What Causes Herding:

Information Cascade or Search Cost ?

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Abstract

In the study, we analyze what could have caused herding behavior in the stock market. Information cascades have often been considered as a major cause. However, we present in this study evidences inconsistent with that hypothesis. Our analysis is in support of an alternative theory based on search cost of investors. Specifically, previous works studied daily data or those with lower frequency based on a herding measure of Lakonishok, Shleifer, and Vishny (1992). In stead, we propose in this study an alternative search model of Vayanos and Wang (2007). We investigated intraday limit book data with the new herding measure by Patterson and Sharma (2006). We find that only certain types of investors tend to herd in the last half hour of the day. Herding tend to occur in trading of high-cap, high turnover stocks, which contradicts prediction of the information cascade hypothesis. Also, those investors tend to herd in trading stocks with low price-book ratios, which is inconsistent with the information cascade hypothesis in the notion of investors giving up their own information. Past returns affect herding behavior of different types of investors differently. In terms of dynamic behavior, we find that one type of investors lead others in herding behavior. Herding behavior appeared in a rising market rather than in a falling market. The search model is compatible with various findings in this study. Our evidences suggest that herding could be more related to intrinsic search cost structure of investors in different time frame rather than being information-induced.

Keywords: Herding, information cascade, search model, limit order book

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I. Introduction

Herding behavior of investors has been a central issue of literatures in behavioral finance. Particularly, Nofsinger and Sias (1999) defined 'herding' as a common investing pattern from clustered investors within a given period. Banerjee (1992) considered 'herded trading behavior' as forgoing investors' own information and following others' strategies. Information cascades have often been considered as a theory characterizing herding behavior, where informed traders ignore their own private signal of information and trade in response to observed trades in the market. However, in a given period, this characterization has to be applicable to all assets in a certain market. One class of participants would follow trading actions of another, and information quality in the period is poor to drive that as argued in Bikhchandani, Hirshleifer, and Welch (1992, BHW) and Avery and Zemsky (1999, AZ). Most of the literatures study herding behavior of institutional investors and has been studied primarily in a medium horizon time frame. Even on a daily basis herding is suggested to be short-lived and, as suggested by Christoffersen and Tang (2009), herding decreases with data frequency, and that herding should be less significant in stocks with larger size and higher turnover.

Vayanos and Wang (2007, VW) introduced a search-based model of asset trading, where search or trading cost differs and investors are constrained financially. Trading concentration occurs in a *clientele* equilibrium where investors with similar cost choose to trade similar assets. The asset with concentrated trading tends to trade at a higher price than one with identical-payoff but require higher trading cost. We find in our study that, in an intra-day time frame, investor herding is not consistent with the prediction of information cascade hypothesis but more so with the search-based equilibrium of VW. We show in our analysis that only Qualified Foreign Institutional Investor (QFII), not all institutional investors, exhibit significant herding behavior on a daily basis. Within a given day, herding only occurs in the period immediately preceding market close. While individual investor's herding follows that of the QFII, other types of institutional investors do not herd after QFII does. For the QFII and individual investors, daily or intra-day herding tend to occur in trading of stocks with large size, higher turnover and lower price-to-book ratios. But the other two types of institutional investors exhibit substantially different patterns. Over a longer period, herding is seen to occur more likely for certain stocks consistently than others. These phenomena are not consistent with the prediction of information cascade theory, but are more supported by the trading concentration produced by a search-cost equilibrium.

There are several elements that distinguish our study from other literatures on herding. Similar to Christoffersen and Tang (2009) we also used daily and intra-day tick data, but the order file we obtained allow us to identify investors as from one out of four types, which are proprietary dealers, investment trust, and QFII. In terms of measuring herding, we adopted the bootstrapped run test method of Patterson and Sharma (2006, PS), which has a major advantage of being constructed from intraday data. Compared with the measure introduced by Lakonishok, Shleifer, and Vishny (1992, LSV), the run test approach works especially better with high frequency data. The LSV measure is more easily to be constructed during a longer period as it does not consider the volume of manager's trading but uses only the number of managers buying and selling. The *t*-test for the LSV measure may also suffer from distributional problems when measuring window gets shorter and shorter, while the test for PS runs relies on sample-generated critical values. Another advantage of the PS method is that it does not require herding to accommodate extreme market conditions.

In the emerging markets, turnover and market volume are more likely generated by individual investors. Herding of individuals is worth studying in these markets not only that it interacts with institutional herding, as suggested in Barber, B. M., Odean, T. and Zhu (2003) and Dorn, Huberman Sengmueller (2008). Individual herding is also an important issue, as indicated by Nofsinger and Sias (1999), since it is influenced by institutional herding. In the past, many works employ monthly as well as quarterly data. However, as high frequency data becomes more available, there are more studies focusing on intraday herding behavior. Mian and Adam (2001) explored intraday stock index returns of Australian Stock Exchange and discovered that volatility rises with frequency of data in a given period. The degree of non-normality exhibited in intra-day data, which posed as a problem for the *t*-test of LSV, is not necessarily information-related but implies certain ties to herding. Cont and Bouchard (2000) investigated how the fat-tailed distribution of stock returns is related to herding behavior, as the deviation from normality under high frequency observation cannot be accounted for by ordinary statistical modeling. We therefore aim at the herding interaction between individual and institutional investors within intra-day periods.

We studied the intra-day herding behavior of the four types of investors in the Taiwan market. As we were able to identify three different institutional investor types, we compared various relations among their behavior. That allows us to clarify if whether herding is driven by the information cascade in the sense of BHW or a search-cost based motivation according to VW. Our empirical results support the latter rather than the much more popular former. The main implication of our results would help, on the one hand, investors in general to locate at any given period the most cost-efficient market to trade, which lowers average trading cost and raise market trading volume. On the other hand, our analysis contributes to regulators as well as exchanges to understand if certain extreme herding phenomenon entails intervention or any other actions.

Unnecessary market alarms could be greatly reduced and hence facilitates market efficiency.

This study contributes to provide an explanation for the portion of volatility that is not due to changes in fundamentals or other known effects, while also adding to the literature on herding behavior of investors and advancing the understanding of the phenomenon and the search for the possible implications of different levels of herding on the market, since empirical relationships are established between herding intensity and market volatility. The results could prove highly relevant in achieving a better understanding of market functioning and serve both academics and practitioners, given that an understanding of which variables affect volatility and the nature of their influence could contribute to much more accurate forecasting and, furthermore, to the definition of new risk measures or new hedging strategies. A brief literature review and discussion of how to measure herding are given in Section II. Data and empirical results are laid out in Section III. Section IV gives detailed discussion and compares implications of our findings on the two competing hypotheses. Conclusion is given in Section V.

II. What causes herding, and how to measure it?

The herding behavior is considered an anomaly that challenges the efficient market paradigm. Although this behavior is considered irrational, it can be rational at an individual level. At a group level it is irrational as it leads to mispricing. Literatures argue that the herding arises from the interaction among the agents, when agents copying each other's decisions. The models of BHW and Bannerjee (1992) considered that individuals make their decisions sequentially at a time, taking into account the decisions of the individuals preceding them. The model proposed by Cont and Bouchaud (2000) considered, instead of a sequential decision process, a random communication structure. Random interactions between agents lead to a heterogeneous market structure. AZ argues that information cascades will be short-lived and fragile as one contrarian trade from the herd can quickly stop an information cascade.

What causes herding

The BHW model assumes all investors can invest either in asset A or B — but not both — at zero cost. An investor with t predecessors will choose A if and only if the conditional probability that A is successful given all private and public information $P(A|H_t, s)$ is greater than 1/2, where H_t denotes the observable history of the decisions of all predecessors up to round t, and $s = a, b$, the private signal. Assuming that all predecessors are perfectly rational Bayesians, an investor follows his private signal to reveal it, unless an informational cascade has started. If a signal can be deduced from the chosen action, it is called an imputed signal. A cascade on asset S, an S—cascade, starts when an investor should buy asset S regardless of his own signal, i.e., when $P(S|H_t, s) > 1/2$, for $s = a, b$. Depending on the a priori probabilities and the signal precisions, this requires a certain number of (imputed) a or b signals. If the first investor chooses A, the second should already disregard his own signal: even with a b signal, the second investor should choose A since

$$P(A \mid ab) = \frac{P(ab \mid A)P(A)}{P(ab \mid A)P(A) + P(ab \mid B)P(B)}$$

A pattern of conformity can arise if initial predictions coincide and the inferred information dominates the private information of subsequent decision makers. The followers go along with a consensus prediction, even if it would not be the "correct" prediction made only on the basis of their own sample.

