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Word-of-mouth effects in individual investors' trading: evidence from Korea

Sujung Choi
Soongsil University, Seoul, South Korea

Abstract

This paper examines the hypothesis of local herding (i.e. own-area effects) by individual investors on a particular stock-month. Using a unique dataset on online and offline individual investors' trading records in Korea, we analyze buying and selling transactions involving 10,000 accounts from February 1999 to December 2005. We find that both online and offline investors in the same area tend to exhibit stronger local herding compared to investors' trades who are geographically remote. Interestingly, online investors not only present stronger own-area effects but also exhibit more pronounced other-area effects compared with offline investors. Furthermore, our analysis indicates that gender and religious affiliation are important in investment behavior, with male and non-religious investors displaying a greater stock market participation in contrast to investors who are female and Protestant.

Keywords Word-of-mouth effects, Local herding, Individual investors, Demographic characteristics, Religion

Paper type Research paper

1. Introduction

Communication with neighbors is important in decision-making because it occurs every day. Through the communication, potential investors can acquire new information and rationally update their information set. On the other hand, potential investors are also exposed to various cognitive biases and consequently, they sometimes irrationally update their beliefs because of those biases (Broadbent, 1958; Mullainathan *et al.*, 2008; Karlsson *et al.*, 2009; Sicherman *et al.*, 2016). In particular, the trading decisions of *individual* investors would be more susceptible to cognitive biases compared to those of *institutional* investors.

For example, Han *et al.* (2022) propose a model of social interaction that contains an ingredient of a conversational bias. They call this bias a "self-enhancing transmission bias," as investors are more likely to brag about their trading successes rather than failures. Attribution biases or impression management tactics could cause this behavioral tendency. If potential investors fail to consider the existence of a transmission bias, they might overestimate the outcomes of investing by other investors through conversations. Therefore, both rationally and irrationally updated beliefs would affect the investors' trading behavior (i.e. investment decision-making).

Even worse, individual investors, relative to institutional investors, often have the limitation of promptly obtaining new material information, so they are at an informational disadvantage when trading (Barber and Odean, 2001). Then, individual investors are more likely to rely on communication with neighbors for their investment decisions than

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institutional investors. Communication can provide new information for potential individual investors regardless of the credibility of the information. Thus, individual investors are heavily affected by the transmitted information through conversations and consequently, their trading would correlate with each other in the neighborhood. Regarding institutional investors, they may obtain new information from various channels as well as communication with their colleagues. We, therefore, expect that individual investors who are geographically close would exhibit herding in their trading at least as much as institutional investors.

Specifically, using a dataset on online and offline individual investors' trading obtained from a Korean brokerage firm, we examine whether the herding that would be caused by communication with neighbors exists in the trading of individual investors. In other words, we hypothesize that a potential investor's decision, such as picking a particular stock within a given month, would correlate with the decisions of his/her neighbors who live in the same local area if they communicate with each other.

Previous theoretical studies indicate that the herding exists in the trading of both institutional and individual investors (Banerjee, 1992; Bikhchandani *et al.*, 1992; Choi, 2016; Han *et al.*, 2022). Bikhchandani *et al.* (1998) suggest that herding, or mimicking a neighbor's behavior, is human nature. Herding may occur when potential investors observe the high performance of other investors' trading on a particular stock in the stock market. As mentioned earlier, through such observations, investors process new information (i.e. Bayesian belief updating) or randomly update their beliefs because of cognitive biases. In any case, the observation of good performances of other investors (i.e. friends and neighbors) also affects the investment decisions of potential investors who are more likely to mimic the behavior of others.

Numerous empirical studies have extensively examined herding, or correlated trading, by institutional investors. For example, Lakonishok *et al.* (1992) propose a herding measure (hereafter referred to as LSV measure) to examine herding by pension fund managers in trading stocks. Using the LSV measure, Wermers (1999) also investigates whether herding exists among mutual fund managers. Both studies find a weak evidence of herding by pension and mutual fund managers in trades of stocks on average, but their findings reveal that much higher herding exists in trades of small stocks and in trading by growth-oriented funds.

Sias (2004) find that institutional investors, especially within the same institutional classification, are more likely to follow other institutional investors with a lag. He suggests that the existence of a quarter-lagged herding is consistent with the hypothesis of information cascades (Banerjee, 1992; Bikhchandani *et al.*, 1992), where institutional investors infer information by observing the trading by other institutional investors. In particular, if the hypothesis of information cascades holds, small stocks would show stronger herding compared to large stocks because signals are noisier in small stocks (Wermers, 1999; Sias, 2004).

In order to show herding among institutional investors in the same city, Hong *et al.* (2005) analyze the mutual funds' quarterly holdings data from March 1997 to December 1998 using the information on locations of funds' headquarters. They argue that local institutional investors herd in trading stocks because they share information with other fund managers in the same city through communication (i.e. word-of-mouth effects). They find that mutual funds headquartered in the same city are more likely to hold a particular stock in a given time compared to other funds headquartered in other cities; thus, the trades by mutual fund managers in the same city on a particular stock contemporaneously correlate with each other. Even after one-quarter, the positive correlation among the trades by local mutual fund managers is stronger compared to the correlation among the trades by fund managers in different cities.

Cohen *et al.* (2008) examine the word-of-mouth effects between mutual fund managers and board senior officers. They show the information transfer through the shared educational network between fund managers and senior officers of a firm. By analyzing the quarterly holdings data of institutional investors, they find that the connected stocks, which are defined as the stocks in which fund managers and senior officers of a firm are tied via their education background, outperform the non-connected stocks.

In the empirical study on herding by institutional investors, it is difficult to separate the effects of two different types of learning, rational (i.e. Bayesian) and irrational (i.e. behavioral). As mentioned by Hong *et al.* (2005), other explanations rather than behavioral learning (i.e. cognitive-bias based effects) might contribute to explaining the trading of institutional investors. Fund managers can obtain reliable information directly from the local firms in which they invest and share the information with other fund managers in the same area (Stein, 2008). In addition, the herding behavior by institutional investors at the city level would be related to the reputational herding of fund managers who are concerned about their careers.

However, analyzing trading data of the individuals who live in the same local area has advantages over the previous studies on institutional investors to support the existence of behavioral learning. Unlike herding by *institutional* investors, herding by *individual* investors, if it exists, may directly indicate the cognitive-bias based effects since other explanations, such as local-investor-relations or reputational herding, may not be possible in the trades by individual investors. Barber *et al.* (2009) also find evidence of the herding behavior by US individual investors. They attribute the correlated trading by individual investors to various psychological biases, such as the representativeness heuristic, the disposition effect and limited attention.

In this paper, we make contributions to the literature on behavioral herding among individual investors in the financial market. We compare own-area effects with other-area effects when investors buy (sell) a particular stock by modifying the regression methods from Hong *et al.* (2005). For example, contemporaneous own-area effects are expected to be stronger compared to contemporaneous other-area effects if a buying (selling) order placed by an individual investor in Seoul on the Samsung Electronics stock in March 2001 is more associated with buying (selling) orders placed by other investors in Seoul on the Samsung Electronics stock in March 2001 than buying (selling) orders from investors across all areas except Seoul. Moreover, if a buying (selling) order on the Samsung Electronics stock in March 2001 correlates with buying (selling) orders on the Samsung Electronics stocks in the past month (i.e. February 2001), we identify the one-month lagged effects.

Using OLS regressions, it is possible to compare own-area effects with other-area effects when an individual investor decides to buy (sell) *a specific stock* out of many in a given month. In other words, when individual investor j living in area k decides to buy stock i in month t, we investigate whether the buying order on a specific stock i correlates with buying orders by other individual investors in the same local area k excluding individual j more than with buying orders by individual investors from other areas in month t (i.e. contemporaneous effects) or in previous months, t-1 (i.e. one-month lagged effects) and t-2 (i.e. two-month lagged effects). When the magnitudes of the regression coefficients measuring own-area effects are larger than those measuring other-area effects, we conclude that local herding on a specific stock among individual investors exists at the area level [1].

