Peer Effects in Investor Trading Decisions: Evidence from a Natural Experiment*

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Abstract

This study examines for evidence of peer effects, via word-of-mouth communication, in investor trading decisions. It specifically exploits a unique setting in China in that groups of individual investors are in the same trading room at the time they place their stock orders. We find strong word-of-mouth effects in the trading decisions of Chinese individual investors. The effect is stronger in investor buys than investor sells of locally-headquartered stocks, while it is stronger in investor sells of non-locally headquartered stocks. The results are robust to several alternative interpretations associated with stock visibility and familiarity, within-branch bias, location, local bias, firm size, and calendar effects. In contrast to existing studies, we find the word-of-mouth influence be mainly dominated by the nearest neighbors from the same branch and not by those from different branches located even in the same city. Hence physical proximity does matter for peer effects in the trading decisions of individual investors.

"People who interact with each other regularly tend to think and behave similarly"

- Robert Shiller (1995)

I. Introduction

Theory suggests that in many economic and social settings, individuals can be influenced by the decisions of others, through "word-of-mouth".[1] Word-of-mouth is prevalent in everyday life, as in choosing a fancy restaurant or a popular movie. In recent years, many financial economists believe that peer influences might also be important in explaining financial phenomena such as banking panics and stock market crashes.[2] However, tests of this proposition are somewhat formidable, because information is exchanged in private conversations and direct observation of the informational flow across individuals is difficult. Thus far, only a few studies have investigated peer-induced trading decisions in stock markets, and these studies have relied on the process of information exchange from aggregate data, particularly using individuals' varying levels of sociability with his friends and neighbors as a proxy for such information exchanged through social networks.

The main objective of this paper is to test for evidence of any peer effects in investor trading decisions. Particularly, we exploit a brokerage rule in Chinese stock markets in that an individual investor is allowed to open only one brokerage account at any brokerage branch in China, and that all her trades have to be placed through this designated branch. Of particular interest to this study is that groups of individual investors are in the same trading room when they place their stock orders. The close physical proximity of these individual investors, who maintain brokerage accounts at the same branch, naturally helps promote constant face-to-face interactions and word-of-mouth exchange of ideas and information. This unique setting offers a natural experiment on the impact of peer effects in financial markets.[3]

[1] See Banerjee (1992), Banerjee and Fudenberg (1999), Bickhchandani, Hirshleifer, and Welch (1992), Cao and Hirshleifer (2002), and Ellison and Fudenberg (1994, 1995).

[2] Glaeser and Scheinkman (2000) provide a detailed survey of the literature.

[3] The ethnographical study of the SHSE by Hertz (1998; chapter 6) details her observation of the extent of social interactions among Chinese individual investors in Shanghai.

This study employs data compiled by the Shanghai Stock Exchange (SHSE) that contain daily detailed records of trades initiated by individual brokerage accounts across the Mainland China for the period April 2001 through April 2002.[4] The data also provide information on the brokerage branches where the trades are executed. Furthermore, the uniqueness of the Chinese investment environment offers us a valuable opportunity to examine several implications of social learning theories that cannot be directly addressed using the widely employed U.S. brokerage accounts data. For example, can the trading behavior of an individual investor be affected by that of other individual investors with whom he interacts? Is there any difference in the diffusion of positive and negative information associated with peer-related trading behavior? Does physical proximity between individual investors matter for peer-induced trading decisions? Are there differential peer effects in investors trading of familiar (local) stocks versus less familiar (non-local) stocks? Our study reveals many interesting findings that not only provide significant insights into the importance of peer effects in individual investor trading behavior, but also have economic implications for asset pricing. Particularly, our evidence might help us better understand the existence of non-fundamental components of stock prices that cannot be explained by traditional asset pricing models.[5]

We perform separate tests of whether the buying and selling decisions of an individual are affected by the decisions of her peers at the same branch or by the decisions of her peers at a different branch. In our analysis, a brokerage branch office is the geographic location of individual investors where we test word-of-mouth effects. This contrasts with studies such as Hong, Kubik, and Stein (2005) and Ivković and Weisbenner (2005) who examine "neighborhood" effects in financial trading decisions at the community or city level. Hong, Kubik, and Stein (2005) examine for evidence of word-of-mouth effects in holdings and trades of U.S. mutual-fund managers located in the same city. Ivković and Weisbenner (2005) examine neighborhood effects in the holdings of U.S. individual investors who live within a 50-mile radius city. Their

[4]The data are similar to the New York Stock Exchange's consolidated equity audit trail data.

[5]A recent study by Mei, Scheinkman, and Xiong (2005) finds evidence that speculative trading is an important determinant of Chinese stock prices.

study employs U.S. brokerage accounts data from a large discount brokerage firm. Both Hong, Kubik, and Stein and Ivković and Weisbenner find evidence of word-of-mouth effects. It is important to emphasize that our work differs from theirs in that we examine for evidence of peer influences in the trading behavior of individual investors who are in the same trading room or branch at the time they place their stock orders. More importantly, while the two studies examine peer effects at the city level, ours is at the branch level within a city. Our naturally experimental setting enables us to disentangle the word-of-mouth interpretation from various alternative explanations, including information from local media.

Results show strong evidence of word-of-mouth effects in the trading decisions of these individual investors, and the effects are stronger in their purchase than sale of locally-headquartered stocks. If individual investors at a branch on average increase their purchase of a stock by 1%, then it is expected that an individual investor of the same branch will increase her purchase of the same by about 3.5% more than an individual investor of another branch. Similarly, if individual investors at a branch on average sell more of a stock by 1%, then it is expected that such a sale will induce an individual investor of the same branch to sell by about 1.6% more, compared to an individual investor from another branch. On average, the other-branch effects are negative, suggesting that the trading decisions of individual investors have little influence on the trading decision of an individual investor from a different branch located in the same city. The results are robust to several alternative interpretations associated with stock visibility and familiarity, within-branch bias, location, local bias, firm size, and calendar effects.

We also test the importance of geographic proximity in word-of-mouth communication. In contrast to Hong, Kubik, and Stein (2005) and Ivković and Weisbenner (2005), we find no evidence of community effects after controlling for local effects. Word-of-mouth effects are strong in the trading decisions of individual investors of close physical proximity, but the effects disappear as the physical distance between investors increases. Specifically, word-of-mouth effects are evident only in the trades of individual investors at the same branch, but not in the trades of individuals from different branches. Therefore, the decisions of individuals are primarily affected by the decisions of their closest "neighbors" who have brokerage accounts at the same branch as they do, but not by the decisions of those who reside in the same city and maintain brokerage accounts at different branches. These findings suggest that close proximity between individual investors is essential to foster face-to-face communication and strong relational ties, both of which in turn facilitate the exchange of information and ideas and the influence of one another's trading decisions. Furthermore, significantly stronger word-of-mouth effects are evident in investor selling, while not investor buying, of non-local stocks. This result perhaps implies that negative word-of-mouth information has a greater impact on individual investors selling of less familiar non-local stocks, compared to positive word-of-mouth information on investor buying of the same. Alternatively, it might also suggest that the disposition effect varies across local and non-local stocks.

Our work is somewhat related to that of Feng and Seasholes (2004) in that both studies test for correlated trading of Chinese individual investors. However, our study differs from theirs in many significant ways. One, we examine for evidence of peer-induced correlated trading at the branch level, while they focus on location-induced correlated trading at the cross-branch level. Two, using a different methodology from ours, Feng and Seasholes document that public or market-wide information can explain about 32% of the correlated net trades between branches. Hence they conclude that public information is a major determinant of correlated trading. In contrast, we find strong peer effects in the trading decisions of individual investors at the branch level, while controlling for cross-branch effects. This finding suggests that word-of-mouth or private information is a source of within-branch correlated trading. Finally, Feng and Seasholes employ brokerage accounts data from a single brokerage firm in Mainland China to examine whether there exists correlated trading in Shenzhen Stock Exchange (SZSE) stocks. On the other hand, we adopt SHSE audit trail data that contain detailed trades of individual brokerage accounts from various branches of different brokerage firms across Mainland China. A detailed discussion of the differences between their single-brokerage firm's data and our SHSE audit trail data is presented in the subsequent section of the paper.

This paper is organized as follows. The next section reviews the literature and develops the hypotheses that we test in this study. Section III describes the data. Section IV contains the baseline results together with various robustness tests. Section V examines the role of geographic proximity in word-of-mouth communication, and the final section concludes and discusses some implications of our findings.

II. Literature Review and Hypotheses Development

Social interactions provide opportunities for information exchanges via word-of-mouth, in which individuals use information about the experiences of others to guide their own decisions, and "observational learning", in which individuals learn from observing other individuals and base decisions on the observed decisions of others.[6] In their theoretical models, Ellison and Fudenberg (1994, 1995) and Banerjee and Fudenberg (1999) discuss the importance of word-of-mouth communication in everyday choices among restaurants or auto mechanics. Shiller (2000; chapter 8) cites several studies indicating that conversation plays a critical role in security investment decisions.