The AZ model is an extended BHW model with a flexible price. The price is set by a market maker who efficiently incorporates all publicly available information. The decision of an investor is straightforward. All information is revealed, and therefore it is incorporated into the price immediately after each decision. The price is a martingale with respect to public information, i.e.,

$$E(p_{t+1} \mid H_t) = p_t$$

for all t, and one cannot take advantage of the knowledge of historical price movements to earn superior returns. As everyone follows his signal, rational herding cannot occur. Note that not trading is never optimal (unless one introduces transaction costs) because subjects always have an informational advantage over the market maker.

Alternatively, VW proposed a model with two assets traded in two markets respectively. Buyers and sellers of asset i by is denoted by μ_b^i and μ_s^i respectively. There is a possibility of either enjoying the full value of the dividend flow or switching to a lower level with a Poisson rate of κ. Because buyers differ in their switching rates κ, they have different reservation values in the bargaining game. Investors are heterogeneous in their horizons, which are inversely related to the switching rates κ. More trading could be generated by shorter horizons as it reduces search times and trading costs. Switching rates could correspond to buyers' characteristics, such as long horizon is more relevant to insurance companies, while shorter ones belong to hedge funds. A clientele equilibrium where market 1 is the one with the most sellers has the following properties:

(a) More buyers and sellers in market 1: $\mu_b^1(\kappa) > \mu_b^2(\kappa)$ and $\mu_s^1(\kappa) > \mu_s^2(\kappa)$

(b) Higher buyer-seller ratio in market 1: $\mu_b^1(\kappa)/\mu_s^1(\kappa) > \mu_b^2(\kappa)/\mu_s^2(\kappa)$

(c) Higher prices in market 1: $p^1(\kappa) > p^2(\kappa)$ for all κ.

Market 1 has not only more sellers than market 2, but also more buyers, and a higher buyer-seller ratio. Moreover, the price that any given buyer expects to pay is higher in market 1. Since there are more sellers in market 1, buyers' search times are shorter. Therefore, holding all else constant, buyers prefer entering into market 1. To restore equilibrium, prices in market 1 must be higher than in market 2. This is accomplished by higher buying pressure in market 1, i.e., higher buyer-seller ratio. In the resulting equilibrium, there is a clientele effect. Investors with high switching rates, who have a stronger preference for short search times, prefer market 1 despite the higher prices. On the other hand, low-switching-rate investors, who are more patient, value more the lower prices in market 2. The clientele effect is, in turn, what accounts for the larger measure of sellers in market 1 since the high-switching-rate buyers turn faster into sellers. So in essence, cost characteristics of investors determine concentration of trading and prices, rather than information about the assets.

LSV measure

LSV (1992) based their criterion on the trades conducted by a group of market participants (fund managers on their empirical application), comparing the actual behavior with an ideal behavior considering independent and random trades.

$$LSV_{i,t} = \left|p_{i,t} - E[p_{i,t}]\right| - E^{NH}\left[\left|p_{i,t} - E[p_{i,t}]\right|\right] \tag{1}$$

Where $p_{i,t}$ is the actual percentages of fund managers that buy stock i at time t. $E[p_{i,t}]$ is the expected value of $p_{i,t}$ defined as the average buying percentage of all managers trading at period t. $E^{NH}[.]$ is the expectation under the hypothesis that there is no herding. $E^{NH}\left[\left|p_{i,t} - E[p_{i,t}]\right|\right]$ is an adjustment factor which is the expected value of the first term under the null hypothesis that there is no herding. The theoretical distribution of $p_{i,t}$ considering independent and random trades for each manager is a binomial distribution with mean $E[p_{i,t}]$.

This measure has one major drawback: it does not consider the volume of manager's trading. The measure uses only the number of managers buying and selling, without regard to the monetary value they trade. Wermers (1999) thus proposed a modification of this herding measure in order to capture differences of behavior when traders are buying or selling.

Cross-sectional standard deviation (CSSD)

Christie and Huang (1995) take another approach and consider aggregate market herding in equity return data. They measure the market impact of herding by considering the dispersion or the cross-sectional standard deviation (CSSD) of returns. The rationale for the use of this dispersion measure is that if market wide herding occurs, returns on individual stocks will be more than usually clustered around the market return as investors suppress their private opinion in favor of the market consensus. Traditional asset pricing theory predicts that the dispersion of returns increases with the aggregate market return due to varying stock sensitivities to market returns. Since dispersion measures the average proximity of individual returns to the mean, when all stock returns move in perfect unison with the market, dispersion is zero. When individual returns differ from the market return, however, the level of dispersion increases. Christie and Huang (1995) contend that when investors ignore the idiosyncratic features of stocks, we would expect to see lower than average level of dispersion during periods characterized by large market movements.

Chang, Cheng and Khorana (2000) modify the Christie and Huang (1995) model to use the cross-sectional absolute standard deviation (CSAD) of returns as a measure of dispersion to detect the existence of herding in the U.S., Hong Kong, Japanese, South Korean and Taiwanese markets. Their model suggests that if market participants herd around indicators, a nonlinear relationship will result between the absolute standard deviation of returns and the average market return during periods of large price movements. They use this model to examine individual returns on a monthly basis and find a significant nonlinear relationship between equity return dispersion and the underlying market price movement of the South Korean and Taiwanese markets. They do not, however, find evidence to support the presence of herding in the developed markets of the U.S., Hong Kong, and Japan.

Christie and Huang (1995) define the cross-sectional dispersion at time *t* as

$$CSD_t = \sum_{i=1}^{n} w_{it}(r_{it} - r_{pt})^2 \qquad (2)$$

where r_{it} (r_{pt}) is the return of security *i* (portfolio *p*) for time *t* and w_{it} is the weight of each stock *i* in portfolio *p* at time *t*. When all securities in the portfolio move in concert CSD_t is zero; conversely, CSD_t is large when the distribution of is dispersed. That is, CSD_t quantifies the average proximity of individual returns to the realized average. If the average volatility of securities comprising the portfolio is assumed to be exogenous, then the volatility of the portfolio will be an increasing function of the average volatility of component securities, while portfolio volatility will be negatively related to the expected cross-sectional dispersion *E[CSD]* of component security returns. An increase in portfolio volatility should generate a decrease in the dispersion of returns. If portfolio volatility is assumed to be exogenous, then *E[CSD]* is positively related to the average volatility of securities. If we define market wide herding to be when all securities in the (market) portfolio move together, then during periods where herding behavior prevails average volatility will be low and dispersion will also be low.

Christie and Huang (1995) use this decomposition to arrive at a test for herding under extreme market conditions, where herding is defined as traders ignoring their private assessment of individual assets and following the trend of the overall market. Thus, if herding occurs, individual returns will converge to the aggregate market return, resulting in decreased dispersion of individual returns from the market return as argued by Gleason, Mathur and Peterson (2003).

Runs Test

Most of the studies carried out to test for herding in capital markets have proved inconclusive. The measure of LSV relies on *t*-test to determine significance of herding, which is affected by distribution characteristics of data. To the extent that measuring herding makes more sense in a short period as pointed out by Christoffersen and Tang (2009), LSV would be less ideal in the analysis of data with higher frequencies. Hence, in recent years various measures have been proposed with a view to overcoming the limitations of past research. Radalj and McAleer (1993) note that the main reason for the lack of empirical evidence of herding may lie in the choice of data frequency, in the sense that too infrequent data sampling would lead to intra-interval herding being missed (at monthly, weekly, daily or even intra-daily intervals). For the purposes of our investigation we used the PS (2006) measure, which we consider the most suitable, since it overcomes this problem of intraday data. PS (2006) has a major advantage over others in that it is constructed from intraday data, that is, a daily indicator is obtained but from intraday data, since we consider this to be the ideal frequency of data to test for the presence investor herding behavior. It does not assume herding to vary with extreme market conditions, and considers the market as a whole rather than a few institutional investors.