Overall, own-area effects are larger in both contemporaneous and lagged (i.e. one-month and two-month) coefficients compared to other-area effects even with several demographic control variables. In particular, the magnitudes of own-area effects are much larger for the infrequently traded stocks. Compared to investors who hold frequently traded stocks, those who hold infrequently traded stocks seem to be more sensitive to the opinion of their neighbors. In other words, for illiquid stocks, investors tend to rely on the word-of-mouth information. On the other hand, for liquid stocks, they obtain information from public news media. Easley *et al.* (1996) argue that infrequently traded stocks are subject to more information-based trading than actively traded stocks; thus, private information is more important for infrequently traded stocks. Therefore, the magnitudes of own-area (other-area) effects become larger (smaller) for the infrequently traded stocks.

Finally, we investigate demographic factors which might be related to investor herding behavior. Interestingly, investors who are male, wealthy and non-religious tend to invest more in the stock market compared to investors who are female and Protestant. In other words, individual investors in the area with higher concentrations of Protestants invest *less* in the stock market compared to individual investors in the area with higher concentrations of Catholics, Buddhists and non-religious people [2]. This interesting finding is consistent with the results from Kumar *et al.* (2011), who explain the tendency in terms of religion-induced gambling propensity of investors [3].

2. Descriptions of data

We analyzed the buying and selling decisions of 10,000 individual accounts from February 1999 to December 2005 with a dataset on individual trading records. Equal numbers of individual accounts were randomly sampled from each brokerage firm branch, so among a total of 10,000 accounts, 5,000 accounts were sampled from home-trading system (HTS) users (i.e. online traders) who trade stocks via the internet, which is available almost everywhere. The other 5,000 accounts were sampled from non-home-trading system (non-HTS) users (i.e. offline traders) who place their buying and selling orders on the phone or by visiting local brokerage firm branches.

The dataset includes several demographic characteristics of the investors such as age, gender, residential zip code and zip code of the brokerage firm branches where each individual investor initially opened their accounts. Even though potential investors prefer the HTS trading, they need to visit a local brokerage firm branch to submit their identification documents and obtain secure user accounts [4]. The transaction history of investors such as prices, volumes, dates and miscellaneous costs on the buying and selling orders are also included in the dataset.

The trading patterns of individual investors are highly diverse; thus, some investors are very active in their trading (i.e. day-trading) while some individual investors buy and hold stocks for a long time (i.e. more than several months). In general, online investors who use the HTS show higher turnover compared to offline investors who place buying and selling orders by visiting or calling the brokerage firm branch.

The advantage of this dataset is that it is possible to examine the relationships among individual trading behavior and various demographic characteristics. However, it would be difficult to investigate the effect of individual trading in aggregate, or noise trading, on the asset prices because the sample size is small relative to the population size. Moreover, each individual's trading frequency was not recorded on a regular time-window basis (i.e. a day or a month). Therefore, it might be difficult to identify how much the daily stock price, in aggregate, would change due to the trading of individual investors or due to the trading activities of other market participants.

To examine the relationship between individual investors' trading and stock prices at the aggregate level, we investigate daily-transaction data for each individual KOSPI stock from the Korea Stock Exchange over a twelve-year period from January 4, 1999 through December 30, 2010 [5]. The data include daily trading information aggregated by each group of market participants such as brokerage firms, insurance firms, mutual funds, private equity funds, commercial banks, pension funds, local governments, individuals and foreigners [6]. A daily sum of all traded shares from buying and selling orders per an individual stock is, by definition, zero due to market clearance. When some groups of market participants are net-buyers, the other groups should be net-sellers. Therefore, we can identify the aggregated trading volume which is initiated by each group of market participants; thus, it is possible to examine the effect on the stock prices by the trades of different market participants.

The contemporaneous correlation in net-buying transactions between individual investors and foreign investors is −0.2376 when we examine the daily transactions by each group of market participants. On the other hand, the correlation between net-buying transactions of foreign investors and the growth rate of the KOSPI index is 0.1780. Therefore, in aggregate, the trading position of Korean individual investors seems to be on the opposite side of foreign investors' position and the market. They are more likely to buy (sell) stocks when foreign investors sell (buy) them or when the market drops down (rises up). Interestingly, a one-day-lagged correlation between net-buying transactions of individual investors and the growth rate of the KOSPI is 0.1433, which means that individual investors buy stocks on the next day after the KOSPI rises up. In other words, Korean individual investors tend to buy stocks after the stock market already rises up.

3. Summary statistics

Panel A in Table 1 shows descriptive statistics of the data by subgroups. The total number of transactions is 3,540,140 for the home trading system (HTS) users and 432,496 for the non-HTS users. The individual investors are classified into six subgroups by the zip codes of their residential areas. Figure 1 shows a map of provinces, or residential areas, in South Korea.

The area size of South Korea is 98,480 km^2 (38,023 $mile^2$), which is slightly smaller than one-fourth of the size of California and slightly larger than the size of Indiana [7]. Its population is around 48.8 millions in 2011, which are approximately 11.5 million more than the population of California. Accordingly, South Korea has one of the world's highest population densities, and most population centers are located in the Northwest, Gyeonggi-Do including Seoul, and the Southwest, Gyeongsang-Do including Busan [8]. In particular, Seoul as a capital city has the largest population (10.5 million), although the area of Seoul account for less than 1% of the South Korea's total area.

In spite of the high densities in some cities, mountains and major rivers cover approximately 70% of South Korea; thus, historically, it has been argued that cultural differences clearly exist due to the lack of communication among residents living in other areas geographically separated by mountains and rivers. Therefore, we focus on the six geographical areas, and residents living in geographically and culturally separated areas are assumed to inactively communicate with each other. In particular, the deep-rooted tendency about the geographically and culturally separated areas is even stronger among elderly residents than young residents because elderly people might have difficulty to access the Internet. In other words, elderly people who are economically inactive might have limitation of obtaining information from people living in different areas.

The size of each area is almost similar except Seoul, the capital city. Since roughly a quarter of the South Korean population lives in Seoul, we consider Seoul as a one area, regardless of its small area size. Panel C shows that Seoul accounts for 30.17% of the offline transactions and 32.11% of the online transactions. Ganwon-Do is similar in size to other provinces, but it accounts for only less than 5% of the South Korean population. Therefore, the population density is highest in Seoul and lowest in Ganwon-Do.

In Panel B, investors' age distributions are contrasted between two types of offline and online trading. Investors in the 40s–60s age group dominate the offline trading, whereas investors in the 30s–50s age groups are most active in the online trading. In general, young online investors are active in searching for new information and observing the trades of others through the internet. The information from diversified channels provides young online investors with buying or selling signals on specific stocks. Consequently, regardless of their location, their trades appear to be more correlated with each other compared to the trades of

Panel A: Number of transactions by age and gender						
Age	Male	%	Female	%	Total	%
Non-HTS (offline trading)						
~30	3,090	1.25	2,902	1.57	5,992	1.39
30–39	16,759	6.78	24,165	13.04	40,924	9.46
40–49	57,527	23.27	60,755	32.79	118,282	27.35
50–60	80,929	32.74	62,174	33.55	143,103	33.09
60–70	68,139	27.57	28,079	15.15	96,218	22.25
70 ~	20,746	8.39	7,231	3.90	27,977	6.47
Total	247,190	100.00	185,306	100.00	432,496	100.00
HTS (online trading)						
~30	22,163	0.86	8,418	0.88	30,581	0.86
30–39	707,799	27.40	169,670	17.74	877,469	24.79
40–49	1,034,809	40.05	431,759	45.14	1,466,568	41.43
50–60	583,819	22.60	278,559	29.12	862,378	24.36
60–70	183,325	7.10	63,732	6.66	247,057	6.98
70 ~	51,724	2.00	4,363	0.46	56,087	1.58
Total	2,583,639	100.00	956,501	100.00	3,540,140	100.00
Panel B: Number of transactions in year						
Year	Buy	%	Sell	%	Total	%
Non-HTS (offline trading)						
1999	38,045	17.48	33,863	15.76	71,908	16.63
2000	36,861	16.93	37,888	17.64	74,749	17.28
2001	29,255	13.44	31,632	14.73	60,887	14.08
2002	23,746	10.91	24,934	11.61	48,680	11.26
2003	19,806	9.10	19,410	9.04	39,216	9.07
2004	23,148	10.63	22,794	10.61	45,942	10.62
2005	46,819	21.51	44,295	20.62	91,114	21.07
Total	217,680	100.00	214,816	100.00	432,496	100.00
HTS (online trading)						
1999	197,844	10.55	176,828	10.62	374,672	10.58
2000	329,769	17.58	301,274	18.10	631,043	17.83
2001	274,753	14.65	251,189	15.09	525,942	14.86
2002	263,164	14.03	235,603	14.16	498,767	14.09
2003	248,784	13.26	213,572	12.83	462,356	13.06
2004	218,384	11.64	191,034	11.48	409,418	11.57
2005	343,124	18.29	294,818	17.71	637,942	18.02
Total	1,875,822	100.00	1,664,318	100.00	3,540,140	100.00
Panel C: Number of transactions in area						
Area	Buy	%	Sell	%	Total	%
Non-HTS (offline trading)						
Jeolla	41,060	18.86	40,009	18.62	81,069	18.74
Chungcheong	15,943	7.32	16,233	7.56	32,176	7.44
Gangwon	2,194	1.01	1,684	0.78	3,878	0.90
Gyeonggi	47,567	21.85	45,809	21.32	93,376	21.59
Gyeongsang	45,174	20.75	46,356	21.58	91,530	21.16
Seoul	65,742	30.20	64,725	30.13	130,467	30.17
Total	217,680	100.00	214,816	100.00	432,496	100.00

