THE RATE OF COMMUNICATION

Shiyang Huang, Byoung-Hyoun Hwang and Dong Lou*

This Draft: July 2020

We study the transmission of financial news and opinions through social interactions. We identify a series of plausibly exogenous shocks, which cause "treated investors" to trade abnormally. We then trace the "contagion" of abnormal trading activity from the treated investors to their neighbors and their neighbors' neighbors. Coupled with methodology drawn from epidemiology, our setting allows us to estimate the rate of communication and how much such rate varies with characteristics of the underlying investor population.

JEL Classification: G11, G12, G14, G20.

Keywords: Social Interaction, Investor Communication, Information Diffusion.

---

* Huang is affiliated with the Faculty of Business and Economics (HKU Business School), The University of Hong Kong, Hong Kong. Hwang is primarily affiliated with the Cornell SC Johnson College of Business, Dyson School of Applied Economics and Management, Cornell University, Warren Hall 310E, Ithaca, NY 14853, USA; Hwang is also with the Korea University Business School, Korea University, Anam-dong, Seongbuk-gu, Seoul, Korea 136-701. Lou is affiliated with the London School of Economics, Houghton Street, London WC2A 2AE, UK; Lou is also affiliated with the CEPR. E-mail: huangsy@hku.hk, bhwang@cornell.edu and d.lou@lse.ac.uk. For helpful comments and suggestions, the authors would like to thank Snehal Banerjee, Nick Barberis, Justin Birru, John Campbell, James Choi, Daniel Ferreira, Bing Han, David Hirshleifer, Dirk Jenter, Matti Keloharju, Ralph Koijen, Ulrike Malmendier, Daniel Paravisini, Lasse Pedersen, Ville Rantala, Scott Yonker, Qiping Xu, and seminar participants at University of Amsterdam, the Chinese University of Hong Kong (Shatin), the Chinese University of Hong Kong (Shenzhen), Copenhagen Business School, Cornell University, the University of Geneva, the University of Hong Kong, Hong Kong University of Science and Technology, the Imperial College Business School, the London School of Economics, the National University of Singapore, Purdue University, the Renmin University Business School, the Rotterdam School of Management, the Shanghai Advanced Institute of Finance, Singapore Management University, Tilburg University, the Toulouse School of Economics, the University of London Birkbeck, Zhejiang University, and participants at the London Empirical Asset Pricing Meeting, the China International Conference in Finance, the Helsinki Finance Summit, the Miami Behavioral Finance Conference, and the American Finance Association Annual Meeting. We are grateful for funding from the Paul Woolley Center at the London School of Economics and to Hong Xiang for excellent research assistance.

1. Introduction

People do not operate in a vacuum; instead, they interact with one another constantly. On the upside, such social interactions ensure that we are privy to the latest news, ideas, and opinions. On the downside, they expose us to the spread of noise or even misinformation. While the theme of contagion and diffusion has been examined by many disciplines (e.g., Berger, 2014, 2016; Jackson, 2014, 2019), there is likely no field that has looked at this subject more extensively than the field of epidemiology.[1] The goal of this study is to draw from the epidemiology literature and to estimate the "effective transmission rate" of financial news and opinion and to assess how much such rate varies with investor characteristics.

The ideal experiment with which to address our research question would be to randomly seed pieces of information among investors and then track their diffusion through the investors' respective networks. Our empirical design draws inspiration from this ideal. In particular, we consider a series of cross-industry stock-financed mergers and acquisitions (M&As). At the completion of each cross-industry stock-financed M&A, investors in the target firm, residing in some industry x, receive shares of the acquirer firm, residing in some industry y. We conjecture that the endowment of shares from the acquirer industry leads at least some of the affected investors to form opinions about the acquirer industry and to start trading firms in the acquirer industry (aside from the acquirer firm itself). If such "target investors" communicate their newly gained industry perspectives to other investors in their neighborhood, we may observe abnormal trading activity in the acquirer industry not only by target investors but also by their neighbors and their neighbors' neighbors. Tracing the contagion of abnormal trading activity in the acquirer industry thus enables us to estimate the degree to which financial information spreads through social interactions and the extent to which such "effective transmission rate" varies with characteristics of the sender of financial information and her receivers.

