  | -0.001 |  |  |  | *e11* |  | -0.021\*\* |  |  |  | *f11* |  | -142.801 |  |  |
|  |  |  | (-0.521) |  |  |  |  |  | (-2.840) |  |  |  |  |  | (-0.663) |  |  |
| 12 | *d12* |  | 0.001 |  |  |  | *e12* |  | -0.001 |  |  |  | *f12* |  | 227.110 |  |  |
|  |  |  | (0.332) |  |  |  |  |  | (-0.158) |  |  |  |  |  | (1.055) |  |  |
| 13 | *d13* |  | 0.001 |  |  |  | *e13* |  | -0.078\*\* |  |  |  | *f13* |  | 372.308 |  |  |
|  |  |  | (0.644) |  |  |  |  |  | (-10.387) |  |  |  |  |  | (1.744) |  |  |
| 14 | *d14* |  |  |  |  |  | *e14* |  |  |  |  |  | *f14* |  |  |  |  |
|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
|  Herding evidence |   | ✕ | ✕ | ✕ | weak (+,-) |   |   | strong (+) | weak (-) | strong (-) | strong (-) |   |   | ✕ | strong (+) | strong (+) | ✕ |

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

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

Tables 8 and 9 report the VAR regression results associated with the equations in which, respectively, the net buying positions of more and less informed 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 more informed trades as the dependent variable (shown in Table 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., self-herding). Across all time periods many of the coefficients of the lagged net buying positions of informed trades are significant and all bar one of these are positive.

 The results presented in Table 9 provide some evidence that less informed trades are correlated with more informed trades in previous periods, as for all the time intervals many of the coefficients of the lagged net buying positions of informed trades are significant. In fact, the evidence points to a negative relationship between the net buying positions of less and more informed trades. In particular, for two of the time intervals (5- and 15- minutes) the significant coefficients of the lagged net buying positions of informed 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 less informed trades follow more informed trades from previous periods, but in a contrary direction.

 In addition, we can see from the causality tests presented in Table 10c that the less-informed trades tend to follow the more informed trades in the 30-minute, and 60-minute time intervals.

In order to test the feedback strategy hypothesis, namely that more and less informed traders adopt positive and negative feedback strategies, respectively, we examine, the coefficients associated with the lagged returns in the equations with the net buying position of more and less informed traders as the dependent variables, respectively ($M\_{t}$/$L\_{t}$). The results are displayed in Tables 8 and 9. There is some evidence of informed 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 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 less informed traders follow feedback strategies. Across all four time intervals only one of the lag return variables in the equation with less informed trader net buying position as the dependent variable is significant (lag 10 for the 30-minute time interval: see Table 9).

4.2.4 *Overall results on behavior and information*

In summary, the results of examining herding behavior amongst more and less informed 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 self-herding amongst more informed 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 informed traders on the basis of stake size or the profitability of their account we find evidence of self-herding in the opposite direction to previous trades.

We find some evidence that less informed traders cross-herd with more informed traders whichever means we use to categorize these groups of traders. They, as expected, appear to mimic the behavior of more informed traders when we distinguish more informed 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 more informed traders when we equate informed traders with successful trades.