PS (2006) propose a statistic that measures herding intensity in terms of the number of runs. The bootstrapped runs test of PS (2006) uses run numbers of buy and sells orders according to Mood (1940) with nontrading adjustments. We utilize this method because our data set contains identification of buy or sell orders, so we would not need Lee and Ready (1991) and Finucane (2002) to determine directions of investors' trading directions. If traders engage in systematic herding, the statistic should take significantly negative values, since the actual number of runs will be lower than expected.

$$x(i,j,t) = \frac{(r_i + \frac{1}{2}) - np_i(1-p_i)}{\sqrt{n}} \qquad i = 1, 2 \tag{3}$$

Where r_i is the actual number of type *i* runs (up runs, down runs or zero runs), *n* is the total number of trades executed on asset *j* on day *t*, ½ is a discontinuity adjustment parameter and p_i is the probability of finding a type of run *i*. Under asymptotic conditions, the statistic $x(i,j,t)$ has a normal distribution with zero mean and variance

$$\sigma^2(i,j,t) = p_i(1-p_i) - 3p_i^2(1-p_i)^2 \tag{4}$$

So the herding intensity statistic is expressed as

$$H(i,j,t) = \frac{x(i,j,t)}{\sqrt{\sigma^2(i,j,t)}} \tag{5}$$

which has an asymptotic distribution of *N*(0,1). Mood (1940) requires state variables to be independent and i.i.d. as well as continuously distributed. As realized transaction price of stock is discrete, $H(i,j,t)$ would have a non-normal distribution and critical values for testing the existence of herding would have to be constructed through bootstrapping the sample.

Data Frequency

However, the data frequency of these studies precludes the detection of herding that occurs within the trading day. The obvious response is to consider intraday data. Gleason, Mathur and Peterson (2003) use intraday U.S. Exchange Traded Funds (ETF) data with the Christie and Huang (1995) and Chang, Cheng and Khorana (2000) models to examine whether traders herd during periods of extreme market movements. They find no evidence of herding in this specialized market. However, ETFs are basket securities, which display different characteristics than shares.

Additional motivation to use high frequency data is related to the volatility literature. The fat tails of the distribution of stock returns correspond to large fluctuations in prices. The fluctuations are difficult to explain in terms of variations in fundamental economic variables as indicated by Shiller (1989), not necessarily relat to the arrival of information (Cutler, Poterba and Summers, 1989), and could be explained as herding. If a large number of agents co-ordinate their actions, the imbalance between buy and sell orders will cause a substantial price change (Bouchaud, 2002). Bouchaud (2002) presents a dynamic model of herding that accounts for volatility clustering by describing the collective behavior of a set of traders exchanging information but having heterogeneous opinions.

III. Data and empirical results

This study employs intra-day limit order book data from the Taiwan Stock Exchange starting from January 1st 2005 to December 31st 2006, covering stocks of 525 firms over a period of 495 trading days. Excluded from the complete pool of stocks listed on the exchange are those with irregularities and unusual exchange sanctions. As the Taiwan Stock Exchange would only release limit book data two years later, the two years are the latest we could obtain so far. The data include the date, exact time in hours, minutes and seconds, stock code, price and volume traded in number of titles of all trades executed during the above-mentioned period. Individual stock returns, market capitalizations, daily turnover and price-book ratios are obtained from the Taiwan Economic Journal (TEJ) database.

We divided the entire daily session between 9:00 AM and 1:30 PM into 9 intervals with 30 minutes in each interval. As our data contains flags identifying the type of investors as proprietary dealers, investment trust, QFII and individuals, we proceed with analysis for each type of investors. Percentages of trading volume in the stock market accounted for by them over the last ten years in Table I. QFII's percentages have apparently grown much faster than the other two types. As a matter of fact, QFII owns one third of the total market capitalization as of end of 2008, which produces the one quarter of daily volume as shown in Table I. Table II reports orders submitted by four types of investors for stocks of 525 firms over the entire data period of 495 days. As the number of individuals is overwhelming, their orders are almost 10 times those of QFII. On average, more than 20% of the individual and proprietary orders are submitted during the first half hour of a regular four and half hour trading session, while only around 15% of orders from the other two types are placed in this period. In the last half hour period, the percentages range between 9% and 19%. Trading in other periods are usually slower than the opening and closing ones.

To construct the herding intensity measures required for our study, we begin by sorting the trades for each day (having excluded all those executed outside normal trading hours) by stock code and measuring the number of up or down zero runs that took place during the day, as well as within each of the nine 30-minute periods. We then compute herding statistic in the respective periods according to PS (2006). A summary of the computed daily herding measures are reported in Table III. It is apparent that herding of QFII is stronger than other three types of investors for a given day.

Similar patterns hold in the case of intra-day herding, which is summarized in Table IV. As critical values for testing significance of herding measure are bootstrapped from different sets of data, the levels of herding within Table III and IV, as well as across them, are not comparable with one another. The computed daily herding measures in Table III are larger in magnitudes than those intra-day ones in Table IV, a pattern consistent with Dorn, *et at.* (2008), which argued that herding measures rise with length of period. We have also reported in Table V average herding measures in 30-minute intervals within each session. The distribution of medians is similar to that across time intervals as in Table II, and across different types of investors as in Table IV. The bootstrapped daily and intra-day critical values for the PS herding measures computed above are in Table VI. The distribution across time and investor is similar to that in Table V, suggesting that the results of significance test would not be too different across these dimensions as well. Table VII demonstrates the situation as expected. In the intra-day context, herding was only significant in the last interval for three types of institutional investors, but not for the individuals. In the daily context, only QFII exhibited significant herding within our data period.

We turn our attention to stock characteristics and their relations to daily and intra-day herding by different types of investors. Table VIII gives the results of herding broken down by market capitalization of a stock. We ranked stocks according to that and assigned all stocks into 5 groups, with S1 being the lowest and S5 being the highest. Interestingly we find QFII and individuals tend to herd, daily or intra-day, in trading stocks with high market capitalizations, while proprietary dealers herded all but those with the highest market capitalization. Investment trust herd only in the closing interval during the day. It is worth noting that, conditioned on the market capitalization, herding of QFII and individuals is uniformly significant across all intra-day intervals, unlike what we observe in Table VII, where they herd only in the last trading interval. Except for the case of investment trust, all three types of investors exhibit herding behavior through out all intra-day intervals. This suggests that in Table VII herding phenomenon was seen through too much noise since stocks with all market caps are pooled together there.

Similar results appear as we group stocks according to daily turnovers as in Dorn *et al.* (2008). Table IX shows that QFII and individuals tend to herd on high turnover stocks, regardless of intra-day intervals. Investment trust herd on stocks with low to middle level of turnovers. Proprietary dealers almost do not herd trading stocks at any time under this categorization except on the ones with the highest turnover during the last trading interval of the day. Categorizing stocks by turnover proves to be effective in removing noises in observing herding behavior in the intra-day context. Ranking stocks according to price-book ratios seem to maintain this effect, as shown in Table X. Both QFII and individuals exhibit herding in trading stocks with low price-book ratios.

Again proprietary and investment trust appeared to exercise the opposite behavior. They herd on trading high-price book ratio stocks. Significance holds in all intra-day intervals, regardless of investor type. There could be other stock characteristics that can achieve the same effect, but we do have clear evidence in indicating what might have preventing us from seeing significant herding behavior in Table VII.

In order to analyze intra-day herding dynamically, we proceed to see if past return of a stock affects herding in the current interval. We measure past returns with

$$R_{i,t} = \ln(\frac{P_{i,t+1}}{P_{i,t}}) \tag{6}$$

where $R_{i,t}$ is the return of stock i in interval t, $P_{i,t}$ is the first transaction price of stock in interval t and $P_{i,t+1}$ is the first transaction price of stock in interval t+1. If there is no trading during the time then the method of Harris (1985) is used to compute intra-day return. Table XI reports the results of regressing herding measure of a certain intra-day interval on the returns, ranked from high (R_1) to low (R_5) into five groups, of previous two intervals. Like our findings on the effects of stock characteristics, QFII and individuals are similar in that their herding measures tend to follow low or negative returns. Investment trust tends to herd after high or positive returns, while there was no effect from past returns on proprietary dealers. These findings are consistent with results on herding distribution among price-book ratio quintiles. QFII and individuals seem to be adopting a contrarian approach in the very short time frame, but the other two types of institutional investors do not.