To implement our empirical tests, we combine detailed trading records of about 70,000 US households from a discount brokerage from 1991 through 1996 with data on all cross-industry M&As that

[1] See, for example, Keeling and Grenfell (2000), Heesterbeek (2002), Heffernan, Smith, and Wahl (2005), and Delamater, Street, Leslie, Yang, and Jacobsen (2019).

occurred over the same time period. We separate cross-industry M&As into those that are stock-financed and those that are cash-financed: we define the former as deals that are at least partially equity-financed; the latter comprise deals that are 100% cash-financed. In cash-financed M&As, target investors receive cash as opposed to shares in the acquirer firm and, as such, are less incentivized to study the corresponding acquirer industry. Cash-financed M&As thus serve as our placebo.

To gauge the validity of our empirical design, we first conduct a simple difference-in-differences analysis to see how much more intensely target investors trade in the acquirer industry in the post-M&A period (excluding trading activity in the acquirer firm itself). We repeat the above difference-in-differences analysis for "target neighbors"; target neighbors are non-target retail investors who reside within three miles of a target investor.

Our results reveal that in the year following the completion of a cross-industry stock-financed M&A, target investors, compared with other investors, more than double the number of trades they execute in the corresponding acquirer industry. This abnormal trading activity in the acquirer industry dies out within two years.

Consistent with the presence of contagion, we find that target neighbors also trade substantially more actively in the acquirer industry compared with investors who do not live within three miles of a target investor. Target investors and target neighbors tend to trade in the same direction; that is, if a target investor is buying in the acquirer industry, so are her neighbors. Consistent with "word of mouth" playing a role in generating our results, our effect becomes statistically and economically weaker the further away an investor resides from a target investor.

In a placebo test to help rule out alternative interpretations, we find that our effect disappears when we consider cash-financed M&As. Moreover, inconsistent with a simple local attention story, we observe little abnormal trading activity when a stock-financed M&A is first announced. Instead, abnormal trading activity accrues only after target investors receive shares of the acquirer firm.

Our main analysis builds on the above findings and utilizes methodology drawn from the epidemiology literature to estimate an analog of the reproduction number; the reproduction number is the average number of new infections generated by a single infective. We hereafter refer to this analog as the rate of communication, or, simply, the communication rate. We also estimate how much the communication rate varies with characteristics of the underlying investor population, including age, income, gender, past investment performances, and measures of lifestyle and state of residence.

Our estimate of the overall communication rate is 0.32 with a 95% confidence interval of 0.17 to 0.46. In other words, one "infected" investor, on average, "infects" 0.32 of her neighbors.[2] As we discuss in Section 2.1, an outbreak will fade if the reproduction number falls below one; a disease will continue to spread and grow if the number is above one. Our communication rate of 0.32 thus suggests that while the transmission of financial information through social interactions is significant, it eventually dies out on its own without intervention, at least in our setting. To put this number in perspective, Cao et al. (2020) estimate that the effective reproduction number of COVID-19 in China during the onset of its outbreak (December 2019–January 2020) was 4.08 with a 95% confidence interval of 3.37 to 4.77.

A key difference between the transmission of a pathogen and the transmission of an idea is that the latter occurs voluntarily. That is, for an idea to transmit, a mere interaction between two individuals is not sufficient. The sender of the information must be motivated to share the idea. The receiver must be willing to listen and consider the idea interesting and credible enough to absorb and act on such idea. This line of thinking forms the basis for our analysis of how much the communication rate varies with characteristics of the underlying investor population.

Our first set of determinants is motived by the homophily literature. The homophily literature notes that people prefer to interact with people of similar backgrounds. They are also more likely to trust information received from such individuals (Lazarsfeld and Merton, 1954; McPherson, Smith-Lovin, and Cook, 2001). Transmissions are thus substantially stronger between people with similar backgrounds (Jackson, 2019).

---

[2] We obtain this estimate when measuring trading activity in the acquirer industry through the number of trades placed in the acquirer industry. All estimates reported in the introduction are based on the number of trades. As we discuss in the main body of the text, the estimates are similar when considering the dollar value of trades.