**Table 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 |
|   | *a0* | -2.571\*\* | -6.634\*\* | -7.989\*\* | -10.132\*\* |   |   |   |   |   |   |   |   |   |   |   |   |
|   |   | (-9.352) | (-7.698) | (-4.223) | (-2.669) |   |   |   |   |   |   |   |   |   |   |   |   |
| Lagged period | *More informed trader coefficients* |  |  *Less-informed trader coefficients* |  |  *Return coefficients* |
| 1 | *a1* | 0.033\*\* | 0.047\*\* | 0.008 | -0.004 |  | *b1* | -0.025\*\* | -0.041\*\* | -0.118\*\* | -0.147\*\* |  | *c1* | -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 | *a2* | 0.031\*\* | 0.038\*\* | -0.023\* | 0.013 |  | *b2* | 0.004 | -0.010 | -0.080\*\* | -0.011 |  | *c2* | -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 | *a3* | 0.012\*\* | -0.014 | 0.011 | 0.048\*\* |  | *b3* | -0.015\*\* | -0.130\*\* | -0.031\*\* | 0.005 |  | *c3* | -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 | *a4* | 0.006 | 0.014 | 0.015 | 0.032\* |  | *b4* | 0.002 | -0.026\*\* | -0.004 | -0.017 |  | *c4* | -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 | *a5* | 0.040\*\* | -0.010 | 0.019 | 0.036\* |  | *b5* | -0.001 | -0.054\*\* | -0.006 | -0.007 |  | *c5* | -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 | *a6* | 0.009\* |  | 0.021\* | 0.035\* |  | *b6* | 0.005 |  | 0.014 | 0.007 |  | *c6* | -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 | *a7* | 0.011\* |  | 0.025\* | 0.005 |  | *b7* | -0.003 |  | -0.004 | -0.002 |  | *c7* | 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 | *a8* | -0.002 |  | 0.036\*\* | -0.020 |  | *b8* | 0.012\* |  | -0.016 | 0.0002 |  | *c8* | -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 | *a9* | -0.005 |  | 0.012 |  |  | *b9* | -0.096\*\* |  | 0.004 |  |  | *c9* | -443.094 |  | -316.224 |  |
|  |  | (-1.210) |  | (1.077) |  |  |  | (-17.417) |  | (0.375) |  |  |  | (-1.674) |  | (-0.420) |  |
| 10 | *a10* | -0.003 |  | 0.014 |  |  | *b10* | 0.009 |  | 0.001 |  |  | *c10* | -179.885 |  | -174.712 |  |
|  |  | (-0.706) |  | (1.256) |  |  |  | (1.660) |  | (0.094) |  |  |  | (-0.680) |  | (-0.232) |  |
| 11 | *a11* | 0.017\*\* |  | -0.0004 |  |  | *b11* | -0.057\*\* |  | -0.002 |  |  | *c11* | -181.022 |  | -36.691 |  |
|  |  | (3.881) |  | (-0.035) |  |  |  | (-10.301) |  | (-0.231) |  |  |  | (-0.684) |  | (-0.049) |  |
| 12 | *a12* | -0.0003 |  | 0.037\*\* |  |  | *b12* | 0.007 |  | -0.002 |  |  | *c12* | -270.808 |  | 1415.1 |  |
|  |  | (-0.068) |  | (3.342) |  |  |  | (1.181) |  | (-0.171) |  |  |  | (-1.023) |  | (1.879) |  |
| 13 | *a13* | -0.0004 |  | -0.009 |  |  | *b13* | 0.006 |  | -0.014 |  |  | *c13* | 87.882 |  | -916.665 |  |
|  |  | (-0.092) |  | (-0.811) |  |  |  | (1.056) |  | (-1.429) |  |  |  | (0.332) |  | (-1.217) |  |
| 14 | *a14* | -0.002 |  | 0.045\*\* |  |  | *b14* | -0.055\*\* |  | -0.027\*\* |  |  | *c14* | -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 (-) |

