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What Causes Herding:

Information Cascade or Search Cost ?

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Abstract

We analyze in this study what could have caused herding 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). We adopt instead the measure of Patterson and Sharma (2006) and argue that the search model of Vayanos and Wang (2007) characterize herding phenomenon better. Our analysis supports their hypothesis employing intraday order book data. We find that stronger order flow herding is driven by lower transactions cost. Herding tend to occur in trading of high-cap, high turnover stocks, which contradicts prediction of the information cascade hypothesis. Information cascade effect, if any, is actually stronger near market close than at open. Therefore our study suggests that herding could be related more to intrinsic search cost structure of investors rather than information related factors.

Keywords: Herding, information cascade, search model, order book
JEL codes: C14, D82, D83, G12, L11

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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 has to be 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 primarily in a medium horizon time frame. On a daily basis, herding is suggested to be short-lived and, as suggested by Christoffersen and Tang (2009), herding increases with data frequency, and that herding should be less significant in stocks with larger size and higher turnover. We find, however, in our study that investor herding, on a intraday basis, is not consistent with the prediction of information cascade hypothesis as herding is more pronounced in stocks with good information quality of the larger firms, with higher turnover and lower price-book ratios. Herding is significantly related to price spreads between buy and sell orders, especially at market open, suggesting an alternative model is needed to characterize the herding phenomenon.

Generally, herding implies a leader-follower behavior pattern in terms of trading. Henker, Henker, and Mitsios (2006), argued that herding should be considered in an intraday context as market participants, at times of extreme price volatility, observe one another in trading patterns to interpret news rather than rely on own private models. Extreme price movements within a short period of time, according to laboratory experiment of sequential trading by Guarino and Cipriani (2008), could generate a no-trade information cascade, rather than trading concentration, in the presence of transactions cost. So the implications of BHW and AZ may have to be modified in the analysis of trading with high frequency. The commonly used herding measure of Lakonishok, Shleifer, and Vishny (1992, LSV) cannot capture the sequential interactions of market participants especially in an intra-day framework. In addition, quote-driven markets have been the focus of previous works on herding and buy/sell orders have to be imputed. However, order-driven trading mechanism, popular in the new electronic trading mechanism around the world, records directly buy and sell orders. The sequential patterns of order flows characterize trading intensity and information distribution, particularly within a very short period of time, of market participants. Also in an intra-day context, herding measurement could be flawed without controlling for factors like day trading, portfolio rebalancing and ETF portfolio tracking. We therefore intend to address the above issues in this study with a cost-based framework of trading concentration as well as a herding measure focusing on order flow patterns.

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 in a search-based equilibrium of VW. We show in our analysis that stronger order flow herding is driven by lower transactions cost. We also find that that herding in stocks with large cap, high turnover and low P/B ratio is more apparent in stocks with returns ranking at the highest deciles, indicating herding results in relative higher prices. Interestingly, information cascade effect decreases as market goes further away from open or near close. Individuals exhibit stronger herding phenomenon, but herding of institutionals are driven more by lower transactions costs. While herding of individual is inconsistent with BHW, that of institutionals seems to support VW more explicitly.

To measure herding, we adopted the bootstrapped run test method of Patterson and Sharma (2006, PS), which captures intraday order sequences in particular. Previous works on data with lower frequency relies on LSV, which is more easily to be constructed within a longer time frame. It does not consider the intensity of trading concentration as trading proceeds, but uses only the proportion of participants buying and selling within a period. To the extent that order flow matters more in shorter periods, LSV cannot be expected to depict characteristics of trading concentration with high frequency data. Runs of buy or sell orders provide more realistic characterization of herding intuitively as well as statistically. The *t*-test for the LSV measure may suffer from distributional problems when measuring window gets shorter and shorter, while the test for PS runs relies on sample-generated critical values and is thus more powerful in making inferences. As LSV measure within a given period may include orders in or not in runs, PS model gives a more rigorous definition of herding than LSV. PS method also does not require herding to accommodate extreme market conditions.

In emerging financial markets, turnover and market volume are often generated by individual investors. Herding of individuals is worth studying in these markets as it interacts with institutional herding, as suggested in Nofsinger and Sias (1999), Barber, Odean and Zhu (2003), and Dorn, Huberman and Sengmueller (2008). 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. To explore further on these issues, we focuses beyond herding phenomenon itself to examine intraday interaction between individual and institutional investors.

We studied intraday herding behavior of the four types of investors in the Taiwan stock market. 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 book data allow us to identify buy and sell orders directly. Investors type, which includes individuals and three types of institutionals, the proprietary dealers, the investment trust, and QFII, are also identified. The identification investor type helps clarifying if herding is driven by 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. We have also found that individual investor's herding follows that of the QFII and investment trust, which suggests the search move of individual investor lags behind institutional investors. As individual investors accounting for 70% of the overall trading volume, their longer trading horizon and lagging behind institutional in information processing lead them to pay a higher transaction cost. Foreign institutionals are seen to herd more in stocks with the three characteristics mentioned above than local institutionals. Yang (2007) showed how marginal institutional investors engage in short-term trading due to cost factors compared to other institutional investor going after long-term values of stocks. Ting (2009) indicated the, within a given period, foreign institutional investors in Taiwan tend to follow those with a higher turnover rate. The short horizon of marginal foreign institutional investor may have induced them to concentrate in trading stocks with the said characteristics.

