Herding and Information Flows in Emerging Markets

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Abstract

This paper presents an in-depth study of individual investor behavior in an emerging stock market. We begin by documenting the existence of correlated buying (herding) among investors. Our sample has approximately the same level of herding as existing studies. A new measure of herding based on a runs test is also proposed. We document which type of investors are prone to herding. Surprisingly, the propensity to herd is correlated (positively) only with length of time that an account has been open. This is the first indication that herd behavior may not be tied to the lack of investor sophistication. We are able to divide investors into isolated groups; each group places its trades at a specific brokerage branch office in the People's Republic of China. The ability to isolate groups of investors allows us to test whether herding is the result of group-psychology. Again, we find no evidence that this is the case. In fact, the decision to buy or sell a given stock is significantly correlated across isolated groups of investors. The correlation of stock buying/selling is even higher within a regional/language group than across different groups. The final result is that herding among individual investors is *negatively* related to stock returns. This suggests that another group in the market buys as prices go up and the individuals in our sample act as liquidity providers.

Keywords: Individual Investors, Behavioral Finance, Emerging Markets

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1 Introduction

Over the past decade, financial economists have become increasingly fascinated with herd behavior in financial markets. Does a well-defined subset of investors tend to buy and sell securities together? Such buying and selling *en-masse* (or "herding") is often behavior attributed to investors in emerging markets. If emerging market investors do engage in herding, what drives this behavior? Do certain types of individuals have a propensity to join the herd? Are investors simply choosing their investment strategy by observing investment decisions of those around them? Or, does a subgroup of investors receive common information? Finally, does the existence of herd behavior affect asset prices? In other words, is the (high) volatility of emerging stock markets tied to investor behavior?

A number of papers document the existence of herd behavior and some show a link between herding and asset prices. However, few empirical studies explain exactly what *causes* herding. The lack of such empirical studies is understandable - financial economists cannot get inside the head of every investor at the time of a trade. It is equally difficult to know what information an investor has when placing a trade. Thus, understanding herding (ex-post) becomes a difficult exercise in data analysis.

This paper provides a thorough investigation of herd behavior. We confirm the results of previous studies regarding the existence of herding. We also propose a new measure of herding based on a runs test. Once herding has been shown to be significant in our data, we document which type of investor joins herds. Later, we provide evidence as to the cause(s) behind the observed herding. Finally, we document the link between herd behavior and changes in asset prices in an emerging market. We show that the causes of the observed herding are consistent with the observed changes in asset prices.

This paper uses new, exciting, and detailed data from the People's Republic of China (PRC) to answer the questions posed above. The data contain information such as which investor buys/sells which stock at what time (down to the second.) The structure of brokerage offices in the PRC tells us exactly where an investor is standing when he or she places an order. Brokerage offices in the PRC require each client to place orders through the branch office where the account was opened. We then consider only trades made through terminals or cashier windows that are physically located in the branch office. The research design and the fact that groups of investors in the PRC actually stand in the same room at the time they place orders allows us to examine isolated groups. Figure 1 provides a sketch of a typical branch office. As we can see, the room allows for a free flow of conversation between investors. If there is ever a chance for financial economists to observe herd behavior within a well-defined group of investors, this set-up would appear to be it.

Thus, the paper proceeds as follows: Section 2 gives an overview of related work; Section 3 discusses the data used in this paper; Section 4 presents our tests and results; Section 5 provides alternative hypotheses and robustness tests; and Section 6 concludes.

2 Existing studies of herd behavior

Herd behavior in financial markets is a broad topic and commonly referred to by a number of names (such as: correlated buying/selling, observational influence, or information cascades.) Hirshleifer and Teoh (2001) provide a review and a "taxonomy of effects" related to this subject. Another nice overview of herding in financial markets is provided by Bikchandani and Sharma (2000). For the purposes of this paper, we measure correlated trading behavior among investors. Rather than use the full taxonomy provided in the review articles, we focus on three broad reasons why economists might observe such behavior: i) Ex-post measurements that show highly correlated buying is simply a small-sample bias; ii) Investors base their investment decisions on those around them; and iii) Heterogeneous investors receive common information. Investors of one type tend to buy (sell) while other types tend to do the opposite.

Herding behavior in the U.S.: Lakonishok, Shleifer, and Vishny (1992) examine the impact of institutional trading in the U.S. on stock prices. The authors find that if money managers of a tax-exempt fund are equally likely to buy or sell a stock in a given quarter, 52.7% of the managers tend to buy (sell) during a quarter while 47.3% do the opposite. Though a slight imbalance of 2.7% could be potentially destabilizing to stock prices, the authors find little evidence of this.

Grinblatt, Titman, and Wermers (1995) find only "weak evidence that funds tend[ed] to buy and sell the same stocks at the same time." The authors did, however, show that approximately 77% of mutual funds bought past winners (which is known as positive feedback trading.)

Nofsinger and Sias (1999) find a strong positive correlation between changes in aggregate institutional ownership and contemporaneous stock returns. Stocks that institutions purchase outperform stocks they sell over the next year.

Wermers (1999) provides an extensive analysis of the mutual fund industry. Like Lakonishok, Shleifer, and Vishny (1992), he finds more herding in small stocks than in the average stock. He also finds that "stocks that herds buy outperform stocks that they sell by 4 percent during the following six months."

There are few studies of individual herding in the United States. Researchers have focused more on individual biases and have not yet turned to group-psychology.

International studies of herd behavior: Choe, Kho, and Stulz (1999) conduct an early study of herding in international markets. They calculate a similar measure of herding as Lakonishok, Shleifer, and Vishny (1992). Choe et. al find strong evidence of herding among foreign institutions operating in Korea before the financial crisis of 1997. The measure of herding falls (slightly) during the crisis, and the authors find little evidence that foreign investors helped destabilize prices. Kim and Wei (1999 and 2002) also document strong herding by foreign investors and off-shore investment funds in Korea during a similar time period.