(*continued*)

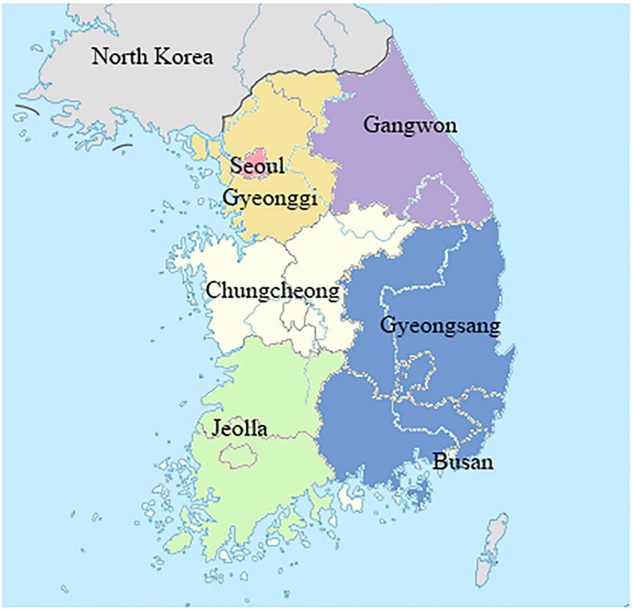
Table 1.
Descriptive statistics

Panel C: Number of transactions in area						
Area	Buy	%	Sell	%	Total	%
HTS (online trading)						
Jeolla	293,033	15.62	250,778	15.07	543,811	15.36
Chungcheong	109,960	5.86	103,107	6.20	213,067	6.02
Gangwon	31,739	1.69	27,284	1.64	59,023	1.67
Gyeonggi	451,235	24.06	400,553	24.07	851,788	24.06
Gyeongsang	392,227	20.91	343,471	20.64	735,698	20.78
Seoul	597,628	31.86	539,125	32.39	1,136,753	32.11
Total	1,875,822	100.00	1,664,318	100.00	3,540,140	100.00

Note(s): Panel A shows descriptive statistics of the number of transactions by each subgroup. The home-trading system (HTS) group places orders via Internet access which is available almost everywhere. The non-HTS group trades stocks by calling or visiting local brokerage firm branches. The total number of sample accounts is 10,000 (i.e. 5,000 from the HTS users and 5,000 from the non-HTS users) from February 1999 through December 2005. Panel B and Panel C present the frequencies of buy and sell transactions on offline and online trading groups

Source(s): Authors' own work

Table 1.



Source(s): Authors' own work

Figure 1. Provinces of South Korea

elderly offline investors. Therefore, young online investors are expected to be affected by remote investors as well as those in their geographical neighborhood.

Interestingly, male investors are more likely to prefer online trading to offline trading compared to female investors because men are generally more familiar with accessing the internet in Korea [9]. The transactions were most active in 2005 for both types of investors and least active in 2003 for offline investors and 2004 for online investors. The number of trades made by online investors is approximately 8.2 times greater than that made by offline investors.

4. Empirical results

This paper examines the geographical herding behavior among local individual investors as follows. First, we define own-area effects and other-area effects. If a buying (selling) transaction by an individual investor in Seoul on the Samsung Electronics stocks in time t is associated more with buying (selling) transactions by other individual investors in Seoul on the Samsung Electronics stocks in time t rather than transactions by investors in other areas, we conclude that contemporaneous own-area effects are stronger than contemporaneous other-area effects. If the buying (selling) transaction on the Samsung Electronics stocks in time t is associated with buying (selling) transactions on the Samsung Electronics stocks in time t-1, we identify one-month lagged effects.

Using OLS regressions which are presented by Hong *et al.* (2005), we compare own-area effects and other-area effects when an individual investor decides to buy (sell) a specific stock. If the magnitudes of coefficients measuring own-area effects are larger compared to those of other-area effects, we conclude that the geographical or local herding exists in the area level. We examine local herding (i.e. own-area effects) by individual investors on a particular stock-month. If the local herding is stronger than herding across all other areas, own-area effects would be stronger than other-area effects in terms of simultaneous trading on a specific stock in a given time period.

Hong *et al.* (2005) use OLS regressions to examine the word-of-mouth effects among local fund managers. Their identification compares own-city effects to other-city effects with buying or selling transactions inferred from the quarterly holdings data of mutual fund managers. The dependent variable is the fractional changes of weights of stock i in its portfolio held by mutual fund j for each stock-quarter. Then, the first explanatory variable on the right hand side of the equation measures the same-city effects by averaging the changes of weights of stock i in the portfolio held by other mutual funds located in the same city except mutual funds in the same fund family. Similarly, the second explanatory variable measures the other-city effects by averaging the changes of weights of stock i which was held by other-city mutual funds. In each city-level regression, the sizes of the coefficients between two explanatory variables are compared.

If word-of-mouth effects exist, the coefficients associated with own-city effects should be larger than those measuring other-city effects in each city-level regression. For example, the changes in weights of stock i which was held by mutual fund j in the New York City should be more correlated to the weight change in stock i held by other mutual funds in the same city, New York City. The weighted average differential of two coefficients is economically and statistically significant, implying that the contemporaneous word-of-mouth effects exist. Even after adding one-lagged explanatory variables in the OLS regression, the contemporaneous effects still remain while the newly added one-lagged effects decrease and become statistically insignificant.

Ng and Wu (2010) also employ similar OLS estimations to examine the correlated trading among individual investors in Mainland China and find significant results at the branch level analyses. Since the analyses are conducted at the branch level, their results seem to be more closely associated with the word-of-mouth effects than with the correlated trading by sharing public information among individual investors.

An advantage of the individual trading data from a brokerage firm is that analyses are available by frequent time-windows (e.g. a month) relative to the quarterly holdings data of institutional investors. However, the trading of individual investors is generally less diversified, and most individual traders do not actively rebalance their portfolio in a short-term. In addition, it is difficult to identify how each individual investor manages his/her whole portfolio of investment, such as bank deposits and pension funds. For stocks, they might open another account in a different brokerage firm. Therefore, the data might not fully reflect the asset allocation by individual investors.

Now, we employ the OLS regressions presented by Hong *et al.* (2005) to identify the own-area effects and other-area effects as follows. For example, for stock i, individual investor j, area k and month t, contemporaneous area effects are measured as:

$$B^i_{j,k,t} = \gamma_k + \alpha_k \frac{1}{(n_{k,t}-1)}\left(\sum\nolimits_{j=1}^{n_{k,t}} B^i_{j,k,t} - B^i_{j,k,t}\right) + \beta_k \frac{1}{n_{c,t}} \sum\nolimits_{j=1}^{n_{c,t}} B^i_{j,c\neq k,t} + controls + \varepsilon^i_{j,k,t},$$

where the $B^i_{j,k,t}$ represents scaled buying (selling) amounts on stock i in month t by individual j in area k. For the $B^i_{j,k,t}$, the individual buying amounts in KRWs are scaled by the total buying amounts on all stocks. The $n_{k,t}$ and $n_{c,t}$ mean the total number of individual investors who buy (sell) stocks in month t in own-area k and all other areas c, respectively. Then, α_k (β_k) would indicate the contemporaneous own-area (other-area) effects.

