Information Diffusion Effects in Individual Investors' Common Stock Purchases: Covet Thy Neighbors' Investment Choices

Zoran Ivković
Michigan State University

Scott Weisbenner
University of Illinois at Urbana-Champaign and NBER

We study the relation between households' stock purchases and stock purchases made by their neighbors. A ten percentage point increase in neighbors' purchases of stocks from an industry is associated with a two percentage point increase in households' own purchases of stocks from that industry. The effect is considerably larger for local stocks and among households in more social states. Controlling for area sociability, households' and neighbors' investment style preferences, and the industry composition of local firms, we attribute approximately one-quarter to one-half of the correlation between households' stock purchases and stock purchases made by their neighbors to word-of-mouth communication. (*JEL* D14, D83, G11)

Although individuals collectively hold about one-half of the U.S. stock market, information diffusion effects among individual investors—the relation between the investment choices made by an individual investor's neighborhood and the investor's own investment choices—have received relatively little attention in the academic literature, probably because of the lack of detailed data. If present, such effects undoubtedly can affect individual investors' asset allocation decisions. Moreover, trades based on information diffusion might be sufficiently correlated and condensed in time to affect stock prices.

In the domain of institutional investors, Hong, Kubik, and Stein (2005) study word-of-mouth effects among mutual fund managers and find that ". . . a manager is more likely to hold (or buy, or sell) a particular stock

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We extend our gratitude to an anonymous discount broker for providing the data on individual investors' positions, trades, and demographics. Special thanks go to Terry Odean for his help in obtaining and understanding the data set. Both authors acknowledge the financial support from the College Research Board at the University of Illinois at Urbana-Champaign. We thank Jean Roth of the NBER for assistance with the 1990 Census data. Finally, we thank seminar participants at the University of Florida and the University of Illinois for their comments and feedback. The views expressed herein are those of the authors and not necessarily those of the National Bureau of Economic Research. Address correspondence to Zoran Ivkovic, Department of Finance, The Eli Broad Graduate School of Management, Michigan State University, 315 Eppley Center, East Lansing, MI 48824-1121, or e-mail: ivkovich@msu.edu or Scott Weisbenner, Department of Finance, University of Illinois at Urbana-Champaign, 340 Wohlers Hall, 1206 South Sixth Street, Champaign, IL 61820, or e-mail: weisbenn@uiuc.edu.

doi:10.1093/rfs/hhm009 Advance Access publication January 29, 2007

in any quarter if other managers in the same city are holding (or buying, or selling) that same stock." This study complements their work by ascertaining whether such trading patterns are a broader phenomenon. For example, individual investors may seek to reduce search costs and circumvent their lack of expertise by relying on word-of-mouth communication with those around them. Indeed, Hong, Kubik, and Stein (2004) present a model in which stock market participation may be influenced by social interaction. Such social interaction can serve as a mechanism for information exchange via "word-of-mouth" and/or "observational learning" [Banerjee (1992), Ellison and Fudenberg (1993, 1995)]. Duflo and Saez (2002, 2003) present evidence of peer effects in the context of retirement plans. They find that an employee's participation in retirement plans and choices within those plans are affected by participation decisions and choices made by other employees in the same department.

In the international arena, Feng and Seasholes (2004) present evidence of herding effects among individual investors who hold individual brokerage accounts in the People's Republic of China. A unique feature of their data (investors seeking to place trades in person can do so only in the brokerage house in which they had opened their accounts) enables Feng and Seasholes to disentangle word-of-mouth effects from common reaction to releases of public information. They find that common reaction to public information (trades placed across branches in the same region, local to the company), rather than word-of-mouth effects (trades placed in the same branch), seems to be a primary determinant of herding in that context.

Grinblatt and Keloharju (2001) find that proximity to corporate headquarters, the language of communication with investors, and the company's CEO's cultural origin are important determinants of Finnish households' stock investments. Whereas these findings could be consistent with word-of-mouth effects influencing portfolio choice, they could also reflect households' tastes for familiarity—preference to invest in companies that disseminate annual financial reports in their native tongues or feature a CEO with the same origin.

We study information diffusion effects among U.S. individual investors by using a detailed data set of common-stock investments 35,673 U.S. households made through a large discount brokerage in the period from 1991 to 1996. Throughout the article, we loosely refer to the correlation between households' investments and their neighbors' investments as "information diffusion." This term is intended to encapsulate several potential reasons why such correlation exists—word-of-mouth effects, similarity in preferences, as well as common local reaction to news. To further characterize information diffusion and word-of-mouth effects, we consider state-level measures of sociability and find that the level of sociability prevailing in the state to which the household belongs (likely a strong correlate of the presence of word-of-mouth effects) can explain a significant portion of the overall diffusion effect. Moreover, we disentangle the diffusion into the influences of common preferences, structure of the local industry, and word-of-mouth effects.

Putting our results in perspective and comparing them with the findings from Feng and Seasholes (2004) delivers a new, richer understanding of the different mechanisms that govern individuals' investment decisions across various societies. Indeed, whereas Feng and Seasholes (2004) report that individual investors' correlated investment decisions are driven by common reaction to locally available news, with no evidence of word-of-mouth effects among Chinese investors, our estimates suggest that word-of-mouth effects among U.S. investors are strong, particularly in more social areas. This discrepancy is consistent with the differences in the fundamental characteristics of the two societies. Freedom House, which has been producing annual ratings of political and civil rights for more than 200 countries for the past three decades [Freedom House (2004)], has ranked the United States among the highest and the People's Republic of China among the lowest along the dimension of civil liberties. An essential ingredient of the civil liberties score is prevalence of open and free discussion (or absence thereof). Coupled with the fact that many, if not most, companies in the People's Republic of China are at least partly government-owned, it is very plausible that exchanging investment-relevant information in a society deprived of open and free discussion and many other civil liberties is rare and modest.

Even within the United States there is variation in sociability (e.g., membership in clubs, trust in other people). If word-of-mouth is an important contributor to households' stock purchases, the observed correlation in a household's portfolio allocation and that of its neighbors should be higher in the more social areas. Other explanations for information diffusion effects, such as correlated preferences and common local reaction to news, should not vary with the sociability of the community. Using state-level variation in sociability measures enables us to differentiate among the competing hypotheses that can explain trading patterns of U.S. investors.

Overall, we find a strong information diffusion effect ("neighborhood effect"): a ten percentage point increase in purchases of stocks from an industry made by a household's neighbors is associated with an increase of two percentage points in the household's own purchases of stocks from that industry. We pay particular attention to the differentiation between information diffusion effects related to local stocks (defined as companies headquartered within 50 miles from the household) and the effects related to nonlocal stocks. Whereas the key neighborhood effects—similarity in preferences, the impact of the structure of the local industry, and word-of-mouth—can prevail among the investments both local and nonlocal to the household, most of those effects will likely be far more pronounced among local investments because, as demonstrated for both professional money managers [Coval and Moskowitz (2001)] and individual investors [Ivković and Weisbenner (2005)], the flow of value-relevant information regarding local companies appears to be higher and of better quality than the comparable flow regarding remote, nonlocal companies.

Not surprisingly, we indeed find that information diffusion effects are considerably stronger for local purchases than for nonlocal ones. For example, if the neighborhood's allocation of local purchases to a particular industry increases by ten percentage points, a household tends to increase its own allocation of local purchases to the industry by a comparable amount. This result adds another dimension to the already documented high degrees of individual investors' locality, both in the United States [Ivković and Weisbenner (2005), Zhu (2002)] and abroad [Grinblatt and Keloharju (2001), Massa and Simonov (2006)]: not only do investors tend disproportionately to invest locally, but there are also strong information diffusion effects in their neighborhood.

We further find that a household's sensitivity to neighbors' investment choices increases with the population of the household's community. Such diffusion in stock trading affects individual investors' asset allocation decisions. For example, although residents in larger metropolitan areas have substantially more diverse investment opportunities and tend to invest more in local stocks, we find that their local stock investments tend to remain just as concentrated as those made by residents of less populated communities (who have a significantly smaller pool of potential local investments). This tendency is consistent with the notion that residents in more populous geographic areas might be exposed to word-of-mouth effects to a higher degree than residents in less highly populated areas.

Finally, to disentangle the contributions of correlated preferences and the structure of the local economy to the observed correlation between individual investors' stock purchases and those of their neighbors from "word-of-mouth" effects, we conduct two tests. First, we consider the level of sociability of the state to which the household belongs and find that the relation between industry-level household purchases and neighborhood purchases is substantially stronger among households in the more sociable states. Second, we consider the households' own preferences (as revealed by the composition of their respective portfolios across industries at the beginning of each quarter), preferences of the households' respective neighborhoods (as revealed by the composition of the neighborhoods' aggregate portfolios), as well as the composition of local firms and workers by industry. We find that one-quarter to one-half of the overall diffusion effect among both local and nonlocal investments cannot be attributed to these sources. We regard the remaining portions of the diffusion effect as a conservative lower bound on the impact of word-of-mouth communication effects on household trading decisions. Disentangling the overall information diffusion effect into word-of mouth communication and other diffusion effects potentially yields further insight as to how correlated trading among individuals may influence stock prices.