3 Data

We use account-level data to investigate herding in financial markets. Our data come from individual brokerage accounts in the People's Republic of China (PRC) and are uniquely suited for the task at hand. The data represent trades placed between May 4, 1999 and December 4, 2000.

3.1 Brokerage accounts in the PRC

Brokerage accounts in the PRC are both similar to, and different from, what we are used to in the U.S. A brokerage firm (the firm) has branch offices (branches) throughout the country, region, or city. Many brokerage firms are regionally focused. Individuals open accounts at a branch office and then place all of their trades *through this one branch.* Thus, there is a critical difference in our study between brokerage firms (our data are from one firm) and branch offices (our data come from seven different branches.)

A branch office may have a number of ways for investors to place trades: terminals in the branch; cashier windows; telephone service; and computer links. Computer links from private computers are uncommon at this time, effectively leaving three channels with which to place a trade. Consider a brokerage firm with five regional branches in the country's largest cities. An individual who opens an account at the Beijing branch must place all his or her trades with the Beijing branch. Even if the individual is visiting Shanghai, he or she may not place trades at the local Shanghai branch. Instead, he or she must call Beijing to place a trade (and may only do so if the account has previously been set up to allow phone trades.)

3.2 The brokerage account data

While investors in the PRC have a number of options for placing trades, we focus on trades that are actually placed at the branch office. We intentionally look at groups of investors who are physically standing near each other during the trading day and, for the time being, do not consider trades that are called-in.[1] We also limit ourselves to secondary trading of shares and do not look at trades relating to IPOs, secondary offerings, or warrants. Our data contain completed trades and not orders that have been submitted and later withdrawn.

Some stocks in the PRC trade infrequently. The highest-volume stock (measured by total value traded in 1999 and 2000) traded 120.84-times more than the lowest volume stock, 7.96-times more than the one hundredth-ranked stock, and 3.14-times more than the seventh-ranked stock. The extreme skewness in trading volume can be seen in Appendix 1: a graph of the distribution of the natural log of trading volume. Since it is infeasible to measure herding in stocks with low volumes, we choose to look only at trades in active stocks. For simplicity we limit ourselves to stocks that are listed on the Shenzhen stock exchange and denominated in local currency (RMB). We initially consider the 100 highest-volume stocks as measured by total value traded in 1999 and 2000. We also examine the seven highest-volume stocks.[2]

Finally, we treat one investor who makes five trades on a given day differently from five different investors making one trade apiece on the same day. This difference in treatment seems natural when studying herding. We sort our data to include only unique buy and sell orders. That is, if an individual investor makes multiple purchases of a stock on a given day, we count this as one purchase.

[1] Later in the paper we use the phone trades as a means to re-check our results.

[2] We choose seven stocks so the number of branch offices matches the number of stocks. This makes interpreting some of our results more straightforward.

3.3 Overview of the data

Table 1 presents an overview of the data. We have collected data from seven branches of one brokerage firm. Panel A shows the total trades before we control for investors who may be breaking up their trades during one day. We can see that the average number of trades per year is 12.28 and higher than in the United States.[3] As described earlier, Panel B shows only unique trades (defined above). Panel C shows trades that are physically placed in a branch office. The data in Panel C are primarily used throughout this study. The difference between Panel B and Panel C comes from investors who place telephone trades. Table 1, Panel C, Column 3 shows there are 66,956 unique buy-trades placed in branch offices over the seventeen month period (80 weeks or 387 trading days) in our sample. The number of sell orders in Column 4 is about 6% less and totals 62,515 trades.

We are looking at 80 weeks, 100 stocks, and 7 branches, which gives 56,700 ways to classify a particular trade (there are 270,900 classifications if we separate trades into 387 trading days instead of 80 weeks). Panel C, Column 5 shows that there are 129,471 total unique trades. If trades are spread evenly over time, across stocks, and across branches, we should see an average of 2.31 trades per week in a given stock at a given branch (or 0.48 trades per day-stock-branch.) However, trades are not spread evenly over time, across stocks, and across branches. Table 1 shows that branch offices A, B, C, and D are much more active than branches E, F, and G.

4 Results

Before beginning our tests, consider the following facts about herding measures: i) For every buyer there is a seller in the market. This holds for any period of time and for any stock.[4] ii) Any herding measure for the whole market is, by definition, zero; iii) A herding measure for any subset of investors with the same characteristics of the whole market is, by definition, also zero. The measure may deviate from zero due to sample size; iv) Herding measures can only be different from zero for a subset of investors *if* the subset tends to buy and sell together; and v) If there exists a subset of investors that tend to buy and sell together, then there exists *at least one other* subset that tends to buy and sell together (the other subset

[3] Note: 12.28 = (276,923 / 14,660) * (52/80) since we have 80 weeks in our sample.

[4] Possible deviations from this rule can arise during stock offerings and stock buy-backs. After, controlling for these events, the above statement is always true.

can simply be the rest of the market.)

Mutual funds, pension funds, foreigners, and individuals are subsets we might expect to act homogenously but differently from other subsets in the market.

4.1 A traditional measure of herding

Existing papers on herding test whether one subset of investors tends to buy or sell the same stock together. The "LSV measure" from Lakonishok, Shleifer, and Vishny (1992) has become popular in the literature and provides just such a test. We begin by considering the proportion ($P_{i,t}$) of number of buys ($B_{i,t}$) to number of total trades ($B_{i,t} + S_{i,t}$) for stock "i" on day "t":

$$P_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}} \tag{1}$$

$$\overline{P_t} = \frac{1}{N}\sum_{i=1}^{N} P_{i,t} \tag{2}$$

The LSV measure of herding is defined as follows:

$$H_{i,t} = \left|P_{i,t} - \overline{P_t}\right| - E\left|P_{i,t} - \overline{P_t}\right| \tag{3}$$

$$H = \frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} H_{i,t} \tag{4}$$

The second term in (3) is an adjustment factor computed under the null hypothesis of no herding. It assumes the number of buys follows a binomial distribution. See Wermers (1999) for further explanation.