Next, we estimate simultaneously both contemporaneous and lagged effects as follows:

$$\begin{aligned} B^i_{j,k,t} = {} & \gamma_k + \alpha_k \frac{1}{(n_{k,t}-1)}\left(\sum\nolimits_{j=1}^{n_{k,t}} B^i_{j,k,t} - B^i_{j,k,t}\right) + \beta_k \frac{1}{n_{c,t}} \sum\nolimits_{j=1}^{n_{c,t}} B^i_{j,c\neq k,t} \\ & + \alpha_{k,1} \frac{1}{n_{k,t-1}} \sum\nolimits_{j=1}^{n_{k,t-1}} B^i_{j,k,t-1} + \beta_{k,1} \frac{1}{n_{c,t-1}} \sum\nolimits_{j=1}^{n_{c,t-1}} B^i_{j,c\neq k,t-1} + \alpha_{k,2} \frac{1}{n_{k,t-2}} \sum\nolimits_{j=1}^{n_{k,t-2}} B^i_{j,k,t-2} \\ & + \beta_{k,2} \frac{1}{n_{c,t-2}} \sum\nolimits_{j=1}^{n_{c,t-2}} B^i_{j,c\neq k,t-2} + u^i_{j,k,t}, \end{aligned}$$

where $\alpha_{k,1}$ ($\beta_{k,1}$) and $\alpha_{k,2}$ ($\beta_{k,2}$) represent the one-month and two-month lagged own-area (other-area) effects, respectively.

When an individual account places multiple buying orders on the same stock within a month, we average the buying amounts to remove the effect of highly active day traders. The buying amounts of highly active day traders would increase if they repeatedly place buying and selling orders on the same stock within a month. If the OLS estimation is dominated by those active day traders, the own-area effects would not be associated with the word-of-mouth effects among individual investors.

The own-area effects term is equally weighted by buying (selling) amounts across all individuals who trade stock i in the same area excluding individual j. The other-area effects term is also equally weighted by buying (selling) amounts across all investors in other areas. If the size α_k is larger than the size β_k, we can conclude that own-area effects are stronger compared to other-area effects.

Therefore, the OLS regressions test whether local herding is stronger than herding across all other areas on buying a stock A rather than buying another stock B in a given month t, on average. Then, the intensity of correlated trading by individual investors *within the same area* is expected to be stronger than the intensity of correlated trading by individual investors *in other areas*. Since we remove the effect of highly active day-traders' trading, we posit that the specifications could be associated with the word-of-mouth effects through communication among individual investors in the same local area.

Tables 2 and 3 report the main OLS estimation results of buying and selling orders, respectively. The non-HTS (i.e. offline) transactions are analyzed in Panel A and Panel B, and the HTS (i.e. online) transactions are analyzed in Panel C and Panel D. (1) reports contemporaneous area effects and (2) and (3) include both contemporaneous and lagged area effects. (4) and (5) report contemporaneous area effects with various individual-level characteristic variables (e.g. gender, age and assets on the account) and area-level demographic information (e.g. population density, usage rates of Internet and religion).

Table 2. Own-area effects versus other-area effects for buying orders

Variables	(1)	(2)	(3)	(4)	(5)
			Panel A: buying orders by the non-HTS (offline) investors: All stocks		
Intercept	0.0031 (54.62)	0.0025 (27.76)	0.0024 (24.91)	−0.2051 (−23.77)	−0.2402 (−27.45)
Own	0.2037 (9.13)	0.1293 (4.88)	0.1112 (4.12)	0.1402 (6.28)	0.1426 (6.41)
Other	0.0683 (6.75)	0.0516 (6.07)	0.0466 (5.82)	0.0742 (7.07)	0.0746 (7.10)
Own (−1)		0.3193 (6.08)	0.2843 (5.50)		
Other (−1)		0.0221 (4.26)	0.0178 (3.35)		
Own (−2)			0.1494 (4.51)		
Other (−2)			0.0055 (1.59)		
Male				0.0012 (15.21)	0.0011 (15.01)
Age				0.0172 (12.27)	0.0174 (12.30)
Age^2				−0.0171 (−14.04)	−0.0169 (−13.91)
Log(Asset)				0.0014 (33.73)	0.0014 (33.26)
Log(Density)				0.0031 (21.72)	0.0018 (16.25)
Internet				−0.0026 (−7.11)	−0.0066 (−9.80)
Protestantism				−0.1065 (−22.49)	
Buddhism					0.0322 (11.83)
CPRATIO					0.0343 (9.42)
No_religion				0.3912 (22.89)	0.3894 (27.11)
Adj. R^2	0.0073	0.0360	0.0409	0.0789	0.0783
No. of observations	134,295	134,295	134,295	134,295	134,295
			Panel B: buying orders by the non-HTS (offline) Investors: Stocks traded infrequently (i.e. at most 5 individuals trade per month)		
Intercept	0.0032 (38.12)	0.0029 (33.07)	0.0028 (27.32)	−0.1835 (−10.86)	−0.2237 (−12.56)
Own	0.3249 (2.28)	0.3196 (2.27)	0.3184 (2.27)	0.3183 (2.29)	0.3178 (2.28)
Other	0.0389 (2.32)	0.0347 (2.22)	0.0347 (2.22)	0.0395 (2.45)	0.0397 (2.47)
Own (−1)		0.2778 (4.77)	0.2514 (4.87)		
Other (−1)		0.0388 (1.44)	0.0289 (0.97)		
Own (−2)			0.1953 (1.96)		
Other (−2)			0.0081 (1.45)		
Male				0.0009 (6.34)	0.0009 (6.35)
Age				0.0063 (2.45)	0.0062 (2.39)
Age^2				−0.0070 (−3.09)	−0.0066 (−2.91)
Log(Asset)				0.0011 (15.73)	0.0011 (15.55)

(*continued*)

Table 2.

Variables	(1)	(2)	(3)	(4)	(5)
Log(Density)				0.0030 (10.18)	0.0021 (11.29)
Internet				−0.0054 (−7.78)	−0.0083 (−6.95)
Protestantism				−0.0993 (−10.33)	
Buddhism					0.0386 (9.12)
CPRATIO					0.0255 (4.14)
No_religion				0.3632 (10.60)	0.3758 (12.52)
Adj. R^2	0.0076	0.0232	0.0260	0.0677	0.0669
No. of observations	34,369	34,369	34,369	34,369	34,369
Panel C: buying orders from the HTS (online) investors: All stocks					
Intercept	0.0005 (38.04)	0.0004 (29.96)	0.0003 (30.49)	−0.0360 (−63.79)	−0.0482 (−67.95)
Own	0.2380 (11.78)	0.1715 (8.79)	0.1568 (8.18)	0.1395 (7.97)	0.1403 (8.01)
Other	0.1503 (12.53)	0.1307 (10.82)	0.1289 (10.66)	0.1931 (15.07)	0.1928 (15.05)
Own (−1)		0.2636 (11.40)	0.2440 (10.98)		
Other (−1)		−0.0095 (−2.12)	−0.0098 (−2.32)		
Own (−2)			0.1002 (10.50)		
Other (−2)			−0.0196 (−8.28)		
Male				0.0002 (39.64)	0.0002 (40.16)
Age				0.0013 (6.30)	0.0013 (6.25)
Age^2				−0.0018 (−8.54)	−0.0018 (−8.51)
Log(Asset)				0.0002 (58.06)	0.0002 (57.77)
Log(Density)				0.0005 (56.24)	0.0006 (51.51)
Internet				−0.0010 (−28.04)	−0.0009 (−17.45)
Protestantism				−0.0185 (−57.84)	
Buddhism					0.0121 (45.80)
CPRATIO					0.0009 (4.30)
No_religion				0.0719 (61.60)	0.0830 (66.90)
Adj. R^2	0.0225	0.0526	0.0582	0.0983	0.0971
No. of observations	722,916	722,916	722,916	722,916	722,916
Panel D: buying orders from the HTS (online) investors: stocks traded infrequently (i.e. at most 10 individuals trade per month)					
Intercept	0.0004 (22.72)	0.0003 (17.03)	0.0003 (13.86)	−0.0246 (−24.06)	−0.0294 (−25.22)
Own	0.5407 (4.58)	0.5256 (4.33)	0.5236 (4.30)	0.5345 (4.57)	0.5340 (4.56)

(continued)

Table 2.