As we see from the results above, herding of investors in the very short run are related to one another to some extent. So we apply a VAR (Vector AutoRegressive) model to explore if there is any leader-follower relation in the herding behavior of various types of investors.

$$Y_t = \alpha + \sum_{i=1}^{4} \beta_i TH_{t-i} + \sum_{i=1}^{4} \gamma_i TH_{t-i} + \sum_{i=1}^{4} \lambda_i TH_{t-i} + \sum_{i=1}^{4} \theta_i TH_{t-i} + \varepsilon_t \text{, } i=1,\ldots,4 \tag{7}$$

where $Y_t = (TH_t, MH_t, FH_t, IH_t)$ with TH_t denoting herding measure of proprietary dealers, MH_t that of investment trust, FH_t that of QFII and IH_t as herding measure of individuals. t denotes a certain intra-day interval. Results of the VAR model suggest that herding of each type of investors is, as expected, highly negatively autocorrelated. Herding measures of QFII affect those of the individuals positively, but not otherwise. Herding of proprietary dealers and investment trust do not affect others, nor are affected by others. These findings further confirm the results previously that when QFII herds, individuals does too.

Whether herding behavior is affected by market direction is another issue worth our attention. Information-induced rational herding should be free of influence from market direction. As we use transaction data rather than order book, we excluded the first and the last 15 minutes to avoid extreme prices. In this analysis, we did not differentiate investor type, but we adopted buy-herding (BH) and sell herding (SH) measures by counting buy and sell runs. Among all the stocks in our data set, we ranked them into three groups, and we employ buy herding (BHV) for the group with top one-third returns and sell herding (SHV) for the bottom one-third. In Table XIII, summary statistics of BHV and SHV across eight intra-day intervals are presented. The magnitudes of the median values of BHV are generally smaller than those of the SHV. The distribution across intervals in Table XIII is similar to that of herding values, but those in the last interval are not as strong. When we observe herding values over various time intervals in Table XIV, we notice that, based on transaction prices, we would not see any significant herding values after pooling all types of investors together. We further separate trading days into bullish or bearish market according to short and long term moving averages of index closes. If $MA_5 > MA_{10} > MA_{24} > MA_{72}$, then the day is considered to be part of a period of bullish market. If moving averages are in the reverse order, then the day is part of a bearish period. There are altogether 253 bullish days and 193 bearish days in the data period. We find both BHV and SHV are significant in all intra-day intervals within the bullish period, but none are significant when the market is bearish. So the results in Table XIV indicate that market direction matters when computing herding values. The market as a whole do not herd when it is going down. This is an apparent contrast to Table VII, where only QFII exhibit herding in the daily context.

Combined with findings in Table XIV, our analysis suggests that, regardless of stock characteristics, in general QFII tend to herd in an up market. Individuals tend to follow QFII in herding behavior. Proprietary dealers and investment trust herd only under certain conditions and not affected by other types of investors. Although results from the comparison of herding with respect to stock characteristics indicate that QFII and individuals invest in values, they do move together with market trend and tend not to trade continually when market is down.

IV. Discussion on the cause of herding

The preliminary test results indicate that according the definition of PS (2006), herding phenomenon in our data set is not consistent with the information cascade hypothesis. First of all, QFII in Taiwan are supposed to be the most informationally informed participants in the stock market, and yet they are the ones giving up own information and followed other informationally more informed ones. Even if this could be a truthful scenario, it is difficult not to observe other institutional investors, such as the proprietary dealers and the investment trust, to herd as well. Moreover, it is even less convincing to perceive individual investors, who accounted for more than two-thirds of market volume and are often considered the least informationally informed, not to herd their trading when observing significant herding pattern of QFII.

Another puzzle posted by Table VII against the information cascade hypothesis is that the last intra-day interval is the only one among all that we find significant herding incidences from all three types of institutional investors. If information cascade is really driving the market, we would expect to see certain levels of herding during the opening interval when information accumulated overnight is released by the informed. The last intra-day interval is often characterized by needs of liquidity and portfolio adjustments. This phenomenon has not been documented in other previous literatures. This result justifies our approach of conducting analysis among intra-day intervals. Unless there are other valid arguments from the information-based hypotheses of herding, we would have to resort to alternative explanation for this finding.

Differences on herding measures among groups categorized by stock characteristics are not consistent with information-based hypotheses either. The majority of the trading volume tends to herd on stocks with the highest market capitalizations, which are supposed to be of the best information quality according to AZ, BHW and Sias (2004). The prediction of these literatures is that herding should be less likely to appear there. The fact that proprietary dealers and investment trust tend to herd on trading of medium-cap stocks suggest their herding behavior might be related to factors other than information. The herding of QFII is consistent with Kang and Stulz (1997), which argued that home bias is a factor, but as results in this study are obtained in a different context we would need other models to support them. Similar argument applies to the analysis of herding by stock turnovers. As a dynamic indicator, daily turnover also reflects information quality in the sense of AZ and BHW. Our finding is opposite to their predictions, suggesting furthermore that behavior in this market does not support the information cascade theory. Orders submitted by proprietary dealers may have been evenly distributed across stocks with different levels of turnovers so that we do not see any significance under this investor type in Table IX. The analysis with respect to price-book ratio is also inconsistent with information theory. Majority of investors herd on trading stocks with low price-book ratio suggest their focus is on stocks likely to be under-valued by market. As the ratio is well known and does not change rapidly in a short period, it is difficult to conceive lots of orders submitted to capture information on something stable.

The search model of VW is based on search cost of various types of investors in the market. Investors with higher search cost, or shorter search horizon, should value liquidity more than others. According to VW, insurance companies have long horizon than the hedge funds. Similarly, we could consider in the Taiwan market QFII and individuals as having lower search horizons than the other two types of institutional investors. In the *clientele* equilibrium, investors with high shorter horizons generate more trading, and this reduces search times and trading costs. They have a stronger preference for short search times, preferring trading in the respective 'sub-market' despite the higher prices. Since there are more sellers in the sub-market with shorter search time, buyers' search times are shorter. Therefore, holding all else constant, buyers and sellers follow one another entering into market.

The search model for trading concentration by VW is capable of explaining the main results in this study. Herding occurs in the last intra-day trading interval as sellers have constraints before immediate closing of the market. Sellers would then follow buyers due to lower search or trading costs involved. The concentration of order flows following one another reflects dynamic optimization of search for best asset allocation by each investor. Information-induced trading is likely to appear in the opening interval, but it is not significant enough *sequentially* to arrive at herding phenomenon. QFII as the only group exhibiting daily herding suggest that they are the ones more uncertain about information on individual stocks, and hence is under more constraint in searching for appropriate asset to invest. The relatively higher search cost of QFII induces them to rush into stocks whenever there is trading liquidity and lower search horizons.

Findings on herding related to stock characteristics can also be explained properly the search model. Stocks with higher market caps and turnovers are the ones easiest to sell in a very short period of time. Sellers with liquidity constraint would naturally flock to markets for these stocks, and that attracts short-horizon investors like QFII and individuals to come in and buy. Stocks with low price-book ratios are themselves subjects implying low search costs, therefore short-horizon buyers would also follow one another in trading them. The focus of attention here is not just the allocation of trading volume across intra-day intervals. Our adoption of the PS bootstrapped runs test assures that herding is series of order flows or transaction prices that show intensive patterns of buyers and sellers following one another. So the argument that our results are consistent with the search model for trading concentration is actually beyond the context of *static* allocation of asset holdings. As a result, we observe 'habitat' type of herding phenomena which are not compatible with panic-driven behavior from information cascade.