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 enhance market trading volume. On the other hand, our analysis contributes to regulators as well as exchanges to understand if certain extreme herding phenomenon entails ramification or any other actions. Unnecessary market alarms could be greatly reduced and market efficiency is hence improved. This study also provides 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 further understanding of herding. 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 agents as they copy 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 would follow 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. Measures of buyers and sellers of asset i are denoted by μ_b^i and μ_s^i respectively. For the buyers, 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.

Individual investors trading for own accounts with unleveraged funds are supposed to have lower switching rates and prefer market 2 in the model above. However, when market moves fast, lack of knowledge could elevate their switching rates so they turn to trade in market 1 instead. Naturally, there should be more herding from the individual investors in an bullish stock market according to prediction (a) and (b). In this market individual investor may prefer to trade stocks with larger market capitalization, higher turnover and lower price-to-book ratios, which require lower search costs. According to prediction (c) above, we would expect the stock characteristic preference to be more eminent in stocks enjoying higher prices than others.

Although foreign institutional investors are now holding about one third of the total values of Taiwanese stocks, their overall turnover rate is in general at around 10% monthly. The positive relation between holdings and turnover within given periods presented by Ting (2009) suggest that marginal foreign institutional investors are incurring risk-adjusted cost situation as discussed in Yang (2007). These marginal foreign institutional investors are under shorter horizons due to liquidity reasons related to allocating funds across borders.

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.

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

Where $p_{i,t}$ is the actual percentages of fund managers that buy stock *i* at time *t*. $E\left[p_{i,t}\right]$ 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. $E^{NH}\left[\left|p_{i,t} - E\left[p_{i,t}\right]\right|\right]$ 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 $E\left[p_{i,t}\right]$.

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).

Data Frequency

The data frequency of many studies precludes the detection of herding that occurs within the trading day. Considering intraday data would uncover issues ignored in studies with lower data frequency yet important to the understanding of herding. 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. 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 related to the arrival of information (Cutler, Poterba and Summers, 1989), and could be explained as herding. If a large number of agents coordinate their actions, the imbalance between buy and sell orders will cause a substantial price change (Bouchaud, 2002). Shortening observation period reduces possibility of extreme price movements and helps the study of herding under normal market condition. The distribution of order data used in this study provides a more comprehensive characterization of investors' intended market moves than realized transaction prices.

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. As LSV measure relies on the proportion of market participants buying or selling within a given period, the complexity of trading motives of various participants dilutes its content of herding intensity. To the extent that measuring herding makes more sense in a short period as pointed out by Christoffersen and Tang (2009) and the fact that LSV does not capture dynamic order flows, it 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 of 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.

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

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.

III. Data and empirical results

This study employs intra-day 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 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 each 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 is usually slower than open and close.

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 intervals. We then compute herding statistic in the respective periods according to PS (2006). A summary of the computed herding measures at any given day are reported in Table III. In computing PS herding measures, only the orders actually filled are included in the computation to avoid reporting unrealistic herding phenomenon. As herding measures are computed separately for each type of investor, they are not comparable across investor type. Similar situation applies to Table IV where herding measures of any given 30-minute interval are given. 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 breaks down Table IV by 30-minute intervals. 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. For all and each type of investors, we bootstrapped their 1%, 5% and 10% critical values. Table VI gives the critical values for all stocks as well as for stocks in top and bottom return deciles. The bootstrapped 30-minute intra-day critical values and percentages of significance for the PS herding measures computed in Table V are given in Table VII. The distribution across time and investor is similar to that in Table V. Across all investors at 1% significance level, the opening interval is the one with the highest percentage, about 70% higher than the bootstrapped percentage. The closing interval has the lowest significance percentage, about 28% below. Among all types of investors, QFII's exhibit the strongest herding behavior in the opening interval, followed by individuals and investment trusts. Herding of proprietary dealers is quite different from the other three types, peaking at mid-day sessions.

The distribution of significant herding percentage in Table VII suggest that intraday herding occurs most likely in the opening interval, which is consistent with predictions of information-based hypotheses on herding. However, if we analyze further how buy and sell orders are distributed during days when herding is significant, we will observe a different pattern. Table VIII gives the sizes of buy and sell orders, in thousand shares, for all days where herding is significant at 1%. The ratios of average buy orders to average sell orders, for days when herding is significant at 1%, is slightly higher than for the entire period. Among investor types, buy-sell ratios are greater than 1 for all institutionals during days of herding, and the ratios for QFII's and Proprietary Dealers are higher than their counterpart in all periods. If we look further into the opening intervals, we find that overall buy-sell ratios during herding days are actually *lower* than the entire period. But for the closing interval, not only the ratios are generally higher than those in the opening interval, but those in herding days are also higher than in the entire period. This indicates that, on the one hand, buying force in the closing interval is stronger than that in the opening interval, which is inconsistent with the information cascade hypothesis as closing interval on average is not one with large amount of information. On the other hand, the fact that herding intensifies buying over selling in herding days, for institutionals in both the opening and the closing intervals, suggest the phenomenon is consistent with predictions of the VW hypothesis. There is a higher buyer-seller ratio in herding days, especially during the closing intervals within these days. If we look at stocks in the top and bottom return deciles, the buy-sell ratios are, as expected, higher in the top return decile. In the bottom return decile, buy-sell ratios are in general lower than 1. But in both the opening and closing intervals of herding days for the two return deciles, the ratios are higher than in the entire period. Buy-sell ratios in the closing intervals are uniformly higher, around 20%, than in the opening intervals. Even for the bottom return decile, there appears to be a stronger, about 24% in magnitude, buying force near market close than right after market open. These findings are not consistent with the information cascade hypothesis but supportive of the search cost model of herding. Although percentages of significant herding statistics in the closing interval are the lowest among all intervals as shown in Tabel VII, the trading concentration from large amount of orders in Table II still exhibit high buyer/seller ratio as predicted in a clientele equilibrium of VW.