Our results complement and extend those of Hong, Kubik, and Stein (2005), suggesting that word-of-mouth effects are a broad phenomenon that affects financial decisions made by both mutual fund managers and individual investors. The two studies provide evidence supportive of word-of-mouth effects using different techniques, thereby adding to the robustness of the overall finding. Hong, Kubik, and Stein (2005) rule out alternative explanations for correlated trading patterns by examining trading activity before and after Regulation FD and by focusing on trades in stocks for which investor relations are unlikely to be a contributing factor (stocks not local to the managers and small stocks). In this article, we disentangle possible explanations for correlated trading patterns by exploiting differences in sociability of communities across the United States as well as introducing several controls for similarity in investment preferences within the community (as manifested by previous household investment decisions) and the composition of the local economy.

The remainder of this article is organized as follows. Section 1 describes the data and summary statistics. We present our basic findings concerning information diffusion, the impact of the size of the population residing in the household's community, and dissipation of diffusion effects with distance from the household in Section 2. We examine the role of sociability and identify the contributions of correlated preferences, the structure of the local economy, and word-of-mouth communication to overall diffusion in individuals' investment choices in Section 3. Section 4 concludes.

1. Data and Descriptive Statistics

1.1 Data

The primary data set, obtained from a large discount broker, consists of individual investors' monthly positions and trades over a 6-year period from 1991 to 1996. It covers the investments that 78,000 households made through the discount broker, including common stocks, mutual funds, and other securities. Each household could have as few as 1 and as many as 21 accounts (the median number of accounts per household is 2). The information associated with each trade includes the account in which the trade was made. A separate data file contains the information associated with each account, including the household to which the account belongs. This structure of the data allows us to associate with each trade the household that made it. For further details see Barber and Odean (2000).

In this article we focus on the common stocks traded on the NYSE, AMEX, and Nasdaq exchanges. Common stock investments constitute roughly three-quarters of the total value of household investments through the brokerage house in the sample. We use the Center for Research in Security Prices (CRSP) database to obtain information on stock prices and returns and COMPUSTAT to obtain several firm characteristics, including company headquarters location (identified by its state and county codes). We use the headquarters location as opposed to the state of incorporation because firms often do not have most of their operations in their state of incorporation.[1]

We exclude the stocks that we could not match with CRSP and COMPUSTAT; they were most likely listed on smaller exchanges. We also exclude stocks not headquartered in the continental United States. The resulting "market"—the universe of stocks about which we could obtain the necessary characteristics and information—is representative of the overall market. For example, at the end of 1991 the "market" consists of 5,478 stocks that cover 89% of the overall market capitalization at the time.

The sample of households used in this study is a subset of the entire collection of households for which we could ascertain their zip code and thus determine their location. We obtain the latitude and longitude for each of the zip codes from the *Gazetteer Place and Zip Code Database* [U.S. Census Bureau (1990)]. Company locations come from the COMPUSTAT Annual Research Files, which contain the information regarding company headquarters' county codes. Finally, we identify the latitude and longitude for each county from the *Gazetteer Place and Zip Code Database* [U.S. Census Bureau (1990)] as well. We use the standard formula for computing the distance $d(\mathrm{a,b})$ in statutory miles between two points a and b as follows:

$$\mathrm{d(a,b)} = arccos\{cos(\mathrm{a}_1)cos(\mathrm{a}_2)cos(\mathrm{b}_1)cos(\mathrm{b}_2) + cos(\mathrm{a}_1) \\ sin(\mathrm{a}_2)cos(\mathrm{b}_1)sin(\mathrm{b}_2) + sin(\mathrm{a}_1)sin(\mathrm{b}_1)\}r \quad (1)$$

where a_1 and b_1 (a_2 and b_2) are the latitudes (longitudes) of the two points (expressed in radians), respectively, and r denotes the radius of the Earth (approximately 3,963 statutory miles).

The sample size necessitates two adjustments. First, instead of fitting regressions on the basis of individual stocks, we aggregate all the buys in each quarter by assigning firms to one of the following 14 industry groups on the basis of their SIC (Standard Industrial Classification) codes: mining, oil and gas, construction, food, basic materials, medical/biotechnology, manufacturing, transportation, telecommunications, utilities, retail/wholesale trade, finance, technology, and services. Moreover, although 35,673 households purchased common

[1] Whereas this is a somewhat imprecise measure, to our knowledge the data that detail the geographic distribution of employees for each company are not available. Moreover, most value-relevant, strategically important information is likely concentrated at the company headquarters.

stocks at some point during the sample period, in each quarter we consider only the households that made some purchases during the quarter. In sum, there are 23 complete quarters in the sample period (1991:1 to 1996:3), 14 industries, and 7,000 to 9000 households that made stock purchases in a quarter. This leads to a total of 2,678,004 observations, where each observation has several control variables, as well as 322 industry-quarter dummy variables (14 industries $\times$ 23 quarters).

In most analyses, we relate the industry composition of a household's purchases during a quarter to the industry composition of all the purchases of the household's neighbors (households located within 50 miles) made during the quarter, plus appropriate controls. We choose this distance because there is evidence that 50 miles captures most of one's social interactions.[2]

Finally, in some analyses we relate the extent of information diffusion to the sociability that prevails in the area surrounding the household. To capture sociability, we use state-level values of the Comprehensive Social Capital Index, as collected and presented in Putnam (2000).[3] We classify households according to their state's Comprehensive Social Capital Index and split the sample of households into sociable and nonsociable ones, where the breakpoint is the sociability measure of the median household in the sample.[4]

1.2 Summary statistics

Table 1 summarizes quarterly household stock purchases at the industry level. Summary statistics are reported annually, as well as for the entire sample period (bottom row of the table). The first column presents the number of household-quarter-industry (h, t, i) combinations in a given year such that household h made at least one purchase in quarter t in industry i. The second column tallies the number of distinct households appearing in the sample in a given year. The third column lists average dollar values of households' quarterly purchases, where median values are reported in parentheses underneath the mean values. The last column breaks down the purchases according to their distances from the household (i.e., whether the firm headquarters is located within 50 miles of the

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[2] For example, according to the 1990 Census, 88% of the population lives within 25 miles of work (98% live within 50 miles). Moreover, if two co-workers each live only 25 miles from work, they may live as many as 50 miles apart.

[3] Robert D. Putnam's "Bowling Alone" (2000) features 14 state-level measures of social capital, such as time spent visiting friends, number of organizations per capita, number of group memberships, and trust in people, along with the specific measure we use in the article, the Comprehensive Social Capital Index. Details are described in their book (see Table 4 and pp. 290–291). The data are available from http://www.bowlingalone.com/data.php3.

[4] To date, researchers have employed a few different sociability measures. For example, in their study of the relation between social interaction and stock market participation, Hong, Kubik, and Stein (2004) use church attendance as a proxy for sociability.

Table 1
Quarterly purchases of stock by households

	# Purchases	# Distinct HHs	Mean quarterly purchase (in $) [median]	Local (%)
1991	36,250	20,366	23,242 [7,113]	16.4
1992	36,270	20,300	23,576 [7,500]	17.0
1993	34,377	18,894	25,150 [7,500]	16.4
1994	28,726	16,307	25,418 [7,388]	17.4
1995	30,299	16,134	38,540 [9,313]	17.8
1996 (Q1–Q3)	25,364	15,483	42,277 [9,725]	17.5
TOTAL	191,286	35,673	28,922 [7 949]	17.1

This table summarizes quarterly household stock purchases at the industry level. Summary statistics are reported annually from 1991 to 1996, as well as for the entire sample period (bottom row of the table). The first column presents the number of household, quarter, industry (h, t, i) combinations in a given year such that household h made at least one purchase in quarter t in industry i. The second column tallies the number of distinct households appearing in the sample in a given year. The third column lists average dollar values of households' quarterly purchases, where median values are reported in parentheses directly underneath the mean values. The last column breaks down the purchases according to their distance from the household (i.e., whether the firm headquarters is located within 50 miles of the household).

household). There are a total of 191,286 "purchases"—household-quarter-industry (h, t, i) combinations for which there was a purchase by household h in quarter t in industry i—with 16,000–20,000 households making purchases each year, for a total of 35,673 distinct households throughout the sample period. The distribution of the dollar values of quarterly purchases is skewed; whereas the mean quarterly purchase was around \$29,000, the median value was substantially smaller, around \$8,000. The fourth column shows individual investors' disproportionate preference for local stocks (17.1% of all purchases), a phenomenon studied in Ivković and Weisbenner (2005) and Zhu (2002).

2. Information Diffusion Effects

2.1 Basic regression specification

We begin by classifying individual stock purchases made by household h in quarter t into industries $i = 1, 2, \ldots, 14$ and compute $f_{h,t,i}$, the dollar-weighted share of a household's quarterly buys in each industry.[5] In various analyses, the aggregation into 14 industries is done across all stock purchases, local purchases only, and nonlocal purchases only. Moreover, for each household h and each quarter t we also compute $F^{50}_{-h,t,i}$, $i = 1, 2, \ldots, 14$, that is, the proportion of buys made by all neighboring households within 50 miles from household h (excluding household h) in each of the 14 industries. For presentational convenience, throughout the article the household industry shares $f_{h,t,i}$ are expressed in percentage points (that is, they are multiplied by 100), whereas neighboring

[5] Note that, by construction, for every h and every t, $\Sigma_{i=1,\ldots,14} \quad f_{h,t,I} = 100$.

household industry shares are not. Finally, we employ industry-quarter effects to allow for marketwide variation in demand across industries and time by defining 322 dummy variables $D_{t,i}$, $t = 1, \ldots, 23$ (from quarter 1991:1 to 1996:3), and $i = 1, 2, \ldots, 14$. These controls ensure that our results are not driven by, for example, technology stocks beating analysts' expectations, which belong to the common information set that may affect buying patterns of all investors, but rather reflect the differences in households' propensity to purchase technology stocks across different communities. In sum, the basic regression is:

$$f_{h,t,i} = \beta \, F^{50}_{-h,t,i} + \sum_{t=1}^{23} \sum_{i=1}^{14} \gamma_{t,i} D_{t,i} + \varepsilon_{h,t,i} \tag{2}$$

For the basic specification without controls other than the 322 dummy variables, the null hypothesis is that information diffusion effects ("neighborhood effects") do not exist, that is, that the coefficient β is zero. A positive β would suggest the presence of information diffusion effects.