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

**Table 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 |
|   | *d0* | 0.469\* | 1.606 | 2.436 | 3.132 |   |   |   |   |   |   |   |   |   |   |   |   |
|   |   | (2.165) | (1.849) | (1.162) | (0.685) |   |   |   |   |   |   |   |   |   |   |   |   |
| Lagged period | *More informed trader coefficients* |  | *Less-informed trader coefficients* |  | *Return coefficients* |
| 1 | *d1* | -0.010\*\* | 0.005 | -0.018 | -0.005 |  | *e1* | 0.078\*\* | 0.044\*\* | -0.006 | 0.004 |  | *f1* | -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 | *d2* | 0.004 | -0.016\* | 0.005 | 0.011 |  | *e2* | -0.007 | 0.030\*\* | -0.027\* | -0.017 |  | *f2* | -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 | *d3* | -0.005 | -0.005 | 0.022 | -0.037\* |  | *e3* | 0.013\*\* | -0.097\*\* | -0.0001 | 0.024 |  | *f3* | 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 | *d4* | -0.0002 | -0.002 | -0.015 | -0.031 |  | *e4* | 0.003 | 0.006 | 0.001 | -0.022 |  | *f4* | -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 | *d5* | -0.002 | -0.006 | -0.021 | -0.120\*\* |  | *e5* | 0.002 | -0.014 | -0.0031 | -0.021 |  | *f5* | -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 | *d6* | 0.002 |  | -0.006 | 0.042\* |  | *e6* | 0.002 |  | -0.003 | -0.012 |  | *f6* | 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 | *d7* | -0.004 |  | -0.001 | -0.023 |  | *e7* | 0.004 |  | -0.008 | 0.011 |  | *f7* | -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 | *d8* | -0.002 |  | -0.041\*\* | 0.063\*\* |  | *e8* | 0.011\* |  | -0.008 | -0.056\*\* |  | *f8* | -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 | *d9* | -0.007\* |  | -0.005 |  |  | *e9* | -0.095\*\* |  | -0.004 |  |  | *f9* | 120.008 |  | 57.393 |  |
|  |  | (-2.084) |  | (-0.417) |  |  |  | (-21.885) |  | (-0.361) |  |  |  | (0.575) |  | (0.069) |  |
| 10 | *d10* | 0.006 |  | -0.023 |  |  | *e10* | 0.019\*\* |  | -0.008 |  |  | *f10* | -132.844 |  | 189.657 |  |
|  |  | (1.801) |  | (-1.904) |  |  |  | (4.414) |  | (-0.688) |  |  |  | (-0.637) |  | (0.227) |  |
| 11 | *d11* | -0.002 |  | -0.097\*\* |  |  | *e11* | -0.003 |  | -0.026\* |  |  | *f11* | 191.435 |  | -2023.600\* |  |
|  |  | (-0.472) |  | (-7.985) |  |  |  | (-0.606) |  | (-2.379) |  |  |  | (0.918) |  | (-2.424) |  |
| 12 | *d12* | -0.0003 |  | 0.049\*\* |  |  | *e12* | 0.001 |  | -0.019 |  |  | *f12* | 29.082 |  | 451.735 |  |
|  |  | (-0.093) |  | (4.020) |  |  |  | (0.290) |  | (-1.735) |  |  |  | (0.139) |  | (0.541) |  |
| 13 | *d13* | -0.0008 |  | -0.018 |  |  | *e13* | 0.005 |  | -0.013 |  |  | *f13* | -72.837 |  | -942.150 |  |
|  |  | (-0.238) |  | (-1.514) |  |  |  | (1.126) |  | (-1.149) |  |  |  | (-0.350) |  | (-1.129) |  |
| 14 | *d14* | 0.003 |  | 0.007 |  |  | *e14* | -0.0000 |  | -0.001 |  |  | *f14* | 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 (-) | ✕ |

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

**Table 10.** *Results of causality tests, in terms of the herding strategies of more(MI)/less(LI) 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 *(more/less informed traders defined by stake)* |
| Time interval | No. of lag | (1)LIfollowMI | (2)MIfollowLI | (3)LI followMI/MI follow LI | (4)NoClearFollowers |
|  |  |  |  |  |  |
| 5 min | 10 |  |  | \*\*/\*\* |  |
| 15 min | 6 |  |  | \*\*/\*\* |  |
| 30 min | 14 |  |  | \*/\*\* |  |
| 1 hour | 6 |  |  | \*/\*\* |  |
|  b. Outcome of Causality Test *(more/less informed traders defined by account profitability)* |
| Time interval | No. of lag | (1)LIfollowMI | (2)MIfollowLI | (3)LI followMI/MI follow LI | (4)NoClearFollowers |
|  |  |  |  |  |  |
| 5 min | 1 |  |  |  | ● |
| 15 min | 13 |  | \*\* |  |  |
| 30 min | 5 |  | \*\* |  |  |
| 1 hour | 5 |  |  | \*\*/\*\* |  |
|  c. Outcome of Causality Test *(more/less informed trades defined by success)* |
| Time interval | No. of lag | (1)LIfollowMI | (2)MIfollowLI | (3)LI followMI/MI follow LI | (4)NoClearFollowers |
|  |  |  |  |  |  |
| 5 min | 14 |  | \*\* |  |  |
| 15 min | 5 |  | \*\* |  |  |
| 30 min | 14 |  |  | \*\*/\*\* |  |
| 1 hour | 8 |   |   | \*\*/\*\* |   |