We now turn our attention to stock characteristics and their relations to daily and intra-day herding by different types of investors. Table IX contains percentages of significant herding values, for quantiles of market capitalization, turnover and P/B ratio, in the entire period as well as for periods of bull and bear market. Percentages of herding values beyond critical values under each significance level provide us with the relative strength of herding behavior. The bull market is defined as when short term moving averages of market index went above long term moving averages, a bull market is defined vice versa. The table shows that, for the entire data period, there are strong patterns for herding to concentrate in large cap and low P/B ratio stocks. This pattern gets stronger in periods of bull market, where herding also increases with turnover. The results in Table IX clearly questions information cascade as a valid explanation on intraday herding. Stronger evidence of this patter in periods of bull market supports predictions from a search model of stock trading in the sense of VW, where there are more buyers than sellers, stock prices are relatively higher, and trading volume is also higher.

Table X applied two regression models to examine the information cascade effects t proxied by market capitalization, turnover and price-book ratio. We performed a panel regression, adjusted for autocorrelation, with generalized least squares random effect based on

$$H_{kt} = \alpha + \sum_{i=1}^{2} \beta_i H_{k,t-i} + \gamma_1 MC_k + \gamma_2 TO_k + \gamma_3 PB_k + \varepsilon_t \tag{6}$$

where t=1,…,495 and k=1,…,525. The information cascade effect is proxied by MC_k, TO_k and PB_k , denoting quantile values of market capitalization, turnover and price-book ratios respectively for a given stock k over the data period. So the smaller the γ's are, the stronger the information cascade effect the result implies. As PB_k is correlated with MC_k and TO_k, to obtain sensible estimates for PB_k we have also conducted a two stage least square estimation with PB_k instrumented by MC_k and TO_k, in the first stage. So γ_1 and γ_2 are estimated according the panel model above, while γ_3 is obtained in the second stage of the panel two stage least square model. The results are against the information cascade hypothesis as in Table IX, and more pronounced in stocks with the highest returns. Across intraday intervals, orders in the opening interval exhibit patterns most against the information cascade hypothesis, with the strongest γ's among all intervals. The implication seems to suggest that the information cascade effect, if any, should be stronger at market close.

Table XI reports results from a model designed to analyze the search cost effect. Herding values are regressed, adjusted for autocorrelation, on the average price difference of buy and sell orders in the following model,

$$H_{kt} = \alpha + \sum_{i=1}^{2} \beta_i H_{k,t-i} + \delta BSD_{kt} + \varepsilon_t \tag{7}$$

Where BSD stands for the price difference between sell and the buy orders associated with all the transaction prices averaged over a given day. Positive values of the coefficient estimate suggest lower price spreads accompanied herding. This effect is the stongest for QFII's and individuals, and decreases from open to close. This finding is consistent with the distribution of buy and sell orders reported in Table VIII. We have also examined specifically two subcategories where MC_k=1, TO_k =1, PB_k =5 (stocks with the poorest information quality) and MC_k=5, TO_k =5, PB_k =1 (stocks with the best information quality) to determine how search cost effect behave there. Results show that herding is not so much related to search cost in stocks with the greatest information quality as it is to those with the poorest information quality.

In order to identity how herding pattern varies among investor types, we report in Table XII 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 Vector AutoRegressive (VAR) model to explore if there is any leader-follower relation in the herding behavior of various types of investors.

$$Y_t = \alpha + \sum_{i=1}^{4} \beta_i TH_{t-i} + \sum_{i=1}^{4} \gamma_i TH_{t-i} + \sum_{i=1}^{4} \lambda_i TH_{t-i} + \sum_{i=1}^{4} \theta_i TH_{t-i} + \varepsilon_t \text{, } i=1,\dots,4 \tag{8}$$

where $Y_t = (TH_t, MH_t, FH_t, IH_t)$ with TH_t denoting, in any given day t, herding measure of proprietary dealers, MH_t that of investment trust, FH_t that of QFII and IH_t as herding measure of individuals. Results of the VAR model suggests that herding within each investor type is, as expected, highly positively autocorrelated. Herding measures of QFII' s and individuals affect each other positively. There is no other relationship found among the four types of investors. The fact that herding of QFII' s also follows that of the individual investors indicates that information cascade cannot characterize trading interactions between the two groups.