Variables	(1)	(2)	(3)	(4)	(5)
Other	0.1279 (5.80)	0.1279 (5.77)	0.1273 (5.74)	0.1293 (5.91)	0.1289 (5.90)
Own (−1)		0.2836 (5.34)	0.2309 (4.31)		
Other (−1)		−0.0068 (−1.98)	−0.0068 (−2.01)		
Own (−2)			0.2671 (3.52)		
Other (−2)			−0.0123 (−3.53)		
Male				0.0001 (9.40)	0.0001 (8.96)
Age				−0.0016 (−2.96)	−0.0015 (−2.78)
Age^2				0.0011 (2.09)	0.0010 (1.85)
Log(Asset)				0.0001 (16.40)	0.0001 (16.47)
Log(Density)				0.0004 (20.49)	0.0003 (13.34)
Internet				−0.0014 (−16.92)	−0.0018 (−15.58)
Protestantism				−0.0135 (−21.15)	
Buddhism					0.0046 (9.94)
CPRATIO					0.0040 (8.26)
No_religion				0.0523 (22.79)	0.0528 (24.59)
Adj. R^2	0.0619	0.0791	0.0900	0.1141	0.1136
No. of observations	112,558	112,558	112,558	112,558	112,558

Note(s): Table 2 shows the OLS estimation results to determine whether, on average, the trading behavior of an individual investor is affected by the trading behavior of other individual investors in the same area and other areas. The dependent variable is buying amount within a stock-month by an individual investor, which is scaled by total buying amount within all stocks in a given month in that area. The trading amount is measured on a KRW basis. The own-area buying intensity for stock i is an equally-weighted average across all individuals in the same area excluding individual j. The other-area buying intensity is also an equally weighted average across all investors in other areas. Therefore, the coefficients of area effects represent, on a given stock-month, how significantly trades of an individual investor would correlate with trades of other investors in the same area and in other areas, respectively

(1) reports only contemporaneous effects; and (2) and (3) include both contemporaneous and lagged effects. The *own* and *other* indicate contemporaneous own-area effects and other-area effects, respectively. The numbers (i.e. −1 and −2) in parentheses of the *own* and *other* mean one-month and two-month lagged effects on each dependent variable. (4) and (5) report area effects with various individual-level characteristic variables (e.g. gender, age and assets on the account) and area-level demographic information (e.g. population density, usage rates of Internet and religion). Following Kumar *et al.* (2011), we define the CPRATIO as the relative proportions of Catholics and Protestants in a given area. The *no_religion* indicates the proportion of non-religious population in the local area. Panels A and B show the OLS estimation results for the non-HTS (i.e. offline) investors who do *not* access the internet to place their orders; and Panels C and D report the OLS estimation results for the HTS (i.e. online) investors. Buying transactions of all stocks are analyzed in Panels A and C. In Panel B and D, we also include the analyses with infrequently traded stocks on which at most five or ten individuals are active each month. The t-statistics in parentheses are calculated by using heteroskedasticity-consistent standard errors

Source(s): Authors' own work

Table 3.
Own-area effects versus other-area effects for selling orders

Variables	(1)	(2)	(3)	(4)	(5)
			Panel A: selling orders by the non-HTS (offline) investors: all stocks		
Intercept	0.0031 (55.32)	0.0024 (24.94)	0.0020 (17.27)	−0.2010 (−23.26)	−0.2339 (−27.14)
Own	0.1458 (7.75)	0.0493 (1.64)	0.0259 (0.97)	0.0808 (5.07)	0.0833 (5.17)
Other	0.0731 (6.77)	0.0513 (6.13)	0.0410 (5.54)	0.0779 (6.98)	0.0783 (6.99)
Own (−1)		0.4450 (7.84)	0.3867 (6.54)		
Other (−1)		0.0220 (4.07)	0.0136 (2.80)		
Own (−2)			0.2813 (3.59)		
Other (−2)			0.0071 (1.59)		
Male				0.0010 (13.21)	0.0010 (12.57)
Age				0.0146 (10.15)	0.0147 (10.23)
Age^2				−0.0144 (−11.79)	−0.0142 (−11.62)
Log(Asset)				0.0013 (32.73)	0.0013 (32.44)
Log(Density)				0.0031 (20.87)	0.0017 (15.03)
Internet				−0.0029 (−7.66)	−0.0070 (−9.74)
Protestantism				−0.1053 (−21.74)	
Buddhism					0.0299 (10.63)
CPRATIO					0.0354 (9.23)
No_religion				0.3870 (22.04)	0.3819 (26.40)
Adj. R^2	0.0049	0.0458	0.0701	0.0703	0.0699
No. of observations	138,231	138,231	138,231	138,231	138,231
			Panel B: selling orders by the non-HTS (offline) investors: stocks traded infrequently (i.e. at most 5 individuals trade per month)		
Intercept	0.0029 (45.88)	0.0025 (19.63)	0.0023 (18.56)	−0.1440 (−11.78)	−0.1752 (−13.11)
Own	0.1923 (3.57)	0.1598 (3.02)	0.1429 (2.75)	0.1681 (2.95)	0.1678 (2.94)
Other	0.0259 (2.15)	0.0190 (1.93)	0.0115 (1.51)	0.0262 (2.20)	0.0266 (2.22)
Own (−1)		0.4823 (2.80)	0.4577 (2.70)		
Other (−1)		0.0145 (1.94)	0.0079 (v1.14)		
Own (−2)			0.3517 (8.31)		
Other (−2)			0.0159 (1.79)		
Male				0.0006 (4.47)	0.0005 (4.15)
Age				0.0082 (4.26)	0.0081 (4.23)
Age^2				−0.0086 (−5.05)	−0.0084 (−4.92)
Log(Asset)				0.0009 (19.40)	0.0009 (19.25)
Log(Density)				0.0023 (10.95)	0.0016 (9.60)
Internet				−0.0050 (−7.30)	−0.0073 (−7.47)

(*continued*)

Variables	(1)	(2)	(3)	(4)	(5)
Protestantism				−0.0777 (−10.86)	
Buddhism					0.0299 (7.71)
CPRATIO					0.0203 (4.35)
No_religion				0.2854 (11.32)	0.2946 (12.86)
Adj. R^2	0.0018	0.0458	0.0758	0.0567	0.0561
No. of observations	36,697	36,697	36,697	36,697	36,697
Panel C: selling orders from the HTS (online) investors: all stocks					
Intercept	0.0005 (20.55)	0.0004 (16.72)	0.0004 (16.97)	−0.0360 (−56.96)	−0.0484 (−64.49)
Own	0.2155 (14.47)	0.1323 (7.36)	0.1203 (7.13)	0.1211 (11.18)	0.1217 (11.23)
Other	0.1098 (3.20)	0.0909 (3.15)	0.0886 (3.15)	0.1308 (3.14)	0.1307 (3.14)
Own (−1)		0.2645 (5.92)	0.2511 (5.77)		
Other (−1)		0.0082 (1.48)	0.0063 (1.19)		
Own (−2)			0.0731 (6.56)		
Other (−2)			−0.0030 (−3.44)		
Male				0.0002 (31.72)	0.0002 (32.54)
Age				0.0010 (3.80)	0.0010 (3.76)
Age^2				−0.0014 (−5.28)	−0.0014 (−5.26)
Log(Asset)				0.0002 (52.39)	0.0002 (52.13)
Log(Density)				0.0006 (48.25)	0.0006 (50.90)
Internet				−0.0011 (−20.65)	−0.0009 (−13.33)
Protestantism				−0.0185 (−50.44)	
Buddhism					0.0124 (46.52)
CPRATIO					0.0008 (3.04)
No_religion				0.0719 (53.70)	0.0834 (62.25)
Adj. R^2	0.0145	0.0498	0.0542	0.0730	0.0721
No. of observations	734,259	734,259	734,259	734,259	734,259
Panel D: selling orders from the HTS (online) investors: stocks traded infrequently (i.e. at most 10 individuals trade per month)					
Intercept	0.0004 (28.29)	0.0004 (19.46)	0.0003 (18.03)	−0.0249 (−15.90)	−0.0296 (−16.95)
Own	0.1229 (3.38)	0.0766 (2.99)	0.0636 (2.71)	0.1090 (3.02)	0.1089 (3.03)
Other	0.0743 (2.06)	0.0717 (2.05)	0.0716 (2.05)	0.0746 (2.05)	0.0745 (2.04)
Own (−1)		0.3074 (5.19)	0.2485 (4.65)		

(*continued*)

Table 3.

