The Correlated Trading and Investment Performance of Individual Investors

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Abstract

We find that individual investors tend to trade in the same direction as other individual investors in the same broker branch. The more pronounced an individual investor's herd behavior, the worse she performs in her investments. The negative association between herding and investment performance is only driven by herding orders that are traded in the same direction as those of other individual investors. Among these herding orders, limit orders have a longer time-to-execution and time-to-cancellation, indicating that these orders tend to be stale orders. Our results suggest that herd behavior imposes a direct cost on individual investors.

Keywords: herding, trading correlation, investment performance, individual investors

JEL Classifications: G02, G15

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1. Introduction

Various financial markets have observed the phenomenon of herding, i.e., when people tend to move in the same direction as others.[1] Despite the plethora of studies on the herd behavior of financial market participants, research on the association between herding and performance is still limited. Moreover, the existing evidence is often mixed. On the one hand, Pool, Stoffman, and Yonker (2015) show that professional money managers who live in close proximity tend to have similar holdings and make similar trades. These fund managers' herding is found to be positively related to fund performance. On the other hand, Clement and Tse (2005) and Jegadeesh and Kim (2010) show that financial analysts tend to herd toward consensus by revising their forecasts and distancing themselves from their prior forecasts. The herding forecasts are less accurate, incorporate less private information, and generate weaker stock market reactions.

Our paper fills a gap in the literature by investigating the relationship between the tendency to herd and investment performance at the individual investor account level. In particular, we examine the following questions: First, do individual investors trade in the same direction as other individual investors, particularly those in the same local branch? Second, is an individual investor's herding tendency associated with her investment performance?

To test these questions, we employ the detailed quote and trade records of index futures in the Taiwan Futures Exchange (TAIFEX) from January 2003 to September 2008. Based on order submissions, we construct an intuitive measure to gauge investors' herding tendencies. For each trading day, we first aggregate the submitted orders at the investor level and calculate each investor's daily net position changes. We then measure an individual investor's herding tendency as the correlation between her daily net position changes and the aggregate daily net position changes of other individual investors who trade in the same broker branch. We exclude the investor herself when calculating the aggregate net position changes of other

[1]See Lakonishok, Shleifer, and Vishny (1992), Trueman (1994), Christie and Huang (1995), Grinblatt, Titman, and Wermers (1995), Nofsinger and Sias (1999), Chang, Cheng, and Khorana (2000), Hong, Kubic, and Solomon (2000), Wylie (2005), and Jiang and Verardo (2013).

individual investors.

Several mutually non-exclusive reasons explain why individual investors may herd with others who trade in the same broker branch. First, individual investors in the same branch may form a herd to trade in the same direction because they receive similar recommendations or newsletters from the branch's financial advisors and respond to the similar information in similar ways (Feng and Seasholes, 2004, and Pirinsky and Wang, 2006). Second, individual investors may discuss their trading ideas with other individual investors in the same branch, and make investment decisions based on information obtained through "word of mouth" (Colla and Mele, 2010). Third, the relative wealth concern (a preference for "keeping up with the Joneses") may reinforce herd behavior if individual investors consider "losing together" to be better than "falling behind" (Hong, Jiang, Wang, and Zhao, 2014). All of these mechanisms may play a role simultaneously in triggering herd behavior in individual investors. Note that, instead of attempting to disentangle these potential mechanisms, we aim to provide evidence of herd behavior in the trading of individual investors within the same branch and, more importantly, to establish a link between herd behavior and investment performance of individual investors.

Our results show that individual investors' daily net position changes are positively correlated. In other words, individual investors tend to trade as a herd. This positive correlation remains when we perform regressions to control for the effects of market return, market volatility, the daily net position changes of other investors with the same broker (excluding those of other investors in the same branch), and the daily net position changes of other investors in the market (excluding those of other investors with the same broker). The results support our first hypothesis that individual investors herd with other individual investors in the same branch. We also show that the individual herd behavior is stronger in days with more extreme market returns and higher volatility.

Next, we examine whether herd behavior is related to other investor traits. In particular, we investigate whether herd behavior stems from a lack of information gathering or processing ability; we expect that investors with lower cognitive abilities or less trading experience will be more likely to herd. Following Kuo, Lin, and Zhao (2015) and Feng and Seasholes (2005), we use the proportion of limit orders submitted at round number prices and the number of trades conducted as proxies for cognitive ability and trading experience, respectively. We find that individual investors with lower cognitive abilities and less trading experience tend to herd more. In addition, the results suggest that individual investors have persistent herding tendencies but that they can learn to mitigate their subsequent herd behaviors.

Having established that herd behavior exists within broker branches, we can now investigate a more interesting question, i.e., the association between herd behavior and investment performance. Intuitively, herding may help investors save in terms of the search cost of information. Investors may find trading in the same direction as others more reassuring and thus pay a price for herding. Alternatively, herding investors might just have lower information gathering and processing skills. We thus conjecture that the higher an investor's herding tendency, the poorer her investment performance will be.

The results show that an individual investor's tendency to herd is negatively associated with her investment performance. When we sort investors into quintiles based on the herding measure of the previous year, we find that the fifth-quintile investors (those who are more inclined to herding) receive lower mark-to-market intraday, 1-day, and 5-day returns in the following year compared with their first-quintile counterparts. This conclusion is supported by multivariate regressions after controlling for other investor characteristics, such as cognitive ability, trading experience, past performance, disposition effect, the tendency to herd with other individual investors with the same broker (but not in the same branch), and the tendency to herd with other individual investors in the market (but not with the same broker). In particular, a one-standard-deviation increase in the herding measure (0.191) leads to a decrease of 0.36 basis points in the mark-to-market intraday return. The results also hold for the mark-to-market 1-day and 5-day returns. More importantly, this loss is not due to the excessive trading of individual investors, which is documented in Barber and Odean (2000) and Barber *et al.* (2009). On the contrary, we find that individual investors who have higher herding tendencies trade less than those who have lower herding tendencies.

We then formalize and test the two explanations for the negative association between herd behavior and investment performance. The first explanation is that, if an individual investor herds because she wants to save the search cost of information or because she finds trading in the same direction as others more reassuring, she pays a direct cost for this herd behavior. This “costly herding” explanation suggests that the documented poor performance of herding investors is mainly driven by herding orders that are in the same direction as those of other individual investors in the same branch. An alternative explanation is that herd behavior reflects a lack of general trading skills, which can be reflected in inferior information processing and gathering abilities. If so, this “lack of trading skills” explanation implies that the herding investors will underperform in both their herding and non-herding orders.

Our results indicate that the negative association between herd behavior and investment performance only appears for herding orders. A one-standard-deviation increase in the trading correlation leads to a 0.92 decrease in basis points in the mark-to-market intraday return for individual investors’ herding orders. By contrast, the coefficients for non-herding orders are not significantly negative. This finding supports the “costly herding” explanation and is inconsistent with the “lack of trading skills” explanation.

We now explore the potential mechanism that causes herding orders to underperform. Linnainmaa (2010) shows that stale limit orders can partly explain the poor performance of individual investors in Finland. Limit orders submitted by individual investors may become stale in the absence of active monitoring, and these orders are more likely to be picked off by informed active traders. Our results are in line with this stale limit orders explanation, showing that the herding limit orders have a longer time-to-execution and time-to-cancellation than the non-herding orders.

Our paper contributes to the herding literature in the following ways. First, to the best of our knowledge, this paper is the first to identify the association between the herd behavior and investment performance of individual investors. The previous literature has presented mixed evidence on the association between professional market participants' herd behavior and performance. Our paper elucidates the herd behavior of non-professional traders and reports a negative correlation between individual herding and investment performance.

Second, we investigate the two channels through which herd behavior can be negatively associated with investment performance. Our findings support the concept of costly herding, i.e., that herding imposes a direct cost on individual investors, as underperformance is only driven by orders that are traded in the same direction as those of other individual investors.

Our paper also relates to studies on the correlation between individual trades and the stock return and return distribution. Dorn, Huberman, and Semgueller (2008) use data from a German broker to show that the correlated trades of individuals can predict the cross-section of stock returns. Barber, Odean, and Zhu (2009) use US Trade and Quote (TAQ) data and show that the small trade imbalance predicts the future stock return negatively over the weekly horizon, but positively over the annual horizon. Kumar and Lee (2006) investigate individual investors with a US broker and find that systematic retail trading explains stock return comovement. Instead of examining the cross-section of stock returns or return comovement, our paper complements their study by documenting the association between herd behavior and investment performance at the investor level.

Notably, our evidence is based on the complete limit order submission and trading records of the TAIFEX over several years rather than those of a single brokerage firm. We use limit order submission rather than executed trades as a measure of herding tendencies, which directly reflects an investor's inclination toward herding in investment decisions.

The remainder of the paper proceeds as follows. Section 2 discusses the literature and the hypotheses. Section 3 describes the quotes and trades data as well as the brokers and branches through which investors trade in the TAIFEX. Section 4 examines herd behavior and its relationship with other investor traits. The association between herd behavior and investment performance as well as two potential interpretations are examined in Section 5 and 6, respectively. We examine the time-to-execution and time-to-cancellation in Section 7. In Section 8, we conclude.

2. Literature Review and Hypothesis Development

2.1 Correlated Trading among Individual Investors

Individual investors may trade in the same direction as other individuals in the same branch for several reasons. First, individual investors in the same branch may receive similar information, such as recommendations or newsletters from the branch financial advisors. Feng and Seasholes (2004) show that the trades of individual investors in the same city tend to be positively correlated. Pirinsky and Wang (2006) and Kumar, Page, and Spalt (2013) document strong comovement in the stock returns of firms that are headquartered in the same geographic area. They show that investors living near a firm's headquarters react similarly to new public information; thus, these investors tend to trade in the same direction. This finding is similar to the information cascade argument in Lakonishok, Shleifer, and Vishny (1992), who interpret institutional herd behavior as money managers' reactions to the same exogenous signals.