Table 2 presents our initial herding results. We group trades by week and stock (and do not consider branches independently at this time.) In Panel A, the average LSV-measure is 0.0312 at a weekly frequency. Under the null hypothesis that trades are independent across stocks and time, the result is significant at all conventional levels.[5]

Table 2, Panel B presents results of studies that also use the same LSV herding measure. The studies look at trades in the USA and Korea for institutional traders as well as individuals. Our herding measure of 0.0312 appears to be in-line with these studies.

[5] We consider trades at both a daily and weekly frequency but this doesn't change our results materially.

4.2 An alternative measure of herding

We propose an alternative measure of herding based on a runs test. There exists some (possibly very) small time interval such that no two trades are placed at the same time. Therefore, if investors herd, we would expect to see "abnormally" long runs of buys or sells. In addition, herding (e.g., long runs) cause the total number of runs per 1,000 trades to be less than we would expect to see if buys and sells arrive randomly. Essentially, the runs test transposes our estimation problem from calendar time to trade time.

From Campbell, Lo, and MacKinlay (1997), we can estimate the statistical significance of a runs test with the following parameters: n = sample size; N_{runs} = number of runs; and π = the ratio of buys to total trades.

$$\begin{aligned} z_{stat} &= \frac{N_{runs} + \frac{1}{2} - 2n\pi\left(1-\pi\right)}{2\sqrt{n\pi\left(1-\pi\right)\left[1-3\pi\left(1-\pi\right)\right]}} \\ &\overset{a}{\sim} N\left(0,1\right) \end{aligned} \tag{5}$$

To test whether traders in our dataset tend to go on buying and selling sprees, we exploit the fact that our data has a time-stamp indicating exactly when each trade is placed. We sort trades by stock ticker, then by date of trade, and finally by time stamp. We re-start our counter whenever: i) investors switch from buying to selling or vice versa; and ii) we consider a new stock.

Table 3 presents the results of our runs test using all unique trades that are placed by investors who are physically in a given brokerage office. Despite having 129,471 unique trades, we have only 54,890 runs. The number of runs is significantly shorter than expected (meaning run lengths are longer than expected) and has corresponding -54.2347 z-stat. Note, investors in our sample buy stocks 51.72% of the time which we can see from Table 1, Panel C (0.5172 = 66,956/129,471). Further evidence of long runs is seen in Figure 2. We compare our empirical distribution to the expected distribution when 51.72% of the trades are buys. Notice the long, right-hand tail.

4.3 The propensity for an individual to herd

We have now confirmed that herding is statistically significant in our sample. Also, a popular measure of herding is similar for our sample and existing studies. We now turn to document what type of investor (if any) is prone to herding. To do this, we first construct a herding score for each stock/week combination in our data. The herding score is equal to: i) the absolute value of the number of buy orders minus the number of sell orders; ii) all divided by the standard deviation of this measure.

Every time an investor trades, we count the stock/week herding score for the investor's trade. The sum of these scores is divided by the number of trades placed to arrive at an individual investor's "propensity to herd." The propensity to herd is then regressed against individual characteristics in Table 4. One might think that traits such as age, gender, trading frequency, diversification, or wealth would be correlated to one's propensity to herd. However, none of these variables has explanatory power. In fact, only the length of time the account has been open is statistically significant. This result is counter-intuitive since we would think that experience would be *negatively* correlated with herding. Table 4 presents some of the first results that herd behavior may not be related to the lack of investor sophistcation.

4.4 Shocks that affect total trades (buys+sell)

Our tests above confirm that individual investors in the PRC tend to herd, but the question remains: what causes this finding? To answer this question, we group investors by the branch office where they (physically) placed their trades. These groups are isolated both across a city and across the country. We believe that this experimental design is such that only publicly available data is observable to isolated groups at the same time. If one group decides to buy a given stock for reasons other than publicly available information, then *we would not* expect to see other isolated groups doing the same. [6]

We begin by looking at the total number of trades (volume) as a reference point to understand herding. We examine the principal component of total trading volume (defined as the number

[6] For this statement to be false, we would need an odd situation such as two friends. One friend would need to be standing and shouting into his/her cell phone in office A and the other friend would need to be shouting into his/her cell phone in office B by cell phone. There is no evidence this happens in the PRC.

of buy orders plus the number of sell orders) across stocks.[7,8] If there is only one factor that determines the trading volume of all stocks, then we should see the first principal component explain 100% of the volume (and the other six principal components will explain 0.00%.) If there is no common factor, then each of the seven factors should explain ($\frac{1}{7}$) or 14.2857% of the variance. By construction, n-principal components explain 100% of the variance of n-time series.

> H_A : if there is no common component in the total number of trades across k-stocks, then the first principal component will explain $\left(\frac{1}{k}\right)$ of the total variance, the first two principal components will explain $\left(\frac{2}{k}\right)$ of the variance in total, and so on.

Table 5a, Panel A shows that the first principal component of total trades (buys+sells) explains 51.71% of the variance of stocks in our sample. We then look at the trading of stocks within each of the branch offices. Table 5a, Panel B shows that the average pairwise correlation of total trades between stocks within a given branch is 26.07% and highly significant. We use Monte Carlo methods and draw from the empirical distributions to construct standard errors. This allows us to take into account the fact that stocks and branches trade at different frequencies. Both of the measures in Table 5a show that the whole stock market in the PRC experiences common shocks. These shocks affect the trading volume of all stocks, regardless of which stocks we look at.