We next address the correlation structure of the error term: observations are independent neither within each household-quarter combination (industry shares necessarily need to add up to one) nor across time (households' preferences are unlikely to change at quarterly frequency). It follows that the OLS regression estimation, although consistent, would produce biased standard errors. Thus, we report the standard errors and resulting tests of statistical significance on the basis of a robust estimator that clusters observations at the household-quarter level for all regressions.

There are several reasons why U.S. individuals' investment choices might be related to those made by their neighbors. At the outset, we note that individual investors might be reacting to the same publicly available information to which their neighbors are reacting. Such tendencies may cause correlated trading. Indeed, Barber, Odean, and Zhu (2006) document that trading patterns are correlated across individual investors, and Barber and Odean (2005) find that individual investors are inclined to buy stocks that have attracted attention. These correlated trading patterns are not necessarily surprising in light of exposure to (the same) publicly available information, as well as to the pronounced presence of the disposition effect [Odean (1998)], tax-motivated trading [Ivković, Poterba, and Weisbenner (2005)], or other behavioral phenomena that might prevail among individual investors, yet need not be driven by information diffusion effects. Our basic set of 322 industry-quarter dummy variables seeks to control for these and other trading factors that do not vary across communities (e.g., when a stock price reaches an all-time high, it does so for all investors) and thereby to allow our specifications to pick up information diffusion effects.

2.2 Information diffusion effects for purchases

We present the results of fitting the regression from Equation (2) in Panel A of Table 2. Within the panel, each row pertains to a different dependent variable. The first row of the panel pertains to the industry share breakdown $f_{h,t,i}$ computed across all buys. Running the basic regression, without any controls other than the 322 industry-quarter dummies, produces the highly statistically significant estimate of 20.7 and thus suggests that a 10 percentage point change in the neighbors' allocation of purchases in an industry is associated with a nearly 2.1 percentage point change in the household's own allocation of purchases in the industry.[6]

As discussed in the introduction, information diffusion that prevails among local and nonlocal stocks may be different. Similarity in preferences, the structure of the local industry, and word-of-mouth effects are likely stronger among local investments. This inquiry is also motivated by studies of local bias among both institutional investors Coval and Moskowitz (1999) and individual investors [Ivković and Weisbenner (2005) and Zhu (2002)]. These studies find that both groups of investors are biased toward holding disproportionately more local stocks in their portfolios. Moreover, Coval and Moskowitz (2001) and Ivković and Weisbenner (2005) present evidence that local investments outperformed nonlocal ones among mutual fund managers and individual investors, respectively.

Separate consideration of local purchases[7] and nonlocal purchases, reported in the next two rows of Table 2, Panel A, indeed reveals that local information diffusion effects are larger than the nonlocal ones by an order of magnitude (119.3 vs. 8.4). For example, if the neighborhood's allocation of purchases to a particular industry increases by ten percentage points, a household tends to increase its own allocation of local purchases to the industry by a comparable amount. This result adds another dimension to the already documented high degrees of individual investors' locality, both in the United States [Ivković and Weisbenner (2005), Zhu (2002)] and overseas [Grinblatt and Keloharju (2001), Massa and Simonov (2006)] by suggesting the possibility that strong information diffusion effects could contribute to individual investors' local bias.

2.3 Information diffusion effects for sales and positions

In Panels B and C of Table 2 we also examine the extent to which households' sale and holding decisions are correlated with those of their

[6] If regressions are estimated for each quarter separately, in which case each quarterly regression only has 14 dummy variables for the industry effects, the estimated coefficient β is highly statistically significant in all twenty-three regressions. Quarterly regressions suggest that information diffusion effects are strong throughout the sample period, with point estimates ranging from 13.6 to 28.3 across the 23 quarters.

[7] In the regressions for local buys we discarded all the h, t, i observations for which there were no firms in industry i within 50 miles from household h in quarter t because household h simply could not have invested into industry i locally.

Table 2
Information diffusion for purchases, sales, and positions

	Composition of HH variable $\leq$ 50 miles	R^2	# Obs.
	Panel A: Purchases		
All buys	20.7 (0.3)***	0.142	2,678,004
Local buys (within 50 miles)	119.3 (1.2)***	0.232	568,247
Nonlocal Buys (outside 50 miles)	8.4 (0.3)***	0.129	2,337,314
	Panel B: Sales		
All sells	30.0 (0.3)***	0.123	2,448,838
Local sells (within 50 miles)	122.4 (1.2)***	0.248	526,273
Nonlocal sells (outside 50 miles)	6.5 (0.3)***	0.104	2,115,722
	Panel C: Positions		
All positions	36.5 (0.3)***	0.087	8,359,442
Local positions (within 50 miles)	153.4 (0.7)***	0.143	2,429,728
Nonlocal positions (outside 50 miles)	17.7 (0.3)***	0.072	7,449,582

This table presents the results of fitting the basic information diffusion regression from Equation (2) over the 23 quarters from January of 1991 to October 1996 :

$$f_{h,t,i} = \beta\, F^{50}_{-h,t,i} + \sum_{t=1}^{23} \sum_{i=1}^{14} \gamma_{t,i} D_{t,i} + \varepsilon_{h,t,i}.$$

Panel A reports regression results relating the composition of households' stock purchases across 14 broad industry groups to the composition of their communities' purchases (the community is defined as all other households within 50 miles). Analogously, Panels B and C present regression results for the composition of sales and positions, respectively. Regressions in all three panels are estimated on subsamples identified by the distance from households to company headquarters (All, Local, and Nonlocal). Standard errors, shown in parentheses, allow for heteroskedasticity, as well as correlation of error terms at the household-quarter level.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

neighbors. We find a similar pattern of results for sale decisions as we do for purchase decisions. For example, estimates from Panel B suggest that a ten percentage point change in the neighbors' sales of stock in an industry is associated with a three percentage point change in the household's own sales of stock in the industry.

Perhaps not surprisingly, the correlation between the composition of a household's positions across industries and that of their neighbors is substantially larger than those for purchases (the coefficients are larger in magnitude by 50% to 100% across the three samples). This larger correlation reflects the fact that positions are the combination of both past purchase decisions and the returns accrued on those investments. The larger correlation for positions relative to trades mirrors the results reported for mutual fund managers in Hong, Kubik, and Stein (2005).

For the remainder of the article, we focus on households' purchase decisions because they are unconstrained, that is, households are free to purchase any stock, and they represent households' active financial decisions. By contrast, in the absence of short selling, sale decisions are limited to the stocks already held (essentially no investors in our sample sold stocks short). Thus, a correlation in selling activity could simply represent an underlying correlation in the original buying activity of those stocks. Moreover, a correlation in positions could in part simply reflect households' inertia, as households could hold similar stocks over a long period of time (and thus experience similar movements in the value of their portfolio positions).[8]

2.4 Information diffusion effects and local population size

In this section, we stratify households according to the size of the population that resides within 50 miles from the household. We define four categories: 0–1 million residents, 1–2.5 million residents, 2.5–5 million residents, and more than 5 million residents. Not surprisingly, the size of the local population and the diversity of local companies are positively related (i.e., local population and the Herfindahl index of industry concentration are negatively correlated). Specifically, the Herfindahl index of the industry composition of firms local to the average household decreases from around 0.5 to around 0.2 as the population increases from 0–1 million local residents to more than 5 million local residents.[9] Yet, although the average dollar amount of quarterly purchases of local individual stocks increases from \$13,000 to \$22,400 as the size of the local population increases from 0–1 million to more than 5 million local residents, the Herfindahl index of households' local purchases across industries remains virtually unchanged—it drops only very slightly from 0.99 to 0.95. Thus, although residents in larger metropolitan areas have substantially more diverse investment opportunities and tend to invest more into local stocks, they tend to remain very focused in their industry allocation. This tendency is consistent with the notion that residents in more populous geographic areas might be exposed to information diffusion effects to a higher degree than residents in less highly populated areas. To confirm this intuition, we run a simple modification of the basic regression from Equation (2) on subsamples selected by the type of purchase (all buys, local buys, and nonlocal buys), wherein information diffusion effects are interacted with indicator variables representing local population size (0–1 million, 1–2.5 million, 2.5–5 million, more than 5 million). The coefficient estimate

[8] In unreported analyses, we have verified that conclusions drawn for the subsequent analyses in the article regarding households' purchase decisions hold for sales and holdings as well (results available upon request).

[9] Firms are divided into 14 industry groups. Thus, a community with equal representation across all industries would have a local firm Herfindahl index of 0.07.

presented in the table for a particular population group represents the total information diffusion effect for that group (i.e., the sum of the diffusion effect for the 0–1 million group and the interaction term for that particular population group).

Across all three regressions presented in Table 3, information diffusion effects in purchases increase with population size. Stronger effects in larger metropolitan areas may stem from a greater flow of investment-relevant information through increased availability of information sources (e.g., business-oriented magazines and newspapers) and advertising efforts, both of which are subject to economies of scale and are typically more substantial in larger metropolitan areas.