IV. Discussion on the cause of herding

The preliminary results of our analysis indicate that, according the method of PS (2006), herding behavior is not consistent with the information cascade hypothesis. First of all, individuals and QFII are the two investor types with the stronger herding behavior. They are supposed to be the most and the least informationally informed in the stock market. This evidence is inconsistent with the cascading order of information among investors according the BWH. Our results also indicate that herding is stronger in stocks with the highest returns during the data period. Herding is also more prominent in days of bull market than in bear market. Although opening intraday interval is most likely trigger information related market moves and contains higher percentage of significant herding days, the buy-sell ratios are uniformly higher in the closing interval, even for stocks with the lowest returns in the data period.

Categorizing stocks according to certain characteristics leads us to further conclusion that herding is not consistent with information-based hypotheses. 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 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. 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. Proprietary dealers and investment trust tend to herd on medium or high a P/B ratio stock, suggesting their behavior might be related to factors other than information.

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 individuals and QFII as having lower search horizons than the other two types of institutional investors. In a *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. According to buy-sell ratios reported in Table VIII, the relative buying strength of QFII's in closing intervals of herding days is 3.4 times that in the opening interval. For individuals the relative strength is only 1.1, and around 0.3 for Proprietary Dealers and Investment trusts. So there could exist certain information-induced herding in the opening interval, but whenever herding takes place, buying is always stronger than selling across the market especially right before market closes. VW search model is an more ideal model than information cascade to explain this phenomenon.

The search model for trading concentration by VW is capable of explaining the main results in this study. Herding occurs in rising stocks within a bull market and there tend to be more buyers than sellers. 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. Therefore at market open when the information cascade is the weakest, as shown in Table X, the search cost effect happens to be the strongest, as found in Table

XI. QFII’s and Individuals, who exhibit the search cost effect on herding, affect each other significantly dynamically. This implication leads us to question strongly again the validity of the information cascade hypothesis.

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, such as individuals and QFII, 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 VAR regression result of individuals following QFII’s is also consistent with a context of VW search model. Herding of QFII’s creates liquidity first and draws individuals to join the respective market for individual stocks, on the other hand individuals help building a clientele equilibrium in the sense of VW, inducing more QFII’s to enter. 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 in a down one. The notion of panic selling in a bearish market is supposed to drive up herding behavior, but results in Table VIII give none at all. If we perceive the up market as one with low search time then we would observe more 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 presentsa set of intra-day 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 stocks with the highest returns and more prominent in days of bull market. Market as a whole, and individuals in particular, is found to herd on 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. 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 individual and QFII investors to rush in to trade when they observe trading concentration emerges. 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 investigate further stocks with statistically significant herding phenomenon for more evidence supporting the search cost model. 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 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.
All Investors	252666	8.222	-143.164	-4.330	-3.113	-5.953	-1.173	5.102
Proprietary Dealers	43356	4.737	-29.643	-3.562	-3.307	-4.636	-2.101	2.321
Investment Trust	32434	4.066	-31.882	-4.656	-4.226	-5.980	-3.130	2.871
QFII	88594	15.215	-59.017	-7.898	-6.429	-10.278	-4.041	5.825
Individuals	251700	7.467	-155.487	-4.508	-3.213	-6.127	-1.234	5.463

Table IV Summary Statistics of 30-minute Interval 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.
All Investors	2044779	6.021	-90.339	-0.895	-0.536	-1.837	0.492	2.272
Proprietary Dealers	189248	4.849	-19.877	-0.464	-0.302	-1.265	0.447	1.466
Investment Trust	149267	5.000	-15.334	-0.652	-0.378	-1.500	0.447	1.526
QFII	600558	8.300	-34.128	-2.075	-1.508	-3.411	-0.192	2.677
Individuals	2016662	6.223	-90.305	-0.938	-0.544	-1.866	0.480	2.403