More interestingly, Table 5b looks at the total number of trades of a single stock in each of the seven branches in our sample. In this way, we can measure a location-based common component to total trades (e.g., across the isolated groups of investors.)

> H_B : if there is no common component of total trades for a single stock that is

[7] Since we have seven branch offices in our sample, we choose to consider only seven stocks. Having the same number of stocks and branches helps us to compare the relative importance of a principal component across stocks vs. a principal component across branches. We choose the seven highest-volume stocks from our sample of the 100 high-volume stocks. When feasible, we perform tests with both the 100-stock sample and the 7-stock sample.

[8] It is important to note that we look at the principal component of normalized variables. This avoids problems that might arise when different time series have very different variances (high volume stocks vs. medium volume stocks.) In these cases, the first principal component will explain the variance of the highest-variance time series rather than explain a common component across time series. Analysis of normalized variance is similar to looking at the correlation matrix rather than the covariance matrix.

trading in n-different locations, then the first principal component across branches will explain $\left(\frac{1}{n}\right)$ of the total variance, the first two principal components will explain $\left(\frac{2}{n}\right)$ of the variance in total, and so on.

In Table 5b, Panel C, we see (on average) the first principal component (across branches) explains 56.74% of the variance of the total trades in a single stock. The first two principal components explain 73.75% of the variance. In addition, when we aggregate trades by stock (across branches), the first principal component explains 73.66% of the variance of total volume. Another look at the same phenomenon shows that the average pairwise correlation for a given stock between branches is 46.17% and very significant. When we compare results in Table 5b to results in Table 5a, we see individual stocks experience shocks. The shocks affect trading volume of this one stock regardless of where investors are placing their trades. In summary, Table 5a shows there are cross-stock shocks. Table 5b shows that stock-specific shocks contain additional power (over the market-wide effects) to explain trading volume.

4.5 shocks that affect net trades (buys-sell) or herding

Rather than look at total trades, we now turn to look at net trades (also known as, "trade imbalances" and defined as the number of buys minus the number of sells).

H_C : if there is no common component in the net number of trades across k-stocks, then the first principal component will explain $\left(\frac{1}{k}\right)$ of the total variance, the first two principal components will explain $\left(\frac{2}{k}\right)$ of the variance in total, and so on.

Table 6a, Panel A shows that net trade imbalances (defined as the number of buy orders minus the number of sell orders) do not have a strong principal component across stocks. A second measure is the average pairwise correlation of net trades between stocks within a given branch. Table 6a, Panel B shows the correlation estimate is insignificant. We can interpret this results as indicating that investors in our sample do not appear (in aggregate) to sell one stock in order to raise funds to by another.

The final, and most important test, involves looking at the net trades in a single stock across branches (i.e., across the isolated groups of investors in our sample.)

H_D : if the decision to buy or sell a given stock is not related to market-wide shocks, then the correlation of net trades will be zero across n-isolated groups of investors. In other words, the first principal component across n-branches will explain $\left(\frac{1}{n}\right)$ of the total variance, the first two principal components will explain $\left(\frac{2}{n}\right)$ of the variance in total, and so on.

When we look at a single stock, the principal components in Table 6b, Panel A appear to have some explanatory power. On average, the first principal component explains 27.57% of the variance of net trades (on average). When we aggregate by all stocks, the first principal component explains 28.64% of the variance of net trades while the first two components explain 51.69% of total volume. Likewise, the average pairwise correlation coefficient is 7.08% which is significant at the 0.0018 level.

To summarize the results up to this point, isolated groups of investors have significantly correlated trading behavior. That is, these groups tend to buy at the same time and sell at the same time, even though the groups of investors are separated by miles and miles. Thus, we are able to rule out any hypothesis that relates herd behavior to group-psychology effects. The theory that a group of investors can work itself into a panic is simply not supported by this study.

4.6 Regional trading correlation

Tables 5b and 6b have another interesting feature. Panel C of both tables shows circumstantial evidence that total trades and net trades are mainly affected by two principal components. A second check and a phone call to the PRC turned up the interesting fact that the branches in our sample are from one of two regions. Branches offices A, B, C, and D are located in Guangdong province while branches E, F, and G are located in the Shanghai municipality. Inhabitants in the first region typically speak Cantonese and Mandarin while inhabitants in the second region typically speak Shanghaiese and Mandarin.

H_E : if information flows do not have a regional / language component, then the correlation of net trades should the same between: i) two branch offices in the same region; and ii) two branch offices in different regions.

Table 7 rejects H_F. Panel B, in particular, shows that investors in the Guangdong province tend to buy and sell at the same time ($\rho = 0.1778$). Investors in the Shanghai municipality tend to buy and sell together($\rho = 0.1171$). But there is little correlation between the buying/selling in Guangdong and buying/selling in Shanghai ($\rho = -0.0062$).

The results in Table 7, Panel B are quite stunning. Investors in four isolated branches in Guangdong province engage in highly correlated investment decisions. We strongly reject the null hypothesis that herd behavior is a small sample bias. We also strongly reject the null hypothesis that herd behavior is caused by group-panics or group-psychology. Instead, there is now evidence to support the theory that informational shocks hit all investors simultaneously. The arrival of new information induces investors to buy or sell (volume is highly correlated.) However, the decision of whether to buy or sell depends on which region / language group the investor is in.

4.7 Herding and asset prices

Our final series of tests relates the existence of herding with asset prices. Again, we use trading volume as a benchmark. In Table 8, Panel A we regress the absolute of returns (for a given stock over a week) on the total number of trades. We use Newey-West standard errors with four lags and find the coefficient on volume is extremely significant. To control for heteroscedascity, we run regressions with normalized variables (1a and 1b) and non-normalized variables (1c and 1d). We also consider trades placed by telephone as a double-check. All results are qualitatively the same.