Consistent with this perspective, we find that the transmission of an investment idea is strongest when there are few differences in age, income, or gender between the sender of financial information and her receiver. While our estimate of the overall communication rate is 0.32, we find that the communication rate between investors of the same age, the same income category, and the same gender rises to 0.47 with a 95% confidence interval of 0.29 to 0.65. When comparing the relative importance of differences in age, income, and gender in slowing down transmission, we find that a ten-year age gap, a one-category difference in income, and being of an alternate gender lowers the communication rate by 9%, 3%, and 12%, respectively. That is, in the investment context, differences in age and gender represent higher barriers to transmission than differences in income.[3]

A key strength of our setting is that we can pinpoint the sender of financial information and her corresponding receivers. We use this feature to uncover notable asymmetries. In particular, our results suggest that while transmissions are strongest among investors of similar age, gender and income, relatively speaking, transmission from older, high-income, female investors to younger, low-income, male investors is stronger than transmission in the reverse direction. One possible explanation for these asymmetries is that investors perceive information conveyed by older, wealthier, female investors as more credible and, thus, are more likely to act on any views transmitted by such investors.

Our second set of determinants relate to investors' past investment performances. The psychology literature finds that people are more likely to share a story and others are more likely to listen if such a story helps receivers re-access positive emotional experiences. That is, people are more likely to converse about a story if the story invokes pleasant memories (Lovett, Peres, and Shachar, 2013; Berger, 2014, 2016). Consistent with this view, Kaustia and Knüpfer (2012), Heimer and Simon (2015), and Escobar and Pedraza (2019) find evidence that investors more frequently share stories of investment success than stories of investment failure. Han, Hirshleifer, and Walden (2020) model the implications of agents' preference for sharing successes over failures.

[3] Our data vendor uses nine income categories based on the following cutoffs: $15,000; $20,000; $30,000; $40,000; $50,000; $75,000; $100,000; and $125,000. A one-category difference in annual income therefore represents a sizeable income difference.

In our particular setting, we conjecture that the communication rate is a function not only of the sender's past investment performance but also of that of the receiver. If receivers have suffered recent investment failures, they are unlikely to entertain a conversation about investment-related topics and, consequently, act on any ideas so transmitted.

In line with this view, we find that the communication rate is the highest, 0.44, when both the sender's and the receiver's recent portfolio performances are above the sample median. If the sender's recent portfolio performance is above the median, yet the receiver's performance is below the median, the communication rate drops by 16% to 0.37. The communication rate is the lowest, 0.29, when both the sender's and the receiver's portfolio performances are below the sample median. Comparing these figures with those based on differences in investors' socioeconomic backgrounds, we can infer that recent investment performances are a stronger determinant of the rate of communication than differences in socioeconomic backgrounds.

Our third and final set of determinants captures similarities (or differences) in lifestyle and state of residence. In short, we find that the communication rate is highest when the sender and the receiver lead a similar lifestyle as approximated through common ownership of unique vehicles (truck, recreational vehicle (RV), motorcycle). Moreover, the communication rate is highest in states for which survey evidence indicates that people spend more time visiting friends (Putnam, 2000).

2. Literature Review and Contribution

Our paper builds on two streams of research: the medical science literature that studies the reproduction number of various diseases and the finance literature providing evidence of the presence of word-of-mouth effects in financial markets.

2.1 The Transmission of a Pathogen

The reproduction number is one of the most fundamental and most frequently examined metrics in epidemiology (e.g., Keeling and Grenfell, 2000; Heesterbeek, 2002; Heffernan, Smith, and Wahl, 2005;

Delamater, Street, Leslie, Yang, and Jacobsen, 2019). The reproduction number is the mean number of infections generated by a single infective. The *basic* reproduction number is the reproduction number when there is no immunity in the population; it describes the maximum epidemic potential of a disease. The *effective* reproduction number is the reproduction number when there is some immunity in the population through either prior exposure or vaccination.

The reproduction number is used to describe the intensity of an outbreak and to gauge its potential size (Heffernan, Smith, and Wahl, 2005). It is also used to estimate the proportion of the population that needs to be vaccinated to contain an epidemic (Anderson and May, 1982, 1985). When no vaccine exists, it is a crucial component in public health planning (Doucleff, 2014; Flaxman et al., 2020).

The reproduction number is naturally a function of the pathogen (e.g., how infectious it is). It is also a function of the host population and the environment (e.g., population density, age distribution, and overall level of hygiene). As a result, even for a given disease there is never a single reproduction number. By its very nature, the reproduction number varies with both time and locale. Such variation is exacerbated by the fact that any true reproduction number has to be estimated (Delamater, Street, Leslie, Yang, and Jacobsen, 2019).