Note: \* indicates significant at 5 percent level,

 \*\* indicates significant at 1 percent level,

 ● not significant

 MI – More informed traders

 LI – Less informed traders

Whichever means we employ to distinguish more and less informed traders, we find evidence that more informed 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 less informed traders follow feedback strategies, other than when we distinguish less informed 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 less informed 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 less informed 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 less informed 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 less informed traders we find consistent evidence for more informed traders following negative feedback strategies but no evidence that less informed traders follow feedback strategies. We also find strong evidence that more informed traders engage in self-herding (although the direction of this herding depends upon the criteria employed for distinguishing more and less informed traders). Furthermore, there is evidence that less informed traders herd on the basis of the actions of more informed traders in earlier periods, although this evidence is much stronger when we distinguish more informed 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 less informed 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](#_ENREF_24)) 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 et al. (1992](#_ENREF_36)) and [Wermers (1999](#_ENREF_63)) 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 more informed traders follow the actions of other informed traders from previous periods (and in the same direction, if we distinguish more and less informed traders on the basis of a successful/unsuccessful trade) is consistent with the findings of [Nofsinger and Sias (1999](#_ENREF_46)) and [Jeon and Moffett (2010](#_ENREF_32)). Our findings also support [Menkhoff and Schmeling (2010](#_ENREF_43)) suggestion that less informed are likely to react to the trading of those they perceive to be better-informed, although, based on what we regard as the most reliable means of classifying more and less informed traders (i.e., on the basis of a successful trade), we find that they act in a contrary fashion to the actions of more informed traders in previous periods.

Our results do not support [Kim and Wei (1999](#_ENREF_33)) conclusion that informed traders employ positive feedback strategies. In fact, we found that more informed traders, categorized by any of the three criteria we employed, tend to employ negative feedback strategies. Our results also lead us to conclude that less informed 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 less informed on what we regard as an unreliable basis, in other words, 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 less informed 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 to distinguish more and less informed 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.

4.2.5 *Differential speed of adjustment to sudden shifts in trading by more and less informed traders*

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

Figures 2a and 2b show how the net buying of more and less informed 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 less informed traders. The unbroken lines in these graphs represent the net buying positions of less/more informed traders while the dotted lines show the bootstrap error bounds (i.e., a 95 percent confidence interval). It is not clear from Figures 2a and 2b that more informed traders respond more quickly (than less informed traders) to sudden shifts in the net buying of more or less informed traders, across the time intervals examined. A similar conclusion is reached when examining Figures 3 and 4. In other words, whichever of the three means we employ to distinguish more and less informed traders, our results lead us to conclude that there is no obvious difference in terms of the response of more and less informed traders to shifts in trading. Our findings, across in a wider range of time intervals and for a variety of means of distinguishing more informed traders, contradict those of [Lee et al. (1999](#_ENREF_39)) and [Lee et al. (2010](#_ENREF_38)) that a sudden change of trading is responded to more slowly by less informed traders.

**Figure 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 2a.** *Impulse response from a shock induced by shifts in the net buying of more informed traders*

****

****

 5 min 15 min 30 min 60 min

**Figure 2b.** *Impulse response from a shock induced by shifts in the net buying of less informed traders*

**Figure 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 3a.** *Impulse response from a shock induced by shifts in the net buying of more informed traders*

****

****

 5 min 15 min 30 min 60 min

**Figure 3b.** *Impulse response**from a shock induced by shifts in the net buying of less informed traders*

**Figure 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 4a.** *Impulse response from a shock induced by shifts in the net buying of more informed traders*

****

****

 5 min 15 min 30 min 60 min

**Figure 4b.** *Impulse response**from a shock induced by shifts in the net buying of less informed traders*

**5. CONCLUSION**

This paper 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 and nature 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 less informed 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 believe there may be reason to 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 et al., 2000](#_ENREF_13); [Zhou and Lai, 2007](#_ENREF_65)). 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 6 we can see that by only examining the degree of herding by more informed traders (defined by their account profitability) on the actions of more informed traders in 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 arisen as result of herding in a positive direction for several assets and herding in a negative 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 adds to the growing market micro structure literature (e.g., [De Long et al. (1990](#_ENREF_20)); [Shleifer and Summers (1990](#_ENREF_57))) by providing new insights into the manner in which the trading of more and less informed traders interacts and the manner in which these groups employ feedback strategies. As expected, we find evidence of self-herding amongst more informed 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 less informed traders cross-herd with more informed traders. However, the manner in which they cross-herd (i.e., mimic or act in a contrary fashion) depended on the manner in which we distinguished more and less informed traders. We find strong evidence that more informed 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 less informed traders follow feedback strategies. We also find no obvious differences in the responses of more and less informed traders to shocks generated by shifts in the net buying activities of more and less informed traders.