Hong, Kubik, and Stein (2005) present the first attempt to study the diffusion of word-of-mouth information among U.S. mutual fund managers located in the same city using quarterly holdings of these managers. Their data set from CDA Spectrum is from March 1997 to December 1998 and includes only the net sales and purchases of stocks that a fund manager transacts during a given quarter. Therefore, they do not have information about how the manager might have bought and sold the same stock within a quarter. Their study therefore assumes that quarterly net transactions are reasonable proxies for quarterly trades. It also assumes that fund managers who are located in the same city have many opportunities to meet in formal or informal gatherings, such as local investor conferences, whereby they exchange ideas by word-of-mouth. They find word-of-mouth effects in the trading decisions of managers in that the decision of a

[6]See Banerjee (1992), Banerjee and Fudenberg (1999), Bickhchandani, Hirshleifer, and Welch (1992), Cao and Hirshleifer (2002), Ellison and Fudenberg (1994, 1995).

manager is more influenced by the decisions of other managers in the same city than by the decisions of those located in other cities.

Ivković and Weisbenner (2005) study word-of-mouth diffusion effects among U.S. individual investors by using information on common stocks that 35,673 households traded through a discount brokerage firm from 1991 through 1996. Similar to that of Hong, Kubik, and Stein (2005), this study assumes that individuals who live in the same city have more opportunities to communicate via word-of-mouth than those not. The two authors disentangle the diffusion among effects of common preferences, structure of the local industry, and word-of-mouth. They find evidence of information diffusion effects in the quarterly investment choices of individuals whose decisions are related to those made by their neighbors, who are located within 50 miles from them. They also show that such effects are stronger in local purchases and in larger metropolitan areas.

These researchers infer the process of information exchange from aggregate data using individuals' varying levels of sociability with his friends and neighbors as a proxy for information exchanged through social networks. Their results cannot rule out alternative interpretations such as common personality traits and preferences, common reaction to public news or announcements, among others. To rule out such interpretations, our baseline experimental study looks at groups of individual investors who maintain accounts at brokerage branches from different brokerage firms located in the same city. Each branch provides an ideal structured environment that facilitates interpersonal face-to-face and word-of-mouth communication. We predict that the trading decision of an individual investor at a given branch is affected more by the trading decisions of other individuals from the same branch than by those of individuals from different branches located in the same city. Our test of this hypothesis differs from those of existing studies in that we differentiate word-of-mouth effects in the buying and selling decisions of individual investors. Typically, individual investors have different motivations for buying and selling a stock. Investor buys are generally motivated by positive information and/or investors' optimistic expectations of the future performance of the stock. On the other hand, investor sells could reflect negative information that causes investors to sell a stock and/or various motivations, such as liquidity needs, portfolio diversification, as well as investors' pessimistic expectations of the stock's future performance. Furthermore, given no short selling is permitted in China, individuals can only sell the stock that they own. Thus, we should expect stronger word-of-mouth effects in investor buys than investor sells. In contrast, prior studies that employ either net buys/sells or total trades (buys and sells) might not be able to accurately capture word-of-mouth effects as such trading information might distort individual buy and sell effects.

Our analysis also attempts to determine the extent to which geographic proximity between "neighbors" helps induce word-of-mouth effects in trading decisions. Geographic proximity encourages face-to-face communication and strong social ties, both of which in turn encourage the flow of word-of-mouth information. Existing social-interaction literature provides no consensus on whether the effect of social interaction is a local or a community effect, nor do the recent few studies that examine the influence of word-of-mouth effects in the financial decisions of individuals. Our study presents the first attempt to test the importance of geographic proximity in word-of-mouth communication.

III. Data Description and Sample Selection

The primary database contains daily detailed records of 77.12 million trades of A-Shares initiated by about 7.24 million individual brokerage accounts across the Mainland China for the period April 2001 through April 2002.[7] The data are compiled by the SHSE for the purpose of audit trail between the stock exchange and member brokerage firms, and are similar to the New York Stock Exchange's consolidated equity audit trail data. For the purpose of this study, we employ only a sample of the data, with its description provided below.

[7]A-Shares are common stocks accessible only to local Chinese investors, whereas B-Shares were initially accessible only to foreign investors until June 2001, a period during which the Chinese markets fully liberalized the B-share market to all domestic investors.

A. Brokerage Accounts and Base Sample

In June 2001 there are 101 main brokerage firms in Mainland China, and these firms have about 2,500 branches nationwide in total.[8] Our study exploits one paradigmatic feature of these brokerage offices – the layout of a typical brokerage office – that facilitates a lot of interactions and open conversations between individuals.[9] Each office typically has a single, huge digital display that individual investors can watch the constant updates of stock prices, as well as the brokerage firm's releases of any public news and brokerage in-house research information. This simple setting of a branch inadvertently promotes social interactions between individual investors who frequent a branch office regularly, and hence offers us an attractive opportunity to study effects of social interactions, via word-of-mouth, in investor trading decisions.

Individuals are allowed to open only one brokerage account at any of the branches in order to trade SHSE stocks, and the account is opened using their National Identity Card.[10] All trades will have to be placed only through the particular branch at which the account is opened.[11] Investors can place their orders through computer terminals, telephone service, or cashier counters located in the branch, or online trading. During the time period of our study, online trading is rare and costly. For example, online accounts comprise of only about 4.8% of the overall investing population in 2001 and about 7.4% in 2002, with online trading turnover of about 4.4% and 9% of the total market turnover, respectively.[12]

A survey conducted by the research department of SZSE (Chen, Li, and Du (2001)) shows that based on 2,587 survey responses, about 8% use online trading, about 70% use cashier counters, and about 19% use in-branch telephone or own telephone. Feng and Seasholes (2004) document that on average about 64% of their sample of SZSE trades are physically placed in a branch office. Therefore, a majority of Chinese individual investors typically place their trades

[8] For more information, see *www.sse.com.cn.*

[9] See Feng and Seasholes (2004) for the layout of a typical trading floor of a brokerage branch office.

[10] Investors, however, are allowed to open more than one account at a different branch for trading SZSE stocks.

[11] This policy does not apply to stocks traded on the SZSE, where investors can open more than one brokerage account.

[12] Chinese Securities Regulatory Commission, *www.csrc.gov.cn.*

in person at their brokerage branch. While our data offer no information on how individual investors place their trades at the branch, we assume that in our sample about 60% of individuals are in their brokerage offices when they place their trades. If the number is smaller than what we have assumed, then this should work against our finding any evidence of strong peer effects in investor trading. Even if they do not trade, individuals generally visit their branch to gather and exchange information with other individuals in the branch, or to receive updated information on the stock market, or at times to deposit money into their brokerage accounts before they can trade (see Hertz (1998)).

Unlike those in the United States, short selling and margin trading are illegal in China. Thus, individuals can sell only stocks that they own, and can buy stocks with immediate cash balances on their accounts.

We select a base sample of brokerage branches that are all located in Shanghai, where the SHSE is located. Out of the 2,500 branches nationwide, 448 are located in Shanghai. We therefore rank all Shanghai branches in our data set according to the number of individual brokerage accounts and also the number of trades generated during the entire sample period. The reasons for this selection criterion are to ensure that (i) each branch has a large enough number of brokerage accounts to facilitate social interactions among individuals, and (ii) investors who resided in the same city would receive the same local or national news. We exclude branches that are from the same brokerage firm as some brokerage firms might tend to attract a certain group of investors who behave more similarly than others. For example, it is possible that groups of investors who belong to a certain social club and hence share similar preferences open their brokerage accounts only with branches of a specific well-known brokerage firm in their neighborhood. To rule out such biases, we choose different brokerage branches, and as a result, our base sample consists of 30 branches with the most number of brokerage accounts and the largest number of trades transacted.

B. Trade Records of Individual Investors

We look at how brokerage accounts trade the 30 highest-volume SHSE stocks measured in terms of total market value traded during the sample period and whose corporate headquarters are all located in Shanghai. We focus on SHSE stocks whose firms are all headquartered in Shanghai because this selection helps differentiate word-of-mouth effects from local stock-preference effects. There is substantial evidence that investors are biased towards holding stocks whose firms are located nearby. Coval and Moskowitz (1999) show that on average the portfolio holdings of mutual funds are tilted toward stocks whose firms are located in the same city as the fund manager. Ivković and Weisbenner (2004) find stronger local bias in the stock investments of U.S. households. Given that we examine Shanghai local stocks, we effectively have disentangled word-of-mouth effects from local bias. The choice of 30 Shanghai-headquartered, actively traded SHSE stocks yields 498,982 trade records of 30 A-Shares initiated by 121,082 individual brokerage accounts from 30 different branches located in Shanghai. Each trade record contains in detail all key elements of a stock transaction, including the stock code, the number of shares purchased or sold, the execution price and date, and an account identifier.

Table I reports descriptive statistics associated with each of the 30 different brokerage branches located in Shanghai. These statistics pertain to the selected 30 SHSE stocks that investors at these branches trade. For convenience, we label the branches *Branch1* to *Branch30*. The number of brokerage accounts varies from 993 (*Branch3*) to 7,416 (*Branch12*), and the average number of accounts is about 4,036. During the entire sample period, these accounts generate almost half a million trades of the 30 stocks. The total numbers of buys and sells are 273,625 and 231,572, respectively. The sum of the buys and sells is greater than the total number of trades, because if an individual buys and sells the same stock on the same day, the two executions will be aggregated into one trade record in our data. The total market value is RMB 3.97 billion for buys and is RMB 3.84 billion for sells. Across the 30 branches, the average purchase size ranges from RMB 5,276 to RMB 26,982, whereas the average sale size is from

RMB 4,940 to RMB 30,236.