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: All Traders								
9:00~9:30	239099	4.7374	-90.3387	-1.3031	-0.8528	-2.2948	0.3015	2.6476
9:30~10:00	233386	5.8000	-67.5619	-1.1487	-0.7423	-2.1429	0.3536	2.4109
10:00~10:30	228812	5.2669	-48.6301	-0.9743	-0.6124	-1.9415	0.4472	2.2851
10:30~11:00	224697	5.4222	-48.2734	-0.8952	-0.5517	-1.8594	0.4575	2.2290
11:00~11:30	220989	4.7958	-45.6915	-0.7983	-0.4472	-1.7321	0.5477	2.1743
11:30~12:00	217516	5.4813	-33.1995	-0.7552	-0.4082	-1.6977	0.5774	2.1649
12:00~12:30	217314	6.0212	-36.4468	-0.6857	-0.3780	-1.5757	0.6255	2.1357
12:30~13:00	223027	5.5156	-46.9705	-0.7474	-0.3974	-1.6503	0.5774	2.1600
13:00~13:30	239939	5.8977	-38.1938	-0.7064	-0.4082	-1.5900	0.5774	2.0739
Panel B: Proprietary Dealers								
9:00~9:30	40373	4.1576	-14.7580	-0.6088	-0.3780	-1.5000	0.4472	1.4571
9:30~10:00	25941	4.1576	-12.3377	-0.4171	0.0000	-1.0690	0.4472	1.4507
10:00~10:30	19765	4.8493	-12.9306	-0.4378	0.0000	-1.2247	0.4472	1.4878
10:30~11:00	16707	4.3333	-11.4785	-0.4321	0.0000	-1.0690	0.4472	1.4696
11:00~11:30	15941	4.1576	-11.1921	-0.4383	0.0000	-1.0690	0.4472	1.4587
11:30~12:00	15434	4.2000	-11.6723	-0.4854	0.0000	-1.2649	0.4472	1.4809
12:00~12:30	14208	4.5000	-14.0418	-0.4911	-0.3015	-1.1471	0.4472	1.4363
12:30~13:00	16628	4.1576	-14.3585	-0.5032	-0.3780	-1.2649	0.4472	1.4634
13:00~13:30	24251	4.7374	-19.8768	-0.2743	0.0000	-1.0000	0.4472	1.4618
Panel C: Investment Trust								
9:00~9:30	21817	4.1576	-13.5346	-0.8690	-0.5774	-1.7321	0.3333	1.6165
9:30~10:00	19821	4.1576	-15.2236	-0.6598	-0.3780	-1.5076	0.4472	1.5128
10:00~10:30	17224	4.3333	-12.4586	-0.5977	-0.3780	-1.2649	0.4472	1.4851
10:30~11:00	16290	4.1576	-11.2366	-0.5820	-0.3780	-1.2649	0.4472	1.4929
11:00~11:30	16051	4.1576	-15.3345	-0.6220	-0.3780	-1.2910	0.4472	1.5258
11:30~12:00	15799	4.3818	-12.4586	-0.6349	-0.3780	-1.2993	0.4472	1.5301
12:00~12:30	15543	4.1576	-13.4350	-0.6955	-0.3780	-1.5076	0.4472	1.5635
12:30~13:00	15136	4.7676	-13.0842	-0.6605	-0.3780	-1.5000	0.4472	1.5467
13:00~13:30	11586	5.0000	-11.7576	-0.4002	0.0000	-1.0000	0.4472	1.3324
Panel D: QFII								

9:00~9:30	71705	6.1279	-34.1282	-2.4953	-1.8856	-3.9104	-0.3780	2.9513
9:30~10:00	67790	7.0491	-28.6726	-2.0979	-1.5076	-3.4112	-0.2582	2.6792
10:00~10:30	65308	7.2449	-27.0949	-1.9835	-1.5076	-3.2733	0.0000	2.5996
10:30~11:00	65246	7.7200	-24.7292	-1.9824	-1.5076	-3.2733	0.0000	2.6021
11:00~11:30	63991	8.3002	-22.9442	-1.9790	-1.5076	-3.2733	0.0000	2.6195
11:30~12:00	64623	7.4136	-23.9833	-1.9917	-1.5076	-3.2857	0.0000	2.6093
12:00~12:30	64794	8.0539	-24.6123	-1.9915	-1.5076	-3.3204	0.0000	2.6571
12:30~13:00	67522	7.5718	-27.1340	-2.1299	-1.5811	-3.5386	-0.2294	2.7134
13:00~13:30	69579	6.2450	-26.3037	-1.9865	-1.5076	-3.2733	-0.1525	2.5745
Panel E: Individuals								
9:00~9:30	236766	4.7374	-90.3053	-1.3650	-0.8950	-2.3534	0.2774	2.7855
9:30~10:00	231031	5.8000	-71.3469	-1.1886	-0.7569	-2.1676	0.3536	2.5343
10:00~10:30	226047	5.1149	-53.1249	-1.0096	-0.6124	-1.9467	0.4472	2.4122
10:30~11:00	221422	6.1470	-56.7684	-0.9251	-0.5252	-1.8600	0.4650	2.3568
11:00~11:30	217153	4.7958	-46.0360	-0.8298	-0.4472	-1.7321	0.5443	2.3024
11:30~12:00	213380	5.0000	-36.8290	-0.7809	-0.3780	-1.6971	0.5774	2.2950
12:00~12:30	213322	6.2225	-39.6919	-0.7274	-0.3780	-1.5811	0.6202	2.2792
12:30~13:00	219795	5.5678	-51.1702	-0.8015	-0.4045	-1.6886	0.5774	2.3143
13:00~13:30	237746	5.8977	-43.4025	-0.7712	-0.4472	-1.6503	0.5392	2.1836

Table VI Bootstrapped Daily Critical Values for Herding Measures

by Return Decile and Investor Type

	Significant level	Critical Value				
		All investors	Proprietary Dealers	Investment Trust	QFII	Individuals
All stocks	1%	-23.3085	-10.8860	-13.8468	-28.3998	-24.9934
	5%	-13.5336	-7.5256	-9.9422	-19.3977	-13.9099
	10%	-10.0530	-6.2869	-8.2915	-15.4251	-10.2904
Top deciles	1%	-19.8238	-11.6374	-13.3006	-24.5394	-20.9225
	5%	-13.6048	-7.3188	-9.4821	-17.7015	-13.8582
	10%	-10.9445	-5.9008	-7.9628	-14.1015	-11.1581
Bottom deciles	1%	-21.3848	-10.6404	-16.5587	-27.8832	-22.6346
	5%	-12.6709	-7.2365	-10.7262	-18.0436	-12.9979
	10%	-9.3482	-6.0722	-8.7508	-14.2123	-9.5883