Table 8, Panel B presents more surprising results. When we regress returns (not absolute values) on *net trades* of individual investors in our sample, we see a significantly negative coefficient. Herding by investors in our sample is *negatively* correlated with contemporaneous stock returns. Again we run regressions with standardized and non-standardized variables. We also use telephone trades as a control group.

This is the final piece of evidence that individual investors are not prone to manic buying sprees that send prices soaring wildly. Instead, all the evidence in this paper is consistent with individual investors providing liquidity to another subset of investors. It is the other subset of investors that has a *positive* correlation between buys and stock returns.

5 Robustness checks

Alternative LSV measures: The LSV measures presented in Table 2 are for the 100 high-volume stocks and did not consider branches independently. We calculate the LSV measure for Branch A only and find little difference in the measure: H=0.0282 (z-stat=13.43). We also calculate the measure for the sub-sample of seven high-volume stocks only. Again the measure does not change much: H=0.0239 (z-stat=5.43) when considering trading at all branches.

Telephone trades as a control group: In Table 8, we use trades placed by telephone as a control group. Coefficients from regressions that use data from these two groups are not very different. This may not be surprising since investors from branch A who use the telephone live near investors who go to the branch office. If common information shocks are generating trading volume then we would not expect to see much difference between these two types of investors.

Table 9 repeats the runs test with different samples of stocks and different groups of investors. Again, there are few discernable differences.

Table 10 shows that correlation within a regional / language group is *higher* when considering telephone trades than physically-placed trades.

6 Conclusion

This paper provides an in-depth look at investor behavior. We document some rather straightforward (but new) items. A traditional herding measure of PRC trade data is similar to existing studies. A runs test can be used to estimate the degree of herding within a well-defined group of investors. And, the propensity of an individual to herd is found to be correlated only with experience. Surprisingly, this correlation is positive.

On a more interesting level, we provide a number of tests that reject psychological theories of herding. We do this through experimental design. That is, we isolate groups of investors who are physically in the same room at the time they place trades. We document that large trade imbalances do exist. However, even though we are set to see correlated buying behavior within a group, we fail to detect it. Instead, we see that separate and isolated groups of investors tend to buy and sell a given stock simultaneously. The correlation of such behavior is statistically significant, especially when we control for regional / language effects.

Finally, individual investors are most likely to herd and buy when prices fall. The existence of herd buying is not correlated to prices spiking upward. It is reasonable to conclude that individual investors provide liquidity to the market. A number of new research topics that are waiting to be explored. In particular, future research needs to identify what group of investors has trades that are negatively correlated with individuals. Presumably, such a group consists of institutions, but this question can only be answered after considerable research effort.

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Figure 1
Layout of a Typical Branch Office

This presents a schematic drawing of a typical brokerage office. Stock prices are shown on a large, electronic board that covers a good portion of one side of the room. Individual investors can place trades in one of two ways. Some investors place trades through terminals that are located around the edge of the branch office. Sophisticated offices allow investors to “log in” by simply swiping a magnetic-strip card. Investors then enter electronic limit orders. A computer blocks any buy order for which the investor doesn’t have sufficient credit or any sell order when the investor does not own the shares. Some margin buying is possible. Other investors place trades at a cashier window after they fill out an order firm. The cashier then enters the buy or sell order into a computer. Again, the computer blocks non-conforming attempts to trade.

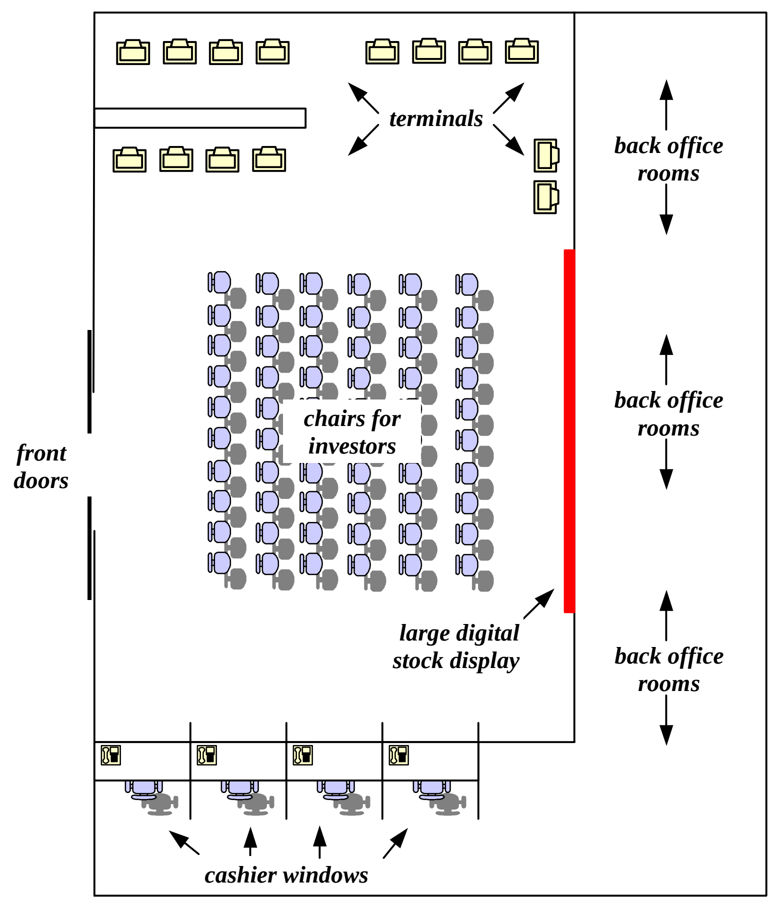

Table 1
Overview of Data

This table presents overview statistics for the data used in this study. Data represent stock (equity) trades placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. Trades, or orders, are placed at one of seven brokerage offices which are responsible for maintaining the investors' account data. We concentrate on a sample of buys and sells of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange. Panel A shows the total number of trades placed in a particular brokerage office during our sample period. We take into account that some individual investors may "break-up" their trades throughout a day. Panel B considers a "unique trade" to be: i) one or multiple trades in the same stock; ii) by a single investor; iii) on the same day. Panel C considers only trades placed by investors who are physically standing in a particular branch office at the time the trade is placed.