The regression of herding on past returns is another piece of evidence that herding is not necessarily information-induced. Herding of QFII and individuals are on stocks with falling prices a short time ago, while investment trust herded on those stocks with rising prices. Information theory cannot explain this pattern. However, search equilibrium is consistent with it since short-horizon investor can assure themselves lower search cost in these stocks. The VAR regression result of individuals following QFII is also indicative of inconsistency in information distribution as individuals are good candidates giving up own information first rather than QFII. In the context of VW search model, herding of QFII creates liquidity first and draws individuals to join the respective market for individual stocks, whereas other institutional investors with longer-horizon would not follow as prices in these markets are already high due to concentration.

Information-based hypotheses are not supported by the examination of market-wide herding under up or down market direction. In our analysis, herding only occur in an up market, not a down one. The notion of panic selling in a bearish market is supposed to drive up herding behavior, but results in Table XIV give none at all. If we perceive the up market as one with low search time then we would observe substantial herding. The down market with confusing signals about individual stocks is not ideal for the short-horizon majority of market and hence we do not see significant herding results.

V. Conclusion

This study presented a set of intra-day limit order book data to study cause of herding behavior in the securities market. We adopted a herding measure that is specifically ideal for high frequency data. Herding measures are not only on a daily level, but also within intra-day time intervals. Although the analysis is the study is still preliminary, we have found strong evidences against the popular information cascade hypothesis for herding. Specifically, we found that herding on an intraday level occurs in the interval right before closing, which are not intuitively reasonable from a perspective of information cascade. QFII and individuals are found to herd on trading of stocks with high market capitalization, high turnover and low price-book ratio, patterns incompatible with information-induced herding. A simple regression yields results where QFII and individuals exhibited herding on stocks with falling prices, and a VAR regression produces a significant support for individuals to follow QFII in herding. Regardless of investor type, the market as a whole herds trading when market is up. These evidences do not support the hypothesis of information cascade for herding.

We propose in this study an alternative hypothesis to explain the herding phenomena we find. The search model for trading concentration by Vayanos and Wang (2007) can fit in well with our analysis. QFII and individual investors, facing more uncertainty inherent in individual stocks, have shorter search horizon and higher search costs in trading individual stocks. As short-horizon investors tend to follow others in making buying and selling decisions, the observed herding behavior near market closes can be justified. High market cap and turnover, and low price-book ratio are also characteristics of a market that is ideal for QFII and individual investors to rush in to trade when they observe trading concentration emerges. Influence of past returns, and market direction on herding, are also compatible with the context of search cost. Therefore we consider the VW model as superior to the information cascade theory of AZ and BHW in explaining intra-day and daily herding of various types of investors.

Although we have presented valid arguments regarding the central issue of this study, there are areas we do have to work on to enrich our study with. We have yet to separate run numbers of market orders from those of limit ones to explore the horizon effects on intra-day herding, especially for the individual investors. Other analysis, such as trading motives of investors, evidence on sequence or development of trading concentration and the dynamics of search equilibrium need to be added to the current model as well.

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Table I Institutional Trading Volume as Percentages of the Taiwan Stock Market

年	Volume Percentages (%)		
	Proprietary dealers	Investment Trust	QFII
1998	1.6	2.6	2.0
1999	1.9	3.4	3.0
2000	1.9	3.8	4.5
2001	1.7	4.1	7.1
2002	1.9	4.1	7.7
2003	2.7	4.1	10.7
2004	3.4	3.1	12.5
2005	4.1	3.4	17.9
2006	3.4	2.7	18.4
2007	2.9	2.7	19.6
2008	3.1	3.4	24.3

Source：Financial Supervisory Commission %

Table II Orders by type of investors and time of day

Averaged across 525 firms over 495 trading days

Investor Type	Time of Day									
	All Day	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30
Proprietary Dealer	8558	1755	1064	834	716	673	651	594	705	1566
Investment Trust	6817	997	838	732	700	706	706	731	744	663
QFII	84086	11273	8883	8174	8166	8146	8455	8876	10201	11912
Individuals	790275	176874	111960	83988	70032	61049	56174	54046	64065	112088

Table III Summary Statistics of Daily Herding Measures by Investor Type

Across 525 firms over 495 trading days

Investor Type	No. of Obs.	Maximum	Minimum	Mean	Median	Q1	Q3	S.D.
Proprietary Dealers	57247	5.303	-29.292	-3.275	-3.000	-4.382	-1.768	2.320
Investment Trust	19751	3.984	-28.918	-4.653	-4.264	-6.008	-2.828	2.972
QFII	95598	14.818	-62.568	-8.119	-6.441	-10.565	-3.975	6.305
Individuals	257550	5.955	-141.450	-4.276	-3.138	-5.573	-1.484	4.902

Table IV Summary Statistics of Intra-day Herding Measures by Investor Type

Across 525 firms over 495 trading days

Investor Type	No. of Obs.	Maximum	Minimum	Mean	Median	Q1	Q3	S.D.
Proprietary Dealers	402050	4.158	-16.084	-1.026	-1.043	-1.942	0.000	1.584
Investment Trust	167190	5.000	-16.146	-1.264	-1.342	-2.138	0.000	1.705
QFII	630220	8.300	-34.622	-2.448	-1.942	-3.800	-0.492	2.858
Individuals	2152600	5.778	-73.488	-1.002	-0.655	-1.890	0.397	2.319

Table V Summary Statistics of Intra-day Herding Measures by Investor Type and Time of Day

Across 525 firms over 495 trading days

Time	No of Obs	Maximum	Minimum	Average	Median	Q1	Q3	S.D.
Panel A: Proprietary Dealers								
9:00~9:30	44672	4.158	-16.084	-1.026	-1.043	-1.942	0.000	1.584
9:30~10:00	28615	4.158	-13.827	-0.783	-0.707	-1.698	0.447	1.584
10:00~10:30	21894	5.303	-14.388	-0.777	-0.707	-1.698	0.447	1.623
10:30~11:00	18551	4.158	-12.493	-0.784	-0.707	-1.633	0.447	1.610
11:00~11:30	17618	4.025	-12.084	-0.798	-0.707	-1.732	0.447	1.607
11:30~12:00	17017	4.158	-11.715	-0.816	-0.707	-1.732	0.447	1.621
12:00~12:30	15568	4.500	-14.042	-0.861	-0.707	-1.732	0.333	1.581
12:30~13:00	18308	4.158	-14.428	-0.826	-0.707	-1.732	0.333	1.591
13:00~13:30	38934	4.737	-19.856	-0.044	0.000	-1.000	0.905	1.583
Panel B: Investment Trust								
9:00~9:30	25072	4.025	-13.681	-1.511	-1.508	-2.500	-0.302	1.758
9:30~10:00	22451	4.158	-16.146	-1.279	-1.342	-2.324	0.000	1.699
10:00~10:30	19662	4.333	-13.160	-1.218	-1.342	-2.121	0.000	1.678
10:30~11:00	18500	4.158	-15.298	-1.206	-1.342	-2.121	0.000	1.678
11:00~11:30	18095	4.323	-15.843	-1.240	-1.342	-2.138	0.000	1.712
11:30~12:00	17579	4.491	-12.807	-1.239	-1.342	-2.138	0.000	1.709
12:00~12:30	16913	4.523	-13.435	-1.303	-1.342	-2.324	0.000	1.726
12:30~13:00	16062	4.768	-13.492	-1.263	-1.342	-2.138	0.000	1.717
13:00~13:30	12852	5.000	-12.924	-0.932	-1.000	-1.890	0.000	1.556
Panel C: QFII								
9:00~9:30	74956	4.564	-34.622	-3.002	-2.335	-4.382	-0.962	3.191
9:30~10:00	70717	6.941	-29.019	-2.532	-2.041	-3.857	-0.600	2.873
10:00~10:30	68085	7.245	-29.278	-2.386	-1.896	-3.703	-0.469	2.767
10:30~11:00	67953	7.720	-29.097	-2.379	-1.890	-3.674	-0.500	2.752
11:00~11:30	66552	8.300	-24.280	-2.354	-1.890	-3.674	-0.429	2.752
11:30~12:00	67191	7.309	-25.341	-2.352	-1.890	-3.747	-0.378	2.740
12:00~12:30	67308	8.054	-25.906	-2.321	-1.890	-3.667	-0.378	2.763
12:30~13:00	69626	7.415	-27.354	-2.438	-1.942	-3.810	-0.500	2.805
13:00~13:30	77828	6.245	-28.874	-2.236	-1.732	-3.638	-0.229	2.926
Panel D: Individuals								
9:00~9:30	254000	4.596	-73.488	-1.504	-1.118	-2.452	0.000	2.585
9:30~10:00	245870	5.196	-67.237	-1.229	-0.863	-2.152	0.218	2.393
10:00~10:30	240690	4.982	-49.227	-1.038	-0.707	-1.939	0.333	2.296
10:30~11:00	236560	5.778	-47.737	-0.945	-0.600	-1.852	0.447	2.255
11:00~11:30	232880	4.715	-36.602	-0.850	-0.519	-1.718	0.458	2.219
11:30~12:00	229560	4.715	-42.783	-0.812	-0.469	-1.697	0.500	2.240
12:00~12:30	228970	5.259	-53.321	-0.770	-0.412	-1.616	0.566	2.247
12:30~13:00	234170	5.048	-54.767	-0.868	-0.500	-1.706	0.480	2.322
13:00~13:30	249890	5.461	-52.281	-0.944	-0.638	-1.769	0.346	2.171