Not surprisingly, even for a given disease, the estimated reproduction numbers reported in the literature vary widely. For instance, in a survey of the literature, Anderson (1982) finds that the reported basic reproduction numbers for measles range from 5.4 through 18. Guerra, Bolotin, Lim, Heffernan, Deeks, Li, and Crowcroft (2017) note an even wider range of feasible reproduction numbers, going from 3.7 through 203.3.

In spite of, or perhaps as a result of, the above challenges, and given the importance of reproduction numbers, a substantial body of work attempts to estimate the reproduction numbers of various pathogens and quantify how much they vary with characteristics of the host and the environment (e.g., Keeling and Grenfell, 2000; Heesterbeek, 2002; Heffernan, Smith, and Wahl, 2005; Guerra, Bolotin, Lim, Heffernan, Deeks, Li, and Crowcroft, 2017).

2.2 Word-of-Mouth Effects in Financial Markets

The concept of contagion has begun to also spark the curiosity of researchers in finance, accompanied by calls "to move from behavioral finance to social finance" (Hirshleifer, 2020 AFA Presidential Address) and to exert greater research effort toward better understanding "the epidemiology of narratives" (Shiller, 2017 AEA Presidential Address).

Shiller and Pound (1989) are perhaps the first to consider the transmission of financial information through social interactions. Shiller and Pound conduct surveys of both retail investors and institutional investors. They conclude that, in general, investors do not derive investment ideas by themselves. Rather, they are drawn to stocks through conversations with their peers.

Evidence in subsequent work supports the notion that transmission of investment ideas through social interactions is both frequent and important. Hong, Kubik, and Stein (2005) find that a fund manager purchases more of a stock when other managers from different fund families in the same city increase their purchases of the same stock. Ivković and Weisbenner (2007) find that the above positive correlation in trading behavior between neighbors extends to retail investors. Hvide and Östberg (2015) utilize micro data, which allow them to identify coworkers at the plant level, and they find that an increase in the fraction of coworkers who make a stock purchase in a given month increases the probability that a worker makes a stock purchase herself.

Our study builds on the above literature. The key distinction is that we identify a series of plausibly exogenous shocks that cause "treated investors" to trade abnormally. We then dynamically trace the percolation of abnormal trading activity through treated investors' social networks. Our approach allows us to provide an actual estimate of the rate of communication between investors. It also allows us to quantify how much this rate varies with investors' socioeconomic backgrounds, recent investment performances, and lifestyles. Metaphorically speaking, while prior literature provides evidence that "people can get sick from each other," to the best of our knowledge our paper is the first to actually provide an estimate of the "contagion rate" and for how much such rate varies with characteristics of the host population. Our estimates can help inform theory; they can also help guide the design of public policy and information campaigns. Of course, estimating the rate of communication is not without its challenges and is subject to various caveats. We discuss these challenges and caveats in Sections 3 and 5.

3. Data

3.1 Data Sources and Descriptive Statistics

We obtain detailed investor-trading records for a subsample of US households for the 1991–1996 period from a discount brokerage firm. These are the same records used by Odean (1998) and Barber and Odean (2001), among others.[4] The brokerage database contains zip code information, which enables us to compute the distance between two investors using the longitude and latitude associated with each zip code, adjusted for curvature.[5] We augment our data with information from the US Census Bureau's zip code database, which, among other things, includes the population and average household income for each zip code.

We match our investor-trading records with data on all M&As that take place from 1991 through 1996. In constructing our M&A sample, we follow the procedure laid out in Mitchell and Pulvino (2001). We require that the acquirer and target firms reside in separate industries. Industries are defined based on the Fama-French 49-industry classification. Using alternative industry classifications, such as the Fama-French 38- or 30-industry classifications or the Global Industry Classification Standard Groups, does not change the main results of the paper (results available upon request). We exclude M&As for which we cannot identify the acquirer or the target industry. We separate M&A deals into those that are stock-financed and those that are cash-financed: we define the former as deals that are at least partially equity-financed; the latter are 100% cash-financed.

Our final sample contains 459 M&As executed from 1991 through 1996, of which 316 are stock-financed and 143 are cash-financed. In Panel A of Table 1, we report summary statistics for these M&A deals. For stock-financed M&As, the median acquirer-market capitalization is $952 million and the median

[4] In our data, one household can have multiple accounts. We conduct our analyses at the household level; that is, we aggregate all accounts held by the same household into one observation. Henceforth, we use the terms "households" and "investors" interchangeably.