Meanwhile, an individual investor may engage in social interactions with other individuals who trade in the same branch as her broker. Colla and Mele's (2010) theory predicts that trades generated by "neighbor" traders are positively correlated and that trades generated by "distant" traders are negatively correlated. Ng and Wu (2010) show that the trading decisions of Chinese investors are influenced by those of peers who maintain brokerage accounts in the same branch. If an individual investor relies on information obtained from social interactions and connections, she may tend to trade in the same direction as other individual investors in the same branch. In this sense, our paper also relates to that of Hong, Kubic, and Stein (2005), who find evidence that fund managers are likely to hold portfolios that are similar to those of other fund managers in the same city.[2]

In addition, the relative wealth concern can also motivate investors in the same branch to

[2]For more evidence that social interactions and connections affect investment decisions, see Ellison and Fudenberg (1995), Hong, Kubic, and Stein (2004), Brown, Ivkovic, Smith, and Weisbenner (2008), Cao, Han, and Hirshleifer (2011), and Ozsoylev *et al*. (2014).

trade in the same direction. Becker, Murphy, and Werning (2005) show that the relative status concern can increase households' risk-taking behaviors. Hong, Jiang, Wang, and Zhao (2014) show that keeping-up-with-the-Joneses preferences can reinforce and amplify individual investors' overconfidence, excessive trading, and familiarity biases. If investors view "losing together" as better than "falling behind," we may observe the correlated trading of individual investors in the same branch.

We thus study herd behavior among individual investors who are within the same branch. In particular, we expect that an individual investor's daily net position change will be positively associated with that of other individual investors in the same branch. With complete records on individual investors' trades and quotes in the TAIFEX, we propose and test our first hypothesis:

Hypothesis 1: Individual investors trade in the same direction as other individual investors in the same broker branch.

2.2 Correlated Trading and Investment Performance among Individual Investors

Nofsinger and Sias (1999) use changes in institutional ownership to measure herd behavior, and they find a positive correlation between institutional herding and contemporaneous stock returns. Wylie (2005) shows that fund managers herd out of stocks with large positive excess-to-benchmark returns in the 12 months preceding the herding period and into stocks with low excess returns during the same period. Dorn, Huberman, and Semgueller (2008) show that the trades of a German broker's clients can predict the cross-section of stock returns.

One common feature of the aforementioned papers is that they focus on the relationship between herding and stock returns at the stock level. We fill a research gap by examining the correlation between herding and investment performance at the investor level. Our data enable us to investigate the heterogeneity among individual investors' tendencies to herd and the ways in which this heterogeneous herd behavior is related to individual investors' investment performance. Our study also extends the literature on the underperformance of individual investors.[3]

Intuitively, herding investors might have poor investment performances because they receive the same inaccurate information or because they have poor information processing and gathering abilities. Based on an investor-level herding tendency measure, we test the following hypothesis:

Hypothesis 2: The herding tendency is negatively associated with an individual investor's subsequent investment performance.

2.3 Costly Herding vs. a Lack of Trading Skills

In this subsection, we propose two hypotheses to interpret the negative association between herding and investment performance. The first explanation is as follow: if an individual investor herds because of search costs or emotional gains, she incurs a cost due to such herding. This "costly herding" hypothesis suggests that the poor performance of herding investors is mainly driven by herding orders. By contrast, orders that are traded in the opposite direction as other individual investors will not underperform.

The other competing hypothesis interprets herd behavior as a reflection of the lack of trading skills that can be manifested by investors' inferior information gathering and processing abilities. This "lack of trading skills" hypothesis is in the same vein as that of Barber, Odean and Zhu (2009), and it implies that herding investors are essentially less sophisticated, such that they will underperform in both their herding and their non-herding orders.

Hypothesis 3A (the Costly Herding Hypothesis): Herding individual investors underperform relative to their non-herding counterparts only for the orders that they submit

[3]See, for example, Barber and Odean (2000), Barber *et al.* (2009); and Kuo and Lin (2013).

in the same direction as other individual investors.

Hypothesis 3B (the Lack of Trading Skills Hypothesis): Herding individual investors underperform relative to their non-herding counterparts for the orders that they submit in the same direction and the opposite direction as other individual investors.

3. Data Description

We use the contract submission and trading records in the TAIFEX from January 2003 to September 2008. The data contain detailed information on the investor type (individual investors vs. other investors), the investor account identity, the broker with whom investors trade index futures, and the broker branch through which orders are placed. The branches are at the city level. For example, a broker in Taiwan may have two branches, the Taipei branch (located in the northern part of Taiwan) and the Kaohsiung branch (located in the southern part of Taiwan). Therefore, investors living in the northern (southern) area typically trade in the Taipei (Kaohsiung) branch. With the information about broker identity and branch identity, we are capable of investigating an individual investor's tendency to herd with other individual investors in the same branch.

3.1 The Taiwan Futures Exchange (TAIFEX)

The TAIFEX adopts an Electronic Trading System (ETS) to process the orders submitted by all branches from 8:45 a.m. to 1:45 p.m., Monday through Friday. The two major types of products traded in the TAIFEX are the Taiwan Stock Exchange Index Futures (TX) and the Mini-Taiwan Stock Exchange Index Futures (MTX). The TX is based on all listed stocks on the Taiwan Stock Exchange, and the MTX is a mini version of the TX, with roughly one-quarter of the margin and the payoff. A one-index-point increase in the transaction price yields a profit of TWD 200 (50) for one TX (MXF) contract. Both types of index futures have five maturity months: the spot month, the next calendar month, and the next three quarterly months. Each type of index futures with a certain maturity month is traded as a unique product in the TAIFEX.[4]

3.2 Taiwan Index Futures Contract Submission and Execution

An important feature in Taiwan index futures trading is that individual investors conduct a large proportion of the trades. Table I shows that, in total, 356 million contracts were submitted from January 2003 to September 2008. Among these contracts, 48.5% were made by individual investors. The total number of contracts executed was 141 million, and individual investors made 74.09% of these transactions. The active participation of individual investors in Taiwan provides us with a suitable environment in which to study the herd behavior of individual investors.

When testing investment performance, we require that investors trade at least ten product days in two consecutive years to have a meaningful trading correlation.[5] After applying this requirement, we are left with 125 million trades and 131,184 investor-year observations.

3.3 Descriptive Statistics of Brokers and Branches

Table II shows the descriptive statistics of the brokers and their branches. The numbers of brokers and branches in the market are quite stable. For example, there are 60 brokers in 2003 and 61 brokers in 2008. The top ten brokers accounted for about two-thirds of the index futures trading in the market. Taiwan has approximately 170 branches, and about half of the total contracts are traded in the top ten branches.

4. Correlated Trading and Related Investor Traits

In this section, we address the following questions: Do individual investors trade in the same direction as other individual investors in the same branch? Is the trading correlation

[4]More institutional details for the TAIFEX can be found in Liu *et al*. (2010), Li *et al.* (2012); Kuo and Lin (2013), and Kuo, Lin, and Zhao (2015).
[5]A similar filter is adopted by Kuo, Lin, and Zhao (2015).

more significant under extreme market conditions? Is herd behavior related to other investor traits?

4.1 Correlated Trading within a Branch

We use the complete order submission records to calculate an individual investor's daily net positions and those of other individual investors who are trading in the same branch. The investor-level herding measure is defined as the correlation between an individual investor's daily net position changes and those of other investors in the same branch within a year. Our definition of daily net position change is essentially the *intended* change in daily net position because the order submission only reflects the intention to herd with other investors, which may not actually be executed. Thus, the herding measure calculated according to this definition of daily net position change is a proxy for the *intention* to herd.[6]

We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position approach. The dummy variable for daily net position change takes a value of 1 if an investor submitted more buy contracts than sell contracts within a trading day; it takes a value of –1 if an investor submitted more sell contracts than buy contracts; and it equals 0 otherwise. The scaled net position change is the difference between the quantities of buy contracts and sell contracts, scaled by the average number of contracts submitted per day in the previous year. A positive dummy variable or a positive scaled net position change essentially indicates that the investor is on the long side of a product (TXF or MXF) within a trading day. The daily net position change of other individual investors is calculated by aggregating the net position changes of all other individual investors who trade in the same branch.

We perform the following regression analysis to formally test herd behavior.

[6]We adopt the intention to herd as our herding measure to account for the fact that some investors may have herding intentions but fail to herd with other investors simply because their orders are not successfully executed. These orders, although not executed, also reflect investors' inclinations to herd with others. The results remain qualitatively the same if we use the executed trades to define daily net positions.

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + Controls + \varepsilon_{i,j,t} \quad (1)$$

where $NetPosition_{i,j,t}$ is investor i's daily net position change on product j on day t. The products include TXF and MXF with the maturity of the spot month, the next calendar month, and the next three quarterly months. $NetPosition_{branch,j,t}$ is the daily net position change of other individual investors in the same branch as investor i. We include the following control variables: the market return, market volatility, the daily net position changes of other investors with the same broker (excluding those in the same branch), the daily net position changes of other individual investors in the market (excluding those with the same broker), and the daily net position changes of institutional investors in the same branch.[7]

Table III shows that an individual investor's daily net position change is positively associated with that of other individual investors in the same branch. The parameter estimates for β_1 are similar in magnitude both before and after controlling for broker-level and market-level herding tendencies. For example, Model 3 shows that individual investors, on average, will be 4.1% more likely to submit buy contracts if other individual investors tend to buy in the market. Collectively, the results show that individual investors tend to trade in the same direction as other individual investors in the same branch. Therefore, when we construct an investor-level herding measure in the following sections, we take the simple correlations of daily net position changes with other individual investors in the same branch for each year.