2.5 Dissipation of information diffusion effects with distance from the household

One would expect information diffusion effects to dissipate as the distance from the household increases. To test this hypothesis, we define regions surrounding the household at increasingly larger distances as follows: 0–50 miles, 50–70.7 miles, 70.7–86.6 miles, 86.6–100 miles, . . ., 141.4–150 miles. These regions each cover a geographic area of the same size ($50^2\pi = 7,854$ square miles). We then run a regression similar to Equation (2), except, instead of having one information diffusion regressor $F^{50}_{-h,t,i}$, the specification now has nine ($F^{50}_{-h,t,i}$, $F^{50-71}_{h,t,i}$, $F^{71-87}_{h,t,i}$, $F^{87-100}_{h,t,i}$, $F^{100-112}_{h,t,i}$, $F^{112-122}_{h,t,i}$, $F^{122-132}_{h,t,i}$, $F^{132-141}_{h,t,i}$, and $F^{141-150}_{h,t,i}$). The results are presented graphically in Figure 1. Across all three panels, that is, for all buys, local buys, and non-local buys, the pattern is the same: there is a rapid and fairly steady exponential decline of the information diffusion coefficients with distance from the household. As one might suspect, a household's purchases of non-local stocks are relatively more sensitive to the decisions made by members of more distant communities than its purchases of local stocks are. That is, going beyond the 50-mile community leads to a substantially faster decline in information diffusion effects in the domain of local stocks than in the domain of non-local stocks.

The Figure illustrates dissipation of information diffusion effects with distance from the household. Regions surrounding the household at increasingly larger distances have the same geographic area ($50^2\pi = 7,854$ square miles). The regression specification is similar to Equation (2), except, instead of having one information diffusion regressor, the specification now has nine—one for each geographic area

2.6 Robustness checks

An issue of potential concern for local information diffusion is that the effect might be driven by some form of inside trading: those who work for a company may be trading in their own company stock and may be selectively releasing pertinent information to their relatives and close

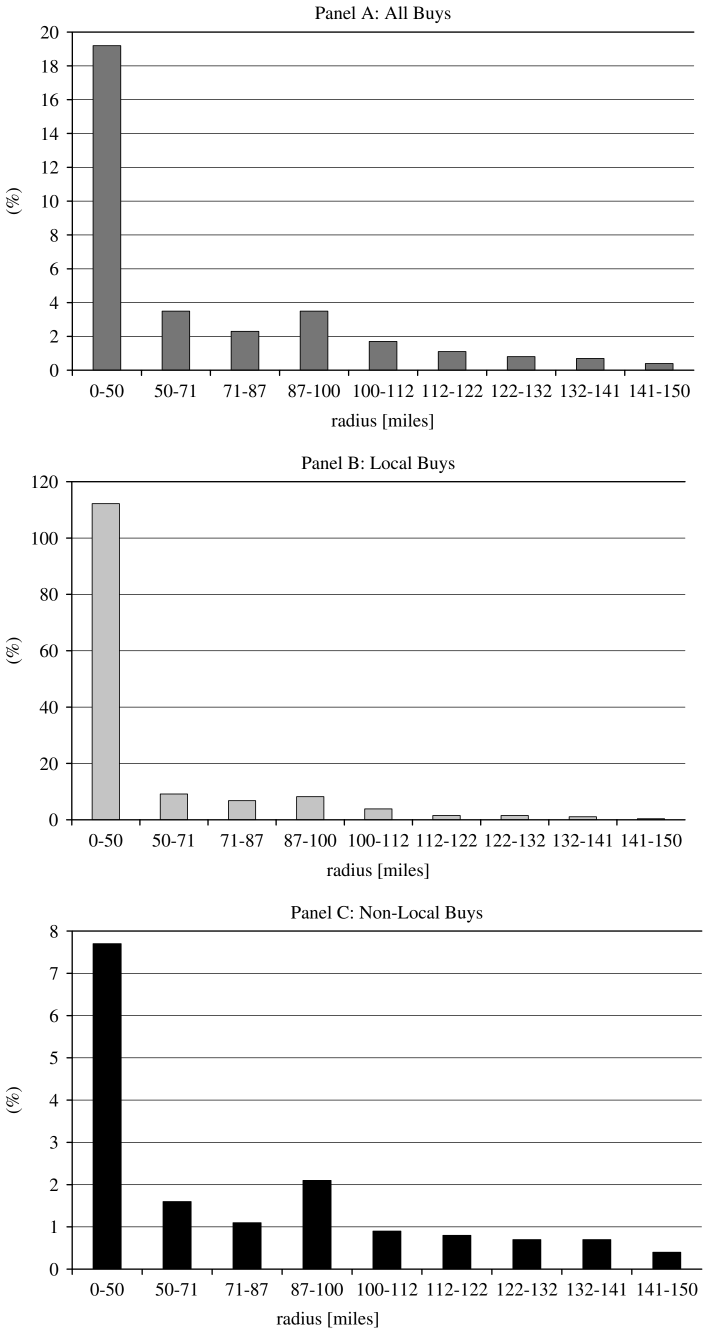

Figure 1
Dissipation of information diffusion.

friends. We regard this effect as somewhat distinct from the other aspects of information diffusion because the information the investors would receive is likely much more precise than the information available through word-of-mouth effects, exposure to local news, influence of company's presence through advertising efforts, company-sponsored events, or social interaction with company employees.

Unfortunately, the data set does not provide information about the investors' current and past employers. We control for the own-company stock explanation, however, by focusing on the plausible assumption

Table 3
Information diffusion for purchases with population interactions

	Composition of HH buys ≤ 50 miles	R^2	# Obs.
All Buys			
Population in millions			
0–1	5.2 (0.4)***	0.147	2,678,004
1–2.5	10.7 (0.8)***		
2.5–5	27.2 (1.0)***		
5+	53.5 (0.9)***		
Local buys			
Population in millions			
0–1	64.2 (4.9)***	0.245	568,247
1–2.5	59.0 (3.0)***		
2.5–5	102.7 (2.3)***		
5+	139.5 (1.6)***		
Nonlocal buys			
Population in millions			
0–1	4.5 (0.4)***	0.129	2,337,314
1–2.5	6.5 (0.8)***		
2.5–5	9.3 (1.1)***		
5+	13.1 (1.0)***		

This table presents the results of fitting a diffusion regression for purchases, a variant of Equation (2) that distinguishes among households according to the size of the population that resides within 50 miles of them into four categories and assesses information diffusion effects in neighborhoods of various sizes:

$$f_{h,t,i} = \left(\beta\ F^{50}_{-h,t,i}\right) * Population\ Interactions$$
$$+ \left(\sum_{t=1}^{23} \sum_{i=1}^{14} \gamma_{t,i} D_{t,i}\right) * Population\ Interactions + \varepsilon_{h,t,i}.$$

The four categories are: 0–1 million, 1–2.5 million, 2.5–5 million, and more than 5 million residents. Regressions are estimated on subsamples identified by the type of purchase (All Buys, Local Buys, and Nonlocal Buys). The coefficient estimates for a particular population group represents the overall information diffusion effect for that group (i.e., the sum of the diffusion effect for the 0–1 million group and the interaction term for that particular population group). Standard errors, shown in parentheses, allow for heteroskedasticity, as well as correlation of error terms at the household-quarter level.
***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

that, if a household's local purchase is motivated by inside information, it is likely to be the household's largest local trade in that quarter. Accordingly, we compute for each household h in quarter t the industry composition of local purchases excluding the single largest stock purchase made by household h in quarter t. In unreported analyses, we find that this specification yields estimates of the local information diffusion effect that are even somewhat larger than the estimates based on the full sample of local investments (152.5 vs. 119.3). Therefore, we do not find evidence that trading in own-company stock drives the estimated information diffusion effects among local investments.

Another issue of potential concern is that the estimates of local information diffusion may be induced by the dominant presence of a company (or industry) in a household's neighborhood. Taking a drastic example, suppose there is only one company (or multiple companies all belonging to the same industry) local to the household. The opportunity set for local investments is therefore very focused and the inability to invest locally in any other industry may bias the results. To assess the impact of industry dominance in the local opportunity set, in unreported analyses we estimate regressions for local purchases on a subsample of purchases—household-quarter-industry (h, t, i) combinations for which the weight of industry i in the portfolio of firms local to household h does not exceed the threshold of 50%, that is, the observations not plagued by the domination of a single company (or industry) in the community. The regression coefficient remains essentially the same; it declines only very slightly, from 119.3 to 111.3, which suggests that the "one-company town" issue does not drive local information diffusion.

3. Disentangling Information Diffusion Effects

The results presented in Section 2 suggest that the stock purchases made by households are strongly related to those made by their neighbors, consistent with word-of-mouth effects playing a strong role in household investment decisions. However, such a correlation in trading activity could also reflect an underlying similarity in preferences or the industry composition of local firms. In regard to U.S. investors, studies have found correlated trading patterns both for institutional investors [Hong, Kubik, and Stein (2005)] and individual investors [Barber, Odean, and Zhu (2006)]. Hong, Kubik, and Stein (2005) consider alternative interpretations to their finding that mutual fund managers engage in word-of-mouth communication and tilt their portfolios accordingly. They use three sets of tests to assess the possibility that their results might be driven by inside information obtained by the money managers directly from company executives (which they term the "local-investor-relations" activity). First, their results are unaffected even if all local stocks are excluded from their regressions. Second, their results are robust among smaller stocks (which, on average, have fewer resources at their disposal to pursue "local-investor-relations" activities). Finally, Hong, Kubik, and Stein (2005) consider the post-Regulation FD period and show that their results persist in the aftermath of explicit regulation that prohibits companies to engage in selective dissemination of information, suggesting once again that "local-investor-relations" strategies do not drive their regression results.