It is clear from our results that to fully understand the herding behavior of more and less informed 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 less informed 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 et al., 1999](#_ENREF_39); [Moore and Payne, 2009](#_ENREF_44)). 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 less informed groups when these are distinguished by stake size. One would expect more informed traders to be able to capitalize on their enhanced knowledge/ability to earn higher profits. In addition, it is likely that more and less informed 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 less informed 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 less informed 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.

References

Adrangi, B., Chatrath, A., 2008. Do commodity traders herd? Financial Review 43 (3), 461-476.

Avramov, D., Chordia, T., Goyal, A., 2006. The impact of trades on daily volatility. Review of Financial Studies 19 (4), 1241-1277.

Balcilar, M., Demirer, R., Hammoudeh, S., 2010. Investor herds and regime-switching: evidence from Gulf Arab Stock Markets. Journal of International Financial Markets, Institutions and Money,

Barber, B.M., Odean, T., Zhu, N., 2009. Do retail trades move markets? Review of Financial Studies 22 (1), 151-186.

Barclay, M.J., Warner, J.B., 1993. Stealth trading and volatility. Journal of Financial Economics 34, 281-305.

Bikhchandani, S., Sharma, S., 2000. Herd behavior in financial markets. IMF Staff Papers 47 (3), 279-310.

Bjønnes, G.H., Rime, D., 2005. Dealer behavior and trading systems in foreign exchange markets. Journal of Financial Economics 75 (3), 571-605.

Bowe, M., Domuta, D., 2003. Investor herding during financial crisis: A clinical study of the Jakarta Stock Exchange. Pacific-Basin Finance Journal 12, 389-418.

Brady, C., Ramyar, R., 2006. White paper on spread betting. Cass Business School.

Carpenter, A., Wang, J., 2007. Herding and the information content of trades in the Australian dollar market. Pacific-Basin Finance Journal 15 (2), 173-194.

Cassola, N., Morana, C., 2006. Volatility of interest rates in the euro area: Evidence from high frequency data. The European Journal of Finance 12 (6-7), 513-528.

Chakravarty, S., 2001. Stealth-trading: Which traders’ trades move stock prices? Journal of Financial Economics 61 (2), 289-307.

Chang, E.C., Cheng, J.W., Khorana, A., 2000. An examination of herd behavior in equity markets: An international perspective. Journal of Banking and Finance 24, 1651-1679.

Chang, E.C., Cheng, J.W., Pinegar, J.M., 1999. Does futures trading increase stock market volatility ? The case of the Nikkei stock index futures markets. Journal of Banking and Finance 23 (5), 727-753.

Chiang, T.C., Li, J., Tan, l., 2010. Empirical investigation of herding behvior in Chinese stock markets: Evidence from quantile regression analysis. Global Finance Journal 21, 111-124.

Chiang, T.C., Zheng, D., 2010. An empirical analysis of herd behavior in global stock markets. Journal of Banking and Finance 34, 1911-1921.

Choe, H., Kho, B.-C., Stulz, R.M., 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997. Journal of Financial Economics 54, 227-264.

Cotter, J., 2005. Uncovering long memory in high frequency UK futures. The European Journal of Finance 11 (4), 325-337.

Coval, J.D.C., Hirshleifer, D.A., Shumway, T., 2005. Can individual investors beat the market? School of Finance Harvard University 4-25,

De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Positive feedback investment strategies and destabilizing rational speculation Journal of Finance 45, 379-395.

Dees, S., Mauro, F.d., Pesaran, M.H., Smith, L.V., 2007. Exploring the international linkages of the euro area: a global VAR analysis. Journal of Applied Econometrics 22 (1), 1-38.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial Economics 19, 69-90.