4.2 Correlated Trading under Extreme Market Conditions

We perform the following two regressions to test whether herd behavior is more significant under extreme market returns and market volatility.

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + \beta_2 NetPosition_{branch,j,t} \times D\_ExtremeRet_{j,t}$$

[7]When calculating the net position of other individual investors with the same broker, we exclude the contracts submitted in the same branch. Similarly, when calculating the net position of other investors in the market, we exclude the contracts submitted in the same branch and by the same broker. Hence, the estimated correlation is not mechanically affected by the variable construction.

$$+\beta_3 D\_ExtremeRet_{j,t} + Controls + \varepsilon_{i,j,t} \qquad (2)$$

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + \beta_2 NetPosition_{branch,j,t} \times D\_ExtremeVol_{j,t}$$
$$+\beta_3 D\_ExtremeVol_{j,t} + Controls + \varepsilon_{i,j,t} \qquad (3)$$

where $NetPosition_{i,j,t}$ and $NetPosition_{branch,j,t}$ are defined similarly as in equation (1). $D\_ExtremeRet_{j,t}$ is a dummy variable that equals 1 if the market return on day t falls within the top or bottom 10% of all trading days and 0 otherwise. $D\_ExtremeVol_{j,t}$ is a dummy variable that equals 1 if the market volatility on day t falls within the top 10% of all trading days.[8] We include the following control variables: the market return, market volatility, and the daily net position changes of other investors with the same broker (excluding those in the same branch), the daily net position changes of other individual investors in the market (excluding those with the same broker), and the daily net position changes of institutional investors in the same branch.

Table IV shows that the association between an investor's daily net position changes and those of other investors is more significant on days with extreme market returns. The parameter estimates for β_2 are significant for all specifications. Table V shows that herd behavior is more evident on trading days that experience extreme volatility. These results reveal the interesting dynamics of herd behavior, i.e., individual investors are more likely to trade in the same direction as other individual investors in the same branch under extreme market conditions.

4.3 Correlated Trading and Related Investor Characteristics

For each year, the investor-level herding tendency measure for each investor is calculated as the correlation between an individual investor's daily net position changes and those of other individual investors who trade in the same branch. To ensure that investors have a meaningful trading correlation measure, we require each investor to have at least ten

[8] Daily market volatility is inferred from the intraday price range of index futures. It is calculated as the difference between the maximum and minimum index levels, divided by the sum of the two.

product-day observations over two consecutive years.[9]

We consider the following investor traits, which may be related to herd behavior. The first is a past tendency toward herding. If herd behavior is an investor trait that can carry over into different periods, we expect that investors who have herded in the past will be more likely to display herd behavior in the future. Second, we examine the effect of cognitive ability on herding tendencies. Cognitive ability is measured as in Kuo, Lin, and Zhao (2015); it is calculated as the proportion of investor *i*'s limit orders that are submitted at prices ending in "X0" in the previous year (X is an integer ranging from 0 to 9). The higher the ratio, the lower investor *i*'s cognitive ability.

The third factor is trading experience, which is proxied by the number of contracts submitted. This measure is in the same vein as that in Feng and Seasholes (2005). The fourth factor is past performance, which is indicated by the average intraday limit order returns from the previous year. The return is calculated as the difference between the execution price and the daily closing price, divided by the execution price. Finally, we examine the disposition effect, which is defined as the difference between the durations of losing and winning round-trip trades, scaled by the average of the two.[10] Odean (1998) shows that the tendency to hold losing investments for too long and to sell winning investments too soon leads to lower after-tax returns. The disposition effect may be associated with herd behavior if an investor displays both characteristics.

For each investor and each year, we calculate the investor-level herding tendency and the measures of other investor traits. We then perform the following regression:

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[9]Our analyses on the association between cognitive limitations and investment performance might potentially be susceptible to the effects of investor attrition (survivorship bias), as documented by Seru, Shumway, and Stoffman (2010). However, we argue that individual investors who have higher herding tendencies will perform worse. Because investors with poor performances are more likely to stop trading, the remaining investors in our empirical analyses after data filtration should have relatively better investment performances. Hence, investor attrition should bias us against finding a negative relationship between correlated trading and investment performance in the quintile analysis. In addition, we also check whether our results are the same when we require the investors to have at least 5 or 15 daily net position observations each year for two consecutive years. The results hold—individual investors who herd more with other individual investors tend to have poorer investment performances.

[10] We follow Jordan and Diltz (2003) and Feng and Seasholes (2005) to calculate round-trip trade performance. A round-trip trade is identified as a newly initiated position, long or short, that is covered.

$$Herding_{branch,i,t} = \alpha + \beta_1 Herding_{branch,i,t-1} + \beta_2 SubRatio_{X0,i,t-1} + \beta_3\, Ln(N_{i,t-1}) + \beta_4 Return_{i,t-1} + \beta_5\, Disposition_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

where $Herding_{branch,i,t}$ and $Herding_{branch,i,t-1}$ are the correlations between investor i's daily net position changes and those of other individual investors trading in the same branch in years t and $t–1$, respectively. $SubRatio_{X0,i,t-1}$ is the measure of cognitive limitations. $Ln(N_{i,t-1})$ is the log of the number of contracts submitted by investor i in year $t–1$. $Return_{i,t-1}$ is the average intraday return of limit orders for the previous year. $Disposition_{i,t-1}$ is the difference between the durations of the previous year's losing and winning round-trips, divided by the average of the two.

Table VI shows that an individual investor's past herding tendency is a strong predictor of her future herding tendency. The first column shows that a one-standard-deviation increase in the past herding tendency (0.191) will lead to a 0.053 increase in the subsequent year's tendency to herd with other individual investors. The parameter estimates for $SubRatio_{X0,i,t-1}$ are also significantly positive, showing that investors with limited cognitive abilities are more prone to herd. The results also show that individual investors with more trading experience and better past performances are less likely to display herd behavior, while those who are more affected by the disposition effect tend to herd more.

In Table VI, we also report the regression analysis of the difference between the herding tendencies in two consecutive years to account for the time-invariant factors of investors' characteristics. The results are consistent with the regression analysis at the herding tendency level. For example, the second column of Table VI shows that individual investors with more trading experience and better past returns are less likely to exhibit herd behavior in the future. This finding is consistent with that of the investor learning literature, i.e., that trading experience helps investors make better investment decisions (Feng and Seasholes, 2005, Dhar and Zhu, 2006, and Seru, Shumway, and Stoffman, 2010).

5. Correlated Trading and Investment Performance

In this section, we combine the order submission records with the execution data to investigate the link between herd behavior and investment performance. We specifically test the second hypothesis, i.e., that the herding tendency is negatively associated with an individual investor's subsequent investment performance.

5.1 The Investor-Level Correlated Trading

Our measure of the investor-level herding tendency is calculated as the correlation between an individual investor's daily net position changes and those of other individual investors who trade in the same branch. This measure is constructed each year for each investor. We employ both the dummy variable and the scaled net position approach to calculate daily net position changes, similar to our calculations in the previous section.

We then sort the individual investors into five groups according to the lagged trading correlation for our quintile analyses. Table VII shows a high degree of heterogeneity in herding tendencies of individual investors. For example, Panel A of Table VII shows that the previous year's average trading correlation (defined using the dummy variable approach) of the Quintile-1 individual investors is –0.186, which is much lower than that (0.369) of the Quintile-5 individual investors. When making investment decisions, the Quintile-5 individual investors exhibit higher herding tendencies than their Quintile-1 counterparts. For the remainder of this paper, investors with higher (lower) trading correlations with other investors are referred to as Q5 (Q1) investors. That is, Q5 (Q1) investors are viewed as those with higher (lower) herding tendencies.

Table VII also shows that the tendency to herd with others is quite persistent. Individual investors with higher trading correlations with other individual investors in the previous year tend to have higher trading correlations with others in the subsequent year.[11] Panel A of Table

[11]The scaled net position approach scales the net position by the previous year's average position, so

VII shows that Q5 individual investors have trading correlations (defined using the dummy variable approach) of 0.369 and 0.165 for the two consecutive years, which are higher than the trading correlations of Q1 investors in both years.

As investors in a herding group submit their orders in the same direction within a trading day, these orders queue for a longer time as they wait to be executed, and their execution probabilities are also lower. This notion implies that the orders of investors who exhibit more herd behaviors face more competition in terms of execution. Table VII shows that, compared with Q1 individual investors, Q5 individual investors have significantly lower execution ratios and longer time-to-execution for their limit orders. These results indicate that more friction in the execution of orders arises when investors herd.

5.2 Trading Correlation and Investment Performance

Investment performance is measured as the mark-to-market return of all orders that initiate a long or short position.[12] Following Bhattacharya et al. (2012), we calculate the intraday return using the difference between the daily closing price and the initiating order's execution price, divided by the execution price. This calculation assumes that the initiating orders are covered (closed out) at the closing price of the trading day. We first calculate the average intraday return weighted by the number of contracts for each investor-year observation. The returns are then averaged with equal weights for all of the investor-year observations in each quintile. To enhance the robustness of our results, we also calculate 1-day and 5-day mark-to-market returns, which employ closing prices of *s+1* and *s+5*, respectively.