[5] The formula is: distance = $\arccos(\cos(a_1)\cos(a_2)\cos(b_1)\cos(b_2) + \cos(a_1)\sin(a_2)\cos(b_1)\sin(b_2) + \sin(a_1)\sin(b_1)) * 3963$, where a_1 and b_1 (a_2 and b_2) are the latitudes (longitudes) of the two zip codes and 3,963 miles is the Earth's radius.

target-market capitalization is $72 million. For cash-financed M&As, the median acquirer-market capitalization is $1,561 million and the median target-market capitalization is $93 million.

We end up with a sample of around 70,000 investor accounts. As can be seen in Fig. 1, which shows a heat map of the number of investors in each state, the investors in our sample are disproportionately clustered on the East Coast and the West Coast. In Panel B of Table 1, we provide summary characteristics for these accounts. The median and mean portfolio sizes are $13,141 and $41,030, respectively. The average investor holds 3.88 stocks in her portfolio and places 0.47 trades a month, with an average monthly trade value of $5,679. The average investor age in our sample is 42 and the average annual household income is $69,500. Panel C provides summary statistics for households (residents) in each zip code.

3.2 Caveats

Perhaps the most appealing feature of our data is that our trading records are highly detailed and the median retail investor in our sample holds (only) three stocks. As a result, substituting any one stock position with another stock from a different industry is likely to have a significant effect on investor attention.

Our data are also subject to several caveats. First, the set of retail investors in our sample is not randomly drawn as, by construction, they are all clients of the same discount brokerage firm. To the extent that having a common broker is an indication of belonging to the same "cluster," given that transmissions are stronger within a cluster than across clusters (Jackson, 2019), our estimate of the overall level of contagiousness of financial information is likely to be upwardly biased. We are less concerned about this particular bias as it merely reinforces our conclusion that, at least for our type of financial news and opinion, transmission dies out on its own without intervention.

We are more concerned about a second shortcoming. The landscape of the US equity market has changed dramatically over the past three decades. This change in landscape does not necessarily invalidate our exercise. After all, by their very nature, transmission rates vary with characteristics of the host and the environment and, thus, with time. However, it does raise questions about whether we can extrapolate our results to today's marketplace.

We are mindful of this concern and, in fact, strongly suspect that today's level of contagiousness is different from its level in the 1990s. In particular, we suspect that, with the advent of modern communication technologies, information has become more contagious.[6] We believe that examining the extent to which the level of contagiousness has changed represents an interesting subject for future research. Relatedly, it would be interesting to explore how much contagiousness varies across distinct types of financial information.[7]

As much as we are mindful of the possibility that our estimate of the overall level of contagiousness does not describe today's marketplace, we suspect that our estimates of how much the level of contagiousness varies with investor characteristics (still) do. The reason is that there are inherent, persistent behavioral components in social structures and norms that likely do not vary dramatically through time or across discussion topics (e.g., the tendency to interact with people of similar age). We thus suspect that whatever variation in transmission we find in our setting applies more broadly. This result would be similar to findings in the epidemiology literature that while the reproduction number varies dramatically across diseases (Doucleff, 2014), there is consistency across diseases in the extent to which reproduction numbers vary with characteristics of the host and the environment, such as population density and the general level of hygiene (Keeling and Grenfell, 2000; Heesterbeek, 2002; Heffernan, Smith, and Wahl, 2005).

4. Our Empirical Setting

A major challenge facing empirical, non-experimental research on diffusion and contagion is the presence of common shocks that affect everyone. To illustrate by example, prior work generally infers the transmission of financial information through positive correlations in trading patterns between investors residing in the same locale. Yet, if two investors in the same locale exhibit correlated trading patterns, how

[6] At the same time, we caution that there is also research suggesting that, even in recent years, a mere seven percent of word of mouth happens online (Berger 2016).
[7] Chen and Hwang (2020) provide some evidence in this regard.

can we be certain that they actually communicate with one another rather than simply have similar backgrounds/tastes/preferences and/or access to the same local information?