Table 3.

Variables	(1)	(2)	(3)	(4)	(5)
Other (−1)		0.0203 (1.10)	0.0203 (1.10)		
Own (−2)			0.3149 (5.89)		
Other (−2)			−0.0136 (−2.25)		
Male				0.0001 (4.73)	0.0001 (4.60)
Age				−0.0029 (−2.79)	−0.0028 (−2.69)
Age^2				0.0024 (2.41)	0.0023 (2.27)
Log(Asset)				0.0001 (14.63)	0.0001 (14.74)
Log(Density)				0.0004 (12.23)	0.0003 (8.32)
Internet				−0.0015 (−9.43)	−0.0020 (−9.43)
Protestantism				−0.0138 (−13.02)	
Buddhism					0.0044 (6.31)
CPRATIO					0.0043 (5.58)
No_religion				0.0536 (14.06)	0.0537 (15.06)
Adj. R^2	0.0037	0.0158	0.0220	0.0244	0.0242
No. of observations	116,677	116,677	116,677	116,677	116,677

Note(s): Table 3 shows the OLS estimation results to determine whether, on average, the trading behavior of an individual investor is affected by the trading behavior of other individual investors in the same area and other areas. The dependent variable is selling amount within a stock-month by an individual investor, which is scaled by total selling amount within all stocks in a given month in that area. The trading amount is measured on a KRW basis. The own-area selling intensity for stock i is an equally weighted average across all individuals in the same area excluding individual j. The other-area selling intensity is also an equally weighted average across all investors in other areas. Therefore, the coefficients of area effects represent, on a given stock-month, how significantly trades of an individual investor would correlate with trades of other investors in the same area and in other areas, respectively
(1) reports only contemporaneous effects; and (2) and (3) include both contemporaneous and lagged effects. The own and other indicate contemporaneous own-area effects and other-area effects, respectively. The numbers (i.e. −1 and −2) in parentheses of the own and other mean one-month and two-month lagged effects on each dependent variable. (4) and (5) report area effects with various individual-level characteristic variables (e.g. gender, age and assets on the account) and area-level demographic information (e.g. population density, usage rates of Internet and religion). Following Kumar *et al.* (2011), we define the CPRATIO as the relative proportions of Catholics and Protestants in a given area. The no_religion indicates the proportion of non-religious population in the local area. Panels A and B show the OLS estimation results for the non-HTS (i.e. offline) investors who do not access the internet to place their orders; and Panels C and D report the OLS estimation results for the HTS (i.e. online) investors. Selling transactions of all stocks are analyzed in Panels A and C. In Panel B and D, we also include the analyses with infrequently traded stocks on which at most five or ten individuals are active each month. The t-statistics in parentheses are calculated by using heteroskedasticity-consistent standard errors
Source(s): Authors' own work

The variable *Age (Age^2)* is scaled by 100 (10,000) for presentational convenience. We conjecture that the buying amounts of individual investors would increase as a concave function of *Age* because disposable income of individual investors peaks at ages 40s or 50s in general. As for the religion-related variables, we define the *CPRATIO* as the relative proportions of Catholics and Protestants in a given area, following Kumar *et al.* (2011). The *no_religion* represents the proportion of non-religious population in the local area. We also analyze the infrequently traded stocks on which at most five or ten individuals are active in a given month *t*.

For all regressions in Table 2, both own-area effects and other-area effects are statistically significant, implying that herding (e.g. picking the Samsung Electronics stock to buy in time *t*) across all areas exists among individual investors on average. The *t*-statistics are calculated using heteroskedasticity-consistent standard errors.

As expected, the own-area effects are larger compared to other-area effects in both contemporaneous and lagged coefficients (i.e. one-month and two-month). For example, as for all buying transactions in Panel A (3), the one-month lagged own-area effects, 0.2843, have the highest correlation with the transactions of an account. Interestingly, own-area effects still continue even after two months as 0.1494, where the coefficient of *Own (−2)* is statistically significant, while other-area lagged effects attenuate in a month as 0.0055, where the coefficient of *Other (−2)* is *not* statistically significant. The statistical significance of one-month lagged own- and other-area effects, or herding in a lag, is somewhat consistent with the results of Sias (2004) who finds herding by institutional investors in a quarter-lag. Sias (2004) explained the herding by institutional investors in a quarter-lag based on the "information cascade hypothesis" which suggests that investors could infer information by observing the trades of other investors.

The magnitudes of own-area effects are much larger for the infrequently traded stocks. For example, if we compare the coefficients of own-area effects with all stocks in Panel A (3) and the ones with infrequently traded stocks in Panel B (3), contemporaneous own-area effect is 0.1112 for all stocks compared with 0.3134 for infrequently traded stocks. On the other hand, contemporaneous other-area effect is 0.0466 for all stocks and 0.0347 for infrequently traded stocks presenting similar magnitudes regardless of the trading frequencies of stocks. As for online investors, Panel C (3) and Panel D (3) show the similar results where own-area effects are even stronger as 0.5236 for illiquid stocks relative to 0.1568 for all stocks. However, other-area contemporaneous effects are 0.1273 for illiquid stocks in Panel D (3) and 0.1289 for all stocks in Panel C (3).

We conclude that investors who hold infrequently traded stocks seem to be more sensitive to the opinion of their neighbors compared to those who hold frequently traded stocks. For illiquid stocks, investors tend to rely on the information via word-of-mouth, but for liquid stocks, they are more likely to obtain information from the news media. Therefore, the magnitudes of own-area (other-area) effects become larger (weaker) for the infrequently traded stocks. Easley *et al.* (1996) argued that infrequently traded stocks are subject to more information-based trading compared to actively traded stocks; thus, private information is more important for infrequently traded stocks.

Barber *et al.* (2009) find evidence of the herding behavior by US individual investors. They attribute the correlated trading by individual investors to various psychological biases, such as the representativeness heuristic, the disposition effect and limited attention. In their study, the representative heuristic explains the buying behavior of individual investors, and the disposition effect is consistent with the selling behavior of individual investors. In other words, investors tend to buy and sell with strong past returns.

This study also presents evidence of herding behavior by Korean individual investors. Particularly, *buying* transactions by offline investors in Table 2 Panel A (1) show stronger own-area effects than *selling* transactions in Table 3 Panel A (1) (i.e. 0.2037 for buying and

0.1458 for selling) even though other-area effects look similar for both buying and selling transactions (i.e. 0.0683 for buying and 0.0731 for selling). It seems not to be clear which psychological biases such as the representativeness heuristic, the disposition effect and limited attention that Barber *et al.* (2009) suggested are related to the buying and selling behavior respectively since we do not analyze the historical returns of stocks in which individual investors are interested. However, the results of stronger own-area effects in *buying* trades by offline investors in Table 2 Panel A than *selling* trades in Table 3 Panel A are consistent with the self-enhancing transmission bias suggested by Han *et al.* (2022).

Investors are likely to brag about good performance of the stocks they already bought; thus, other investors through the conversation might be interested in buying the stocks that their neighbors already bought. On the other hands, investors might be reluctant to discuss their unsuccessful investment in which they would sell stocks. Therefore, if the self-enhancing transmission bias affects the decision of investors, buying trades by individual investors would be more correlated with those by other investors who are geographically close than selling trades, especially for offline investors.