Panel A: Total Trades in Dataset

Branch Office	# of Accts	# of Buy Orders	# of Sell Orders	Buy+Sell Orders
A.	1,939	24,092	21,296	45,388
B.	2,685	22,882	22,074	44,956
C.	2,707	31,657	29,448	61,105
D.	2,997	23,140	20,894	44,034
E.	1,450	14,288	11,216	25,504
F.	1,580	10,924	8,568	19,492
G.	1,302	19,829	16,615	36,444
total	**14,660**	**146,812**	**130,111**	**276,923**

Panel B: Unique Trades in Dataset

Branch Office	# of Accts	# of Buy Orders	# of Sell Orders	Buy+Sell Orders
A.	1,939	16,096	14,719	30,815
B.	2,685	15,937	15,455	31,392
C.	2,707	18,700	18,615	37,315
D.	2,997	19,488	18,447	37,935
E.	1,450	8,638	7,447	16,085
F.	1,580	7,438	6,458	13,896
G.	1,302	9,187	8,582	17,769
total	**14,660**	**95,484**	**89,723**	**185,207**

Panel C: Unique Trades That Were Physically Placed in a Branch Office

Branch Office	# of Accts	# of Buy Orders	# of Sell Orders	Buy+Sell Orders
A.	1,423	11,046	10,059	21,105
B.	1,855	9,845	9,559	19,404
C.	1,864	12,810	12,614	25,424
D.	2,210	12,694	11,814	24,508
E.	1,046	6,728	5,772	12,500
F.	1,284	6,527	5,712	12,239
G.	972	7,306	6,985	14,291
total	**10,654**	**66,956**	**62,515**	**129,471**

Table 2
Initial Herding Results Using the LSV Measure

This table presents an average herding measure ("H") based on Lakonishok, Shleifer, & Vishny (1992) and defined below. Panel A presents results based on our sample of data: stock (equity) trades are placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days or 80 weeks. We concentrate on a sample of trades of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange. Panel B presents results from other academic studies that use the same LSV herding measure.

$$P_{i,t} = \frac{B_{i,t}}{B_{i,t} + S_{i,t}} \qquad H_{i,t} = \left|P_{i,t} - \overline{P}_t\right| - E\left|P_{i,t} - \overline{P}_t\right|$$

$$\overline{P}_t = \tfrac{1}{N}\sum_{i=1}^{N} P_{i,t} \qquad H = \tfrac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T} H_{i,t}$$

Panel A: Herding Measure for China

	Daily	Weekly
Mean	0.0271	0.0312
z-stat	*(30.11)*	*(22.29)*
Median	0.0044	0.0141

Panel B: Herding Measures in Comparable Studies

Study	Country	Sample	Freq.	LSV Measure
a) Grinblatt et al (1995)	USA	Mutual Funds	Quarterly	0.0250
b) LSV (1992)	USA	Pension Funds	Quarterly	0.0270
c) Wermers (1999)	USA	Mutual Funds	Quarterly	0.0340
d) Choe et. al. (1999)	Korea	Foreigners	Daily	0.0365
e) Kim & Wei (2002)	Korea	Foreign Inst.	Monthly	0.0434
f) Kim & Wei (2002)	Korea	Foreign Indiv.	Monthly	0.1117
g) Choe et. al. (1999)	Korea	Foreigners	Daily	0.2124

Panel B notes: a) all funds, all quarters, from Table 4; b) all cases, from Table 2; c) all funds, 1975-1994, five or more trades, from Table II; d) represents a lower-bound estimate from this study, average of all measures before crisis and during crisis, from Table 4; e) non-resident institutions, average of tranquil period, pre-crisis period, and in-crisis period, from Table 5; f) non-resident individuals, average of tranquil period, pre-crisis period, and in-crisis period, from Table 5; g) represents an upper-bound estimate from this study, average of all measures before crisis and during crisis, from Table 3;

Table 3
Herding Results Using a Runs Test

This table presents the results of a runs test. Stock trades (either buys or sells) are placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days or 80 weeks. We concentrate on a sample of trades of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange. If our sample has abnormally long runs, then the total number of runs will be low and the Z-stat will be significantly negative. If our sample consists of buy trades that are immediately followed by sell trades, then the total number of runs will by high and the Z-stat will be significantly negative.

$$z = \frac{N_{runs} + \frac{1}{2} - 2n\pi(1-\pi)}{2\sqrt{n\pi(1-\pi)[1-3\pi(1-\pi)]}} \overset{a}{\sim} N(0,1)$$

n	**Nruns**	**π = p(Buy)**	**z-stat**
129,471	54,890	0.5172	-54.2347

Figure 2

This figure presents the distribution of run lengths (either buy or sell trades.) Stock (equity) trades are placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days or 80 weeks. We concentrate on a sample of trades of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange. Our data show a greater preponderance of long runs than one might expect given the number of buys in and sells in our data set.