Some studies address this common-shock problem through natural experiments, which generate random assignments of individuals to classes or cohorts (e.g., Duflo and Saez, 2003; Lerner and Malmendier, 2013; Shue, 2013). Others follow a regression discontinuity approach (e.g., Anderson and Magruder, 2012). Still others conduct field studies. For instance, Banerjee, Chandrasekhar, Duflo, and Jackson (2019) seed information on a raffle in three subsets of rural villages in India: in the first subset, the information is seeded with randomly selected individuals; in the second subset, the information is seeded with village elders; in the third subset, the information is seeded with individuals nominated by villagers as the "best gossipers." Banerjee et al. then analyze which setting generates the highest information diffusion rate by counting the number of phone calls made by all villages.

Our empirical design draws inspiration from that of Banerjee, Chandrasekhar, Duflo, and Jackson (2019). Rather than seeding a raffle, our setting seeds attention to an industry among US retail investors; we think that our seeding through M&As is plausibly exogenous to the backgrounds/tastes/preferences of retail investors. Rather than count the number of phone calls made, we check for abnormal trading activity in the acquirer industry between target neighbors.

There are of course other differences but, overall, we consider the general idea behind our research design to be similar to that of Banerjee et al. and we believe we can draw appropriate causal inferences. The next two subsections conduct two simple difference-in-differences analyses to gauge the soundness of our general idea.

4.1 Does the Endowment of Acquirer Shares Lead to Increased Trading in the Acquirer Industry by Target Investors?

First, we gauge the validity of our assumption that the endowment of acquirer shares draws target investors' attention to the corresponding acquirer industry and that elevated attention, in turn, increases trading activity (Barber and Odean, 2008).

We estimate the following regression equation:

$$Trading\ Act_{i,m} = a_m + \beta_1\ Target\ Investor_{i,m} + CONTROL * \gamma + \varepsilon_{i,m}, \tag{1}$$

where *Trading Act*$_{i,m}$ is the number (or dollar value) of trades by investor i in the acquirer industry after cross-industry stock-financed M&A *m* as a fraction of her total number (or dollar value) of trades across all industries. Since the exact completion date is missing for many M&As, we examine total trading behavior in months 7 through 18 after the M&A is announced as, on average, it takes around six calendar months for a stock-financed M&A to complete (Giglio and Shu, 2014).

Since target investors are bound to sell their holdings in the acquirer firm, we exclude the acquirer firm when calculating trading activity in the acquirer industry. To exclude dormant accounts, we require that investors place at least one trade (in any stock) in the year prior to and the year following the M&A.

We further require that households have no trading/holdings in the acquirer industry in the year prior to the M&A announcement. We do so for two reasons. First, target investors that have prior holdings in the acquirer industry could "mechanically" sell their existing holdings upon receiving acquirer shares to reduce their overall exposure to the acquirer industry. Second, we conjecture that target investors with no prior trading/holdings in the acquirer industry are more likely to be "shocked/treated" by the endowment of shares in the acquirer industry.

The main independent variable in our regression equation is *Target Investor*$_{i,m}$, which equals one if investor i holds shares in the target firm in the month prior to the M&A announcement and zero otherwise. Since we require all investors to have no stock holdings/trading in the acquirer industry prior to the M&A, our analysis is essentially a difference-in-differences analysis and the coefficient estimate of *Target Investor*$_{i,m}$ indicates how much more intensely target investors trade in the acquirer industry in the post-M&A period relative to the pre-M&A period, compared with the remaining investor population over the same period.[8]

[8] In other words, instead of Eq. (1), we could include observations in the one-year period prior to an M&A announcement and the one-year period following M&A completion and estimate a regression of trading activity in the acquirer industry on a target investor indicator and a post-M&A indicator as well as an interaction term between the two indicator variables, along with other controls and fixed effects. The estimate of the interaction term will be identical to our estimate of *Target Investor*$_{i,m}$ in Eq. (1).

Our control variables fall into one of two groups: (a) investor characteristics and (b) zip code characteristics. The former include household income, number of children, number of family members, age, gender, and marital status. The latter include zip code population, fraction of male residents, average home value, average number of household members, and average household income. In our full specification, we also include M&A fixed effects to absorb any M&A-specific effects. The standard errors are clustered at the zip-code- and the year-month-of-an-M&A-announcement level.