At this juncture, it is necessary to draw the similarities and differences between our data and those of Feng and Seasholes (2004). The latter have account-level data of a single brokerage firm, and their analysis is based on trade information from seven branches of this particular firm. In contrast, our data set is compiled by the SHSE for the purpose of audit trail. While our original data set contains daily detailed records of 77.12 million trades of SHSE A shares initiated by 7.24 million brokerage accounts across Mainland China, it excludes trade records of many smaller brokerage branches with a small number of accounts or fewer number of trades.[13] Given the rich data set we have, we are able to select different branches of different brokerage firms with the most number of brokerage accounts and trade records. For example, the average number of brokerage accounts across our sample of 30 branches is 4,036 compared to 1,139 in Feng and Seasholes's sample of 7 branches (see their Table I on page 2,124). In the latter, the number of brokerage accounts varies from 365 to 1,775.[14] However, the advantage of their data over ours is that they are able to identify the means in which the trades are placed, i.e. whether by phone, terminals at a branch, cashier windows, or computer links.

IV. Word-of-Mouth Effects in Investor Trading Decisions

A. Baseline Specifications

We introduce two simple specifications to test word-of-mouth effects in investor trading decisions. While our reduced-form models are similar to that of Hong, Kubik, and Stein (2004), we separate the word-of-mouth effects on investor buying and selling decisions. Our base specification for investor buys is given by

$$Buy^j_{i,b,t} = \sum_b \alpha^B_b \cdot \{Buy^j_{-i,k,t} \cdot B(k = b)\} + \sum_b \beta^B_b \cdot \{Buy^j_{k,t} \cdot B(k \neq b)\} + \varepsilon^j_{i,b,t}, \qquad (1)$$

[13]The total trading volume generated by all accounts in our data set indicates that our data contain about 34% of the total market trading volume over the sample period.

[14]Note that they focus on stocks that are traded on the SZSE.

and for investor sells is given by

$$Sell^j_{i,b,t} = \sum_b \alpha^S_b \cdot \{Sell^j_{-i,k,t} \cdot B(k = b)\} + \sum_b \beta^S_b \cdot \{Sell^j_{k,t} \cdot B(k \neq b)\} + \epsilon^j_{i,b,t}, \qquad (2)$$

where $Buy^j_{i,b,t}$ ($Sell^j_{i,b,t}$) is the ratio of the value of stock j purchased (sold) by investor i at a given branch b to her total purchase (sale) value of the SHSE stocks, or her buy (sell) ratio in stock j at time t; $Buy^j_{-i,k,t}$ ($Sell^j_{-i,k,t}$) is the equal-weighted average of buy (sell) ratios in stock j for all investors, excluding investor i, whose trades are placed through branch b at time t; $Buy^j_{k,t}$ ($Sell^j_{k,t}$) is the equal-weighted average of buy (sell) ratios in stock j for all investors in brokerage branch b at time t; $B(k = b)$ is an indicator that takes the value of one if branch k and branch b are the same, and zero if otherwise; $B(k \neq b)$ takes the value of one if branch k and branch b are not equal, and zero if otherwise. Given that the interpretations of specifications (1) and (2) are similar other than the former examines investor buys effects while the latter on investor sells, our subsequent discussion shall focus only on specification (1).

Specification (1) states that an individual's decision to buy stock j is potentially influenced by the decisions of her peers in the same branch as well as by the decisions of her peers in other branches.[15] For each of the 30 branches, we estimate α^B_b and β^B_b parameters that capture, respectively, the "own-branch" and "other-branch" effects. For instance, α^B_1 measures how the buying decisions of individual investors from *Branch1* affect the buying decision of individual investor i from *Branch1*, and β^B_1 measures how the buying decisions of individual investors from the other 29 branches affect the buying decision of investor i from *Branch1*. Our first hypothesis on word-of-mouth information transmission implies that, for any branch b, the own-branch effect should always be larger than the other-branch effect (i.e., $\alpha^B_b > \beta^B_b$). The implication would be consistent with our prediction that the buying (selling) decision of an individual is influenced more by the buying (selling) decisions of other individuals from the same branch than those of

[15] We also employed an alternative specification:

$$Buy^j_{i,b,t} = \alpha_b \cdot Buy^j_{-i,b,t} + \beta_b \cdot EW\{Buy^j_{k,t}\} + \varepsilon^j_{i,b,t},$$

where $EW\{Buy^j_{k,t}\}$ is $\frac{1}{29}\sum_k Buy^j_{k,t} \cdot B(k \neq b)$, the equal-weighted average buy-ratio across all branches other than branch b. A similar specification is conducted for sells. The results of these alternative models yielded qualitatively similar to those reported in the paper.

other individuals from other branches. If correlated trading by individual investors from a branch is driven by their common interpretation of some public information that the national or city media releases to the public, then the own-branch coefficient should be insignificantly different from the other-branch coefficient (i.e., $\alpha_b^B = \beta_b^B$). For example, if publicly-known information is transmitted to the city where all of our sample branches are located, we assume that investors in any of the branches would be informed of, or would have received such information.

The difference between the own-branch and other-branch coefficients determines the relative importance of the own-branch and other-branch word-of-mouth effects in investor trading behavior. To draw inferences on the extent of their relative importance (i.e. word-of-mouth effects) in the trading decisions of individual investors, we provide two test statistics: one based on an equal-weighted average of the differences between own-branch and other-branch coefficients, and another based on an accounts-weighted average. The latter weighting scheme is primarily motivated by the existing evidence that individuals are more likely to participate in the stock market if there is a greater participation rate among individuals in the local community (see Hong, Kubik, and Stein (2004) and Brown, Ivković, Smith, and Weisbenner (2005)).

The effect of word-of-mouth depends on the geographic proximity of individual investors. In our particular setting, a brokerage branch office is the geographic location of the individual investors that facilitates our test of the word-of-mouth effect. We select a monthly time interval to allow for the speed of word-of-mouth information to be exchanged among individuals at the same brokerage branch.[16] Existing studies use varying time intervals from weekly (Feng and Seasholes (2004)), quarterly (Hong, Kubik, and Stein (2004) and Ivković and Weisbenner (2005)) to yearly information (Brown, Ivković, Smith, and Weisbenner (2005)).

[16] Our baseline results are robust even when we employ a weekly time interval for our analysis. Results are available upon request.

B. Baseline Results

Table II contains regression estimates of (1) and (2), with $t-$statistics in parentheses computed using Newey-West heteroskedasticity and autocorrelation consistent standard errors. It also presents the equal- and accounts-weighted average differences between own- and other-branch coefficients.

The table reveals strong evidence of word-of-mouth effects in the trading decisions of individual investors who place their trades through the same branch. For investor buys, the equal- and accounts-weighted average differences between own- and other-branch coefficients are 3.52 ($t-$statistic = 7.0) and 3.88 ($t-$statistic = 4.8), respectively. For example, based on the equal-weighted differential, if all individual investors, except individual i, of branch b increase their purchase of a particular stock by 1%, then it is expected that individual i will increase her purchase of the same by 3.5% more than an individual investor of another branch. For individual branches, 28 of the 30 own-branch coefficients are positive, and 26 of them are larger than their other-branch counterparts. Out of the 28 positive coefficients, 23 are statistically significant at the 5% level and 2 at the 10% level. The 2 negative own-branch coefficients are statistically insignificant at conventional levels. This finding strongly suggests that an individual's buying decision is more influenced by their peers from the same branch than those from other branches.

We find weaker word-of-mouth effects at the cross-branch level. As Table II indicates, 20 of the 30 other-branch coefficients are negative, and more than half are statistically significant at the 5% level. On the other hand, almost all of the remaining 10 positive other-branch coefficients are statistically significant at conventional levels; the magnitude of these coefficients is generally smaller than their own-branch counterparts. The weak evidence of cross-branch peer effects suggests that constant face-to-face interactions seems necessary to facilitate word-of-mouth information transmission among individual investors. Alternatively, it also suggests no community or city effects, an evidence that contradicts those previously reported using U.S. data. Nevertheless, a formal analysis of word-of-mouth effects at the community level shall be performed in subsequent sections.

Furthermore, the results suggest word-of-mouth effects, albeit weaker, in investor sells. The magnitude of the weighted-average differentials is less than half that of their buys counterparts. The equal- and accounts-weighted average differentials for investor sells are 1.58 ($t-$statistic = 5.0) and 1.71 ($t-$statistic = 3.4). Across the branches, 24 of the 30 own-branch coefficients for investor sells are positive, but only 19 of these positive coefficients are statistically significant at conventional levels and also are larger than their other-branch counterparts. The weaker word-of-mouth effects in the selling decisions of individual investors, as compared to their buying decisions, is consistent with our prediction. With no short-selling permitted in Mainland China, when investors sell, they can sell only stocks that they currently own in their brokerage accounts. Also, as discussed earlier, individuals sell their stocks for various reasons, including liquidity needs, diversification, portfolio rebalancing, among others, other than word-of-mouth information.