Table VI Bootstrapped Daily and Intra-day Critical Values for Herding Measures by Time of Day and Investor Type

	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30	All Day
Panel A: Proprietary Dealers										
1%	-1.0442	-0.8030	-0.8015	-0.8109	-0.8273	-0.8436	-0.8903	-0.8553	-0.0633	-3.2998
5%	-1.0386	-0.7977	-0.7950	-0.8030	-0.8182	-0.8367	-0.8817	-0.8467	-0.0568	-3.2910
10%	-1.0361	-0.7942	-0.7914	-0.7994	-0.8140	-0.8323	-0.8771	-0.8420	-0.0537	-3.2867
Panel B: Investment Trust										
1%	-1.5359	-1.3058	-1.2448	-1.2366	-1.2704	-1.2707	-1.3323	-1.2974	-0.9634	-4.7092
5%	-1.5287	-1.2974	-1.2384	-1.2258	-1.2615	-1.2611	-1.3234	-1.2857	-0.9543	-4.6864
10%	-1.5247	-1.2933	-1.2340	-1.2208	-1.2562	-1.2549	-1.3192	-1.2800	-0.9495	-4.6789
Panel C: QFII										
1%	-3.0270	-2.5589	-2.4099	-2.4028	-2.3810	-2.3767	-2.3463	-2.4627	-2.2588	-8.1694
5%	-3.0205	-2.5511	-2.4025	-2.3972	-2.3722	-2.3687	-2.3390	-2.4543	-2.2529	-8.1536
10%	-3.0169	-2.5461	-2.3995	-2.3938	-2.3684	-2.3649	-2.3349	-2.4506	-2.2495	-8.1448
Panel D: Individuals										
1%	-1.5145	-1.2416	-1.0492	-0.9551	-0.8597	-0.8233	-0.7802	-0.8795	-0.9537	-4.2995
5%	-1.5117	-1.2369	-1.0455	-0.9522	-0.8571	-0.8204	-0.7778	-0.8754	-0.9511	-4.2930
10%	-1.5102	-1.2352	-1.0437	-0.9508	-0.8555	-0.8187	-0.7762	-0.8737	-0.9494	-4.2891

Table VII Daily and Intra-day Herding Measures by Time of Day

Averaged across 525 firms over 495 trading days

Investor Type	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30	All Day
All Investors	-1.4906	-1.1708	-0.9600	-0.8541	-0.7394	-0.6868	-0.6237	-0.7163	-0.8801	-4.7384
Proprietary Dealers	-0.9310	-0.7270	-0.7120	-0.7060	-0.7102	-0.7043	-0.7932	-0.7444	-0.1119***	-3.1957
Investment Trust	-1.5088	-1.2691	-1.2097	-1.2018	-1.2317	-1.2289	-1.2972	-1.2649	-0.9606**	-4.6746
QFII	-2.9980	-2.5393	-2.3851	-2.3799	-2.3517	-2.3450	-2.3212	-2.4216	-2.2585**	-8.1668**
Individuals	-1.5013	-1.2242	-1.0317	-0.9378	-0.8418	-0.8041	-0.7635	-0.8618	-0.9418	-4.2741

Table VIII Daily and Intra-day Herding Measures by Time of Day and Market Caps

Market Cap	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30	All Day
Panel A: Proprietary Dealere										
S1(Lowest)	-0.8265	-0.8399***	-0.8722***	-0.5167	-0.7016	-0.6176	-0.7647	-0.8385	-0.093***	-2.7431
S2	-1.0907***	-1.1471***	-1.1547***	-1.4177***	-1.2911***	-1.0481***	-1.0469***	-0.9891***	-0.1296***	-3.4213***
S3	-1.0762***	-1.0842***	-1.077***	-1.2008***	-1.0798***	-1.0788***	-1.2635***	-0.9585***	-0.1395***	-3.1086
S4	-0.9478	-0.8607***	-0.9264***	-0.956***	-0.9502***	-0.8993***	-1.081***	-0.9459***	-0.1548***	-3.0247
S5(Highest)	-0.9199	-0.6428	-0.6181	-0.5838	-0.6013	-0.6068	-0.677	-0.6748	-0.1262***	-3.2913**
Panel B: Investment Trust										
S1(Lowest)	-1.2002	-1.1957	-1.4679	-1.2213*	-1.3551***	-1.2106	-1.0561	-1.153	-1.0342***	-5.0614***
S2	-1.4246	-1.2767	-1.2131	-1.2432***	-1.2074	-1.1779	-1.2425	-1.2602	-1.0469***	-4.5703
S3	-1.5054	-1.2526	-1.2914***	-1.2231*	-1.2483	-1.201	-1.3174	-1.2544	-1.1408***	-4.8265***
S4	-1.5072	-1.2874	-1.2112	-1.1971	-1.2297	-1.215	-1.2695	-1.229	-1.0153***	-4.6025
S5(Highest)	-1.5232	-1.2636	-1.2094	-1.1956	-1.2272	-1.2539	-1.3221*	-1.2925**	-0.9025	-4.6777
Panel C: QFII										
S1(Lowest)	-1.5823	-1.5367	-1.4364	-1.4215	-1.3435	-1.2495	-1.4676	-1.3844	-1.1103	-5.4392
S2	-1.706	-1.5464	-1.4214	-1.5077	-1.4554	-1.4154	-1.429	-1.4659	-1.4008	-5.4722
S3	-1.977	-1.7747	-1.6505	-1.6517	-1.612	-1.6148	-1.592	-1.6805	-1.6005	-5.7887
S4	-2.1569	-1.8117	-1.716	-1.6912	-1.6786	-1.6273	-1.5965	-1.6957	-1.4824	-6.336
S5(Highest)	-3.5876***	-2.9858***	-2.7784***	-2.7688***	-2.732***	-2.7406***	-2.7242***	-2.8424***	-2.7552***	-10.013***
Panel D: Individuals										
S1(Lowest)	-0.0943	0.0741	0.1832	0.2479	0.3015	0.349	0.3733	0.3401	0.2029	-1.2989
S2	-0.6955	-0.4534	-0.2918	-0.1998	-0.0974	-0.0484	-0.0035	-0.0755	-0.2705	-2.3647
S3	-1.2692	-0.9628	-0.7656	-0.6577	-0.5347	-0.4749	-0.4092	-0.4984	-0.6642	-3.5113
S4	-1.8052***	-1.4723***	-1.2284***	-1.1082***	-0.9875***	-0.9421***	-0.8688***	-0.9738***	-1.1581***	-4.8399***
S5(Highest)	-3.5093***	-3.0238***	-2.7021***	-2.565***	-2.4183***	-2.3896***	-2.3907***	-2.6362***	-2.6405***	-9.2406***