For online investors in Table 2 Panel C (1) and Table 3 Panel C (1), the coefficients of both own-area (i.e. 0.2380 for buying and 0.2155 for selling) and other-area effects (i.e. 0.1503 for buying and 0.1098 for selling) are large and statistically significant, which implies that the trades of online investors are correlated across all areas as well as their local area when they pick a particular stock to buy or sell in time t.

In addition, in Table 2 presenting the results from *buying* transactions, the coefficients of *other-area* effects by online investors in Panel C (1) are relatively large compared to offline investors in Panel A (1) (i.e. 0.1503 for online vs. 0.0683 for offline). Therefore, regardless of the location of investors, the online investors' *buying* transactions are more correlated with each other than the offline investors' trades. In Table 3 showing the results from *selling* transactions, the coefficients of *own-area* effects by online investors in Panel C (1) are much larger than those by offline investors in Panel A (1) (i.e. 0.2155 for online vs 0.1458 for offline). This implies that own-area effects in *selling* transactions are also stronger for online investors than offline investors. In conclusion, online investors would be affected by the communication with other investors across all areas, or they more actively move together by the public information from news media compared to offline investors.

As for various control variables included in Tables 2 and 3, investors who are male, wealthier and non-religious tend to invest in the stock market more than investors who are female, younger and Protestant. Since the dependent variables are buying or selling amounts within a stock-month by an individual investor, we interpret the signs of coefficients as the tendency in active stock market participations by individual investors. That is, in almost all regressions, the signs of coefficients in *Male*, *Age*, *Log(Asset)*, *Log(density)*, *Buddhism*, *CPRATIO* and *No_religion* are positive and statistically significant. In contrast, the signs of coefficients in *Age^2*, *Internet* and *Protestantism* are negative and statistically significant.

Interestingly, as for the religion factor, individual investors who live in the area with higher concentrations of Protestants invest less in the stock market compared to those who live in the area with higher concentrations of Catholics, Buddhists and non-religious people. This finding is consistent with the results of Kumar *et al.* (2011) who explain the tendency in terms of religion-induced gambling propensity of investors.

Table 4 shows area-level regression results to examine whether local correlated trading exists in each area when investors buy (sell) a particular stock in a given month. In the four area-level regressions including Jeolla, Gyeonggi, Gyeongsang and Seoul, own-area effects by offline-investors are much stronger than other-area effects although both own-area and other-area effects are statistically significant. For example, in Panel A, the equation of Jeolla offline investors reports 0.2376 as the coefficient of contemporaneous own-area effects, whereas the coefficient of contemporaneous other-area effect is only 0.0740. Therefore, we conclude that

Area	Jeolla	Chungcheong	Gangwon	Gyeonggi	Gyeongsang	Seoul
			Panel A: no lags			
			Buying orders by the non-HTS (offline) investors			
Intercept	0.0024 (20.63)	0.0065 (25.25)	0.0393 (7.14)	0.0024 (46.04)	0.0025 (45.26)	0.0016 (28.93)
Own	0.2376 (3.19)	0.0593 (3.24)	−0.1964 (−2.05)	0.1818 (6.49)	0.1752 (8.28)	0.3053 (8.03)
Other	0.0740 (5.72)	0.4230 (4.32)	13.4986 (6.01)	0.0676 (8.68)	0.0443 (3.02)	0.0330 (3.44)
No. of observations	26,123	10,625	1,070	28,973	27,802	39,702
			Buying orders by the HTS (online) investors			
Intercept	0.0004 (11.75)	0.0013 (15.65)	0.0047 (8.89)	0.0004 (32.47)	0.0003 (15.83)	0.0002 (13.89)
Own	0.2248 (6.57)	0.1676 (3.41)	−0.0153 (−1.07)	0.1399 (9.86)	0.2465 (10.09)	0.3139 (7.84)
Other	0.2363 (4.69)	0.4670 (4.20)	4.4873 (4.30)	0.1131 (8.75)	0.1446 (6.43)	0.1061 (9.18)
No. of observations	115,632	46,980	11,626	166,613	153,934	228,131
			Selling orders by the non-HTS (offline) investors			
Intercept	0.0025 (37.98)	0.0062 (29.24)	0.0528 (6.61)	0.0024 (49.81)	0.0024 (45.36)	0.0015 (45.65)
Own	0.2169 (8.47)	0.0590 (2.11)	−0.1546 (−3.80)	0.1374 (7.25)	0.1298 (7.35)	0.2419 (10.69)
Other	0.0351 (3.49)	0.4870 (5.35)	8.7613 (2.90)	0.0628 (5.79)	0.0993 (6.54)	0.0533 (8.23)
No. of observations	26,868	10,681	1,013	29,321	28,323	42,025
			Selling orders by the HTS (online) investors			
Intercept	0.0004 (21.98)	0.0013 (34.05)	0.0023 (1.75)	0.0004 (31.47)	0.0003 (13.61)	0.0001 (5.41)
Own	0.2039 (14.35)	0.1059 (9.30)	−0.0385 (−1.56)	0.1554 (11.70)	0.1593 (6.67)	0.2821 (3.72)
Other	0.2482 (6.72)	0.4892 (7.72)	9.2304 (3.42)	0.0483 (2.39)	0.1981 (4.70)	0.1438 (4.90)
No. of observations	116,203	47,255	11,690	169,226	156,208	233,677
			Panel B: one-month lag			
			Buying orders by the non-HTS (offline) investors			
Intercept	0.0021 (22.11)	0.0059 (20.96)	0.0229 (4.02)	0.0022 (40.90)	0.0021 (39.71)	0.0014 (29.73)
Own	0.2094 (2.76)	0.0266 (1.25)	−0.2357 (−2.59)	0.1506 (5.28)	0.1176 (5.31)	0.2662 (6.71)
Other	0.0588 (5.32)	0.3972 (4.24)	8.6498 (3.68)	0.0573 (7.58)	0.0350 (2.93)	0.0279 (3.21)
Own (−1)	0.1406 (5.01)	0.1886 (3.06)	0.1669 (2.52)	0.1212 (5.38)	0.2235 (8.67)	0.1295 (7.99)
Other (−1)	0.0326 (3.92)	0.0294 (1.32)	9.6858 (4.30)	0.0163 (4.44)	0.0281 (4.63)	0.0118 (3.06)
No. of observations	26,123	10,625	1,070	28,973	27,802	39,702

(*continued*)

Table 4.
Own-area effects versus other-area effects (area-level results)

Table 4.

Area	Jeolla	Chungcheong	Gangwon	Gyeonggi	Gyeongsang	Seoul
			Buying orders by the HTS (online) investors			
Intercept	0.0004 (12.35)	0.0011 (15.80)	0.0040 (8.94)	0.0003 (31.91)	0.0003 (16.37)	0.0001 (13.37)
Own	0.2033 (6.25)	0.1294 (2.41)	−0.0467 (−3.03)	0.1099 (7.53)	0.2199 (8.28)	0.2587 (6.19)
Other	0.2232 (4.62)	0.4086 (3.84)	4.0253 (3.98)	0.0993 (7.72)	0.1339 (5.72)	0.0947 (8.32)
Own (−1)	0.0687 (6.65)	0.1703 (7.49)	0.1635 (4.69)	0.1067 (10.16)	0.1102 (10.42)	0.1281 (6.11)
Other (−1)	0.0334 (2.40)	0.0897 (2.98)	0.8397 (2.22)	0.0159 (3.60)	0.0065 (2.08)	0.0146 (3.63)
No. of observations	115,632	46,980	11,626	166,613	153,934	228,131
			Selling orders by the non-HTS (offline) investors			
Intercept	0.0022 (29.79)	0.0051 (15.29)	0.0459 (7.32)	0.0021 (41.82)	0.0022 (35.91)	0.0013 (37.94)
Own	0.1616 (6.36)	0.0196 (0.63)	−0.2254 (−4.03)	0.0830 (5.08)	0.0907 (5.48)	0.1914 (8.06)
Other	0.0293 (3.43)	0.3902 (5.34)	7.2025 (2.29)	0.0527 (5.54)	0.0824 (5.93)	0.0435 (7.38)
Own (−1)	0.2017 (8.94)	0.3345 (3.27)	0.3726 (3.15)	0.1860 (7.52)	0.1591 (5.74)	0.1392 (7.88)
Other (−1)	0.0169 (2.45)	0.0902 (2.63)	2.5419 (1.25)	0.0308 (5.10)	0.0253 (4.51)	0.0249 (5.82)
No. of observations	26,868	10,681	1,013	29,321	28,323	42,025
			Selling orders by the HTS (online) investors			
Intercept	0.0004 (17.53)	0.0013 (28.86)	0.0018 (1.39)	0.0003 (29.37)	0.0003 (13.53)	0.0001 (5.52)
Own	0.1717 (10.19)	0.0842 (6.99)	−0.1031 (−3.94)	0.1026 (8.31)	0.1420 (6.13)	0.2523 (3.62)
Other	0.2222 (5.74)	0.4467 (8.28)	8.2276 (2.75)	0.0451 (2.41)	0.1861 (4.19)	0.1321 (4.39)
Own (−1)	0.0674 (2.31)	0.0712 (2.41)	0.3207 (5.36)	0.1262 (6.54)	0.0559 (3.83)	0.0780 (5.22)
Other (−1)	0.0481 (1.75)	0.0572 (3.17)	0.0891 (0.39)	0.0160 (4.05)	0.0059 (1.69)	0.0111 (2.75)
No. of observations	116,203	47,255	11,690	169,226	156,208	233,677