As Hong, Kubik, and Stein (2005) point out, none of these "local-investor-relations" alternative explanations are likely to dominate the arena of individual investors. In fact, Feng and Seasholes (2004) report that Chinese individual investors' correlated investment decisions are driven by common reaction to locally available news, with no evidence of word-of-mouth effects on stock trades. However, given the differences in the fundamental characteristics of the U.S. and Chinese societies (i.e., differences in civil liberties such as open and free discussion), it is plausible that motivations for stock purchases could also be substantially different across the two cultures.

Moreover, it is important to differentiate among competing sources of the overall information diffusion effect among U.S. individual investors because they likely have different levels of influence on the market. For example, word-of-mouth effects may create a more dynamic exchange of information that may lead to a ripple effect of further information dissemination, which in turn may have an impact on stock prices.

Thus, we devise two alternative strategies to disentangle the sources of the observed correlation between a household's stock purchases and those of its neighbors. The first strategy considers the sociability of a household's state. Using the comprehensive statewide sociability measure from Putnam (2000) (available for all 50 states except Alaska and Hawaii), we assign a certain level of sociability to every household in our sample, and then define a dummy variable associated with each household that labels it as a household in either a high or a low sociability area. We interact that dummy variable with the neighborhoods' industry-level purchases. Within the United States, there is variation in sociability (i.e., membership in clubs, trust in other people, etc.) across states. If word-of-mouth is an important contributor to a household's stock purchases, then the observed correlation in a household's portfolio allocation and that of their neighbors should be higher in more social areas. Other explanations for information diffusion effects, such as correlated preferences and common local reaction to news, should not vary with the sociability of the community. We interpret the coefficients associated with sociability, which represent the increased influence of neighbors' investment choices on an individual's own portfolio in social areas relative to less social communities, as measures of the word-of-mouth effects.

The second strategy considers three key contributions to the overall information diffusion effect, namely, word-of-mouth communication, correlated preferences (which may incorporate common local reaction to news events), and the structure of the local economy. We use the composition of the neighborhood's aggregate portfolio to reveal the neighborhood's preferences and the accumulation of their reactions to past news. Analogously, we use the composition of a household's own portfolio position to reveal its own preferences and accumulated reactions to past news. We further use the degree of conformity of the household portfolio composition to the portfolio composition of the neighborhood to identify households with preferences and reactions similar to their neighbors', as well as those whose preferences and reactions are very different from their neighbors'. Upon controlling for the composition of households' neighborhood portfolios and households' own portfolio compositions, as well as the structure of the local economy, we view the correlation between the household's stock purchases and those of its neighbors that survives such rigid controls as a conservative lower bound on the magnitude of the word-of-mouth effect.

Strikingly, our estimates of the contribution of word-of-mouth communication are very similar across households that conformed to their neighbors very closely and those that held very disparate portfolios. This finding is reassuring because it suggests that the strategy we employed to control for the effect of common preferences and the cumulative common reactions to news did not lead to materially different estimates of the word-of-mouth effect across the two sets of households.

3.1 Controlling for word-of-mouth effects: the area sociability proxy

In this section we report the results of the analyses in which we identify a proxy for the word-of-mouth effect and interact that measure with diffusion coefficients in a regression specification very similar to that from Equation (2). Our proxy for the word-of-mouth effect is the sociability of the area surrounding a household. To capture sociability, we use state-level values of the Comprehensive Social Capital Index, as collected and presented in Putnam (2000).[10] We define a dummy variable that indicates high and low area sociability levels by classifying households according to their state's Comprehensive Social Capital Index (Putnam, 2000) and splitting the households into sociable and non-sociable ones (the breakpoint is the sociability measure of the median household in the sample). Further recognizing that sociability effects may be stronger in the areas with more population, we also develop a specification in

[10] In some robustness checks we also consider key components of the overall social capital index such as measures of the time spent visiting friends, number of organizations per capita, number of group memberships, and trust in people. Results are highly consistent with those based on the specifications that employ the Comprehensive Social Capital Index.

which we interact the diffusion coefficient with both the sociability dummy and the population measures (as defined in Section 2.4 and Table 3).

Table 4 presents the results of both analyses across all buys, local buys, and nonlocal buys (Panels A, B, and C, respectively). Within each panel, the first section reports regression results for specifications involving area sociability measures only, whereas the second section reports results of the more complicated specifications that also include interactions with population measures.

Focusing first on the specifications without population interactions, diffusion effects are considerably stronger among households located in the more sociable areas. A ten percentage point increase in neighbors' purchases of stocks from an industry is associated with a 1.5 percentage point increase in the household's own purchases of stocks from that industry in nonsocial areas, while the diffusion effect increases to 2.5 percentage points for households in social states. Thus, the correlation in household purchases is significantly stronger in the states that are more sociable (i.e., in the states in which individuals are more inclined, e.g., to be members of clubs and to trust each other). For all buys and nonlocal buys, the increased influence of neighbors' investment choices on an individual's own portfolio in more social areas relative to less social areas (a proxy for the word-of-mouth effect) is 40% (10.0/24.6 and 3.0/9.8, respectively) of the total information diffusion effect. For local buys, the "word-of-mouth" share of the total correlation between neighborhood and household purchases is 17% (20.1/119).

Specifications that also incorporate population interactions yield similar relative increases across all population groups, with the exception of the households located in the smallest communities (surrounded by fewer than 1 million people within a 50-mile radius), for which increased sociability does not translate into any statistically significant changes in information diffusion. Parallel to the results from Table 3, the correlation in stock picks increases with the increase of population, and, broadly speaking, so does the incremental contribution of area sociability (the coefficients in the bottom row of each of the six analyses reported in Table 4).

These results suggest that word-of-mouth communication is an important contributor to information diffusion effects, amounting to perhaps one to two-fifths of the overall correlation between individual and community stock purchases.

3.2 Controlling for correlated preferences and structure of local economy

3.2.1 The role of correlated preferences. A potential source of correlated purchases among households in a geographic area is that those households may have similar preferences. Individual investors might be influenced

Table 4
Information diffusion, area sociability, and area population

	Full sample	Population in millions 0–1	1–2.5	2.5–5	5+	R^2	# obs.
Panel A: All buys							
Buys of HHs ≤ 50 *miles*	14.6***					0.147	2,634,338
	(0.4)						
Buys of HHs ≤ 50 *miles** *Sociability above median*	10.0***						
	(0.3)						
Buys of HHs ≤ 50 *miles*		5.3***	9.3***	22.5***	42.3***	0.148	2,634,338
		(0.6)	(0.8)	(1.1)	(1.0)		
Buys of HHs ≤ 50 *miles** *Sociability above median*		0.0	3.1***	7.4***	9.0***		
		(0.6)	(0.7)	(0.6)	(0.4)		
Panel B: Local buys							
Buys of HHs ≤ 50 *miles*	98.9***					0.236	566,735
	(1.4)						
Buys of HHs ≤ 50 *miles** *Sociability above median*	20.1***						
	(0.7)						
Buys of HHs ≤ 50 *miles*		63.1***	48.2***	92.1***	117.0***	0.249	566,735
		(5.6)	(3.2)	(2.6)	(2.1)		
Buys of HHs ≤ 50 *miles** *Sociability above median*		0.8	20.7***	13.8***	16.8***		
		(4.6)	(2.3)	(1.4)	(0.8)		
Panel C: Non-local buys							
Buys of HHs ≤ 50 *miles*	6.8***					0.129	2,295,090
	(0.4)						
Buys of HHs ≤ 50 *miles** *Sociability above median*	3.0***						
	(0.3)						
Buys of HHs ≤ 50 *miles*		4.6***	6.2***	6.1***	8.5***	0.130	2,295,090
		(0.6)	(0.9)	(1.1)	(1.1)		
Buys of HHs ≤ 50 *miles** *Sociability above median*		−0.1	0.8	4.8***	3.7***		
		(0.6)	(0.7)	(0.7)	(0.5)		

This table presents results of stratifying households according to the sociability of the state to which the household belongs and the size of the population that resides within 50 miles of the household into eight categories and assessing information diffusion effects in neighborhoods of various sociability and size by running the following regression (a variant of Equation (2)):

$$f_{h,t,i} = \left(\beta\ F^{50}_{-h,t,i}\right) * Sociability\ and\ Population\ Interactions + \left(\sum_{t=1}^{23}\sum_{i=1}^{14}\gamma_{t,i}D_{t,i}\right) * Population\ Interactions + \varepsilon_{h,t,i}.$$

To capture sociability, we use state-level values of the Comprehensive Social Capital Index (available for all 50 states except Alaska and Hawaii), as collected and presented in Putnam (2000). We classify households according to their state's Comprehensive Social Capital Index and split the sample of households into sociable and nonsociable ones, where the breakpoint is the sociability measure of the median household in the sample. The four population categories are: 0–1 million, 1–2.5 million, 2.5–5 million, and more than 5 million residents. Regressions are estimated on subsamples selected by the type of purchase and presented in three panels accordingly (All Buys, Local Buys, and Nonlocal Buys). Panel A presents results based on the sample of all buys, whereas Panels B and C focus only on local and nonlocal buys, respectively. Each panel presents results of fitting two specifications. The first specification only features the sociability measure (without controls for the local population), whereas the second one is the full specification as outlined above. As in Table 2, Panel B, the coefficient estimates presented for a particular population group represents the overall information diffusion effect for that group (i.e., the sum of the diffusion effect for the 0–1 million group and the interaction term for that particular population group). Standard errors, shown in parentheses, allow for heteroskedasticity, as well as correlation of error terms at the household-quarter level.
***, **, * denote significance at the 1%, 5%, and 10%, respectively.

by their neighbors' investment choices because they wish to conform and keep pace with their neighbors' wealth and investment habits [Bernheim (1994), Campbell and Cochrane (1999), and Shore and White (2003)]. Moreover, to the extent that individuals choose their place of residence according to their preferences, and those tend to be correlated among the residents of the same geographic area, it is possible that similar tastes might govern investment decisions even without explicit communication with their neighbors. Finally, it is plausible that individual investors' own preferences are correlated over time; individuals might have an inclination to conform to some of their previous investment choices (e.g., favoring stocks from the same industry as they previously did).