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we require the investor to have two consecutive years of trading to calculate the herding measure. In addition, because we are performing a lead-lag regression, investors essentially need to have made trades for three consecutive years. For the dummy variable approach, the investors are only required to have trades for two consecutive years because the positions are not scaled. As such, the number of observation is larger for this approach.

[12] We only use initiating orders to evaluate the mark-to-market returns. Please note that the sum of mark-to-market returns for an initiating order and that for a closing order do not necessarily reflect the true performance of a round-trip trade. If the initiating and closing orders are executed on two different days, we are essentially using two different daily closing prices to calculate the returns. Hence, the sum of the two returns is an inaccurate calculation of the investor's performance. Therefore, only initiating orders are used to calculate the mark-to-market returns.

Figure 1 plots the mark-to-market returns against the quintile ranks of investors based on their previous year's herding measure. We find that intraday returns almost monotonically decrease with the trading correlations. Similar patterns exist for 1-day and 5-day returns. These patterns provide convincing evidence that herding tendencies and investment performance are negatively correlated for individual investors.

Table VIII presents the statistical tests between individual investors with high and low herding tendencies. Panel A of Table VIII shows that, if we use the dummy variable to define daily net position changes, the Q5 individual investors underperform their Q1 counterparts by 2.7 basis points within a trading day. The inferior performance of the Q5 investors continues to deteriorate, and the performance gap widens to 5.7 basis points for the 5-day mark-to-market returns. Similar results can be found in Panel B of Table VIII, where we utilize the scaled net position approach to define the herding measure.

Table VIII also indicates that individual investors in all quintiles experience negative mark-to-market returns. This finding is consistent with those in the literature that individual investors tend to lose money on their investments.

We then perform the following cross-sectional regression:

$$Return_{i,t} = \alpha + \beta_1 Herding_{brach,i,t-1} + \beta_2 SubRatio_{X0,i,t-1} + \beta_3 \, Ln\left(N_{i,t-1}\right) + \beta_4 Return_{i,t-1} + \beta_5 \, Disposition_{i,t-1} + \beta_6 Herding_{broker,i,t-1} + \beta_7 Herding_{market,i,t-1} + \varepsilon_{i,t} \quad (5)$$

where $Return_{i,t}$ is the average mark-to-market returns for investor i in year t. $Herding_{branch,i,t-1}$ is the correlation between investor i's daily net position changes and those of other individual investors who trade in the same branch in year *t–1*. We employ two specifications for the daily net position change: the dummy variable approach and the scaled net position approach. $SubRatio_{X0,i,t-1}$ is investor i's level of cognitive limitations in line with in Kuo, Lin, and Zhao (2015), and it is calculated as the proportion of investor i's limit orders submitted at "X0" price points in the previous year (X is an integer ranging from 0 to

9). $Ln(N_{i,t-1})$ is the logged number of limit orders submitted by investor i in year *t–1*, which serves as a proxy for her trading experience. $Return_{i,t-1}$ is the average mark-to-market intraday returns in the previous year. $Disposition_{i,t-1}$ is the difference between the durations of previous year's losing and winning round-trips, divided by the average of the two. Controlling for cognitive limitations, trading experience, past performance, and the disposition effect helps us single out the effect of herding on investment performance. We also control for the tendency to herd with other investors with the same broker and the tendency to herd with other investors in the market.

Table IX shows significantly negative coefficients for the trading correlation of individual investors. In the first column of Table IX, the estimated β_1 equals –0.019, indicating that a one-standard-deviation increase in the trading correlation (0.191) leads to a 0.36-basis-point decrease in the mark-to-market intraday return. Similar results hold for the mark-to-market 1-day and 5-day returns.

Notice that the parameter estimates of $SubRatio_{X0,i,t-1}$ are significantly negative, implying that investors with lower cognitive abilities have poorer performances. This finding is consistent with those in Kuo, Lin, and Zhao (2014). Past intraday returns are positively associated with subsequent returns, indicating that investment performance endures over time. Moreover, the coefficients for $Disposition_{i,t-1}$ are all significantly negative, suggesting that the disposition effect is detrimental to the investment performance of individual investors. This finding is consistent with those of Odean (1998).

6. Costly Herding or a Lack of Trading Skills?

We test the two explanations for the negative association between individual investors' herd behaviors and investment performances. The "costly herding" hypothesis predicts that the documented poor performance of herding investors is mainly driven by herding orders, while the "lack of trading skills" hypothesis indicates that individual investors with higher herding tendencies will underperform when their orders are submitted in the same direction as others and when they trade against the crowd.

We first perform a quintile analysis. We sort individual investors into quintiles based on their herding tendencies over the course of a year and examine the performance of herding and non-herding orders in the subsequent year. Herding orders are defined as orders that are traded in the same direction as those of other individual investors in the same branch. Non-herding orders are those that are traded in the opposite direction of those of other individual investors. The average mark-to-market returns are calculated separately for herding orders and non-herding orders for each investor in each year.

Table X shows that the underperformance of Q5 individual investors relative to Q1 investors mainly derives from herding orders. In Panel A of Table X, we use the dummy variable approach to define daily net position changes and find that, within a trading day, the herding orders of Q5 investors underperform relative to those of Q1 investors by 4.5 basis points. By contrast, the non-herding orders of Q5 investors underperform by only 0.5 basis points, which is statistically insignificant. Similar results can be observed for 1-day and 5-day returns.

To formally test the performance difference between herding and non-herding orders, we run the following cross-sectional regression:

$$\begin{aligned} Return_{i,t} = \ & \alpha + \beta_1\, Herding_{brach,i,t-1} + \beta_2 \left(Herding_{brach,i,t-1} \times D_{herding_{\,i,t-1}} \right) \\ & + \beta_3 D\_herding_{i,t-1} + \beta_4 SubRatio_{X0,i,t-1} + \beta_5\, Ln\left(N_{i,t-1}\right) + \beta_6 Return_{i,t-1} \\ & + \beta_7\, Disposition_{i,t-1} + \beta_8\, Herding_{broker,i,t-1} + \beta_9\, Herding_{market,i,t-1} + \varepsilon_{i,t} \quad (6) \end{aligned}$$

where $Return_{i,t}$ is the average mark-to-market returns for investor *i* in year *t*, which is calculated separately for herding orders and non-herding orders. $Herding_{branch,i,t-1}$ is the correlation between investor *i*'s daily net position changes and those of other individual investors who trade in the same branch in year *t–1*. The dummy variable $D\_herding_{i,t-1}$ equals 1 if the return is calculated for herding orders and 0 otherwise. $SubRatio_{X0,i,t-1}$ is the measure for cognitive limitations in line with Kuo, Lin, and Zhao (2015), and it is calculated as the proportion of investor i's limit orders submitted at "X0" price points in the previous year (X is an integer ranging from 0 to 9). $Ln(N_{i,t-1})$ is the log of the number of contracts submitted in the previous year. $Return_{i,t-1}$ is the average mark-to-market return for the previous year. $Disposition_{i,t-1}$ is the difference between the durations of the previous year's losing and winning round-trips, divided by the average of the two. We control for $Herding_{broker,i,t-1}$ and $Herding_{market,i,t-1}$, the tendency to trade in the same direction as other investors with the same broker (but not in the same branch) or in the market (but not with the same broker).

Table XI shows that the negative association between individual herding and investment performance only appears for herding orders. The parameter estimates for β_2 are significantly negative, while those of β_1 are not significant. For example, in the first column, the estimated β_2 equals –0.048, implying that a one-standard-deviation increase in the trading correlation (0.191) leads to a 0.92-basis-point decrease in the mark-to-market intraday return for the herding orders. Similar results hold for the mark-to-market 1-day and 5-day returns. Overall, our findings support the "costly herding" hypothesis, i.e., that the poor performance of investors with high herding tendencies is driven by their herding orders.

7. Time-to-Execution and Time-to-Cancellation of Herding Orders

According to Linnainmaa (2010), limit orders are likely to have lower returns if they become stale and are subsequently picked off by informed active traders. To determine whether the herding limit orders of herding investors become stale after submission, we will now examine the time-to-execution and time-to-cancellation of these orders.

Time-to-execution is defined as the time elapsed between order submission and order execution for executed limit orders. Time-to-cancellation is the time elapsed between order submission and order cancellation for limit orders that are submitted and then retracted by individual investors. These staleness measures can serve as indicators of how actively investors monitor their limit orders. We sort individual investors into quintiles based on the trading correlation in one year and calculated the average time-to-execution (cancellation) of their herding limit orders and their non-herding limit orders in the subsequent year.[13]

Figure 2 shows that herding limit orders, on average, take a longer time to be executed. Although not tabulated here, we also performed a t-test that showed that the difference in time-to-execution is significant between herding and non-herding orders and that the difference is more significant among Q5 individual investors. Figure 3 presents similar results for time-to-cancellation. In sum, our results are consistent with the conjecture that the herding limit orders of herding investors are left unmonitored in the limit order book for a longer time and, in turn, become stale. This staleness may partially explain the negative association between trading correlation and investment performance.

8. Conclusion

This paper investigates individual herd behavior at the investor level. We find that individual investors tend to trade in the same direction as other individual investors in the same branch. They tend to herd more under extreme market conditions. Based on a measure of investor-level herding tendencies, we find that past herd behavior is a strong determinant of the current tendency to herd. Individual investors with lower cognitive abilities and less trading experience tend to trade more in the same direction as other individual investors in the same branch.