Note(s): Table 4 shows the area-level OLS regression results to determine whether own-area effects exist in each local area when investors buy (sell) a particular stock in a given month. Panel A reports only contemporaneous effects. Panel B include both contemporaneous and one-month lagged effects. The *own* and *other* represent contemporaneous own-area effects and other-area effects, respectively. The numbers (i.e. −1 and −2) in parentheses of the *own* and *other* mean one-month and two-month lagged effects on each dependent variable. The *t*-statistics in parentheses are calculated by using heteroskedasticity-consistent standard errors
Source(s): Authors' own work

buying trades by investors living in the Jeolla area on a particular stock-month are more correlated with buying trades by other Jeolla investors than those by investors living in other five areas.

On the other hand, the other two areas, Gangwon-Do and Chungcheong-Do, exhibit stronger other-area effects than own-area effects, which seem to be contrary to the local herding hypothesis among individual investors. As a possible explanation, the sample sizes of both areas are relatively small in our trading dataset. Gangwon-Do is the lowest-density rural area, so it accounts for only 0.9% (1.67%) of the offline (online) transaction sample. Chungcheong-Do also accounts for 7.44% (6.02%) of the offline (online) transaction sample. Thus, it might be difficult to identify strong own-area effects where the decision of picking a particular stock to buy (sell) by investors is highly correlated with each other who are geographically close since most investors would live apart from others due to the low population density.

5. Conclusions

In everyday life, communication is important for acquiring new information. Investors decide whether to buy or sell stocks based on the new acquired information. If word-of-mouth effects exist, the trades of investors would correlate with each other, especially in the neighborhood. To examine word-of-mouth effects, this paper investigates own-area and other-area effects among individual investors in the Korean stock market.

The empirical results reveal that for offline investors, own-area effects, or correlated trades by individual investors who are geographically close, are stronger than other-area effects in both contemporaneous and lagged coefficients. For online investors, own-area effects are also stronger than other-area effects, but the magnitudes of coefficients in other-area effects are much larger than those for offline investors. So, we conclude that other-area effects on online investors' trades is strong as well as own-area effects relative to those on offline investors' trades.

Online communications have been rapidly growing, and the channels of information available to individual investors have diversified in recent years. Accordingly, as a channel for obtaining new information, the importance of online communication with others has increased for online investors. Therefore, online investors would be less affected by their geographical neighborhood; however, they would be more affected by the information shared with the whole population via the internet.

Even though the information shared through the internet is often less reliable, individual investors are frequently vulnerable to rumors if they mainly rely on the online resources for obtaining new information. For example, on January 6, 2012, a false rumor about an explosion at a nuclear power plant in North Korea spread through instant messaging [10]. A group of people including a college student purposely circulated the false rumor to manipulate the stock market and earned $54,314 in profits from the panic of the stock market. Even on that day, the South Korean won (KRW) declined by as much as 0.9% against the dollar.

That is, rumors easily spread over the stock market these days, and naïve investors are affected by online rumors even though overflowing online information is less attentive for individual investors. The word-of-mouth effects within the geographical neighborhood (own-area effects) are strong for both offline and online investors, and for the whole population, the word-of-mouth effects could be stronger through the internet these days. Therefore, the Financial Supervisory Service (FSS) would be necessary to scrutinize online rumors, or false information, to protect naïve individual investors.

In fact, it is not be sufficient to confirm the existence of word-of-mouth effects among individual investors only by exploring the correlated trading of investors because we do not directly observe the communication among individual investors in the neighborhood. There could be unobserved factors that may trigger common behavior among individual investors who are geographically close; thus, their behavior is similar even if there were no word-of-mouth communication. In other words, it would be difficult to disentangle the possible sources of herding behavior among individual investors through the empirical analyses in this paper. However, as a first step, it is important to establish that the word-of-mouth effects exist among individual investors who are geographically close.

Notes

1. The LSV herding measure tests whether investors simultaneously trade on the same side in a given stock-period (i.e. whether more investors are buying, rather than selling, the same stock in a given period). On the other hand, own-area (other-area) effects in the OLS regression indicate whether investors in the same (different) local area are *buying* the same stocks rather than *buying* other stocks. In sum, the LSV measure examines the similarity of the trading direction, either buying or selling, among investors, but the magnitudes of the regression coefficients in own-area (other-area) effects implies how strongly the buying transactions on a specific stock are correlated among investors living in the same (different) local area. For convenience, this study uses *local herding* interchangeably with *own-area effects*.
2. Women choose less risky portfolio (Jianakoplos and Bernasek, 1998) and show lower overconfidence (Barber and Odean, 2001). By running experiments, Eckel and Fullbrünn (2015) exhibit that female-oriented financial markets are less likely to generate large bubbles than male-oriented ones.
3. As for the effects of local religion on trading behavior of investors, Shu *et al.* (2012) provide evidence that mutual funds located in high (low) Catholic (Protestant) areas tend to take more speculative risks exhibiting higher fund return volatilities, greater portfolio turnover and more aggressive interim trading. Hilary and Hui (2009) also examine if local religious beliefs are associated with corporate investment decisions. They find that firms located in highly religious counties exhibit lower risk exposure (i.e. higher ROA and less R&D investments).
4. The real-name financial transaction system was introduced in Korea on August 12, 1993. Under the system, financial institutions should verify the identity of an individual conducting financial transactions by checking his/her name, personal identification number and photo ID.
   (Sources: http://www.imolin.org/doc/amlid/korea_real_name_financial_transaction_act.pdf; http://www.hanabank.com/contents/pri/gui/ibk/ibk10/Financial_Transactions_Guide.pdf).
5. The KOSPI (Korea Composite Stock Price Index) is the index of all stocks traded on the KSE (Korea Stock Exchange). The KOSPI, a representative stock market index of South Korea, is similar to the Dow Jones Industrial Average or S&P 500 in the US.
6. Since December 1, 2003, the daily transaction data from the KSE are classified separately for resident foreigners who live in Korea more than 6 months and nonresident foreigners who live less than 6 months and invest from outside Korea. More than 95% of resident foreigners were individual investors while more than 87% of nonresident foreigners were institutional investors from December 1996 through November 1997 (Kim and Wei, 2002).
7. Sources: The US Department of State (http://www.state.gov/r/pa/ei/bgn/2800.htm); The Seoul Metropolitan Government (http://english.seoul.go.kr/gtk/about/fact.php?pidx=3).
8. The "Do"(道) in Korean means a province of South Korea.
9. The timeframe we analyzed using the dataset is from February 1999 to December 2005.
10. Sources: Bloomberg (http://www.bloomberg.com/news/2012-02-21/six-arrested-in-s-korea-over-nuclear-rumors.html)

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Corresponding author
Sujung Choi can be contacted at: sjchoi1@gmail.com