To explore the effect of correlated preferences, we define two variables for each (h, t) observation. First, we define the industry composition of stock positions of neighboring households (excluding household h itself) at the end of quarter $t-1$. Second, we define the industry composition of stock positions of the household itself at the end of quarter $t-1$. The inclusion of these two position-related variables in the specification explicitly accounts for any underlying correlation in trading activity attributable to a similarity in preferences within a community that manifests itself in a similarity of stock purchases within the community or a similarity in an individual's own stock preferences over time. This approach requires merging purchases in quarter t with positions at the end of quarter $t-1$. Although there is substantial overlap between household identifiers for trades and positions in the database, the matching is imperfect and it allowed us to retain around two-thirds of the original observations used in previous analyses.

3.2.2 The structure of the local economy. Companies routinely seek to generate a certain presence in the local community. One immediate effect of such endeavors is investors' enhanced familiarity with local companies, generated through social interaction with employees and company efforts such as local advertising and sponsoring local events. Investors' propensity to invest in the companies (industries) they are familiar with, and perhaps even informed about, undoubtedly constitutes one important facet of information diffusion. Moreover, the local presence of a company may enhance the probability of circulation of very precise, inside information, an issue we addressed to a certain extent in Section 2.

To capture the impact of the structure of the local economy, we define variables that characterize the distribution of the local economy and local labor force across industries. Specifically, for each (h, t, i) observation we define two variables: the fraction of market value of publicly traded companies local to household h in quarter t in industry i and the fraction of the labor force local to household h in quarter t employed in industry i.[11]

Including these two variables should pick up both the effects that stem from familiarity with local companies and the potential direct company-stock effect. For example, if there are many employees working for construction companies in the area, a household's propensity to invest in construction firms could stem from word-of-mouth effects—social interaction between these employees and other households—or from those employees' propensity to invest in their own company stock (company-stock effects).

3.2.3 The results. The results of relating the industry composition of a household's investments to the neighborhood's preferences, the household's own preferences, and the structure of the local economy are presented in Table 5. Panel A has three sections, containing estimates for all buys, local buys, and nonlocal buys, respectively. Within each section, we first show the baseline result, which is aligned very closely with the corresponding baseline result in Table 2, Panel A.[12] The following row in each section shows the results with the two additional independent variables that capture preferences for industry allocation. Both variables are statistically significant, which suggests that households' purchases across industries are related to the common preferences that prevail in their neighborhoods, as well as their own revealed preferences (as described by their current stock positions). For example, the point estimates suggest that households entering the quarter with a stock portfolio fully concentrated in a particular industry allocate 31 to 48 percentage points more of their quarterly purchases to that same industry. The point estimate of β, interpreted as the information diffusion effect unrelated to such preferences (i.e., the word-of-mouth component), is equal to one-half of the magnitude of the estimated effect of the overall information diffusion for all buys and nonlocal buys, and to one-third for local buys.

The third row in each section of Panel A includes the variables that capture the structure of the local economy. Both local-economy variables are positively related to the allocation of household purchases across industries and are statistically significant, although they tend to attenuate the estimate of β to a much lesser degree than the two variables related to preferences. Whereas the effect of the structure of the local economy is

[11] Our measure of the industry composition of the local labor force is based on the composition of employees at publicly traded companies, which we obtain from COMPUSTAT. For the purpose of this analysis we assume that all the company's employees are employed in the same county in which the company headquarters is located. This is a somewhat imprecise measure, but, to our knowledge, more precise panel data regarding the geographic distribution of the employees for each company are not available.

[12] We attribute the small discrepancies between the point estimates (e.g., 19.9 in Table 5 vs. 20.7 in Table 2 for all buys) to the differing numbers of observations, that is, to the different samples employed in the respective analyses.

present for all the subsamples, the impact is by far the strongest for local buys. Specifically, a 10 percentage point change in the presence of a certain industry (as measured by firm values) is associated with a 4.7 percentage point change in the allocation of a local household's local purchases across industries. The impact of the industry-level structure of the local labor force is also noticeable (1.4 percentage point change), though it is not as strong. The higher correlations of the local economy variables with local buys could partially reflect company-stock issues, namely, the propensity to invest in a firm for which household members work (or have worked). On the other hand, the significant correlations of the local economy variables with nonlocal buys likely do not reflect this concern; instead, they likely reflect the notion that households' familiarity with local investment opportunities influences households' nonlocal investments as well.

The fourth row in each section features the results of relating the industry composition of a household's investments to both preferences (the neighborhood's and the household's own) and the structure of the local economy. Estimates of the effects of all the four variables are positive and statistically significant. Most importantly, the point estimate of β, interpreted as the information diffusion effect unrelated to either preferences or the structure of the local economy, approximately equals one-half of the magnitude of the estimated effect of the overall information diffusion for all buys and non-local buys, and one-third for local buys.[13]

The final analysis reported in Panel A of Table 5 seeks to capture differences among households along unobservable characteristics by running the baseline regression from Equation (2) with the inclusion of household-industry-level fixed effects. This is a very rigorous test because it presents a higher standard than the baseline specification: it relates the *change* in a household's allocation of purchases to an industry from its time series average allocation of purchases to the industry with the *change* in its neighborhood's allocation of purchases to the industry from the neighborhood's time series average allocation of purchases to the industry. For example, an investor who likes technology stocks may happen to live in an area in which others independently also happen to invest in technology stocks. Such a noncausal correlation would lead toward the detection of diffusion effects in a cross-sectional regression even if investors acted independently. By contrast, to identify diffusion effects in a panel regression requires that, in response to a change in community technology stock investment, the household should change its allocation to technology stocks in the same direction. Results in the last row of each

[13] This is a very robust estimate. Inspection of quarterly estimates (unreported for brevity) suggests that word-of-mouth communication accounts for 40 to 50% of the overall information diffusion effect (i.e., correlation of household stock purchases with that of their neighbors) in the vast majority of quarters, with a range of 21 to 56%.

section in Panel A suggest that information diffusion effects remain strong in the household fixed-effects framework, especially for local buys (3.6 for all buys; 17.7 for local buys; 2.4 for nonlocal buys), though the magnitudes are substantially reduced compared to the cross-sectional analyses.

The extent to which households' portfolios conform to those of their neighbors can serve as a proxy for identifying households whose purchasing decisions are driven to varying degrees by the desire to adhere (inadvertently or not) to the preferences and common news prevailing in their neighborhood. For example, if a household shared the investment preferences with its neighborhood and responded to news similarly to the way its neighborhood did, over time its portfolio composition would be very similar to that of its community.

We sort households into two types according to the extent to which their household portfolio allocations at the industry level conform to those of their neighbors; the metric we use is the average absolute deviation in industry portfolio shares between a household and its neighborhood. Results in Panels B and C of Table 5 suggest that, whereas initially there are substantial differences in information diffusion effects (i.e., coefficients associated with the composition of buys of neighboring households) across the two groups, once the variables that capture preferences and the structure of the local economy are included in the regression, the estimated coefficient β (i.e., the relation between a household's purchases and its neighbors' purchases) becomes fairly similar across the two types of investors. Specifically, the β for local (nonlocal) buys across the two groups of investors are 46.2 and 29.4 (3.9 and 2.9), respectively, and are no longer significantly different at the 1% level. This suggests that the two positions-related variables indeed are successful in capturing the effect of common preferences because, once they are included in the specification, the remaining information diffusion effect, which we attribute to word-of-mouth communication, is very comparable across investors who have stock portfolios very similar to their neighbors and those whose portfolios are quite different from their neighbors'.

3.3 Unifying the two approaches to information diffusion effect attribution

The previous two sections each approached the task of assessing the contribution of word-of-mouth effects to the overall correlation between individual and community stock purchases from a different angle. Remarkably, the estimates of that contribution qualitatively are in close agreement: across all specifications, word-of-mouth effects account for about one-quarter to one-half of the overall diffusion effect.

In unreported results, we fit a specification that unites the two approaches: coefficients from the full specification from the previous section (including the neighborhoods' purchases, neighborhoods' positions, household positions, structure of local firms' market value, and structure of the local labor force) are interacted with the dummy variable capturing neighborhoods' sociability used in Section 3.1. For the subsample of all buys, for example, the coefficient associated with buys of neighboring households from Table 5, 9.0, translates into 6.1 among households located in less sociable neighborhoods and 11.2 among households located in more sociable neighborhoods.