We find a negative relationship between correlated trading and investment performance. Individual investors with higher herding tendencies, i.e., those who have a higher trading correlation with other individual investors in the same branch, experience significantly lower intraday, 1-day, and 5-day returns. Furthermore, the negative association between herding and investment performance is only driven by herding orders, perhaps because herding limit orders are left unattended and become stale in the limit order book. These results suggest that

[13]Note that we include market orders to calculate the trading correlation, but we exclude them when we examine the staleness of limit orders.

herding with other individuals in the same branch imposes a direct cost on individual investors.

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Table I. Descriptive Statistics of the Contract Submission and Execution

This table reports the contract submission and execution for Taiwan index futures in the Taiwan Futures Exchange from January 2003 to September 2008. In 2008, we only have data from January to September. We report the contract submission and execution separately for individual investors and for all investors.

Year	Number of contracts submitted		Number of contracts executed	
	Individual investors	All investors	Individual investors	All investors
2003	20,479,796	23,772,865	13,368,205	15,658,666
2004	27,092,659	35,753,033	17,064,625	21,605,716
2005	21,614,051	31,959,855	11,495,052	16,011,381
2006	29,350,667	55,730,194	16,690,159	23,350,421
2007	33,519,275	94,626,065	20,105,789	28,997,746
2008	40,443,859	113,790,443	25,721,625	35,352,722
Total	172,500,307	355,632,455	104,445,455	140,976,652

Table II. Descriptive Statistics of the Brokers and the Branches

This table reports the concentration ratio of the top brokers and their branches where investors can trade the index futures in Taiwan from January 2003 to September 2008. In 2008, we only have data from January to September. The concentration ratio is reported separately for top-5, top-10, top-50, and all brokers (branches), and it is calculated as the proportion of contracts traded in top brokers (branches) out of total number of contracts traded in the market.

Year	Top-N brokers or branches	Number of brokers	Concentration ratio of top-N brokers (%)	Number of branches	Concentration ratio of top-N branches (%)
2003	Top-5	5	41.86	5	30.32
	Top-10	10	64.20	10	50.24
	Top-50	50	99.52	50	94.24
	All	60	100.00	183	100.00
2004	Top-5	5	41.95	5	30.45
	Top-10	10	65.48	10	52.78
	Top-50	50	99.78	50	95.12
	All	57	100.00	167	100.00
2005	Top-5	5	39.39	5	28.34
	Top-10	10	63.22	10	52.23
	Top-50	50	99.25	50	94.40
	All	64	100.00	171	100.00
2006	Top-5	5	43.24	5	32.05
	Top-10	10	67.74	10	55.51
	Top-50	50	99.48	50	95.13
	All	65	100.00	171	100.00
2007	Top-5	5	44.30	5	35.78
	Top-10	10	68.36	10	54.26
	Top-50	50	99.55	50	94.25
	All	63	100.00	177	100.00
2008	Top-5	5	47.43	5	35.25
	Top-10	10	72.67	10	54.08
	Top-50	50	99.80	50	95.51
	All	61	100.00	175	100.00

Table III. Regression Analysis on Correlated Trading

This table reports the parameter estimates of the following regression:

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + Controls + \varepsilon_{i,j,t}$$

where $NetPosition_{i,j,t}$ is investor i's daily net position change on product j at day t. The products are TXF and MXF with the maturity of the spot month, the next calendar month, and the next three quarterly months. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. $NetPosition_{branch,j,t}$ is the daily net position change of other individual investors in the same branch as investor i. We also control for the market return, the market volatility, and the daily net position changes of institutional investors. When calculating the net position changes of other investors in the same broker, we exclude the contracts submitted in the same branch. Similarly, when calculated the position changes of other investors in the market, we exclude the contracts submitted in the same branch and the same broker. Standard errors are adjusted for heteroskedasticity. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach			Scaled Net Position Approach		
variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$NetPosition_{branch,j,t}$	0.0553***	0.0538***	0.0412***	0.0735***	0.0734***	0.0637***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables						
Market return	–2.5871***	–2.6501***	–2.3026***	–1.5631***	–1.5679***	–1.2365***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market volatility	–0.0072***	–0.0069***	–0.0067***	–0.0054***	–0.0055***	–0.0050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.0297***	0.0282***	0.0236***	0.0247***	0.0249***	0.0194***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Broker-level positions	No	Yes	Yes	No	Yes	Yes
Market-level positions	No	No	Yes	No	No	Yes
Institutional positions	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,631,851	1,631,851	1,631,851	1,575,817	1,575,817	1,575,817
Adjusted R^2	0.0063	0.0067	0.0099	0.0010	0.0011	0.0028

Table IV. Correlated Trading on Days with Extreme Returns

This table reports the parameter estimates of the following regression:

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + \beta_2 NetPosition_{branch,j,t} \times D\_ExtremeRet_{j,t} + \beta_3 D\_ExtremeRet_{j,t} + Controls + \varepsilon_{i,j,t}$$

where $NetPosition_{i,j,t}$ is investor *i*'s daily net position change on product *j* at day *t*. The products are TXF and MXF orders with the maturity of the spot month, the next calendar month, and the next three quarterly months. $D\_ExtremeRet_{j,t}$ is the dummy variable for the days with top or bottom 10% daily market return. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. $NetPosition_{branch,j,t}$ is the daily net position change of other individual investors in the same branch as investor *i*. We also control for the market return, the market volatility, and the daily net position changes of institutional investors. When calculating the net position changes of other investors in the same broker, we exclude the contracts submitted in the same branch. Similarly, when calculated the position changes of other investors in the market, we exclude the contracts submitted in the same branch and the same broker. Standard errors are adjusted for heteroskedasticity. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach			Scaled Net Position Approach		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$NetPosition_{branch,j,t}$	0.0547***	0.0535***	0.0415***	0.1009***	0.1008***	0.0892***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NetPosition_{branch,j,t} \times D\_ExtremeRet_{j,t}$	0.0138***	0.0126***	0.0074***	0.0674***	0.0668***	0.0528***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$D\_ExtremeRet_{j,t}$	–0.0220***	–0.0209***	–0.0202***	–0.0156***	–0.0156***	–0.0152***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Control variables						
Market return	–2.2622***	–2.3267***	–2.0157***	–1.2062***	–1.2149***	–1.0158***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market volatility	–0.0045***	–0.0047***	–0.0039***	–0.0045***	–0.0046***	–0.0033***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.0305***	0.0297***	0.0239***	0.0276***	0.0277***	0.0218***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Broker-level positions	No	Yes	Yes	No	Yes	Yes
Market-level positions	No	No	Yes	No	No	Yes
Institutional positions	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,631,851	1,631,851	1,631,851	1,575,817	1,575,817	1,575,817
Adjusted R^2	0.0062	0.0066	0.0100	0.0009	0.0010	0.0027

Table V. Correlated Trading on Days with Extreme Volatility

This table reports the parameter estimates of the following regression:

$$NetPosition_{i,j,t} = \alpha + \beta_1 NetPosition_{branch,j,t} + \beta_2 NetPosition_{branch,j,t} \times D\_ExtremeVol_{j,t} + \beta_3 D\_ExtremeVol_{j,t} + Controls + \varepsilon_{i,j,t}$$

where $NetPosition_{i,j,t}$ is investor i's daily net position change on product j at day t. The products are TXF and MXF orders with the maturity of the spot month, the next calendar month, and the next three quarterly months. $D\_ExtremeRet_{j,t}$ is the dummy variable for the days with the top 10% daily market volatility. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. $NetPosition_{branch,j,t}$ is the daily net position change of other individual investors in the same branch as investor i. We also control for the market return, the market volatility, and the daily net position changes of institutional investors. When calculating the net position of other investors in the same broker, we exclude the contracts submitted in the same branch. Similarly, when calculated the position changes of other investors in the market, we exclude the contracts submitted in the same branch and the same broker. Standard errors are adjusted for heteroskedasticity. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach			Scaled Net Position Approach		
Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
$NetPosition_{branch,j,t}$	0.0564***	0.0552***	0.0427***	0.1036***	0.1034***	0.0916***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$NetPosition_{branch,j,t} \times D\_ExtremeVol_{j,t}$	0.0106***	0.0093***	0.0041***	0.1096***	0.1088***	0.0779***
	(0.000)	(0.000)	(0.003)	(0.000)	(0.000)	(0.000)
$D\_ExtremeVol_{j,t}$	–0.0077***	–0.0071***	–0.0088***	–0.0068**	–0.0062**	–0.0067**
	(0.001)	(0.002)	(0.000)	(0.017)	(0.028)	(0.019)
Control variables						
Market return	–2.2432***	–2.3094***	–1.9932***	–1.2013***	–1.2102***	–1.0078***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market volatility	–0.0073***	–0.0074***	–0.0058***	–0.0064***	–0.0066***	–0.0051***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.0314***	0.0305***	0.0239***	0.0283***	0.0286***	0.0223***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Broker-level positions	No	Yes	Yes	No	Yes	Yes
Market-level positions	No	No	Yes	No	No	Yes
Institutional positions	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,631,851	1,631,851	1,631,851	1,575,817	1,575,817	1,575,817
Adjusted R^2	0.0061	0.0065	0.0099	0.0009	0.0010	0.0027

Table VI. Correlated Trading and Other Known Investor Traits

This table reports the parameter estimates of the following regression:

$$Herding_{branch,i,t}\ or\ (Herding_{branch,i,t} - Herding_{branch,i,t-1}) = \alpha + \beta_1\ Herding_{branch,i,t-1} + \beta_2 SubRatio_{X0,i,t-1} + \beta_3\ Ln(N_{i,t-1}) + \beta_4 Return_{i,t-1} + \beta_5\ Disposition_{i,t-1} + \varepsilon_{i,t}$$