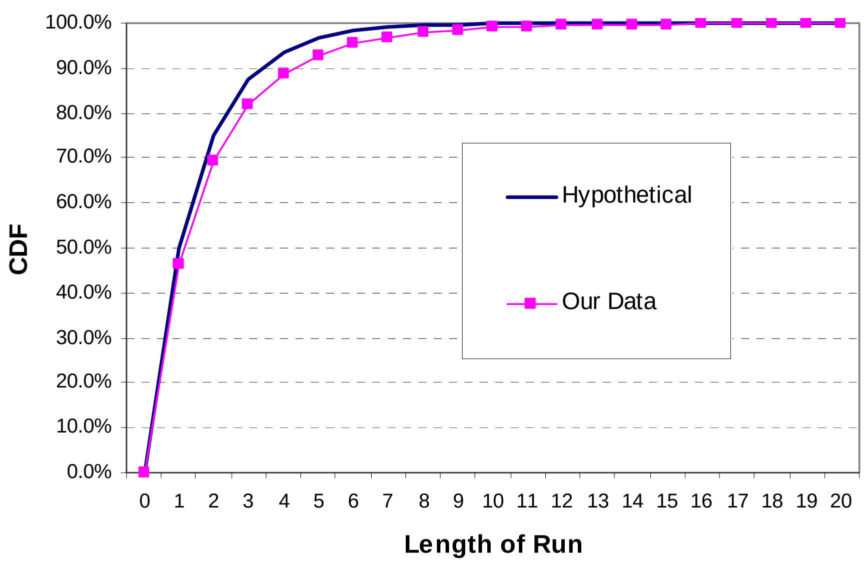

Table 4
Propensity to Herd and Investor Characteristics
(Initial Results Only)

This table investigates whether certain types of investors are more likely to herd than others. Data come from the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days or 80 weeks. This table concentrate only on the trades from one branch office (A) for one stock (#000001) that is listed on the Shenzhen Stock Exchange. We first construct a variable that measures whether an investor is more likely to trade during weeks with high net trade imbalances (i.e., herding periods.) Details about the measure are given in the text. We regress our measure on various investor traits. The table shows coefficient estimates and t-stats based on White standard errors.

Dependent Variable: Individual's Propensity to Herd

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Age	0.0017						0.0010
t-stat	*(1.30)*						*(0.66)*
Gender (1=Male)		0.0424					0.0417
t-stat		*(1.25)*					*(1.22)*
Time Acct. Open			0.0035				0.0033
t-stat			*(3.59)*				*(3.35)*
Transactions per Month				-0.0001			-0.0002
t-stat				*(-0.16)*			*(-0.25)*
# of Stocks Held in Port					0.0013		0.0019
t-stat					*(0.42)*		*(0.50)*
Acct. Balance (RMB)						-0.0000	-0.0000
t-stat						*(-0.77)*	*(-0.47)*
Constant	Y	Y	Y	Y	Y	Y	Y

Table 5a
Shocks that Affect Total Trades (Buys + Sells)

The table examines total trading activity where total trades is defined as the number of unique buy orders that are physically placed in a branch office plus the number of unique sell orders. Panel A shows results from a principal component analysis where we have normalized total trades for each stock or branch by its standard deviation. Panel B shows the average pairwise correlation coefficient of total trades between stocks within a given brokerage office. Panels A & B are different ways to understand that the stock market experiences common shocks. These shocks affect the trading volume of all stocks, regardless of which stocks we look at.

Panel A: Principal Component for Total Trades (Buys+Sells) per Week Measured Across All Stocks

	1st comp	2nd comp	3rd comp
% of variance explained	51.7077	14.4179	12.0200

Panel B: Average Pairwise Correlation of Total Trades (Buys + Sells) Measured Between Stocks Within a Given Branch

average pairwise correlation	0.2607
z-stat	*(10.61)*

Table 5b
Shocks that Affect Total Trades (Buys + Sells)

The table examines total trading activity where total trades is defined as the number of unique buy orders that are physically placed in a branch office plus the number of unique sell orders. Panel C shows results from a principal component analysis where we have normalized total trades for each stock or branch by its standard deviation. Panel D shows the average pairwise correlation coefficient of total trades between stocks within a given brokerage office. Panels C & D are different ways to understand that a stock experiences common shocks. These shocks affect the trading volume of this one stock, regardless of where investors are placing their trades.

Panel C: Principal Component for Total Trades (Buys+Sells) per Week Measured for a Given Stock Between Branches

	1st comp	2nd comp	3rd comp
% of variance explained (average per stock)	56.7414	16.0125	10.4639
% of variance explained (for all stocks)	73.6592	11.7651	6.2663

Panel D: Average Pairwise Correlation of Total Trades (Buys + Sells) Measured for a Given Stock Between Branches

average pairwise correlation	0.4717
z-stat	*(19.44)*

Table 6a
Shocks that Affect Net Trades (Buys - Sells)

The table examines net trading activity where net trades is defined as the number of unique buy orders that are physically placed in a branch office minus the number of unique sell orders. Panel A shows results from a principal component analysis where we have normalized net trades for each stock or branch by its standard deviation. Panel B shows the average pairwise correlation coefficient of net trades between stocks within a given brokerage office. Panels A & B are different ways to understand that the stock market does not experience common shocks to net trades. We can interpret this result as indicating that investors in our sample do not appear (in aggregate) to sell one stock in order to raise funds to buy another stock.

Panel A: Principal Component for Net Trades (Buys-Sells) per Week
Measured Across All Stocks

	1^{st} comp	2^{nd} comp	3^{rd} comp
% of variance explained	21.2358	17.1945	16.3576

Panel B: Average Pairwise Correlation of Net Trades (Buys-Sells)
Measured Between Stocks Within a Given Branch

average pairwise correlation	0.0065
z-stat	*(0.28)*

Table 6b
Shocks that Affect Net Trades (Buys - Sells)

The table examines net trading activity where net trades is defined as the number of unique buy orders that are physically placed in a branch office minus the number of unique sell orders. Panel A shows results from a principal component analysis where we have normalized net trades for each stock or branch by its standard deviation. Panel B shows the average pairwise correlation coefficient of net trades between stocks within a given brokerage office. Panels C & D are different ways to understand that a given stock experiences common buying or selling shocks. That is, the decision to buy or sell a given stock is significantly correlated across isolated groups of individual investors.