It is evident that informal information transmission, via word-of-mouth, induces correlated trading by investors who have brokerage accounts at the same branch. More importantly, our finding of a stronger within-branch correlation than cross-branch correlation suggests that the decision of an investor is more likely to be affected by the decisions of others from the same branch than by the decisions of others from different branches. However, one might argue that the stronger own-branch effect relative to the other-branch effect possibly subsumes the significant cross-branch correlation of individual trades shown in Feng and Seasholes (2004). Using the principal components analysis, the two authors find that public information accounts for about 32% of the correlated trading by investors located in the same city. Thus, we argue that the 68% of the correlated trades must stem from private or word-of-mouth information. Using their methodology,[17] we compute the average pairwise-correlation coefficients to be 0.350

[17]At a given branch, we first calculate the monthly buy intensity and sell intensity across our entire sample period. The buy (sell) intensity is measured as the total buy (sell) value of the 30 sample SHSE stocks divided by the total buy (sell) value of all SHSE stocks placed through a branch. We then measure the pairwise correlation of buys and of sells between any two branches. There are 435 pairs for 30 branches.

(z-statistic = 26.95) for investor buys and 0.516 (z-statistic = 43.47) for investor sells.[18] While our cross-branch correlation of investor trades of about 35 to 52% is consistent with theirs, this evidence further substantiates our within-branch effect shown in Table II. Overall, it implies that the within-branch word-of-mouth effects cannot simply be driven by common local or national market shocks.

C. Additional Results

Does word-of-mouth communication only influence the trading decisions of investors who live in Shanghai, a large financial city? While we believe this is unlikely the case, we verify our results by replicating our above study using similar information on individual investors who live in a different city. We select Beijing, a smaller and a non-financial city that is about 1,093 kilometers away from Shanghai. In contrast to those in Shanghai, there is a smaller number of brokerage branch offices located in Beijing. Using the same criteria as we did in selecting branches in Shanghai, we select 20 Beijing-located brokerage branches from 20 different brokerage firms. As in the preceding subsection, we also select 30 different SHSE stocks that are all headquartered in Beijing and that have the largest market turnover relative to their counterparts headquartered in the same city. The unreported summary statistics indicate that the number of brokerage accounts at the 20 Beijing branches ranges from 1,419 to 7,067; their average number is 2,776 as compared to 4,036 for Shanghai. The total number of buy and sell trades executed by all individual investors at the 20 branches are 104,028 and 87,711, respectively. The total market value of buys is RMB 2.601 billion and of sells is RMB 2.827 billion. While the sample of different Beijing brokerage branches is smaller than our baseline Shanghai sample, the number of brokerage accounts in the former is large enough for our analysis. To conserve space, we do not report the detailed regression results, but instead we provide a brief discussion below.

In general, the results are broadly consistent with those of Table II. We find strong word-of-

[18] The z-statistics are calculated using the asymptotic approximation of standard errors of correlation coefficient described in Feng and Seasholes (2004).

mouth effects that are also more pronounced in investor buying than investor selling. Almost all of the estimates of own-branch buy coefficients are positive, and 12 of the 20 coefficients are statistically significant at the 5% level and 2 at the 10% level. The difference between the own- and other-branch coefficients remains mainly positive and statistically significant. The accounts- and equal-weighted averages of the differences between own- and other-branch coefficients for investor buys are both 1.25 with $t-$statistics of 4.7 and 6.4, respectively. For investor sells, 12 of the own-branch coefficients are positive, and 7 of them are statistically significant at conventional levels. The accounts- and equal-weighted average differentials are 1.02 ($t-$statistic=4.2) and 1.14 ($t-$statistic=3.1). The results suggest that the trading decision of an individual from a Beijing branch is significantly affected by the trading decision of other individuals from the same branch than by the trading decisions of individuals from other branches located in the same city. Overall, the results indicate that word-of-mouth effects in the trading decisions of individual investors is robust across the two different cities.

V. Word-of-Mouth and Alternative Interpretations

Thus far, we have established strong evidence that individual investors who place their trades through the same branch do influence each other's trades via word-of-mouth. However, our results can also be consistent with alternative interpretations such as within-branch induced bias or stocks with greater investor recognition and familiarity. In this section, we perform tests that help distinguish several alternative stories from word-of-mouth effects.

A. Within-Branch Bias

There are a couple of possible factors that might induce within-branch bias and hence generate the trading patterns of individual investors that we have found in the preceding section. One, even though they offer no stock recommendations, brokerage firms in Mainland China do frequently release firm-specific or industry-wide information as well as their in-house research reports to their brokerage account holders. Individuals might react similarly to such information or reports and hence trade the same stock. This herd behavior should not be mistakenly interpreted as an outcome of word-of-mouth communication. Two, there are social factors (correlated social effects) that might contribute to the observed correlated decisions of individual investors at the same branch. For instance, in Mainland China, employees of a large listed, particularly state-owned, firm generally receive housing benefits from the company. The subsidized housing is located typically in a neighborhood near their workplace. Naturally, these employees would open their brokerage accounts at a brokerage branch in their neighborhood. When they exhibit stock preferences of the companies they work for, such non-communicative behavioral patterns are also consistent with those of word-of-mouth effects.

To control for any within-branch bias, we estimate regression models (1) and (2) by stock. This approach permits us to examine how individuals trade a particular stock relative to their peers at the same branch and how they trade relative to their peers from the remainder 29 branches. If trading behavior is induced by social factors or brokerage-specific research information, then our earlier finding of correlated trading should only be evident in certain stocks. Table III summarizes the equal- and accounts-weighted averages of the differences between own- and other-branch coefficients by stock. The last row of the table shows the aggregate weighted-average differential.

Consistent with the baseline regression results, the results of Table III indicate that both the equal- and accounts-weighted average differentials associated with investor buys are all positive across the 30 different stocks. Based on the equal-weighting measure, the own-branch coefficient on average exceeds the other-branch coefficient by 1.67 (*Stock 9*) to 7.18 (*Stock 26*), and based on the accounts-weighting measure, it exceeds by 2.52 (*Stock 22*) to 7.21 (*Stock 5*). Almost all of the weighted-average differentials are statistically significant at the 5% level. Their aggregate weighted-average differential is between 4.34 ($t-$statistic=15.8) and 4.80 ($t-$statistic=17.8). Similarly, except for those of *Stock 4* and *Stock 17*, we find most of the weighted-average differentials for investor sells are positive, but only 21 of the equal-weighted and 24 of the accounts-weighted differentials are statistically significant at the 5% level. Their aggregate equal- and accounts-weighted differentials are 2.57 ($t-$statistic=8.2) and 2.66 ($t-$statistic=9.1), respectively. The results are, in general, consistent with those reported in Table II, and more importantly, they show that our earlier evidence of word-of-mouth effects is not attributed to the within-branch bias induced by specific-stock preferences of individual investors, or by their correlated trading due to branch-specific releases of information or research reports.

We have also employed alternative specifications of baseline models (1) and (2) to examine the within-branch bias. Instead of performing stock-by-stock regressions, we incorporate stock dummy variables in (1) and (2) to control for specific-stock effects. The equal- and accounts-weighted averages of the differences between own- and other-branch coefficients for investor buys are 3.5 ($t-$statistic=6.9) and 3.9 ($t-$statistic=4.8), and those for investor sells are 1.6 ($t-$statistic=5.1) and 1.7 ($t-$statistic=3.5). The results are almost identical to those reported in Table III, thereby implying that neither the stock preference of individual investors nor group psychology plays a significant role in the base results.

B. Familiarity and Visibility

There are behavioral patterns of individual investors that can produce buying and selling patterns similar to those induced by word-of-mouth. While we have ruled out local bias in our results, there is a possibility that individuals from the same branch merely invest in the same stocks because those are the stocks that they are more familiar with, or that have greater visibility in the markets. For example, the Merton (1987) investor-recognition hypothesis states that investors do not have equal information and hence they invest only in those stocks that they know about. Several international studies find strong support of the Merton hypothesis,[19] and recent U.S. studies also show similar evidence using data on individual investors. Huberman (2001) shows that customers of the regional Bell operating companies in every state tend to overweight their holdings in the telephone company that provides its service than another

[19]Kang and Stulz (1997), Amihud, Mendelson, and Uno (1999), Bailey, Chung, and Kang (1999), Foerster and Karolyi (1999), among others.

telephone company. He argues that his results reflect investors' inclination to invest in familiar companies rather than local bias. Zhu (2002) reaches the same conclusion using data from a large U.S. brokerage firm. It is plausible that such trading behavior might drive our earlier findings.

To address the above issue, we test whether word-of-mouth effects are driven by familiarity or by stocks with greater investor recognition or visibility. We suggest three different stock characteristics that are commonly employed as proxies for visibility/recognition and familiarity in the existing literature. One would expect more information to be available for stocks with more visibility and greater recognition. The first proxy variable is a stock's membership of a stock index. It is often argued that a stock that is a constituent of an index has more visibility or greater investor recognition than one not. In our selected 30 stocks whose firms are all headquartered in Shanghai, 9 are members of the popular SHSE30 index, while the rest are not.

The other two variables are firm size and the listing period of the stock. In their study of the Japanese market, Kang and Stulz (1997) contend that more information is generally available on large firms. The larger the firm, the more visible is the stock. Finally, the length of time that a stock is being listed on the SHSE is indicative of how visible it is in the markets. While China has the largest and one of most robust growing economies in the world, its equity markets are still in its nascent stage. Its two domestic stock exchanges, the SHSE and the SZSE, were only established in December 1990 and July 1991, respectively. Thus, stocks that have been listed for a longer period ought to have greater visibility or recognition in the markets. To separate the 30 stocks based on firm size and the listing period, we first sort all stocks traded on the SHSE based on their size and listing period, respectively. We next assign stocks to large and small groups, or long and short listing-period groups by using the median stock of each sort as a breakpoint. As a result, we have 26 large stocks and 4 small stocks, and 21 long-listing stocks and 9 short-listing stocks.