Where $Herding_{branch,i,t}$ and $Herding_{branch,i,t-1}$ are the correlation between investor i's daily net position changes and those of other individual investors trading in the same branch in year t and $t–1$. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. $SubRatio_{X0,i,t-1}$ is the measure for cognitive limitation, and it is calculated as the proportion of investor i's limit orders submitted at "X0" price points in the previous year (X is an integer ranging from 0 to 9). $Ln(N_{i,t-1})$ is the log of number of contracts submitted in the previous year. $Return_{i,t-1}$ is the average mark-to-market intraday returns in the previous year. $Disposition_{i,t-1}$ is the difference between the previous year's duration of losing and winning round-trips, divided by the average of the two. Standard errors are adjusted for heteroskedasticity. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach		Scaled Net Position Approach	
Variables	$Herding_{branch,i,t}$	$Herding_{branch,i,t} - Herding_{branch,i,t-1}$	$Herding_{branch,i,t}$	$Herding_{branch,i,t} - Herding_{branch,i,t-1}$
$Herding_{branch,i,t-1}$	0.234***	–0.782***	0.239***	–0.761***
	(0.000)	(0.000)	(0.000)	(0.000)
$SubRatio_{X0,i,t-1}$	0.037***	0.035***	0.026***	0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
$Ln(N_{i,t-1})$	–0.005***	–0.005***	–0.004***	–0.004***
	(0.000)	(0.000)	(0.000)	(0.000)
$Return_{i,t-1}$	–0.030***	–0.029***	–0.026***	–0.026***
	(0.000)	(0.000)	(0.000)	(0.000)
$Disposition_{i,t-1}$	0.019***	0.018***	0.021***	0.021***
	(0.000)	(0.000)	(0.000)	(0.000)
Intercept	0.071***	0.204***	0.204***	0.204***
	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effect	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes
Number of obs.	131,184	131,184	63,430	63,430
Adjusted R^2	0.067	0.381	0.104	0.342

Table VII. Trading Correlation and Trading Statistics in Two Consecutive Years

In this table we sort investors into quintiles by the herding measure in one year, and report the descriptive statistics for the investor-year pair with two consecutive years. Quintile-5 (Q5) investors are more inclined to herding. The branch-level trading correlation is the correlation between an investor's daily net position changes and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. Execution ratio is the proportion of contracts executed for undeleted limit orders. Time-to-execute is the interval between the order submission time and the execution time for all executed limit order contracts. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. The Satterthwaite p-value assumes unequal variances of investor performance in quintiles 1 and 5. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Panel A: Dummy Variable Approach

Trading Statistics	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Number of Investors	30,942	30,942	30,942	30,943	30,942		
Descriptive statistics in the sorting year							
Average trading correlation	–0.186	–0.012	0.076	0.17	0.369		
Number of contracts submitted	367	717	638	430	360		
Number of contracts executed	185	387	347	242	142		
Execution ratio	0.86	0.855	0.849	0.836	0.827		
Time-to-execute (s)	452	455	486	543	609		
Descriptive statistics in the subsequent year							
Average trading correlation	0.037	0.058	0.08	0.107	0.165	0.128***	0.000
Number of Contracts submitted	517	702	620	486	466	–51.182	0.520
Number of contracts executed	261	373	338	283	196	–65.592***	0.003
Execution ratio	0.869	0.863	0.859	0.851	0.843	–0.026***	0.000
Time-to-execute (s)	427	434	459	506	552	125.147***	0.000

Panel B: Scaled Net Position Approach

Trading Statistics	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Number of Investors	14,680	14,681	14,681	14,681	14,681		
Descriptive statistics in the sorting year							
Average trading correlation	–0.177	–0.018	0.06	0.15	0.347		
Number of contracts submitted	366	837	905	712	579		
Number of contracts executed	204	433	468	383	194		
Execution ratio	0.856	0.857	0.854	0.843	0.829		
Time-to-execute (s)	444	442	458	520	599		
Descriptive statistics in the subsequent year							
Average trading correlation	0.021	0.045	0.062	0.092	0.16	0.139***	0.000
Number of Contracts submitted	444	698	752	621	632	187.459	0.166
Number of contracts executed	239	372	394	360	215	–23.758	0.397
Execution ratio	0.869	0.868	0.866	0.854	0.847	–0.022***	0.000
Time-to-execute (s)	438	431	446	500	553	115.033***	0.000

Table VIII. Trading Correlation and Mark-to-Market Returns

In this table we sort investors into quintiles by the herding measure in one year, and report the mark-to-market returns for the investor-year pair in the subsequent year. Quintile-5 (Q5) investors are more inclined to herding. Herding with the branch is defined as the correlation between an investor's daily net positions and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. Mark-to-market intraday return is the difference between the trade price and the daily closing price divided by the trade price. Mark-to-market 1-day and 5-day returns are calculated in a similar fashion. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. The Satterthwaite p-value assumes unequal variances of investor performance in quintiles 1 and 5. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Panel A: Dummy Variable Approach

Mark-to-market returns (%)	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Intraday	–0.067	–0.063	–0.069	–0.080	–0.095	–0.027***	0.000
1-day	–0.105	–0.103	–0.111	–0.131	–0.144	–0.039***	0.000
5-day	–0.187	–0.186	–0.207	–0.236	–0.244	–0.057***	0.000

Panel B: Scaled Net Position Approach

Mark-to-market returns (%)	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Intraday	–0.067	–0.058	–0.065	–0.083	–0.098	–0.031***	0.000
1-day	–0.106	–0.094	–0.104	–0.125	–0.140	–0.034***	0.000
5-day	–0.158	–0.153	–0.177	–0.187	–0.197	–0.039***	0.001

Table IX. Regression Analysis for the Trading Correlation and Mark-to-Market Returns

In this table we report the parameter estimates for the following panel regression:

$$Return_{i,t} = \alpha + \beta_1\, Herding_{brach,i,t-1} + \beta_2 SubRatio_{X0,i,t-1} + \beta_3\, Ln(N_{i,t-1}) + \beta_4 Return_{i,t-1} + \beta_5\, Disposition_{i,t-1} + \beta_6\, Herding_{broker,i,t-1} + \beta_7\, Herding_{market,i,t-1} + \varepsilon_{i,t}$$

where $Return_{i,t}$ is the average mark-to-market returns for investor *i* at year *t*. $Herding_{branch,i,t-1}$ is the correlation between individual investor *i*'s daily net position changes and those of other individual investors trading in the same branch in year *t–1*. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. $SubRatio_{X0,i,t-1}$ is the measure for cognitive limitation in Kuo, Lin, and Zhao (2015), and it is calculated as the proportion of investor i's limit orders submitted at "X0" price points in the previous year (X is an integer ranging from 0 to 9). $Ln(N_{i,t-1})$ is the log of number of contracts submitted in the previous year. $Return_{i,t-1}$ is the average mark-to-market return in the previous year. $Disposition_{i,t-1}$ is the difference between the previous year's duration of losing and winning round-trips, divided by the average of the two. We control for $Herding_{broker,i,t-1}$ and $Herding_{market,i,t-1}$, the tendency to trade in the same direction with other individual investors of the same type trading in the same broker or in the market. When calculating the daily net position changes of other investors in the same broker, we exclude the orders from the same branch. Similarly, when calculating the daily net position change of other investors in the market, we exclude orders from the same branch and the same broker. Standard errors are adjusted for heteroskedasticity. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach			Scaled Net Position Approach		
Variables	Intraday (%)	1-day (%)	5-day (%)	Intraday (%)	1-day (%)	5-day (%)
$Herding_{branch,i,t-1}$	–0.019***	–0.039***	–0.057***	–0.015**	–0.019*	0.001
	(0.000)	(0.000)	(0.002)	(0.012)	(0.097)	(0.982)
$SubRatio_{X0,i,t-1}$	–0.041***	–0.083***	–0.201***	–0.034***	–0.063***	–0.165***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ln(N_{i,t-1})$	0.007***	0.012***	0.014***	0.007***	0.012***	0.010***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
$Return_{i,t-1}$	0.085***	0.038***	0.016***	0.088***	0.039***	0.030***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
$Disposition_{i,t-1}$	–0.022***	–0.030***	–0.023***	–0.026***	–0.034***	–0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
$Herding_{broker,i,t-1}$	0.004	0.024***	0.024	–0.011*	0.013	0.020
	(0.348)	(0.005)	(0.219)	(0.094)	(0.306)	(0.505)
$Herding_{market,i,t-1}$	–0.033***	–0.041***	–0.107***	–0.056***	–0.057***	–0.058*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.069)
Intercept	–0.090	–0.134	–1.006***	–0.087***	–0.544***	0.890***
	(1.000)	(1.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	93,155	93,150	93,110	45,830	45,827	45,811
Adjusted R^2	0.033	0.014	0.014	0.043	0.016	0.017

Table X. Trading Correlation and Mark-to-Market Returns of Herding and Non-Herding Orders

In this table we sort investors into quintiles by the herding measure in one year, and report the mark-to-market returns of herding and non-herding orders for the investor-year pair in the subsequent year. Quintile-5 (Q5) investors are more inclined to herding. Herding with the branch is defined as the correlation between an investor's daily net position changes and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. Mark-to-market intraday return is the difference between the trade price and the daily closing price divided by the trade price. Mark-to-market 1-day and 5-day returns are calculated in a similar fashion. We calculate the returns separately for herding orders and non-herding orders. The herding orders are identified as the orders that are trading at the same direction as other investors in the same branch, while the non-herding orders are the orders that are trading in the opposite direction of to the other investors in the same branch. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. The Satterthwaite p-value assumes unequal variances of investor performance in quintiles 1 and 5. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Panel A: Dummy Variable Approach