Panel C: Principal Component for Net Trades (Buys-Sells) per Week Measured for a Given Stock Between Branches

	1st comp	2nd comp	3rd comp
% of variance explained (average per stock)	27.5712	19.3641	15.7106
% of variance explained (for all stocks)	28.6389	23.0486	12.5854

Panel D: Average Pairwise Correlation of Net Trades (Buys-Sells) Measured for a Given Stock Between Branches

average pairwise correlation	0.0708
z-stat	*(2.92)*

Table 7
Regional Trading Correlation

This table presents overview statistics of cross-office trading activity. Data represent stock (equity) trades placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days. Trades are placed at one of seven brokerage offices and the office is responsible for maintaining the investors' account data. We concentrate on a sample of buys or sells of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange. Panel A shows the average pair-wise correlation of total trades. Panel B shows the average pair-wise correlation of the net trades. For net trades, especially, the decision to buy or sell is more correlated within a regional / language group than across such groups.

Panel A: Average Correlation of Total Trades (Buys+Sells)

By Stock; Across Branches

	Guangdong	Shanghai
Guangdong	0.5695	
Shanghai	0.4111	0.4705

Deviation from Average

	Guangdong	Shanghai
Guangdong	+0.0978	
Shanghai	-0.0605	-0.0011

note: average correlation for all branches = 0.4717 (from Table 5b)

Panel B: Average Correlation of Net Trades (Buys-Sells)

By Stock; Across Branches

	Guangdong	Shanghai
Guangdong	0.1778	
Shanghai	-0.0062	0.1171

Deviation from Average

	Guangdong	Shanghai
Guangdong	+0.1070	
Shanghai	-0.0770	+0.0463

note: average correlation for all branches = 0.0708 (from Table 6b)

Table 8
Herding and Stock Returns

This table presents regression results of returns on trading activity in our sample. Data represent stock (equity) trades placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days. Trades are placed at one of seven brokerage offices and the office is responsible for maintaining the investors' account data. We concentrate on a sample of buys or sells of 7 high-volume stocks that are listed on the Shenzhen Stock Exchange.

Panel A: Regressions of Absolute Value of Returns on Total Number of Trades

	(1a)	(2a)	(3a)	(4a)
Dependent Var	$\mid r_{i,t} \mid / \sigma_i$	$\mid r_{i,t} \mid / \sigma_i$	$\mid r_{i,t} \mid$	$\mid r_{i,t} \mid$
Stk dummies	Yes	Yes	Yes	Yes
In Branch / Tel	In Branch	Telephone	In Branch	Telephone
Indep. Var	$Tot_{i,t} / \sigma_{Tot,i}$	$Tot_{i,t} / \sigma_{Tot,i}$	$Tot_{i,t}$	$Tot_{i,t}$
β-hat	0.2939	0.2415	0.0022	0.0035
Std Err	NW 4 lags	NW 4 lags	NW 4 lags	NW 4 lags
T-stat	5.59	3.89	3.33	3.33

Panel B: Regressions of Returns on Net Number of Trades

	(1b)	(2b)	(3b)	(4b)
Dependent Var	$r_{i,t} / \sigma_i$	$r_{i,t} / \sigma_i$	$r_{i,t}$	$r_{i,t}$
Stk dummies	Yes	Yes	Yes	Yes
In Branch / Tel	In Branch	Telephone	In Branch	Telephone
Indep. Var	$Net_{i,t} / \sigma_{Net,i}$	$Net_{i,t} / \sigma_{Net,i}$	$Net_{i,t}$	$Net_{i,t}$
β-hat	-0.1773	-0.1997	-0.0040	-0.0070
Std Err	NW 4 lags	NW 4 lags	NW 4 lags	NW 4 lags
T-stat	-2.82	-4.29	-3.53	-4.84

Table 9
In-branch vs. Telephone Runs Tests

This table presents a runs test of either buy or sell trades. Stock (equity) trades are placed by individual investors in the People's Republic of China between May 4, 1999 and December 4, 2000. This time period represents 387 trading days or 80 weeks. We concentrate on a sample of trades of 100 high-volume stocks that are listed on the Shenzhen Stock Exchange and a sub-sample of the seven highest-volume stocks. We also consider trades placed by investors who physically trade from a given branch office and those who use a telephone to place their trades.

# of Stocks	**In-branch or Telephone**	**n**	**Nruns**	**π = p(Buy)**	**z-stat**
100	In-branch	129,471	54,890	0.5172	-54.2347
100	Telephone	55,736	24,878	0.5118	-25.1791
7	In-branch	18,065	7,617	0.5126	-20.9570
7	Telephone	8,610	3,640	0.5031	-14.3184

Table 10
Regional / Language Correlation of Telephone Trades

By Stock; Across Branches

	Guangdong	Shanghai
Guangdong	0.3012	
Shanghai	0.0143	0.0824

Deviation from Average

	Guangdong	Shanghai
Guangdong	+0.1884	
Shanghai	-0.0985	-0.0304

note: average correlation for all branches = 0.1128 (not reported previously)

Appendix 1
Trading Volume in the PRC

The figure graphs the distribution of the natural log of trading volume. Trading volume is defined as the total value of stock traded (in RMB) over the two-year period 1999-2000. The data come from the Shenzhen stock exchange and represent the aggregate trading volume across all stocks.