There also is a stark contrast between the impact of area sociability on the coefficients associated with the structure of local firm market value (as defined by the share of market capitalization of local firms across the 14 industries) and those associated with the structure of the local labor force (as defined by the share of employees across the 14 industries in the area). Whereas high area sociability reduces the importance of the share of local firm market value in a particular industry on household investment choice, it increases the influence of the fraction of local employees in a particular industry. Among households in less sociable states, the fraction of local firm market value in a particular industry is a more important predictor of the fraction of a household's stock purchases in that same industry than the local employee share is. However, among households in more sociable states, the fraction of local firm market value in a particular industry is uncorrelated with the fraction of a household's stock purchases in that same industry, whereas the industry-composition of local workers has increased importance over household stock picks. These findings further suggest that the state-level measure of sociability we employ is useful in isolating the word-of-mouth effect on investment decisions.

3.4 Do lagged purchases in one neighborhood predict purchases in another neighborhood?

In our final analysis, we explore whether lagged purchases in one neighborhood predict the purchases in another neighborhood. Up to this point, we focused primarily on relating household investment decisions to those made by their immediate neighbors. Figure 1 shows that purchases made by a household are related not only to those made in the immediate community but also, to some extent, to those made in more distant communities. However, as one might suspect, and as is confirmed in Figure 1, a household's purchases of nonlocal stocks are more sensitive to the decisions made by members of more distant communities than its purchases of local stocks are. That is, going beyond the 50-mile community leads to a substantially faster decline in information diffusion effects in the domain of local stocks than in the domain of nonlocal stocks. Simply put, households are relatively less likely to be influenced by nonlocals when making their local stock picks.

Table 5
Information diffusion, correlated preferences for industry allocation, and structure of local economy

	Composition of						
Buys	Buys of HHs ≤ 50 miles	Positions of HHs ≤ 50 miles	Positions of this HH	Firms ≤ 50 miles	Workers ≤ 50 miles	R^2	# obs.
Panel A: All households							
All	19.9***					0.134	1,786,666
	(0.4)						
All	9.8***	16.5***	32.5***			0.204	1,786,666
	(0.4)	(0.5)	(0.2)				
All	17.4***			4.8***	4.0***	0.135	1,786,666
	(0.4)			(0.3)	(0.3)		
All	9.0***	14.5***	32.4***	1.9***	2.7***	0.204	1,786,666
	(0.4)	(0.6)	(0.2)	(0.3)	(0.3)		
All (HH-industry fixed effects)	3.6***					0.323	1,786,666
	(0.5)						
Local	128.9***					0.249	265,509
	(1.7)						
Local	43.6***	58.8***	47.5***			0.417	265,509
	(1.7)	(2.3)	(0.5)				
Local	85.1***			46.9***	14.2***	0.276	265,509
	(1.8)			(1.4)	(1.3)		
Local	36.8***	40.1***	46.2***	18.1***	5.6***	0.421	265,509
	(1.7)	(2.4)	(0.5)	(1.2)	(1.1)		
Local (HH-industry fixed effects)	17.7***					0.577	265,509
	(2.5)						
Nonlocal	7.4***					0.121	1,510,390
	(0.4)						
Nonlocal	3.7***	7.2***	31.2***			0.186	1,510,390
	(0.4)	(0.6)	(0.2)				
Nonlocal	7.0***			0.7***	1.0***	0.121	1,510,390
	(0.4)			(0.3)	(0.3)		
Nonlocal	3.6***	7.0***	31.2***	−0.1	0.8***	0.186	1,510,390
	(0.4)	(0.6)	(0.2)	(0.3)	(0.3)		
Nonlocal (HH-industry fixed effects)	2.4***					0.305	1,510,390
	(0.5)						
Panel B: Similar HH Portfolios (Average Absolute Deviation in Industry Positions from HHs within 50 miles is in *Bottom* Quartile)							
All	30.0***					0.205	446,670
	(0.8)						
All	10.3***	17.5***	35.9***			0.245	446,670
	(0.8)	(1.3)	(0.5)				
All	9.5***	15.5***	35.7***	2.1***	2.0***	0.245	446,670
	(0.8)	(1.3)	(0.5)	(0.6)	(0.6)		
Local	148.6***					0.543	66,390
	(4.2)						
Local+	53.7***	66.8***	40.1***			0.586	66,390
	(4.8)	(6.4)	(1.7)				
Local+	46.2***	53.3***	39.2***	1.6	16.6***	0.587	66,390
	(4.8)	(6.9)	(1.7)	(3.3)	(2.8)		
Nonlocal	14.9***					0.173	377,608
	(0.8)						
Nonlocal+	3.9***	9.2***	33.6***			0.207	377,608
	(0.8)	(1.3)	(0.5)				

Table 5
(continued)

	Composition of						
Buys	Buys of HHs ≤ 50 miles	Positions of HHs ≤ 50 miles	Positions of this HH	Firms ≤ 50 miles	Workers ≤ 50 miles	R^2	# obs.
Nonlocal+	3.9***	9.1***	33.6***	0.3	0.0	0.207	377,608
	(0.8)	(1.3)	(0.5)	(0.6)	(0.6)		
Panel C: Disparate HH Portfolios (Average Absolute Deviation in Industry Positions from HHs within 50 miles is in Top Quartile)							
All	4.5***					0.067	446,670
	(0.7)						
All	6.4***	7.2***	27.8***			0.143	446,670
	(0.7)	(0.9)	(0.3)				
All	5.7***	5.7***	27.8***	2.2***	2.0***	0.143	446,670
	(0.7)	(0.9)	(0.3)	(0.5)	(0.5)		
Local	60.6***					0.064	66,390
	(3.2)						
Local+	40.6***	52.4***	45.7***			0.265	66,390
	(3.1)	(4.1)	(0.7)				
Local+	29.4***	29.1***	43.9***	30.0***	3.4	0.275	66,390
	(3.0)	(4.0)	(0.8)	(2.2)	(2.3)		
Nonlocal	0.1					0.063	377,608
	(0.7)						
Nonlocal+	3.1***	2.3***	27.1***			0.135	377,608
	(0.7)	(0.9)	(0.3)				
Nonlocal+	2.9***	2.0**	27.1***	0.1	0.8	0.135	377,608
	(0.7)	(0.9)	(0.3)	(0.5)	(0.6)		

This table presents results of assessing the contribution of word-of-mouth effects to the overall information diffusion effect (i.e., correlation of household stock purchases with those made by of their neighbors). Accordingly, we regress households' industry-level purchases on neighbors' purchases, variables capturing correlated preferences for industry allocation, variables capturing the structure of the local economy, and 322 industry-time dummy variables (a variant of Equation (2)). Two variables for each (h, t) observation are used to capture correlated preferences. First, we define the industry composition of stock positions of neighboring households (excluding household h itself) at the end of quarter $t-1$. Second, we define the industry composition of stock positions of the household itself at the end of quarter $t-1$. To capture the impact of the structure of the local economy, for each (h, t, i) observation we define two variables: the fraction of market value of companies local to household h in quarter t in industry i and the fraction of the labor force local to household h in quarter t employed in industry i. In this framework, estimates of β are conservative lower bounds on the contribution of word-of-mouth effects to the overall information diffusion effect. Panel A has three sections, containing estimates for all buys, local buys, and nonlocal buys, respectively. Within each section, we first show the baseline result (i.e., Equation (2)). The following row in each section shows the results with the two additional independent variables that seek to capture preferences for industry allocation. The third row in each section of Panel A includes the variables that capture the structure of the local economy. The fourth row in each section features the results of relating the industry composition of a household's investments to both preferences (the neighborhood's and own) and the structure of the local economy. The final analysis, reported in the fifth row in each section, seeks to capture differences among households along unobservable characteristics by running the baseline regression from Equation (2) with the inclusion of household-industry-level fixed effects. Panels B and C show results of replicating the key analyses from Panel A on two subsamples of households. Specifically, we sort households into two types according to the extent to which their household portfolio allocations at the industry level conform to those of their neighbors; the metric we use is the average absolute deviation in industry portfolio shares between a household and its neighborhood. Standard errors, shown in parentheses, allow for heteroskedasticity, as well as correlation of error terms at the household-quarter level.

***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

+ denotes that the difference in coefficients across the similar and disparate samples is not significant at the one percent level.

Thus, a natural place to look for dissemination of information across communities is in a household's purchase of nonlocal stocks. In particular, do the financial decisions of nearby households have less of an effect over time, whereas the decisions made by more distant households have increasing influence over time? To examine this issue, we use the same 150-mile area surrounding a given household we employed to produce the results in Figure 1. We relate the composition of a household's quarterly purchases of nonlocal stocks across industries to the contemporaneous purchases and prior purchases (with a one-quarter and two-quarter lag) made by the households in the immediate 50-mile neighborhood as well as those located 50–150 miles away (for simplicity, we divide these more distant households into two rings of equal area around the immediate 50-mile community).