Economou, F., Gavriilidis, K., Goyal, A., Kallinterakis, V., 2015. Herding dynamics in exchange groups: Evidence from Euronext. Journal of International Financial Markets, Institutions and Money 34, 228-244.

Eguíluz, V.M., Zimmermann, M.G., 2000. Transmission of information and herd behavior: An application to financial markets. Physical Review Letters 85 (26), 5659-5662.

Falkenstein, E.G., 1996. Preferences for stock characteristics as revealed by mutual fund portfolio holdings. The Journal of Finance 51 (1), 111-135.

Fama, E.F., 1970. Efficient capital markets: A review of theory and empirical work. Journal of Finance 25, 383-420.

Froot, K.A., Scharfstein, D.S., Stein, J.C., 1992. Herd on the street: Information inefficiencies in a market with short-term speculation. Journal of Finance 47, 1461-1484.

Ghysels, E., Seon, J., 2005. The Asian financial crisis: The role of derivative securities trading and foreign investors in Korea. Journal of International Money and Finance 24 (4), 607-630.

Granger, C.W.J., 1969. Investigating causal relations by econometric models and cross spectral methods. Econometrica 37, 424-438.

Henker, T., Wang, J.-X., 2006. On the importance of timing specifications in market microstructure research. Journal of Financial Markets 9 (2), 162-179.

Hirshleifer, D., Subrahmanyam, A., Titman, S., 1994. Security analysis and trading patterns when some investors receive information before others. The Journal of Finance 49 (5), 1665-1698.

Hsieh, S.F., 2013. Individual and institutional herding and the impact on stock returns: Evidence from Taiwan stock market. International Review of Financial Analysis 29, 175-188.

Jain, A.K., Gupta, S., 1987. Some evidence on "herding" behavior of U. S. banks. Journal of Money, Credit and Banking 19 (1), 78-89.

Jegadeesh, N., Kim, W., 2010. Do analysts herd? An analysis of recommendations and market reactions. Review of Financial Studies 23 (2), 901-937.

Jeon, J.Q., Moffett, C.M., 2010. Herding by foreign investors and emerging market equity returns: Evidence from Korea. International Review of Economics and Finance 19 (4), 698-710.

Kim, W., Wei, S.-J., 1999. Foreign portfolio investors before and during a crisis. Working Papers

Center for International Development at Harvard University 6,

Koop, G., Pesaran, M.H., Potter, S.M., 1996. Impulse response analysis in nonlinear multivariate models. Journal of Econometrics 74 (1), 119-147.

Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53 (6), 1315-1335.

Lakonishok, J., Shleifer, A., Vishny, R.W., 1992. The impact of institutional trading on stock prices. Journal of Financial Economics 32, 23-43.

Law, D., Peel, D.A., 2002. Insider trading, herding behaviour and market plungers in the British horse-race betting market. Economica 69 (274), 327-338.

Lee, B.S., Li, W., Wang, S.S., 2010. The dynamics of individual and institutional trading on the Shanghai Stock Exchange. Pacific-Basin Finance Journal 18 (1), 116-137.

Lee, Y.-T., Lin, J.-C., Liu, Y.-J., 1999. Trading patterns of big versus small players in an emerging market: An empirical analysis. Journal of Banking and Finance 23 (5), 701-725.

Liew, V.K.-S., 2004. Which lag length selection criteria should we employ? Economics Bulletin 3 (33), 1-9.

Madhavan, A., 2000. Market microstructure: A survey. Journal of Financial Markets 3 (3), 205-258.

Malkiel, B.G., 2003. The efficient market hypothesis and its critics. Journal of Economic Perspectives 17 (1), 59-82.

Megginson, W.L., 1997. Corporate Finance Theory. Addison-Wesley, Reading.

Menkhoff, L., Schmeling, M., 2010. Trader see, trader do: How do (small) FX traders react to large counterparties’ trades? Journal of International Money and Finance 29 (7), 1283-1302.

Mobarek, A., Mollah, S., Keasey, K., 2014. A cross-country analysis of herd behavior in Europe. Journal of International Financial Markets, Institutions and Money 32, 107-127.