Mark-to-market returns (%)	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Herding orders							
Intraday	–0.034	–0.033	–0.042	–0.061	–0.079	–0.045***	0.000
1-day	–0.103	–0.107	–0.119	–0.145	–0.155	–0.052***	0.000
5-day	–0.325	–0.340	–0.372	–0.407	–0.386	–0.061***	0.000
Non-herding orders							
Intraday	–0.093	–0.088	–0.091	–0.091	–0.098	–0.005	0.127
1-day	–0.093	–0.084	–0.083	–0.089	–0.094	–0.001	0.856
5-day	0.002	0.032	0.035	0.041	0.032	0.029**	0.022

Panel B: Scaled Net Position Approach

Mark-to-market returns (%)	Q1	Q2	Q3	Q4	Q5	Diff (Q5–Q1)	p-value
Herding orders							
Intraday	–0.041	–0.035	–0.044	–0.064	–0.087	–0.046***	0.000
1-day	–0.099	–0.094	–0.102	–0.132	–0.148	–0.048***	0.000
5-day	–0.279	–0.291	–0.298	–0.346	–0.327	–0.048***	0.002
Non-herding orders							
Intraday	–0.083	–0.079	–0.080	–0.092	–0.095	–0.012***	0.005
1-day	–0.096	–0.080	–0.089	–0.095	–0.099	–0.003	0.732
5-day	0.001	0.026	0.015	0.039	0.043	0.042**	0.015

Table XI. Regression Analysis for Trading Correlation and Mark-to-Market Returns of Herding and Non-Herding Orders

In this table we report the parameter estimates for the following panel regression:

$$Return_{i,t} = \alpha + \beta_1\, Herding_{brach,i,t-1} + \beta_2\left(Herding_{brach,i,t-1} \times D\_herding_{i,t-1}\right) + \beta_3\, D\_herding_{i,t-1} + \beta_4 SubRatio_{X0,i,t-1} + \beta_5\, Ln\left(N_{i,t-1}\right) + \beta_6 Return_{i,t-1} + \beta_7\, Disposition_{i,t-1} + \beta_8\, Herding_{broker,i,t-1} + \beta_9\, Herding_{market,i,t-1} + \varepsilon_{i,t}$$

where $Return_{i,t}$ is the average mark-to-market returns for investor *i* at year *t*. The returns are calculated separately for herding orders and non-herding orders. The herding orders are identified as the orders that are trading at the same direction as other investors in the same branch, while the non-herding orders are the orders that are trading in the opposite direction of to the other investors in the same branch. $Herding_{branch,i,t-1}$ is the correlation between investor *i*'s daily net position changes and those of other individual investors trading in the same branch in year *t–1*. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. The dummy variable $D\_herding_{i,t-1}$ equals to 1 if the return is of herding orders, and 0 otherwise. $SubRatio_{X0,i,t-1}$ is the measure for cognitive limitation in Kuo, Lin, and Zhao (2014), and it is calculated as the proportion of investor *i*'s limit orders submitted at "X0" price points in the previous year (X is an integer ranging from 0 to 9). $Ln\left(N_{i,t-1}\right)$ is the log of number of contracts submitted in the previous year. $Return_{i,t-1}$ is the average mark-to-market return in the previous year. $Disposition_{i,t-1}$ is the difference between the previous year's duration of losing and winning round-trips, divided by the average of the two. We control for $Herding_{broker,i,t-1}$ and $Herding_{market,i,t-1}$, the tendency to trade in the same direction with other investors of the same type trading in the same broker or in the market. When calculating the daily net position changes of other investors in the same broker, we exclude the orders from the same branch. Similarly, when calculating the daily net position changes of other investors in the market, we exclude orders from the same branch and the same broker. Standard errors are adjusted for heteroskedasticity. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Independent	Dummy Variable Approach			Scaled Net Position Approach		
Variables	Intraday (%)	1-day (%)	5-day (%)	Intraday (%)	1-day (%)	5-day (%)
$Herding_{branch,i,t-1}$	0.002	–0.000	0.054**	0.011	0.008	0.108***
	(0.723)	(0.987)	(0.044)	(0.228)	(0.657)	(0.004)
$Herding_{branch,i,t-1} \times D\_herding_{i,t-1}$	–0.048***	–0.056***	–0.131***	–0.067***	–0.072***	–0.151***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.002)	(0.002)
$D\_herding_{i,t-1}$	0.047***	–0.033***	–0.373***	0.038***	–0.023***	–0.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$SubRatio_{X0,i,t-1}$	–0.029***	–0.068***	–0.152***	–0.030***	–0.060***	–0.134***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Ln\left(N_{i,t-1}\right)$	0.004***	0.009***	0.008***	0.004***	0.009***	0.006**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.044)
$Return_{i,t-1}$	0.064***	0.024***	0.013***	0.058***	0.019***	0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$Disposition_{i,t-1}$	–0.021***	–0.028***	–0.017***	–0.023***	–0.028***	–0.017***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)
$Herding_{broker,i,t-1}$	0.001	0.023**	0.042**	–0.008	0.017	0.014
	(0.871)	(0.012)	(0.031)	(0.242)	(0.218)	(0.630)
$Herding_{market,i,t-1}$	–0.026***	–0.027***	–0.065***	–0.046***	–0.036**	–0.018
	(0.000)	(0.005)	(0.002)	(0.000)	(0.018)	(0.569)
Intercept	–0.084***	–0.080***	–0.059	–0.068***	–0.080***	0.101**
	(0.000)	(0.000)	(0.133)	(0.000)	(0.000)	(0.017)
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Branch fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	205,490	205,423	204,309	100,352	100,316	99,817
Adjusted R^2	0.019	0.006	0.023	0.021	0.006	0.023

Figure 1. Correlated Trading and Mark-to-Market Returns

In this table we sort individual investors into quintiles by the herding measure in one year, and report the descriptive statistics for the investor-year pair in the subsequent year. Quintile-5 (Q5) investors are more inclined to herding. Herding with the branch is defined as the correlation between an investor's daily net position changes and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. The daily net position change dummy variable takes the value of 1 if an investor submitted more buy contracts relative to sell contracts within a trading day, takes value of –1 if an investor submitted more sell contracts than buy contracts, and 0 otherwise. The scaled net position change is the difference between the number of buy contracts and the sell contracts, scaled by the daily average number of contracts submitted in the previous year. Mark-to-market intraday return is the difference between the trade price and the daily closing price divided by the trade price. Mark-to-market 1-day and 5-day returns are calculated in a similar fashion. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years. The Satterthwaite p-value assumes unequal variances of investor performance in quintiles 1 and 5. *, **, and *** indicate significance levels of 0.1, 0.05, and 0.01, respectively.