Table VII Bootstrapped Intra-day Critical Values and Herding Significance Percentages

by Intraday Intervals and Investor Type

Critical Values		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 Investors										
1%	-9.182	1.70%	1.29%	1.01%	0.94%	0.82%	0.82%	0.79%	0.85%	0.72%
5%	-5.080	7.35%	6.28%	5.26%	4.93%	4.50%	4.37%	4.09%	4.31%	3.74%
10%	-3.676	13.90%	12.38%	10.75%	10.00%	9.21%	8.89%	8.18%	8.66%	7.76%
Proprietary Dealers										
1%	-5.528	0.81%	1.03%	1.15%	1.17%	1.13%	1.13%	1.08%	1.05%	0.81%
5%	-3.497	5.72%	4.63%	5.11%	4.95%	4.55%	5.61%	4.89%	5.04%	3.98%
10%	-3.676	11.80%	9.44%	10.09%	9.27%	9.69%	10.88%	9.87%	10.16%	7.93%
Investment Trusts										
1%	-6.084	1.42%	0.90%	0.77%	0.82%	0.98%	0.99%	1.07%	1.16%	0.49%
5%	-4.264	6.88%	4.75%	4.34%	4.56%	4.82%	4.94%	5.51%	5.17%	3.00%
10%	-3.463	13.31%	10.01%	9.12%	9.23%	9.82%	10.05%	10.95%	10.45%	6.28%
QFII's										
1%	-12.073	1.85%	1.02%	0.83%	0.81%	0.81%	0.80%	0.90%	1.05%	0.84%
5%	-8.068	7.06%	5.10%	4.43%	4.50%	4.63%	4.48%	4.84%	5.27%	4.36%
10%	-6.347	13.23%	10.11%	9.18%	9.18%	9.40%	9.35%	9.65%	10.40%	8.92%
Individuals										
1%	-9.627	1.55%	1.22%	1.01%	0.97%	0.87%	0.86%	0.83%	0.92%	0.73%
5%	-5.093	7.17%	6.10%	5.23%	4.90%	4.50%	4.43%	4.22%	4.48%	3.82%
10%	-3.645	13.93%	12.17%	10.52%	9.84%	9.11%	8.80%	8.31%	8.85%	7.97%

Table VIII Daily and Intra-day Buy and Sell Orders, All Days and When Herding Is Significant at 1%

By Investor Type

In thousand shares

Investor Type	9:00~9:30				13:00~13:30				All Day			
	All days		Days when herding is significant at 1%		All days		Days when herding is significant at 1%		All days		Days when herding is significant at 1%	
	Average buy orders per lot	Average sell orders per lot	Average buy orders per lot	Average sell orders per lot	Average buy orders per lot	Average sell orders per lot	Average buy orders per lot	Average sell orders per lot	Average buy orders per lot	Average sell orders per lot	Average buy orders per lot	Average sell orders per lot
	All Stocks											
All	14.19	14.24	15.09	18.33	19.92	18.07	22.82	18.53	8.50	8.45	9.64	9.56
Proprietary Dealers	29.77	24.81	68.96	15.11	23.37	25.39	26.57	19.69	21.66	22.17	26.22	8.61
Investment Trusts	41.53	31.41	56.62	29.49	31.58	27.62	66.09	53.32	28.68	25.34	13.77	12.88
QFII’s	27.12	26.18	43.95	25.22	69.19	59.72	130.17	26.60	17.10	17.34	14.05	12.39
Individual	10.54	11.12	10.05	22.82	9.76	10.18	9.66	17.31	7.29	7.36	7.02	7.67
	Top Stock Return Decile											
All	5.43	5.24	6.46	5.87	5.67	5.29	7.15	5.65	5.44	5.28	5.99	5.96
Proprietary Dealers	17.95	15.20	6.36	12.28	11.91	12.60	9.25	12.80	14.96	14.39	6.49	5.33
Investment Trusts	25.99	17.91	25.48	18.95	22.56	17.95	14.28	5.22	19.33	16.13	11.66	11.08
QFII’s	7.93	6.76	4.73	3.95	13.30	12.61	5.88	4.24	7.52	7.06	4.28	3.90
Individual	5.02	4.95	5.47	5.32	5.00	4.83	3.00	3.07	5.02	4.94	5.18	5.33
	Bottom Stock Return Decile											
All	10.81	10.64	15.53	13.06	12.39	12.39	18.76	12.67	10.53	10.85	10.17	12.83
Proprietary Dealers	32.68	31.13	34.55	20.14	26.12	29.81	56.59	37.77	25.82	28.30	31.04	12.15
Investment Trusts	58.67	46.06	180.25	24.81	41.04	31.32	45.81	56.36	39.80	34.26	14.58	13.49
QFII’s	18.88	18.87	19.95	6.95	45.79	46.07	39.87	42.69	20.61	20.84	18.02	10.53
Individual	10.22	9.98	12.58	12.53	9.92	10.18	9.35	10.77	9.64	9.91	8.64	10.71