The regression results are reported in Panel A of Table 2. The dependent variable in the first three columns is based on the number of trades, while that in the next three columns is based on the dollar value of trades. Column (1), in which we report results when controlling for investor and zip code characteristics, shows that target investors increase their trading activity in the acquirer industry by an incremental 2.53 percentage points compared with other investors (*t*-statistic = 5.38). To put this number in perspective, the unconditional trading activity in any industry is 2.04 percentage points. That is, the endowment of acquirer stocks induces target investors to more than double their normal trading activities in the average industry. As can be seen in Columns (2) and (3), including M&A fixed effects has virtually no impact on our results. The regression coefficients reported in Columns (4)–(6), which are based on the dollar value of trades, are almost identical to those reported in Columns (1)–(3).

Overall, the results reported in Table 2 support our assumption that the endowment of acquirer shares induces at least some target investors to pay greater attention to the acquirer industry and trade more actively in the acquirer industry.

4.2 Does Increased Trading Activity in the Acquirer Industry Spill Over to Target Neighbors?

Our second difference-in-differences analysis tests whether there is any contagion in abnormal trading activity in the acquirer industry from target investors to their neighbors. We use a narrow definition of "neighbors"—investors who live within a three-mile radius—as we presume that the likelihood of two individuals coming into direct contact with each other rapidly diminishes with distance. We impose the same data requirements as for target investors. That is, we exclude the acquirer firm when calculating trading activity in the acquirer industry; we exclude dormant accounts; and we require that investors have no holdings/trading in the acquirer industry in the prior year. In doing so, we can directly compare the regression coefficients across the two settings.

We estimate a regression equation similar to Eq. (1):

$$Trading\ Act_{i,m} = a_m + \beta_1\ Target\ Neighbor_{i,m} + CONTROL * \gamma + \varepsilon_{i,m}, \quad (2)$$

where *Target Neighbor*$_{i,m}$ is an indicator variable that takes the value of one if investor *i* lives within three miles of a target investor and is not a target investor herself. If an investor lives within three miles of more than one target investor, we count them only once. In additional tests, we replace our indicator variable with the number of target investors who live within three miles of an investor. The results are virtually unchanged (Online Appendix Table A1.1). The coefficient estimate of *Target Neighbor*$_{i,m}$ informs us how much more intensely investors residing within three miles of a target investor increase their trading in the acquirer industry in the post-M&A period relative to the pre-M&A period, compared with all other investors in our sample over the same time frame. To ensure that target investors do not enter our counterfactuals, we exclude target investors from our sample when estimating Eq. (2).

The results are reported in Panel B of Table 2. When controlling for investor and zip code characteristics, we find that the number of trades increases by 46bps more for investors who live within three miles of a target investor (*t*-statistic = 6.57) than for investors who do not live within three miles of a target investor. After adding M&A fixed effects, the coefficient estimate of *Target Neighbor*$_{i,m}$ turns to 22bps (*t*-statistic = 3.14). The results based on the dollar value of trades are very similar. For example, the coefficient estimate of *Target Neighbor*$_{i,m}$ in the full specification is now 21bps (*t*-statistic = 3.05).

The results reported in Online Appendix Table A1.2 show that target investors and their neighbors tend to trade in the same direction; that is, if a target investor is buying in the acquirer industry, so are her neighbors. Moreover, Online Appendix Table A1.3 shows that, on the extensive margin, about one in ten target neighbors increase their trading activity after the M&A event. Combined with our result in Panels A and B of Table 2 that the estimate of *Target Investor* is ten times larger in magnitude than the estimate of

Target Neighbor, our result on the extensive margin suggests that once "infected," target neighbors exhibit similarly abnormal trading activity in the acquirer industry as target investors.[9]

If social interactions play a major role in generating our results, our effect should vary substantially with our definition of neighbors. Panel A of Online Appendix Table A1.5 presents results when we vary the distance over which we define neighbors. When we broaden our definition of neighbors to investors who live between three to seven miles of a target investor, the coefficient estimate of *Target Neighbor* in the full regression specification drops to 18bps. As we further increase the distance to between seven to fifteen miles (15 to 30 miles), the coefficient estimate of *Target Neighbor* drops to 15bps (2bps). This rapid decrease in the coefficient estimates is consistent with the idea that word-of-mouth effects decay quickly with distance.

In additional analyses, we also experiment with the time period over which we measure investors' trading activity. Specifically, instead of focusing on the one-year period after the estimated M&A completion, that is, from months 7 through 18 after the M&A is announced, we expand our window to years two and three. In short, M&As no longer have a discernible impact on target neighbors' trading activity in years two and three after M&A completion (Panel B in Online Appendix Table A1.5).