Figure 1.A. Dummy Variable Approach

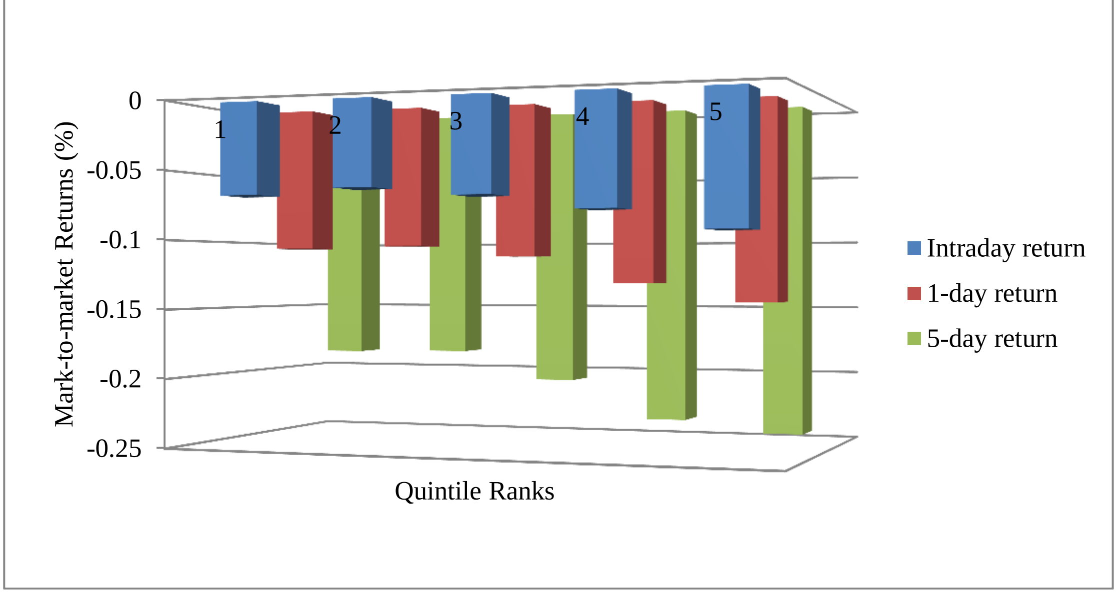

Figure 1.B. Scaled Net Position Approach

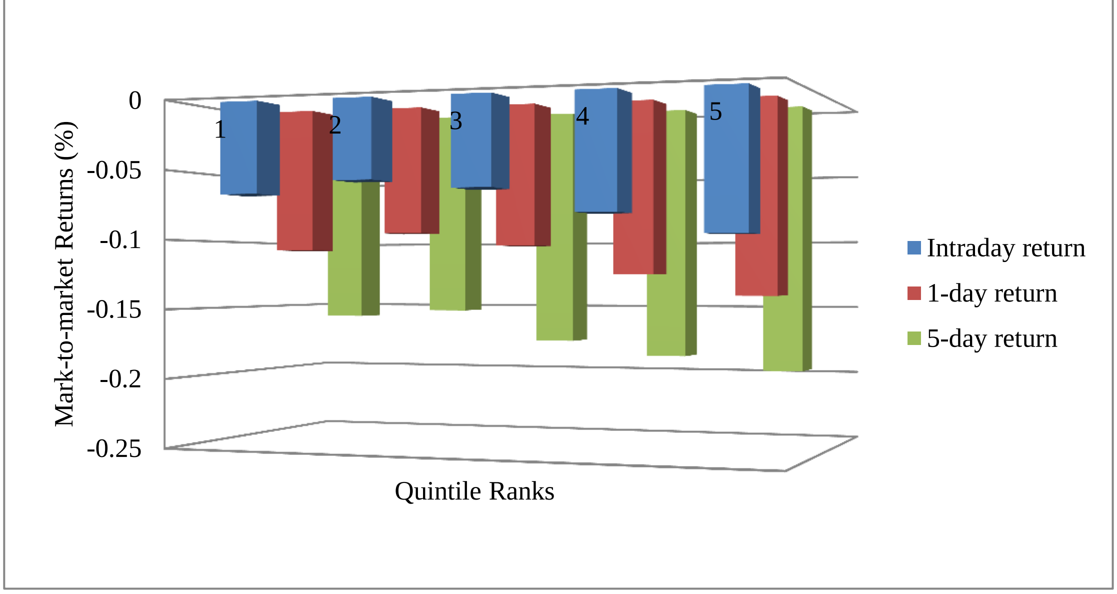

Figure 2. Time-to-Execution of Herding and Non-Herding Orders

In this table we sort investors into quintiles by the herding measure in one year, and plot the time-to-execution of herding and non-herding orders for the investor-year pair in the subsequent year. Quintile-5 (Q5) investors are more inclined to herding. Herding with the branch is defined as the correlation between an investor's daily net position changes and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. Time-to-execution is the interval from order submission to execution for executed limit orders. The herding orders are identified as the orders that are trading at the same direction as other investors in the same branch, while the non-herding orders are the orders that are trading in the opposite direction of to the other investors in the same branch. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years.

Figure 2.A. Dummy Variable Approach

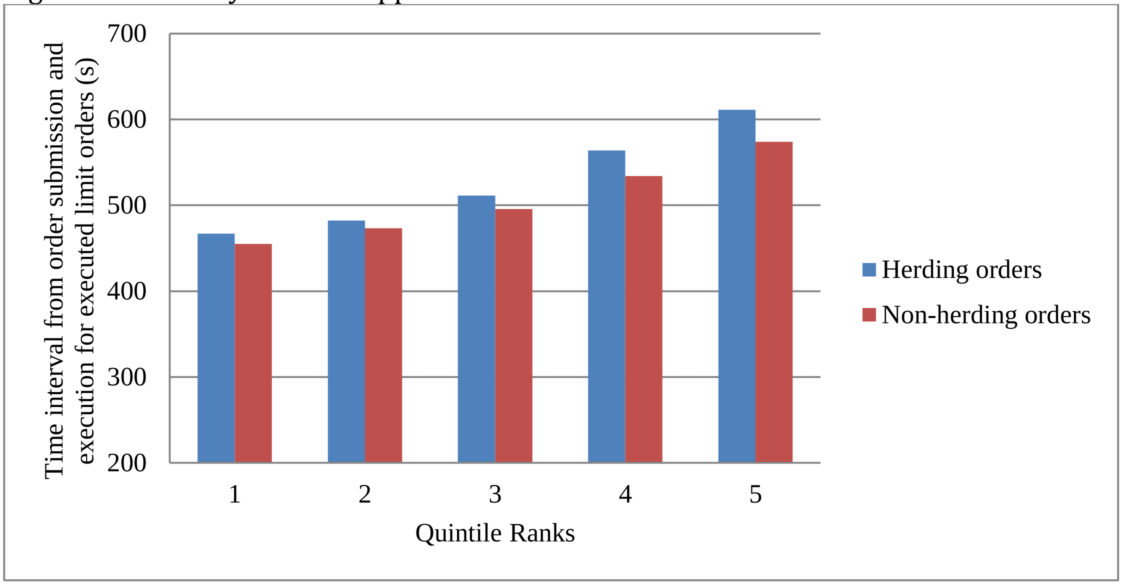

Figure 2.B. Scaled Net Position Approach

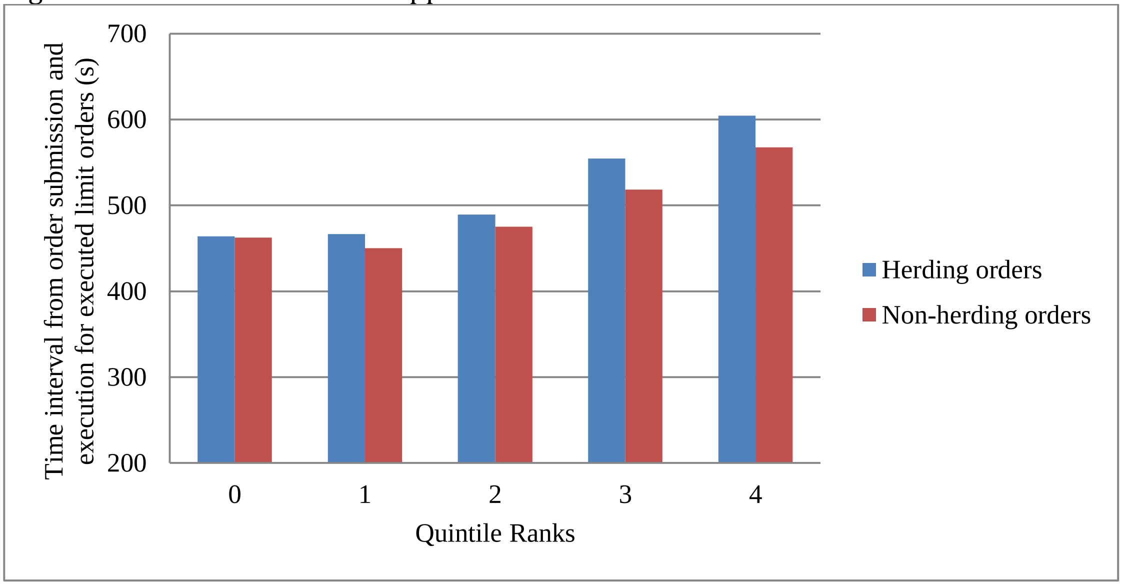

Figure 3. Time-to-Cancellation of Herding and Non-Herding Orders

In this table we sort investors into quintiles by the herding measure in one year, and plot the time-to-cancellation of herding and non-herding orders for the investor-year pair in the subsequent year. Quintile-5 (Q5) investors are more inclined to herding. Herding with the branch is defined as the correlation between an investor's daily net position changes and those of other individual investors trading in the same branch. We employ two specifications for the daily net position changes: the dummy variable approach and the scaled net position. Time-to-cancellation is the interval from submission to cancellation for orders that are submitted and then deleted by individual investors. The herding orders are identified as the orders that are trading at the same direction as other investors in the same branch, while the non-herding orders are the orders that are trading in the opposite direction of to the other investors in the same branch. All items are first calculated for each investor-year observation and then averaged up in each quintile. To ensure reasonable herding measures, we require that investors must submit at least product-days in each of the two consecutive years.

Figure 3.A. Dummy Variable Approach

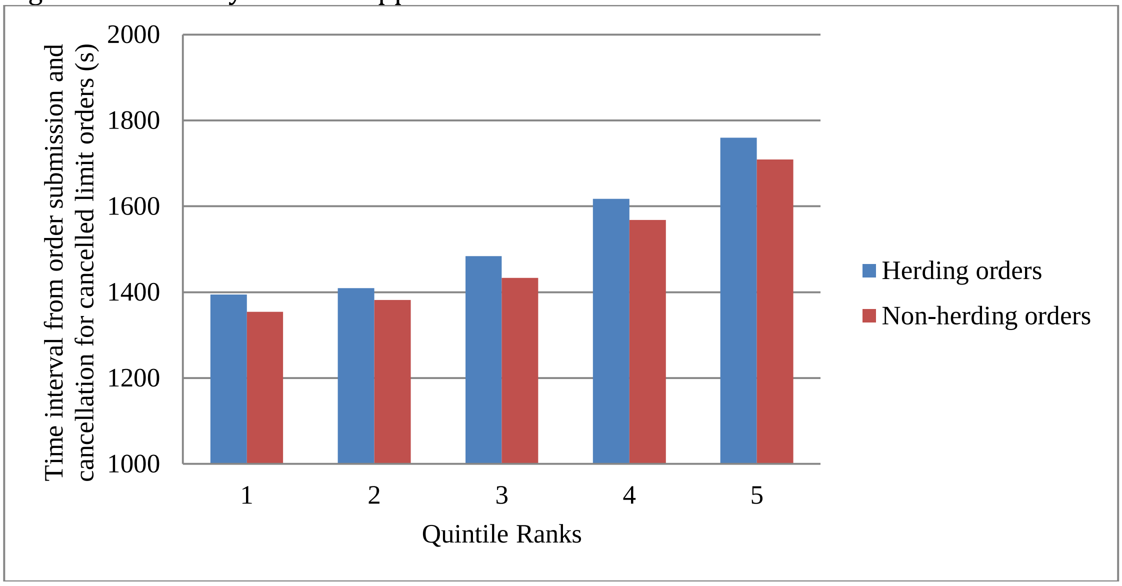

Figure 3.B. Dummy Variable Approach