Table IX Daily Herding Significance Percentages by Market Caps, Turnovers and P/B Ratios

By Market Type

	All Periods				Bull Market				Bear Market			
Size Quantiles	Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values		
		1%	5%	10%		1%	5%	10%		1%	5%	10%
S1 (Lowest)	-0.80812	0.01%	0.10%	0.38%	-1.375	0.05%	0.17%	0.51%	-.0.762	0.00%	0.03%	0.11%
S2	-1.86253	0.01%	0.29%	1.09%	-2.333	0.09%	0.34%	1.26%	-1.612	0.01%	0.22%	0.79%
S3	-3.08607	0.04%	1.10%	3.54%	-3.378	0.13%	1.49%	4.17%	-2.805	0.01%	0.50%	2.85%
S4	-4.24691	0.23%	2.73%	8.14%	-4.595	0.16%	2.96%	9.07%	-3.956	0.06%	2.02%	7.54%
S5 (Highest)	-7.81885	4.54%	20.19%	35.68%	-8.136	5.05%	23.01%	39.25%	-7.402	4.22%	17.85%	32.75%
Turnover Quantiles	Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values		
		1%	5%	10%		1%	5%	10%		1%	5%	10%
T1 (Lowest)	-1.82259	1.38%	5.66%	9.73%	-2.054	1.61%	7.81%	10.36%	-1.674	1.26%	4.70%	9.15%
T2	-2.46654	1.45%	5.47%	9.73%	-2.791	1.68%	7.16%	10.63%	--2.255	1.18%	4.39%	9.14%
T3	-2.67146	0.75%	3.94%	7.83%	-2.979	1.86%	5.28%	9.82%	-2.338	0.83%	2.57%	6.94%
T4	-3.09628	0.69%	3.57%	7.17%	-3.394	2.11%	5.04%	9.31%	-2.741	0.90%	2.01%	6.59%
T5 (Highest)	-5.24758	0.72%	6.37%	15.40%	-5.652	2.56%	8.77%	17.97%	-4.684	0.39%	4.93%	12.97%
P/B Ratio Quantiles	Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values			Median Herding Values	% of Herding Values Lower than Critical Values		
		1%	5%	10%		1%	5%	10%		1%	5%	10%
P1 (Lowest)	-4.61069	1.62%	8.54%	16.98%	-4.850	2.33%	10.62%	18.68%	-4.409	1.29%	6.75%	13.89%
P2	-4.3726	1.89%	8.60%	16.12%	-4.502	2.88%	10.71%	18.13%	-4.018	1.35%	7.09%	13.54%
P3	-3.02499	1.03%	4.60%	9.14%	-3.181	1.94%	6.89%	11.96%	-2.820	0.62%	3.76%	7.43%
P4	-2.71063	0.29%	2.18%	5.19%	-2.901	0.46%	3.15%	7.40%	-2.376	0.16%	1.67%	5.51%
P5 (Highest)	-1.42887	0.08%	0.81%	2.06%	-1.886	0.19%	1.46%	3.42%	-1.207	0.02%	0.41%	1.4%

Table X Information Cascade Effects, Intraday and Intraday Intervals

The information cascade effect is proxied by three variables, MC_k, TO_k and PB_k , denoting quantile values of market capitalization, turnover and price-book ratios respectively for a given stock k over the data period. We performed a panel regression with generalized least squares random effect based on

$$H_{kt} = \alpha + \sum_{i=1}^{2} \beta_i H_{k,t-i} + \gamma_1 MC_k + \gamma_2 TO_k + \gamma_3 PB_k + \varepsilon_t$$

where t=1,…,495 and k=1,…,525. The smaller the γ's are, the stronger the information cascade effect is. As PB_k is correlated with MC_k and TO_k, to obtain sensible estimates for PB_k we have also conducted a two stage least square estimation with PB_k instrumented by MC_k and TO_k, in the first stage. So γ_1 and γ_2 are estimated according the panel model above, while γ_3 is obtained in the second stage of the panel two stage least square model.

Time	No of obs.	γ_1	γ_2	γ_3
Intraday				
All stocks	246,444	-0.6841 (0.0069)**	-0.2004 (0.0054)**	1.1535 (0.0118)**
Top Return Decile	25,284	-0.8358 (0.0205)**	-0.3543 (0.0185)**	2.1752 (0.0665)**
Bottom Return Decile	27,584	-0.6741 (0.0193)**	-0.5597 (0.0201)**	1.4546 (0.0362)**
Intraday intervals				
9:00-9:30	223,518	-0.4177 (0.0043)**	-0.1720 (0.0036)**	0.7787 (0.0079)**
9:30-10:00	215,344	-0.4206 (0.0042)**	-0.1592 (0.0035)**	0.7525 (0.0076)**
10:00-10:30	208,294	-0.4207 (0.0041)**	-0.1446 (0.0034)**	0.7423 (0.0076)**
10:30-11:00	202,241	-0.4137 (0.0042)**	-0.1262 (0.0034)**	0.7165 (0.0076)**
11:00-11:30	196,426	-0.4072 (0.0042)**	-0.1102 (0.0034)**	0.6935 (0.0077)**
11:30-12:00	201,367	-0.4987 (0.0040)**	-0.1284 (0.0034)**	0.6855 (0.0078)**
12:00-12:30	191,570	-0.3922 (0.0042)**	-0.0880 (0.0034)**	0.6538 (0.0077)**
12:30-13:00	199,926	-0.4008 (0.0041)**	-0.0919 (0.0033)**	0.6679 (0.0075)**
13:00-13:30	224,232	-0.3875 (0.0036)**	-0.0846 (0.0029)**	0.6107 (0.0061)**