Moore, J.M., Payne, R. 2009. Size, specialism and the nature of informational advantage in inter-dealer foreign exchange trading. Working Paper, Warwick Business School. 2009.

Muscarella, C.J., Piwowar, M.S., 2001. Market microstructure and securities values: Evidence from the Paris Bourse. Journal of Financial Markets 4 (3), 209-229.

Nofsinger, J.R., Sias, R.W., 1999. Herding and feedback trading by institutional and individual investors. The Journal of Finance 54 (6), 2263-2295.

Nolte, I., Nolte, S., 2011. How do individual investors trade? The European Journal of Finance, 1-27.

Nyholm, K., 1999. Estimation of the effective bid-ask spread on high frequency Danish bond data. The European Journal of Finance 5 (2), 109-122.

Odean, T., 1998. Are investors reluctant to realize their losses? The Journal of Finance 53 (5), 1775-1798.

Patel, J., Zeckhauser, R., Hendricks, D., 1991. The rationality struggle: Illustrations from financial markets. The American Economic Review 81 (2), 232-236.

Pryor, M., 2011. The financial spread betting handbook. Harriman House LTD, Chipenham.

Ryoo, H.-J., Smith, G., 2004. The impact of stock index futures on the Korean stock market. Applied Financial Economics 14 (4), 243-251.

Schmeling, M., 2007. Institutional and individual sentiment: Smart money and noise trader risk? International Journal of Forecasting 23 (1), 127-145.

Schnitzlein, C.R., 2002. Price formation and market quality when the number and presence of insiders is unknown. Review of Financial Studies 15 (4), 1077-1109.

Schnytzer, A., Snir, A., 2008. Herding in imperfect betting markets with insider traders. The Journal of Gambling Business and Economics 2, 1-15.

Shiller, R.J., 1981. Do stock prices move too much to be justified by subsequent changes in dividends? American Economic Review 71 (3), 421-436.

Shiller, R.J., 1995. Conversation, information, and herd behavior. The American Economic Review 85 (2), 181-185.

Shiller, R.J., 1999. Human behavior and the efficiency of the financial system. Handbook of Macroeconomics 1, 1305-1340.

Shiller, R.J., 2005. Irrational Exuberance. Princeton University Press, Oxfordshire.

Shiller, R.J., Fischer, S., Friedman, B.M., 1984. Stock prices and social dynamics. Brookings Papers on Economic Activity 1984 (2), 457-510.

Shleifer, A., Summers, L.H., 1990. The noise trader approach to finance. The Journal of Economic Perspectives 4 (2), 19-33.

Sias, R.W., 2004. Institutional herding. Review of Financial Studies 17 (1), 165-206.

Sirri, E.R., Tufano, P., 1998. Costly search and mutual fund flows. The Journal of Finance 53 (5), 1589-1622.

Tan, L., Chiang, T.C., Mason, J.R., Nelling, E., 2008. Herding behavior in Chinese stock markets: An examination of A and B shares. Pacific-Basin Finance Journal 16 (1-2), 61-77.

Verousis, T., ap Gwilym, O., 2011. Return reversals and the compass rose: Insights from high frequency options data. The European Journal of Finance 17 (9-10), 883-896.

Voronkova, S., Bohl, M.T., 2005. Institutional traders’ behavior in an emerging stock market: Empirical evidence on Polish pension fund investors. Journal of Business Finance and Accounting 32 (7-8), 1537-1560.

Wang, F.A., 2010. Informed arbitrage with speculative noise trading. Journal of Banking and Finance 34 (2), 304-313.

Wermers, R., 1999. Mutual fund herding and the impact on stock prices. The Journal of Finance 54 (2), 581-622.

Xia, W., Gao, X., Jiang, J. 2009. Anomalies and heterogeneity of China stock markets in the financial crisis. International Conference on New Trends in Information and Service Science. 2009.

Zhou, R.T., Lai, R.N., 2007. Herding and positive feedback trading on property stocks. Journal of Property Investment and Finance 26, 110-131.

Zhou, W.-X., Sornette, D., 2009. A case study of speculative financial bubbles in the South African stock market 2003–2006. Physica A: Statistical Mechanics and its Applications 388 (6), 869-880.

1. 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. [↑](#footnote-ref-1)
2. 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. [↑](#footnote-ref-2)