Figure 2 illustrates information diffusion effects across distance from the household and time since purchase. Whereas the effects of the immediate 50-mile community and the households contained in the first ring surrounding the immediate community decline monotonically over time, the influence of the purchases made by the households contained in the second ring (the area farthest from the household) actually increase over time. In other words, whereas the contemporaneous purchases made by a household's closest neighbors have a larger impact on one's own

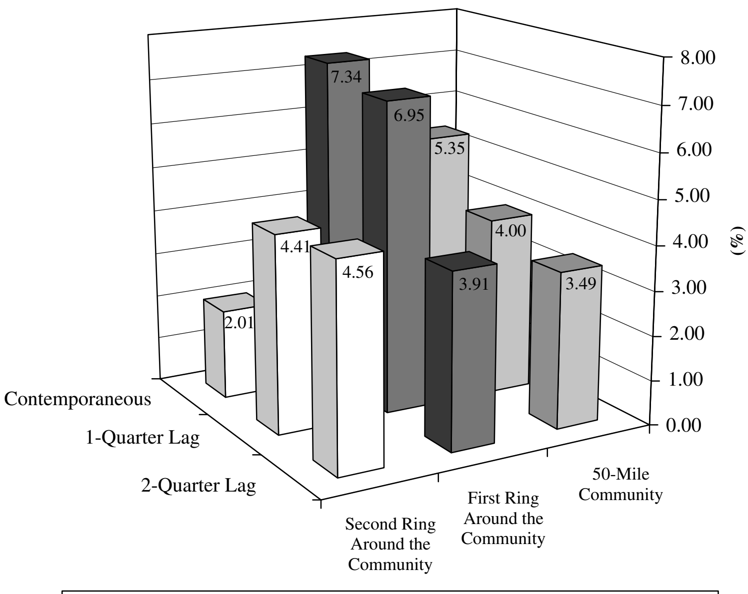

Figure 2
Information diffusion effects associated with investments in nonlocal stocks those made by time and space.

purchases than the decisions made by those neighbors one or two quarters ago, the reverse is true for the effect of more distant households' investment choices on a given household—the purchases made by the more distant households one and two quarters ago have a larger effect on a given household's purchases *this* quarter than those made by the households from distant communities contemporaneously. Indeed, our unreported tests suggest that the difference *over time* in the information diffusion effects of both the immediate 50-mile community and the first ring are statistically different from those of the more distant second ring.[14]

To be clear, a household's immediate neighbors always have a bigger influence on its purchases than distant neighbors do (whether measured contemporaneously, with a one-quarter lag, or with a two-quarter lag). However, the *pattern* of information diffusion effects across time and space is broadly consistent with a gradual dissemination of information from one community to another.

The Figure illustrates information diffusion effects by distance from the household and time since purchase. The regression specification underlying the Figure is similar to Equation (2). However, instead of focusing only on contemporaneous purchases made by other households within 50 miles, we now relate the composition of a given household's purchases not only to those made by other households within 50 miles but also to those located 50–150 miles away (for simplicity, divided into two rings of equal area around the immediate 50-mile community). The regression specification allows purchases made by surrounding communities to affect a given household's purchase of nonlocal stocks contemporaneously, with a one-quarter lag, and with a two-quarter lag.

[14] The regression specification underlying the results displayed in Figure 2 is similar to Equation (2). However, instead of focusing only on contemporaneous purchases made by other households within 50 miles, we now relate the composition of a given household's purchases not only to those made by other households within 50 miles but also to those located 50–150 miles away (for simplicity, divided into two rings of equal area around the immediate 50-mile community). The regression specification allows purchases made by surrounding communities to affect a given household's purchase of nonlocal stocks contemporaneously, with a one-quarter lag, and with a two-quarter lag:

$$\begin{aligned} f_{h,t,i} = {} & \beta_{50,Contemporaneous}\, F^{50}_{-h,t,i} + \beta_{50,\,1-quarter\ lag}\, F^{50}_{-h,t-1,i} + \beta_{50,\,2-quarter\ lag}\, F^{50}_{-h,t-2,i} \\ & + \beta_{1st\ Ring,Contemporaneous}\, F^{1st\ Ring}_{-h,t,i} + \beta_{1st\ Ring,1-quarter\ lag}\, F^{1st\ Ring}_{-h,t-1,i} \\ & + \beta_{1st\ Ring,2-quarter\ lag}\, F^{1st\ Ring}_{-h,t-2,i} + \beta_{2nd\ Ring,Contemporaneous}\, F^{2nd\ Ring}_{-h,t,i} \\ & + \beta_{2nd\ Ring,1-quarter\ lag}\, F^{2nd\ Ring}_{-h,t-1,i} + \beta_{2nd\ Ring,2-quarter\ lag}\, F^{2nd\ Ring}_{-h,t-2,i} \\ & + \sum_{t=1}^{23} \sum_{i=1}^{14} \gamma_{t,i} D_{t,i} + \varepsilon_{h,t,i}. \end{aligned} \tag{3}$$

4. Conclusion

We focus on the relation between the investment choices made by an individual investor's neighborhood (households located within 50 miles from the investor) and the investor's own investment choices. Using a detailed set of common-stock investments that nearly 36,000 households made in the period from 1991 to 1996, we find strong evidence of information diffusion: baseline estimates suggest that a ten percentage-point increase in purchases of stocks from an industry made by a household's neighbors is associated with a two percentage point increase in the household's own purchases of stocks from that industry, with the effect larger for local stock purchases.

The findings are robust to controls for inside information effects, domination of a single company (industry) in the neighborhood, and household fixed effects. In sum, there is strong evidence that individuals' stock purchase decisions are related to those made by their neighbors. The strength of the information diffusion effect is considerable; for example, investors in more populous areas, where, on average, there are many more local investment choices, still are very concentrated in their purchases. To the extent that their investment choices are related to their neighbors', the information diffusion effect is likely at least partially responsible for individual investors' lack of diversification.

Putting our results in perspective and comparing them with the findings from Feng and Seasholes (2004) delivers a new, richer understanding of the different mechanisms that govern individuals' investment decisions across various societies. Whereas Feng and Seasholes (2004) report that individual investors' correlated investment decisions are driven by common reaction to locally available news, with no evidence of word-of-mouth effects among Chinese investors, our estimates suggest that word-of-mouth effects among U.S. individual investors are strong, particularly in the more social areas. This discrepancy likely reflects differences in civil liberties and in the extent of presence of open and free discussion across the two societies. Exploring the role of societal characteristics in portfolio decisions appears to be a fruitful area for further research.

Our results, in conjunction with those of Hong, Kubik, and Stein (2005), suggest that word-of-mouth effects are a broad phenomenon that affects financial decisions made by both mutual fund managers and individual investors. Because word-of-mouth effects may create a dynamic exchange of information that could lead to a ripple effect of further information dissemination, which in turn may have an impact on stock prices, understanding the interplay between individual and institutional trading across time and space might yield insights into price dynamics in the stock market.

References

Banerjee, A., 1992, "A Simple Model of Herd Behavior," *Quarterly Journal of Economics*, 107, 797–817.

Barber, B., and T. Odean, 2000, "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance*, 55, 773–806.

Barber, B., and T. Odean, 2007, "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors," *Review of Financial Studies*, forthcoming.

Barber, B., T. Odean, and N. Zhu, 2006, "Systematic Noise," Working paper, UC Davis and UC Berkeley.

Bernheim, B. D., 1994, "A Theory of Conformity," *Journal of Political Economy*, 102, 841–877.

Campbell, J. Y., and J. H. Cochrane, 1999, "By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior," *Journal of Political Economy*, 107, 205–251.

Coval, J. D., and T. J. Moskowitz, 1999, "Home Bias at Home: Local Equity Preference in Domestic Portfolios," *Journal of Finance*, 54, 1–39.

Coval, J. D., and T. J. Moskowitz, 2001, "The Geography of Investment: Informed Trading and Asset Prices," *Journal of Political Economy*, 109, 811–841.

Duflo, E., and E. Saez, 2002, "Participation and Investment Decisions in a Retirement Plan: The Influence of Colleagues' Choices," *Journal of Public Economics*, 85, 121–148.

Duflo, E., and E. Saez, 2003, "The Role of Information and Social Interactions in Retirement Plan Decisions: Evidence from a Randomized Experiment," *The Quarterly Journal of Public Economics*, 118, 815–842.

Ellison, G., and D. Fudenberg, 1993, "Rules of Thumb for Social Learning," *Journal of Political Economy*, 101, 93–126.

Ellison, G., and D. Fudenberg, 1995, "Word of Mouth Communication and Social Learning," *Quarterly Journal of Economics*, 110, 93–125.

Feng, F., and M. Seasholes, 2004, "Correlated Trading and Location," *Journal of Finance*, 59, 2117–2144.

Freedom House, 2004, "Freedom in the World Country Ratings," available at http://www.freedomhouse.org/ratings/allscore04.xls.

Grinblatt, M., and M. Keloharju, 2001, "How Distance, Language, and Culture Influence Stockholdings and Trades," *Journal of Finance*, 56, 1053–1073.

Hong, H., J. D. Kubik, and J. C. Stein, 2004, "Social Interaction and Stock-Market Participation," *Journal of Finance*, 59, 137–163.

Hong, H., J. D. Kubik, and J. C. Stein, 2005, Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers," *Journal of Finance*, 60, 2801–2824.

Ivković, Z., J. Poterba, and S. Weisbenner, 2005, "Tax-Motivated Trading by Individual Investors," *American Economic Review*, 95, 1605–1630.

Ivković, Z., and S. Weisbenner, 2005, "Local Does as Local is: Information Content of the Geography of Individual Investors' Common Stock Investments," *Journal of Finance*, 60, 267–306.

Massa, M., and A. Simonov, 2006, "Hedging, Familiarity and Portfolio Choice," *Review of Financial Studies*, 19, 633–685.

Odean, T., 1998, "Are Investors Reluctant to Realize their Losses?" *Journal of Finance*, 53, 1775–1798.

Putnam, R. D., 2000, *Bowling Alone: The Collapse and Revival of American Community*, Simon and Schuster, New York.

Shore, S. H., and J. White, 2003, "External Habit Formation and the Home Bias Puzzle," Working Paper, Harvard University.

U.S. Census Bureau, 1990, Gazetteer Place and Zip Code Database.

Zhu, N., 2002, "The Local Bias of Individual Investors," Working paper, Yale School of Management.