Estimates of β's for autocorrelation terms are all extremely significant and are not reported. Standard deviations are in the parentheses and ** denotes significant a t 1%.

Table XI Search Cost Effect on Herding, Intraday and Intraday Intervals

The search cost effect is proxied by, BSD_{kt} , the average difference of buy and sell orders associated with transaction prices on a given stock within the period of interest. We performed a panel regression with generalized least squares random effect based on

$$H_{kt} = \alpha + \sum_{i=1}^{2} \beta_i H_{k,t-i} + \delta BSD_{kt} + \varepsilon_t$$

where t=1,…,495 and k=1,…,525. A greater δ implies stronger herding is accompanied by lower order price spreads, suggesting a stronger the search cost effect in a clientele equilibrium. Regressions are also conducted for given stock characteristic categories. The category of $\{MC_k=1, TO_k=1, PB_k=5\}$ is selected as the intersection of stocks are expected to have the poorest information quality for trading and strong herding should not have been driven by a strong search cost effect if information cascade effect does affect herding. The category of $\{MC_k=5, TO_k=5, PB_k=1\}$ is supposed to have the best information quality and is analyzed as a contrast.

Time	No of obs.	δ	R-squared
Intraday			
All investors	245,462	0.6139 (0.0093)**	0.5273
Proprietary Dealers	23,388	0.1104 (0.0347)**	0.1205
Investment Trusts	11,649	0.2430 (0.0554)**	0.0381
QFII's	62,439	0.7271 (0.0385)**	0.2503
Individuals	244,005	0.7254 (0.0107)**	0.4732
Intraday intervals			
9:00-9:30	222,640	0.4561 (0.0056)**	0.3360
9:30-10:00	214,523	0.4321 (0.0062)**	0.2837
10:00-10:30	207,330	0.4094 (0.0065)**	0.2589
10:30-11:00	201,505	0.3724 (0.0067)**	0.2303
11:00-11:30	195,722	0.3529 (0.0068)**	0.2179
11:30-12:00	190,921	0.3402 (0.0069)**	0.2141
12:00-12:30	190,895	0.3517 (0.0068)**	0.2205
12:30-13:00	199,202	0.3679 (0.0066)**	0.2322
13:00-13:30	223,350	0.3900 (0.0053)**	0.2613
For Given Stock Characteristic Categories			
MC_k=1, TO_k=1, PB_k=5	6,644	0.1531 (0.0155)**	0.1686
MC_k=5, TO_k=5, PB_k=1	5,892	-0.0357 (0.0829)	0.2032

Estimates of β's for autocorrelation terms are all extremely significant and are not reported. Standard deviations are in the parentheses and ** denotes significant a t 1%.

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

The VAR regression is based on the following models,

$$Y_t = \alpha + \sum_{i=1}^{2} \beta_i TH_{t-i} + \sum_{i=1}^{2} \gamma_i MH_{t-i} + \sum_{i=1}^{2} \lambda_i FH_{t-i} + \sum_{i=1}^{2} \theta_i IH_{t-i} + \varepsilon_t$$

where t is the day index and $Y_t = (TH_t, MH_t, FH_t, IH_t)$ 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.

Dependent Variable	TH_t		MH_t		FH_t		IH_t	
	β_1	β_2	γ_1	γ_2	λ_1	λ_2	θ_1	θ_2
TH_t	0.1822**	0.1626**	-0.0071	0.0103	0.0012	-.0008	0.0035	-0.0103**
	(0.0134)	(0.0134)	(0.0089)	(0.0090)	(0.0043)	(0.0043)	(0.0032)	(0.0032)
MH_t	0.0219	0.0307	0.1517**	0.0452**	-0.0010	0.0073	0.0321	-0.0108**
	(0.0196)	(0.0196)	(0.0132)	(0.0133)	(0.0063)	(0.0063)	(0.0045)	(0.0046)
FH_t	0.0384	0.0413	-0.0079	0.0049	0.3402**	0.1137**	0.0892**	0.0299**
	(0.0412)	(0.0418)	(0.0281)	(0.0282)	(0.0134)	(0.1341)	(0.0096)	(0.0097)
IH_t	-0.0344	0.1247	-0.0660	-0.0754	0.0648**	0.2930**	0.3221**	0.1342**
	(0.0572)	(0.0572)	(0.0385)	(0.0387)	(0.0184)	(0.0184)	(0.0131)	(0.0133)

Standard deviations are in the parentheses and ** denotes significant at 1%.