Test results of the three stock characteristics using baseline models (1) and (2) are summarized in Table IV. Panels A to C of the table present equal- and accounts-weighted average differences between own- and other-branch effects associated with the respective characteristic. The overall result of the table shows no evidence that visibility or investor recognition contributes to the word-of-mouth effect in investor trading decisions. Panels A through C show all positive equal- and accounts-weighted differentials, suggesting that on average own-branch coefficients are consistently greater than other-branch coefficients.

It is apparent that within-branch word-of-mouth communication has no bearing on the visibility or familiarity of a stock, and also is unlikely to be driven by public information. All the 30 stocks in our sample are local stocks that are all headquartered in Shanghai. There is no reason to believe that investors who reside in Shanghai are unfamiliar with these stocks. Furthermore, it is less likely that public information is a contributory factor to the correlated trading by investors at the branch level, because these individuals are all located in the same city as the SHSE. There should not be any significant time lag for public information to get transmitted across the city. Thus, we interpret that the diffusion of private information is a more likely source of word-of-mouth effects in the trading decisions of individual investors.

C. Calendar Effects

Here we test whether our results are driven by a particular month of the year by re-estimating the baseline regressions by month.[20] For each month, we estimate the own- and other-branch coefficients and their differences associated with investor buys and investor sells. Then, we compute the Fama-Macbeth cross-sectional averages of the accounts- and equal-weighted differentials. For investor buys, all the unreported own-branch coefficients are greater than their other-branch counterparts, and 9 of the weighted-average differentials are statistically significant at the 5% level. The Fama-Macbeth cross-sectional equal- and accounts-weighted differential averages are 3.59 ($t-$statistic=6.3) and 3.67 ($t-$statistic=6.6), respectively. For investor sells,

[20] We also estimated an alternative model by incorporating 12 month-dummy variables in the baseline regression models. The results remained materially unchanged.

all the own-branch coefficients are also greater than their other-branch counterparts, but only 6 of the differentials are statistically significant at conventional levels. The Fama-Macbeth cross-sectional equal- and accounts-weighted differential averages are 2.54 ($t-$statistic=3.2) and 2.63 ($t-$statistic=3.6), respectively. In general, the results are substantially the same as those of Table II, thereby indicating no evidence of any calendar month effects.

VI. Word-of-Mouth Effects and Geographic Proximity

A. Physical Proximity of Individual Investors

One controversy in the social-interaction literature is whether individuals are influenced only by their closest neighbor (i.e., "local" peer effects) or by the average behavior of individuals in a large community ("community" peer effects).[21] A natural question that arises is: How important is physical proximity between individual investors in order to facilitate word-of-mouth communication? This section therefore explores the role of proximity in the strength of word-of-mouth spread.

Physical proximity encourages face-to-face communication and strong relational ties, both of which in turn facilitate the flow of word-of-mouth information. Several recent studies have shown evidence of either local or community peer effects in the financial decisions of individuals. Duflo and Saez (2002, 2003) show how the decisions of non-faculty employees to participate in a particular retirement plan are influenced by the decisions of their coworkers. Their finding is based on a group of individuals of close geographic proximity, such as a university. Brown, Kubik, and Weisbenner (2004), Ivković and Weisbenner (2005), and Hong, Kubik, and Stein (2005) provide strong evidence of community effects. These studies use a measure of sociability such as individuals' social interactions with friends and neighbors who reside in the same city as a proxy for information exchange through social networks. Such a measure, however, constitutes an indirect test of community effects.

[21]The literature is summarized in Glaeser and Scheinkman (2000).

Our rich data afford us to test whether proximity facilitates word-of-mouth in the trading decision of an individual investor. If word-of-mouth effects are only evident at the branch level, we infer this as evidence of local peer effects. If word-of-mouth information gets transmitted across individuals from different branches that are located near to each other, we infer this as evidence of community peer effects. To implement this test, we first determine the geographic proximity between the 30 sample Shanghai branches by locating each branch's coordinates on the map of Shanghai. We then determine the downtown area of the Shanghai city by taking the Shanghai city council as the center. As a result, there are 15 branches located within a 5-kilometer radius from the Shanghai city council, and we categorize them as "close" branches. The remaining branches that are outside of the 5-kilometer radius and scattered across the city are categorized as "far" branches.

To examine whether our earlier evidence of local word-of-mouth effects is extended beyond the geographic proximity of a branch, we modify the baseline specification (1) as follows.

$$\begin{aligned} Buy^j_{i,b,t} \quad = \quad & \sum_b \alpha^B_b.\{Buy^j_{-i,k,t}.B(k=b)\} + \sum_b \beta^B_b.\{Buy^j_{k,t}.B(k \neq b)\} \\ & + \sum_b \tau^B_b.D_\tau.\{Buy^j_{k,t}.B(k \neq b)\} + \varepsilon^j_{i,b,t}, \end{aligned} \tag{3}$$

where D_τ is a branch dummy that takes the value of one if $k \in \{close\}$, and 0 if otherwise. In contrast to (1), specification (3) has an additional term with a parameter τ^B_b, which measures the incremental influence of the buying decisions of individual investors from a close branch on the buying decision of individual investor i in *Branch* b. If community peer effects exist, then the buying decision of an individual in *Branch* b is influenced not only by the decisions of individuals at her own branch, but also by the decisions of those whose brokerage offices are located near hers. Then the coefficient on τ^B_b should be positive. The same interpretation can be applied to investor selling activity. For brevity, we do not present the specification for investor selling; the specification is similar to (3) other than replacing investor buys with investor sells. Given that the magnitude and the statistical significance of the own-branch effect α^B_b remain fairly constant, Table V only summarizes estimates of τ^B_b and β^B_b of "close" branches associated with investor buys and estimates of their counterparts associated with investor sells.

The table reveals one distinct result: the trading decisions of individuals from near branches have virtually no incremental influence on the trading decision of an individual investor from a close-by branch. In other words, individual investors from other branches, whether near or far, exhibit no differential peer effects in the trading decisions of an individual investor from another branch. While 9 estimates of the τ_b^B coefficient associated with investor buys are positive, only 1 is statistically significant at the 5% level. Similarly, while 8 of the τ_b^S coefficient associated with investor sells are positive, none of them is statistically significant. These findings provide reinforcing evidence of no community peer effects – diffusion of word-of-mouth information is only effective at the branch level.

Thus, geographic proximity matters. Increased face-to-face interaction helps foster word-of-mouth communication between individual investors of close geographic proximity as it is within a brokerage office, and not within a 5-kilometer radius community, and in turn affects the trading decisions of the investors. The evidence of no community peer effects in the financial decisions of individual investors is inconsistent with existing U.S. studies such as Hong Kubik, and Stein (2005) and Ivković, Zoran, and Scott Weisbenner (2005). The difference in the results might be attributable to the level of advancement of information technology in each country. During our sample period, distance-spanning technology such as e-mail and video conferencing is very costly and rare in Mainland China, but not in the U.S. With a highly efficient distance-spanning technology in the U.S., it is possible that word-of-mouth gets transmitted quickly between individuals who are not necessarily closest neighbors, thereby implying that physical proximity might not matter in the U.S. as much as in Mainland China.

B. Geographic Proximity to Corporate Headquarters

Thus far, our baseline analysis focuses primarily on the base sample consisting of only SHSE stocks. As discussed earlier, our purpose of selecting these stocks is to distinguish word-of-mouth effects from local stock-preference effects. The evidence of local bias is now well documented

– investors tend to prefer stocks whose firms are headquartered nearby, or that they are more familiar (Coval and Moskowitz (1999), Huberman (2001), among others). Such evidence is consistent with the notion that close geographic proximity between investors and corporate headquarters facilitates informational flow and helps reduce information acquisition cost. In the context of the social-interaction literature (see, for example, Hong, Kubik, and Stein (2004)), this translates to lower "participation costs" for individual investors with greater geographic proximity to the corporate headquarters of the firms they invest in. If, indeed, participation costs are associated with geographic proximity, then this implies that word-of-mouth communication would play a more critical role in influencing individual investors in trading distant- than locally-headquartered stocks. In this case, individual investors might rely more on word-of-mouth information when making investment decisions on stocks that they face greater participation costs.

In this subsection, we test whether there exist any differential word-of-mouth effects in local vs. non-local stock trades of individual investors. Specifically, are word-of-mouth effects stronger in trades of Beijing (non-local) or Shanghai (local) headquartered stocks by Shanghai investors? We therefore estimate the following specification for investor buys.

$$\begin{aligned} Buy^j_{i,b,t} \;=\; & \sum_b \alpha^B_b.\{Buy^j_{-i,k,t}.B(k=b)\} + \sum_b \beta^B_b.\{Buy^j_{k,t}.B(k \neq b)\} \\ & + \sum_b \lambda^B_b.D_\lambda.\{Buy^j_{-i,k,t}.B(k=b)\} + \varepsilon^j_{i,b,t}, \end{aligned} \tag{4}$$

where D_λ is a stock dummy that takes the value one if the corporate headquarter is located in Beijing, and 0 if otherwise. We also estimate a similar specification for investor sells. If individuals are influenced more by the decisions of their peers, through word-of-mouth, when deciding to trade non-local (Beijing) stocks that they are less familiar, the parameter λ^B_b in investor buys and λ^S_b in investor sells should always be positive. Estimates of (4) for investor sells and those of their counterparts for investor sells are presented in Table VI.