***: significant at 1%，**: significant at 5%，*: significant at 10%

Table IX Daily and Intra-day Herding Measures by Time of Day and Turnovers

Stock Turnover Quantiles	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30	All Day
Panel A: Proprietary Dealer										
T1(Lowest)	-0.7679	-0.6549	-0.7363	-0.6801	-0.6819	-0.8168	-0.7013	-0.8402	0.1271	-3.0983
T2	-0.8002	-0.6114	-0.6642	-0.6305	-0.6666	-0.6411	-0.7863	-0.7648	0.0264	-3.1497
T3	-0.8570	-0.6431	-0.6607	-0.6641	-0.6306	-0.6875	-0.7276	-0.6866	-0.0400	-3.1188
T4	-0.9302	-0.6898	-0.6707	-0.6844	-0.6634	-0.6127	-0.7699	-0.7508	-0.1629***	-3.1396
T5(Highest)	-0.9903	-0.7666	-0.7430	-0.7529	-0.7667	-0.7262	-0.8196	-0.7274	-0.1854***	-3.2250
Panel B: Investment Trust										
T1(Lowest)	-1.3908	-1.2835	-1.4114***	-1.2526***	-1.3544***	-1.4547***	-1.4654***	-1.4954***	-1.067***	-4.3298
T2	-1.3437	-1.2232	-1.1564	-1.1768	-1.281***	-1.3482***	-1.4295***	-1.4595***	-1.0493***	-4.3856
T3	-1.4118	-1.3058***	-1.33***	-1.3138***	-1.3385***	-1.3628***	-1.3893***	-1.363***	-1.0482***	-4.5893
T4	-1.453	-1.2871	-1.2792***	-1.248***	-1.2665***	-1.3125***	-1.3439***	-1.2993***	-0.9866***	-4.7895***
T5(Highest)	-1.5851***	-1.2558	-1.1448	-1.1299	-1.1321	-1.0919	-1.1734	-1.1233	-0.8796	-4.819***
Panel C: QFII										
T1(Lowest)	-2.0768	-1.6876	-1.5508	-1.5421	-1.5510	-1.5886	-1.5339	-1.6549	-1.5677	-6.3101
T2	-2.8661	-2.3835	-2.2303	-2.2254	-2.1918	-2.1744	-2.1734	-2.2947	-2.2239	-8.0108
T3	-3.1745***	-2.6825***	-2.509***	-2.4856***	-2.4441***	-2.4601***	-2.4038***	-2.5361***	-2.3997***	-8.5638***
T4	-3.2839***	-2.7971***	-2.6156***	-2.6061***	-2.5709***	-2.5528***	-2.5582***	-2.6286***	-2.4582***	-8.7081***
T5(Highest)	-3.1888***	-2.7179***	-2.5834***	-2.5816***	-2.5685***	-2.5481***	-2.5281***	-2.6084***	-2.3208***	-8.377***
Panel D: Individuals										
T1(Lowest)	-0.2677	-0.1043	-0.0026	0.0254	0.0628	0.0726	0.0777	0.0168	-0.1229	-1.8695
T2	-0.9747	-0.6813	-0.5234	-0.4493	-0.3754	-0.3392	-0.3418	-0.4506	-0.6262	-3.272
T3	-1.3829	-1.1000	-0.8990	-0.7994	-0.7006	-0.6599	-0.6270	-0.7626	-0.9354	-4.1298
T4	-1.8734***	-1.5498***	-1.3213***	-1.2035***	-1.0729***	-1.0327***	-0.9656***	-1.0993***	-1.2213***	-5.0846***
T5(Highest)	-2.8782***	-2.4043***	-2.0643***	-1.8802***	-1.6971***	-1.6227***	-1.5341***	-1.6308***	-1.6496***	-6.9046***

***: significant at 1%，**: significant at 5%，*: significant at 10%

Table X Daily and Intra-day Herding Measures by Time of Day and Price-Book Ratios

Price-Book Ratio Quantile	9:00~ 9:30	9:30~ 10:00	10:00~ 10:30	10:30~ 11:00	11:00~ 11:30	11:30~ 12:00	12:00~ 12:30	12:30~ 13:00	13:00~ 13:30	All Day
Panel A: Proprietary Dealer										
B1(Lowest)	-0.8483	-0.615	-0.5803	-0.5579	-0.5692	-0.5674	-0.6557	-0.5574	-0.0463	-3.0089
B2	-0.9722	-0.7727	-0.7604	-0.7818	-0.7714	-0.7595	-0.809	-0.8488**	-0.1636***	-3.3554***
B3	-0.959	-0.8401***	-0.8494***	-0.8683***	-0.8966***	-0.9606***	-1.0101***	-0.8643***	-0.1554***	-3.3005***
B4	-1.0057	-0.7635	-0.7906	-0.9207***	-0.8382***	-0.8777***	-0.9769***	-0.8678***	-0.1627***	-3.1849
B5(Highest)	-0.9907	-0.8853***	-0.9468***	-0.9763***	-0.9384***	-0.8578***	-1.0093***	-0.804	-0.0671***	-3.0747
Panel B: Investment Trust										
B1(Lowest)	-1.4546	-1.1622	-1.0751	-1.0842	-1.0918	-1.0798	-1.1587	-1.113	-0.8481	-4.4954
B2	-1.5928***	-1.3579***	-1.3292***	-1.2667***	-1.3435***	-1.339***	-1.3923***	-1.3479***	-1.021***	-4.757***
B3	-1.5167	-1.4671***	-1.4236***	-1.3415***	-1.4377***	-1.4234***	-1.462***	-1.5356***	-1.1835***	-4.8249***
B4	-1.581***	-1.532***	-1.4861***	-1.5119***	-1.5239***	-1.6201***	-1.6525***	-1.5778***	-1.2035***	-5.0841***
B5(Highest)	-1.6441***	-1.7157***	-1.7401***	-1.7169***	-1.9118***	-1.8728***	-1.8981***	-1.8048***	-1.3149***	-5.3407***
Panel C: QFII										
B1(Lowest)	-3.1707***	-2.6988***	-2.5237***	-2.5132***	-2.4609***	-2.4545***	-2.4348***	-2.5258***	-2.5034***	-8.555***
B2	-3.3485***	-2.8226***	-2.6612***	-2.624***	-2.5845***	-2.5836***	-2.5759***	-2.6773***	-2.5722***	-8.8786***
B3	-2.9259	-2.476	-2.284	-2.2925	-2.293	-2.2994	-2.2297	-2.3396	-2.1333	-8.0898
B4	-2.2818	-1.8858	-1.7863	-1.8109	-1.791	-1.7598	-1.7688	-1.884	-1.5086	-6.7481
B5(Highest)	-2.4111	-2.0317	-1.9045	-1.9035	-1.9293	-1.933	-1.9659	-2.0719	-1.6055	-6.9557
Panel D: Individuals										
B1(Lowest)	-2.4714***	-2.038***	-1.7619***	-1.6349***	-1.4954***	-1.4589***	-1.4077***	-1.5385***	-1.5568***	-6.3752***
B2	-2.0564***	-1.7197***	-1.4887***	-1.3645***	-1.2577***	-1.2222***	-1.1785***	-1.3103***	-1.4056***	-5.6196***
B3	-1.4085	-1.1538	-0.967	-0.8809	-0.7706	-0.7343	-0.7089	-0.8299	-0.944	-4.1226
B4	-1.0322	-0.7927	-0.6223	-0.5428	-0.4482	-0.3944	-0.3554	-0.4356	-0.581	-3.1751
B5(Highest)	-0.4825	-0.2951	-0.1671	-0.0967	-0.0294	0.0049	0.0499	-0.0011	-0.157	-2.0464

***: significant at 1%，**: significant at 5%，*: significant at 10%

Table XI Daily Herding Measures Regressed on Past Returns

Day Lags	Return Quintile R1	R2	R3	R4	R5
Panel A: Proprietary Dealers					
T-1	-3.1958	-3.1865	-3.1808	-3.1733	-3.1985
T-2	-3.1999	-3.2238	-3.1738	-3.1839	-3.1658
Panel B: Investment Trust					
T-1	-5.0914***	-4.7652***	-4.5211	-4.3643	-4.635
T-2	-4.8717***	-4.7554***	-4.6313	-4.713***	-4.5065
Panel C: QFII					
T-1	-8.1359	-7.9466	-7.9024	-8.0379	-8.5625***
T-2	-8.0744	-8.0115	-8.0589	-8.0854	-8.4006***
Panel D: Individuals					
T-1	-4.4663***	-3.893	-3.7956	-4.1488	-5.0619***
T-2	-4.3674***	-3.995	-3.9097	-4.2248	-4.8711***

***: significant at 1%，**: significant at 5%，*: significant at 10%

Table XII VAR Regressions of Intra-day Herding Measures among Investors

The VAR regression is based on the following models,

$$HV_t = \alpha + \sum_{i=1}^{4} \beta_i TH_{t-i} + \sum_{i=1}^{4} \gamma_i MH_{t-i} + \sum_{i=1}^{4} \lambda_i FH_{t-i} + \sum_{i=1}^{4} \theta_i IH_{t-i} + \varepsilon_t$$

where *t* is the day index and HV_t takes on the values of TH_t for proprietary dealers, MH_t for proprietary dealers, FH_t for proprietary dealers and IH_t for proprietary dealers.