The table reveals a number of notable observations. Consistent with the results in Table II, the word-of-mouth effect is strong and significant in both investor buys and sells. This result provides corroborating evidence of word-of-mouth effects in the trading decisions of individual investors who all place their trade orders through the same branch. It is important to stress that these results are not driven by the trades in Shanghai-headquartered stocks. The reason is that we also replicated the baseline specifications using trades of 30 Beijing-headquartered stocks by Shanghai investors, and we found the results to be robust.

The word-of-mouth effects in investor buying of Beijing-headquartered stocks, while positive, are not significantly different from those of Shanghai-headquartered stocks. Both the equal- and weighted averages of own-branch coefficients associated with investor buys are statistically insignificant at conventional levels. Word-of-mouth communication seems to have similar influences on the buying decisions of an individual investor from the same branch, regardless of whether it is a local or non-local stock. This finding seems consistent with the argument offered in the social-interaction literature that, all things being equal, an individual investor finds it equally attractive to buy non-local stocks when there is high participation rate among her peers.

More interestingly, we find stronger and statistically significant word-of-mouth effects in investor sells of Beijing-headquartered stocks by individual investors who reside in Shanghai. The equal- and accounts-weighted averages of own-branch coefficients associated with only Beijing-headquartered stocks are 0.82 ($t-$statistic=2.9) and 0.97 ($t-$statistic=3.1) for investor sells, as opposed to 0.66 ($t-$statistic= 1.6) and 0.41 ($t-$statistic=1.2) for investor buys. These findings contrast those of Table II. Apparently, negative word-of-mouth information tends to have a greater influence on individual investors selling non-local than local stocks, while positive information exhibits no differential influence. Perhaps the evidence suggests that when individual investors have no local knowledge of Beijing-headquartered stocks, they are less willing to hold on to such stocks when they receive negative information. Alternatively, it might suggest that the disposition effect varies across local and non-local stocks.

VII. Conclusion and Discussion

This study employs a new and interesting data set to examine direct peer effects, via word-of-mouth, in the trading decisions of groups of individual investors, who placed their trades mostly in person at their brokerage branch office located in the same city – Shanghai. The key advantage of our data is that it allows us not only to directly measure peer effects, but also to construct various tests that distinctly discriminate between word-of-mouth effects and alternative interpretations.

Results indicate strong word-of-mouth effects in the trading decisions of individual investors who are in the same room at the time they place their trades. The influence of word-of-mouth information is more pronounced in investor buys than investor sells of locally-headquartered stocks. The evidence is robust to several alternative interpretations associated with familiarity or stock visibility, within-branch bias, local bias, location, firm size, and calendar effects.

Our study also contributes to the social-interaction literature. It shows that not only word-of-mouth influences the financial behavior of individual investors, but also physical proximity between individual investors matters for word-of-mouth effects. While informal exchanges of information via word-of-mouth is effective in influencing the financial decisions of individual investors, it is especially effective at the branch level that conveniently facilitates constant face-to-face interaction and exchange of information. This evidence suggests that the decision of an individual is influenced mainly by the decisions of her closest "neighbors", who maintain brokerage accounts at the same branch as she does and with whom she is more likely to interact, but not by the decisions of those who reside in the same city and maintain brokerage accounts at a different branch.

Furthermore, the results show significantly stronger word-of-mouth effects in investor sells, while no difference in investor buys, of non-local than local stocks. It is evident that individual investors tend to react more to negative word-of-mouth information when deciding to sell shares of a non-local stock that they are less familiar. This finding might also suggest that the disposition effect varies across local and non-local stocks.

If informational flows are facilitated by social relationships, social relationships are facilitated by social proximity (where lower social proximity results in lower costs of establishing a social relationship), and social proximity is mediated by geographic proximity (i.e., two individuals face a lower cost for establishing a relationship if they are co-located than if they are not, all else equal), then we should find that co-location leads to participation rates that are higher than we would otherwise expect. Our overall evidence supports this prediction.

Finally, our results offer several implications about asset prices under short-sales restrictions. Existing literature argues that in a market with no short selling, market prices normally reflect the valuation of optimists, and that this simply creates an upward bias in asset prices (Miller (1977) and Figlewski (1981)). Sufficient divergence of beliefs in the market thus drives prices away from fundamentals, generating a non-fundamental component (or speculative premium) in asset prices (Harrison and Kreps (1978) and Scheinkman and Xiong (2003)). With stringent short-sale constraints and dominance of inexperienced individual investors in Mainland Chinese markets, individual investors excess reliance on word-of-mouth (or un-verified) information intensifies the divergence of asset valuations, aggravating the speculative trading. It is also likely that stronger word-of-mouth in investor buys strengthens the effect of short-sale restrictions, amplifying the magnitude of speculative component of asset prices. This implication is in accord with the recent evidence provided by Mei, Scheinkman, and Xiong (2005). The study shows that a significant fraction of the price difference between the dual-class shares may be due to the fact that trading in A-share markets is more likely to be driven by speculation than by liquidity factors. Peer effects, via word-of-mouth, perhaps explain partly this investor speculative trading.

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Table I
Descriptive Statistics of Brokerage Accounts by Branch

For each branch office, the table presents the number of brokerage accounts, the total number of trades, the number of buy trades, the number of sell trades, the total buy value in RMB millions, the total sell value in RMB millions, and their respective average values in RMB in the last two columns. All these statistics are associated with the base sample of 30 stocks that are headquartered in Shanghai. Sample period is between April 2001 and April 2002.

Branch	No. of Accounts	No of Trades	No. of Buys	No. of Sells	Total Buys	Total Sells	Average Buy	Average Sell
Branch1	4105	16266	8936	7480	81.14	76.65	6830	6718
Branch2	2696	11465	6287	5289	112.73	111.22	13044	13466
Branch3	993	2833	1542	1309	53.09	44.99	26866	23968
Branch4	3616	15208	8360	7006	140.91	138.98	12679	13188
Branch5	5387	31055	16797	14761	120.81	111.08	5276	4940
Branch6	3573	14017	7405	6860	148.41	142.91	15721	15774
Branch7	6575	37646	19912	18415	443.42	454.56	16913	17760
Branch8	6723	27690	15185	12818	142.61	134.48	7075	6895
Branch9	4651	19525	10894	8853	146.28	128.69	10110	9533
Branch10	1773	7446	3998	3533	61.03	59.16	11213	11086
Branch11	5099	19372	10745	8811	150.25	168.64	10478	12485
Branch12	7416	27522	15317	12534	163.60	150.73	8077	7786
Branch13	3378	13402	7351	6228	101.16	118.85	10573	12992
Branch14	3944	19239	10395	9097	150.68	143.62	10963	10950
Branch15	5294	20437	11285	9377	115.11	104.41	7667	7374
Branch16	7018	24221	13438	10948	177.89	163.78	9931	9742
Branch17	1471	5200	2869	2398	100.45	104.04	26982	30236
Branch18	2252	10092	5526	4764	125.72	118.28	17297	17155
Branch19	5262	19435	10987	8664	127.63	115.14	8765	8396
Branch20	3333	14266	7935	6580	113.18	104.23	10852	10722
Branch21	2635	12214	6599	5878	135.34	131.08	15496	15614
Branch22	6180	21842	12214	9769	118.64	105.62	7328	6899
Branch23	2036	8247	4639	3686	79.39	91.48	13152	16260
Branch24	2999	12921	7047	5992	90.22	83.31	9567	9272
Branch25	2891	12003	6736	5521	129.29	120.94	14444	14226
Branch26	3698	13753	7440	6519	91.94	91.25	10040	10575
Branch27	3333	16468	8743	7978	103.46	107.66	8874	9382
Branch28	3202	10578	5800	4858	138.61	130.93	18544	18317
Branch29	7180	25975	14388	11770	161.90	143.49	8414	8096
Branch30	2369	8644	4855	3876	140.04	139.64	22054	23146
TOTAL	121082	498982	273625	231572	3965	3840		

Table II
Own-Branch vs. Other-Branch Word-of-Mouth Effects in Buying and Selling Decisions of Individual Investors

The table reports results of own-branch and other-branch effects as determinants of investor trading decisions and for both 'Investor Buys' and 'Investor Sells'. These effects are given by baseline specifications (1) (investor buys) and (2) (investor sells), as defined in the text. Their associated $t-$statistics in parentheses are computed using Newey-West heteroskedasticity and autocorrelation consistent standard errors. The two rows above the number of observations indicate the equal-weighted (EW) and accounts-weighted (AW) average differences between own-branch coefficients and other-branch coefficients across the 30 branches.

	Investor Buys				Investor Sells			
	Own Branches	t-Stat.	Other Branches	t-Stat.	Own Branches	t-Stat.	Other Branches	t-Stat.
Branch1	8.617	(16.2)	0.773	(2.22)	6.973	(14.5)	2.837	(8.63)
Branch2	5.109	(8.33)	-3.033	(-7.03)	2.395	(4.39)	-1.582	(-3.60)
Branch3	5.975	(12.8)	-0.603	(-2.09)	1.984	(6.70)	-0.966	(-4.61)
Branch4	7.219	(11.7)	3.511	(8.12)	3.842	(8.14)	1.342	(3.54)
Branch5	4.559	(5.65)	-1.507	(-6.87)	4.155	(4.44)	2.042	(8.13)
Branch6	8.281	(14.6)	-0.085	(-0.25)	5.544	(12.4)	1.621	(4.95)
Branch7	0.028	(0.06)	1.763	(5.82)	-2.244	(-4.91)	1.832	(6.53)
Branch8	3.126	(5.70)	-0.789	(-5.51)	1.830	(3.39)	0.322	(2.05)
Branch9	8.140	(15.2)	2.547	(9.07)	2.591	(5.01)	-0.276	(-0.85)
Branch10	6.757	(13.7)	1.001	(4.11)	1.415	(4.04)	-1.274	(-5.45)
Branch11	5.239	(12.0)	1.009	(5.95)	2.042	(12.0)	0.419	(6.47)
Branch12	0.499	(0.87)	1.482	(6.74)	-0.307	(-0.91)	0.298	(1.59)
Branch13	6.629	(14.1)	1.722	(8.36)	4.574	(13.6)	1.899	(10.2)
Branch14	2.638	(5.90)	-0.176	(-0.93)	4.511	(10.3)	2.883	(17.3)
Branch15	4.036	(6.39)	-0.616	(-1.84)	2.455	(7.13)	-0.667	(-3.07)
Branch16	2.296	(4.50)	-0.574	(-4.13)	2.348	(5.13)	0.309	(1.87)
Branch17	-0.895	(-1.12)	-4.071	(-12.7)	0.310	(0.39)	1.810	(5.36)
Branch18	1.442	(2.58)	-0.008	(-0.05)	3.601	(7.81)	0.996	(8.10)
Branch19	1.211	(2.17)	0.106	(0.54)	0.315	(0.82)	-0.208	(-1.07)
Branch20	1.635	(2.70)	-1.262	(-3.74)	0.248	(0.47)	-0.050	(-0.15)
Branch21	0.735	(7.91)	-0.129	(-2.45)	0.341	(3.16)	-0.579	(-11.9)
Branch22	0.459	(1.35)	-0.119	(-1.27)	-0.513	(-1.88)	-0.333	(-3.84)
Branch23	9.145	(7.28)	-0.014	(-0.07)	3.119	(1.82)	0.016	(0.07)
Branch24	-0.218	(-0.40)	-2.361	(-11.6)	-0.619	(-1.22)	-1.787	(-6.86)
Branch25	3.523	(3.54)	-0.516	(-2.97)	0.294	(0.30)	-0.877	(-6.63)
Branch26	1.161	(4.07)	-0.053	(-0.51)	2.185	(8.97)	0.904	(7.82)
Branch27	1.197	(1.97)	-0.999	(-8.58)	-1.470	(-2.15)	-2.290	(-11.8)
Branch28	2.636	(4.30)	0.620	(2.75)	4.470	(9.03)	2.098	(7.61)
Branch29	0.731	(1.93)	-0.451	(-3.61)	-0.754	(-2.16)	-1.570	(-10.5)
Branch30	0.628	(1.85)	-0.346	(-4.67)	0.265	(0.92)	-0.636	(-7.64)
EW differential	3.524	(6.96)			1.579	(5.02)		
AW differential	3.875	(4.76)			1.706	(3.44)		
Nobs.	222721				195358			

Table III
Word-of-Mouth Effects and Within-Branch Bias

The table reports own-branch effects and other-branch effects in investor trading decisions by stock. The investor buys and sells results are reported separately. We summarize the regression results by averaging the differences between own-branch and other-branch coefficients across 30 branches. EW Diff. shows the equal-weighted average differences between own- and other-branch coefficients across 30 branches. AW Diff. shows the accounts-weighted differentials, with number of accounts in each branch as the weight. All $t-$statistics are reported in parentheses. The last row reports the aggregate weighted-average differential.

	Investor Buys				Investor Sells			
	EW Diff.	t-Stat.	AW Diff.	t-Stat.	EW Diff.	t-Stat.	AW Diff.	t-Stat.
Stock1	5.648	(5.22)	5.517	(4.76)	2.781	(2.78)	3.158	(3.22)
Stock2	7.165	(6.54)	6.319	(6.78)	1.585	(1.99)	1.805	(1.87)
Stock3	4.832	(6.75)	4.786	(5.73)	1.770	(2.41)	2.065	(2.64)
Stock4	3.091	(3.03)	3.109	(2.37)	-0.716	(-0.45)	0.629	(0.46)
Stock5	5.853	(5.77)	7.211	(4.87)	2.162	(3.12)	2.043	(2.93)
Stock6	4.055	(5.58)	4.634	(4.24)	2.446	(3.34)	2.681	(2.75)
Stock7	3.112	(4.36)	3.756	(3.75)	5.592	(4.54)	5.404	(4.31)
Stock8	3.268	(3.35)	3.263	(2.82)	1.466	(2.52)	1.847	(3.36)
Stock9	1.670	(1.59)	2.580	(2.01)	2.468	(2.84)	3.026	(3.08)
Stock10	5.466	(5.67)	5.507	(5.00)	3.175	(2.55)	2.714	(3.07)
Stock11	2.317	(2.12)	2.651	(2.35)	2.220	(2.69)	2.331	(2.24)
Stock12	3.641	(4.13)	3.584	(3.78)	0.915	(0.68)	2.248	(2.25)
Stock13	3.312	(3.21)	4.539	(3.80)	3.277	(4.64)	3.440	(4.18)
Stock14	4.951	(5.02)	5.076	(4.17)	3.450	(3.52)	3.733	(3.11)
Stock15	4.519	(5.61)	4.451	(4.99)	4.312	(1.56)	2.488	(2.68)
Stock16	5.187	(6.09)	5.529	(5.33)	2.608	(2.99)	3.347	(3.77)
Stock17	3.737	(3.15)	4.225	(3.30)	-0.204	(-0.27)	-0.301	(-0.38)
Stock18	3.165	(2.65)	2.777	(2.53)	1.698	(1.91)	2.431	(2.20)
Stock19	6.401	(6.60)	6.672	(4.86)	6.252	(5.12)	6.428	(4.63)
Stock20	6.114	(7.25)	6.656	(6.05)	0.612	(0.67)	0.275	(0.33)
Stock21	4.342	(4.50)	4.695	(3.54)	0.779	(0.94)	0.460	(0.63)
Stock22	2.320	(2.29)	2.522	(1.76)	2.168	(2.79)	1.979	(2.36)
Stock23	5.621	(4.91)	6.324	(4.15)	1.108	(1.39)	1.713	(2.10)
Stock24	2.116	(3.62)	2.684	(3.16)	4.048	(9.38)	3.896	(7.69)
Stock25	3.835	(6.47)	4.318	(4.67)	2.838	(4.02)	3.020	(3.29)
Stock26	7.178	(6.42)	7.188	(6.02)	4.412	(5.91)	4.590	(4.49)
Stock27	4.912	(4.78)	5.258	(3.95)	4.804	(4.57)	5.759	(4.25)
Stock28	2.856	(2.77)	3.294	(3.00)	0.539	(0.68)	0.526	(0.71)
Stock29	3.633	(4.20)	4.818	(3.91)	1.840	(2.68)	1.735	(2.06)
Stock30	5.964	(4.67)	5.575	(4.52)	3.588	(3.93)	4.253	(3.59)
Aggregate Average	4.343	(15.8)	4.797	(17.8)	2.466	(8.24)	2.657	(9.08)

Table IV
Word-of-Mouth Effects and Visibility/Investor Recognition

The table presents results of own-branch effects vs. other-branch effects with investor recognition and visibility controls. We use three proxies for visibility/investor recognition: (i) stock membership of the SHSE30 index, (ii) firm size, and (iii) the listing period of a stock. For (i), we divide stocks into two groups according to whether the stock is a member of SHSE30. For (ii) and (iii), we rank all stocks on the SHSE into two groups according to the market capitalization of the stock (firm size) and the listing period of the stock, respectively. The median stock determines the breakpoint for large vs. small stocks or short vs. long listing period. Then we assign each of 30 stocks based on the breakpoints. We use baseline models (1) and (2) to estimate the own- vs. other-branch coefficients for each characteristic-based sample. We also test the differences in the weighted-average coefficients between two subgroups associated with each visibility/recognition proxy variable. 'EW' shows the equal-weighted average difference between own- and other-branch coefficients across the two subgroups, together with its associated $t-$statistic in parentheses. 'AW' differential shows the accounts-weighted differential, with number of accounts in each branch as the weight.