Dep. Var.						MH_t				FH_t				IH_t			
	α	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4	λ_1	λ_2	λ_3	λ_4	θ_1	θ_2	θ_3	θ_4
TH_t	0.126***	-0.648***	-0.477***	-0.303***	-0.169***	0.044	0.055*	0.031	0.031	0.007	0.042**	0.006	-0.014	-0.006	-0.001	-0.003	-0.002
	[2.963]	[-26.321]	[-16.885]	[-10.652]	[-7.096]	[1.531]	[1.703]	[1.074]	[1.293]	[0.381]	[2.206]	[0.359]	[-0.941]	[-0.501]	[-0.097]	[-0.233]	[-0.246]
MH_t	0.322***	0.007	0.03	0.006	-0.01	-0.569***	-0.305***	-0.174***	-0.078***	-0.01	0.003	-0.025	-0.013	-0.003	0.008	0.001	-0.004
	[8.319]	[0.332]	[1.172]	[0.232]	[-0.458]	[-21.899]	[-10.438]	[-6.528]	[-3.615]	[-0.661]	[0.149]	[-1.535]	[-0.976]	[-0.344]	[0.774]	[0.079]	[-0.474]
FH_t	-0.068	-0.004	-0.031	-0.019	-0.031	-0.018	0.051	-0.01	0.032	-0.44***	-0.219***	-0.193***	-0.046**	-0.017	0.003	-0.011	0.003
	[-1.07]	[-0.118]	[-0.73]	[-0.44]	[-0.868]	[-0.42]	[1.055]	[-0.236]	[0.889]	[-17.094]	[-7.663]	[-7.221]	[-2.002]	[-1.006]	[0.159]	[-0.65]	[0.187]
IH_t	0.136	0.012	0.001	0.089	0.038	0.234***	0.182**	0.103	0.026	0.119***	0.154***	-0.019	-0.008	-0.535***	-0.327***	-0.138***	-0.066***
	[1.423]	[0.217]	[0.022]	[1.382]	[0.703]	[3.625]	[2.509]	[1.556]	[0.486]	[3.074]	[3.582]	[-0.465]	[-0.225]	[-21.282]	[-12.187]	[-5.299]	[-3.059]

Table XIII Summary Statistics of Intra-day Buy and Sell Herding

Herding Type	Time of Day	Sample Size	Maximum	Minimum	Average	Median	Q1	Q3	S.D.
BHV	9:15~9:45	249904	4.5227	-67.3480	-1.3780	-1.0000	-2.3349	0.0976	2.4267
	9:45~10:15	244246	4.9193	-54.0750	-1.1270	-0.7845	-2.0580	0.2774	2.2682
	10:15~10:45	239981	5.7384	-43.5880	-0.9998	-0.6860	-1.9206	0.3562	2.1956
	10:45~11:15	236571	5.0000	-36.1900	-0.8988	-0.5774	-1.8058	0.4472	2.1628
	11:15~11:45	236753	5.0000	-31.4460	-0.7579	-0.4932	-1.7306	0.5774	2.2385
	11:45~12:15	230662	5.1760	-42.0630	-0.7666	-0.4472	-1.6398	0.5071	2.1287
	12:15~12:45	233804	5.1911	-45.2080	-0.7905	-0.4472	-1.6537	0.5000	2.1605
	12:45~13:15	239190	5.4306	-48.5690	-0.8913	-0.5571	-1.7538	0.4472	2.2118
SHV	9:15~9:45	249904	2.5298	-12.5990	-1.3628	-0.9839	-2.3311	0.1280	2.4348
	9:45~10:15	244246	2.6458	-14.3030	-1.1113	-0.7625	-2.0526	0.3078	2.2764
	10:15~10:45	239981	4.1576	-11.5550	-0.9847	-0.6547	-1.9126	0.3906	2.2036
	10:45~11:15	236571	3.8996	-9.9796	-0.8842	-0.5729	-1.7852	0.4472	2.1719
	11:15~11:45	236753	3.0000	-13.2960	-0.7504	-0.4867	-1.7288	0.5774	2.2431
	11:45~12:15	230662	3.1305	-13.4890	-0.7531	-0.4417	-1.6378	0.5388	2.1363
	12:15~12:45	233804	2.8402	-12.5660	-0.7669	-0.4313	-1.6378	0.5388	2.1692
	12:45~13:15	239190	3.0000	-21.2890	-0.8580	-0.5130	-1.7321	0.4865	2.2254

Table XIV Buy and Sell Herding by Market Type and Length of Interval

General Market								
Panel A：30 minute intervals								
Herding Type	9:15~9:45	9:45~10:15	10:15~10:45	10:45~11:15	11:15~11:45	11:45~12:15	12:15~12:45	12:45~13:15
BHV	-13.9290	-11.4450	-10.0750	-9.4882	-9.2198	-8.8051	-8.8403	-9.9461
SHV	-12.1820	-10.0700	-9.2781	-8.5621	-8.3385	-7.9064	-8.8159	-10.1090
Panel B：60 minute intervals								
	9:15~10:15	9:45~10:45	10:15~11:15	10:45~11:45	11:15~12:15	11:45~12:45	12:15~13:15	—
BHV	-18.2940	-15.4160	-14.0310	-13.3920	-12.8720	-12.4350	-13.1510	—
SHV	-15.6160	-13.5520	-12.5550	-11.8490	-11.3430	-11.7800	-13.5050	—
Panel C：120 minute intervals								
	9:15~11:15	9:45~11:45	10:15~12:45	10:45~12:45	11:15~13:15	—	—	—
BHV	-23.6230	-20.9220	-19.4490	-18.6270	-18.4760	—	—	—
SHV	-20.1050	-18.1140	-17.0110	-16.8080	-17.8920	—	—	—
Bullish Market								
Panel A：30 minute intervals								
BHV	-15.0370***	-12.3700***	-10.6850***	-10.4370***	-9.8819***	-9.6768***	-9.3279***	-10.7510***
SHV	-13.1210***	-10.7130***	-10.2490***	-9.0417***	-9.0490***	-8.3325***	-9.7134***	-10.9660***
Panel B：60 minute intervals								
BHV	-19.9970***	-16.6510***	-15.3210***	-14.6660***	-14.0770***	-13.4950***	-14.1390***	—
SHV	-16.8740***	-14.8110***	-13.7490***	-12.7930***	-12.2590***	-12.8500***	-14.8630***	—
Panel C：120 minute intervals								
BHV	-25.7150***	-22.7540***	-21.2280***	-20.3550***	-20.0210***	—	—	—
SHV	-21.7990***	-19.7160***	-18.4490***	-18.2410***	-19.5030***	—	—	—
Bearish Market								
Panel A：30 minute intervals								
BHV	-12.5680	-10.1630	-8.9626	-8.0699	-8.1817	-7.5133	-7.9759	-8.7815
SHV	-10.8450	-9.0491	-7.9988	-7.6464	-7.1007	-7.1141	-7.5394	-9.1016
Panel B：60 minute intervals								
BHV	-16.4970	-13.9000	-12.3980	-11.8490	-11.4020	-11.1180	-11.9630	—
SHV	-14.1780	-12.1920	-11.3170	-10.6570	-10.3100	-10.6160	-12.0730	—
Panel C：120 minute intervals								
BHV	-21.3540	-18.8350	-17.3130	-16.6920	-16.6890	—	—	—
SHV	-18.3770	-16.4660	-15.6100	-15.3250	-16.2970	—	—	—