	Investor Buys				Investor Sells			
	EW	$t-$Stat	AW	$t-$Stat	EW	$t-$Stat	AW	$t-$Stat
	Panel A: SHSE30 Membership							
SHSE30	3.602	(7.56)	3.988	(4.91)	2.193	(5.61)	2.248	(4.42)
Non-SHSE30	3.531	(6.50)	3.859	(4.61)	1.388	(4.29)	1.535	(3.02)
Difference	0.071	(0.10)	0.129	(0.11)	0.805	(1.59)	0.712	(0.97)
	Panel B: Firm Size							
Large	3.529	(6.78)	3.902	(4.65)	1.577	(4.92)	1.680	(3.42)
Small	3.995	(7.06)	4.175	(5.50)	2.087	(3.79)	2.700	(3.45)
Difference	-0.466	(-0.61)	-0.273	(-0.24)	-0.510	(-0.80)	-1.020	(-1.10)
	Panel C: Stock Listing Period							
Long	3.655	(6.83)	4.045	(4.66)	1.702	(5.20)	1.803	(3.58)
Short	3.866	(7.75)	4.164	(5.47)	1.436	(4.22)	1.684	(3.25)
Difference	-0.211	(-0.29)	-0.119	(-0.10)	0.266	(0.56)	0.118	(0.16)

Table V
"Community" Peer Effects in Trading Decisions of Individual Investors

The table summarizes the test results of "close-branch" ("local" effects) or "community" word-of-mouth effects in the trading decisions of individual investors. For this analysis, we group the 30 branches in Shanghai into "close" and "far" branches. The near branches consist of 15 brokerage offices that are located within a 5-kilometer radius, encompassing the downtown area of Shanghai city with the Shanghai city council as the center. The 15 far branches are located outside of the 5-kilometer radius and generally scattered across the large city. To examine community peer effects, we run the following regression model.

$$\begin{aligned} Buy^j_{i,b,t} &= \sum_b \alpha^B_b.\{Buy^j_{-i,k,t}.B(k=b)\} + \sum_b \beta^B_b.\{Buy^j_{k,t}.B(k \neq b)\} \\ &\quad + \sum_b \tau^B_b.D_\tau.\{Buy^j_{k,t}.B(k \neq b)\} + \varepsilon^j_{i,k}, \end{aligned} \tag{3}$$

where D_τ is a branch dummy that takes the value one if $k \in \{near\}$, and 0 if otherwise. The parameter τ^B_b measures how the buying decisions of individual investors at nearby branches influence the buying decision of individual investor i at branch b (i.e., the community effect) and β^B_b measures the other-branch effect. The regression model for investor sells, not shown, is an analogy of (3), with buys replaced by sells.

	Investor Buys				Investor Sells			
	β^B_b	t-Stat.	τ^B_b	t-Stat.	β^S_b	t-Stat.	τ^S_b	t-Stat.
Branch1	0.772	(2.22)	0.131	(0.16)	2.843	(8.65)	0.500	(0.71)
Branch5	-1.505	(-6.87)	-2.192	(-1.48)	2.046	(8.15)	0.243	(0.13)
Branch7	1.757	(5.79)	-1.405	(-1.96)	1.829	(6.52)	-1.167	(-1.81)
Branch8	-0.786	(-5.50)	-1.068	(-0.97)	0.327	(2.08)	0.156	(0.16)
Branch12	1.488	(6.77)	0.683	(0.69)	0.303	(1.61)	0.153	(0.30)
Branch13	1.720	(8.35)	0.126	(0.15)	1.901	(10.2)	-1.250	(-2.35)
Branch14	-0.169	(-0.90)	0.667	(0.94)	2.885	(17.3)	1.068	(1.41)
Branch17	-4.077	(-12.7)	-0.268	(-0.18)	1.818	(5.39)	-2.210	(-1.54)
Branch18	-0.012	(-0.08)	-2.754	(-2.72)	0.996	(8.08)	-0.474	(-0.53)
Branch21	-0.127	(-2.43)	0.047	(0.27)	-0.580	(-11.9)	0.090	(0.44)
Branch22	-0.120	(-1.27)	0.495	(0.80)	-0.332	(-3.82)	0.329	(0.62)
Branch23	-0.015	(-0.07)	5.269	(2.05)	0.013	(0.06)	-0.322	(-0.09)
Branch26	-0.056	(-0.54)	0.177	(0.37)	0.906	(7.84)	-0.056	(-0.13)
Branch27	-1.000	(-8.60)	-1.106	(-0.92)	-2.282	(-11.7)	0.855	(0.69)
Branch29	-0.449	(-3.59)	0.264	(0.35)	-1.570	(-10.5)	-0.087	(-0.14)
EW differential	-0.172	(-0.46)	-0.062	(-0.13)	0.740	(1.87)	-0.145	(-0.66)
AW differential	0.133	(0.29)	-0.215	(-0.74)	1.149	(2.25)	-0.201	(-0.75)

Table VI
Word-of-Mouth Effects in Local vs. Non-Local Stock Trades

The table summarizes the estimates of γ_b^Y and λ_b^Y, where Y denotes either investor buying or selling, and the Buy specification is as follows.

$$Buy_{i,b,t}^j = \sum_b \gamma_b^B.\{Buy_{-i,k,t}^j.B(k=b)\} + \sum_b \beta_b^B.\{Buy_{k,t}^j.B(k \neq b)\} + \sum_b \lambda_b^B.D_\lambda.\{Buy_{-i,k,t}^j.B(k=b)\} + \varepsilon_{i,k}^j$$

where D_γ is a stock dummy that takes the value one if the corporate headquarter is located in Beijing, and 0 if otherwise. We estimate a similar specification for investor selling. γ_b^Y and λ_b^Y capture own-branch effects associated with trades of Shanghai- (local-) and Beijing-headquartered (non-local) stocks and of only Beijing-headquartered stocks, respectively. All $t-$statistics in parentheses are computed using Newey-West heteroskedasticity and autocorrelation consistent standard errors.

	Investor Buys				Investor Sells			
	γ_b^B	t-Stat.	λ_b^B	t-Stat.	γ_b^S	t-Stat.	λ_b^S	t-Stat.
*Branch*1	7.492	(15.8)	-0.234	(-0.29)	7.827	(18.3)	2.837	(4.37)
*Branch*2	5.790	(10.9)	1.305	(1.73)	4.876	(11.4)	1.364	(1.99)
*Branch*3	5.157	(12.3)	-1.725	(-2.68)	2.280	(8.28)	1.270	(2.27)
*Branch*4	7.284	(12.9)	0.783	(1.12)	4.712	(11.5)	2.690	(4.09)
*Branch*5	3.733	(6.29)	-1.895	(-3.07)	2.738	(3.42)	-1.458	(-1.78)
*Branch*6	8.380	(15.9)	-2.682	(-2.98)	4.607	(11.9)	-0.439	(-0.64)
*Branch*7	-1.749	(-4.41)	2.001	(3.44)	-3.454	(-9.29)	-0.364	(-0.64)
*Branch*8	2.893	(5.05)	5.480	(3.95)	1.890	(3.76)	-0.316	(-0.56)
*Branch*9	6.398	(13.0)	0.340	(0.44)	4.083	(8.50)	1.572	(1.69)
*Branch*10	4.654	(9.81)	-0.444	(-0.50)	1.942	(5.93)	0.710	(1.05)
*Branch*11	4.569	(11.9)	-1.130	(-1.31)	2.169	(13.6)	3.298	(4.57)
*Branch*12	-0.497	(-1.15)	2.914	(5.62)	-1.506	(-5.06)	0.782	(1.92)
*Branch*13	6.247	(14.5)	-1.112	(-1.68)	3.906	(12.1)	-0.672	(-1.00)
*Branch*14	2.610	(6.28)	-1.528	(-2.92)	2.986	(7.00)	-0.746	(-1.53)
*Branch*15	4.494	(7.48)	1.668	(1.36)	2.698	(8.05)	3.227	(2.92)
*Branch*16	1.964	(4.16)	-1.501	(-2.41)	2.066	(4.64)	-1.099	(-1.81)
*Branch*17	0.356	(0.50)	1.842	(2.54)	0.646	(0.86)	1.686	(2.00)
*Branch*18	1.575	(2.96)	1.349	(1.21)	3.259	(6.83)	-2.168	(-4.51)
*Branch*19	0.806	(1.60)	2.590	(1.87)	0.068	(0.18)	1.611	(3.07)
*Branch*20	1.975	(3.70)	-0.807	(-0.94)	0.498	(1.06)	1.754	(2.88)
*Branch*21	0.750	(7.37)	4.806	(6.44)	0.318	(2.90)	0.997	(2.00)
*Branch*22	0.273	(0.82)	-1.929	(-1.56)	-0.503	(-1.69)	-1.144	(-1.01)
*Branch*23	8.128	(6.55)	-3.352	(-2.61)	3.400	(2.02)	-1.017	(-0.59)
*Branch*24	-0.006	(-0.01)	1.393	(1.44)	0.125	(0.26)	2.596	(4.34)
*Branch*25	2.981	(2.96)	2.620	(2.34)	0.822	(0.91)	2.981	(3.09)
*Branch*26	0.900	(3.74)	3.121	(2.89)	2.651	(10.4)	2.113	(3.54)
*Branch*27	0.851	(1.52)	-1.128	(-1.77)	-0.325	(-0.52)	1.896	(2.71)
*Branch*28	1.755	(2.73)	1.419	(1.27)	3.818	(7.70)	-0.735	(-0.72)
*Branch*29	0.709	(1.89)	4.189	(4.03)	0.464	(1.33)	0.663	(1.03)
*Branch*30	0.298	(1.02)	1.367	(1.63)	0.429	(1.37)	0.546	(0.84)
EW Ave.	3.049	(6.29)	0.657	(1.60)	1.808	(5.73)	0.815	(2.87)
AW Ave.	3.419	(4.54)	0.412	(1.17)	1.919	(3.98)	0.965	(3.07)
Nobs.	315582				284559			