We believe that M&As are unlikely to be a function of similarities in backgrounds between target investors and their neighbors. In addition, M&As are unlikely to reflect commonalities in preference or taste, in particular given that our analysis focuses on retail investors. Our study is therefore less subject to the aforementioned common shocks problem.

A critical reader might argue that our setting is still subject to a local media coverage concern: Local media coverage of a given M&A happens to be disproportionally higher in areas in which target investors and their neighbors reside. This disproportionately high local media coverage could lead to abnormally high trading activity in the acquirer industry without investors' directly communicating with one another.

[9] The results reported in Online Appendix Table A1.4 show that target neighbors significantly increase their trading activity not only in the acquirer industry (excluding the acquirer firm) but also in the acquirer firm itself.

Inconsistent with a simple local attention story, we observe little abnormal trading activity when M&As are first announced. Instead, abnormal trading activity accrues only after target investors receive shares of the acquirer firm (Panel C in Online Appendix Table A1.5).

We also conduct a placebo test around cross-industry cash-financed M&As. If, for some reason, media coverage of M&As is greater in areas with a greater concentration of target investors, we should observe similar patterns around cash-financed M&As. In contrast, if our results are driven by the endowment of acquirer shares generating word-of-mouth effects, we should observe no noticeable patterns around cash-financed M&As. The results are reported in Table 3. Again, inconsistent with a simple local attention story, the coefficient estimates of *Target Investor* are only one-fifth of those found for stock-financed M&As and statistically not reliably different from zero. The coefficient estimates of *Target Neighbor* are all close to zero. In Online Appendix Table A1.6, we conduct a second placebo test, the results of which again suggest that local media coverage alone cannot generate the results we observe. In robustness checks, we further exclude households in states where the target or acquirer firm has any business operations identified using both headquarters and factory locations and we continue to make similar observations. [10]

Overall, we find strong evidence that the endowment of acquirer shares draws target investors' attention to the corresponding acquirer industry and that elevated attention, in turn, increases trading activity. We also find strong evidence that abnormal trading activity in the acquirer industry spills over from target investors to their neighbors.[11]

---

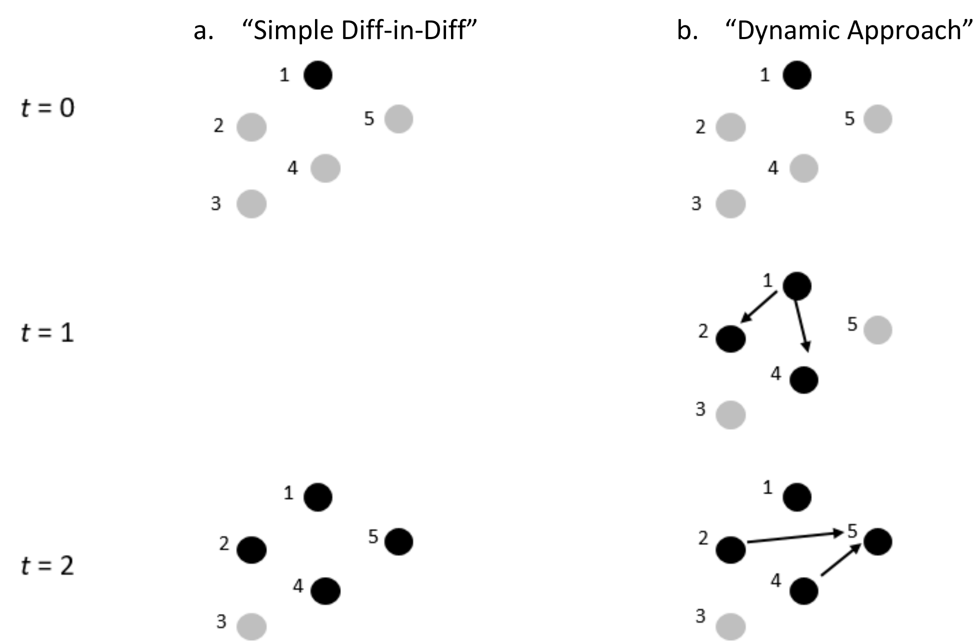
[10] A final potential concern is that holdings in the target firm are not random. Some investors may build exposure to the acquirer industry by, indirectly, purchasing shares of the target firm in anticipation of the M&A. To assess the relevance of this channel, we define target investors using lagged holdings information. In Online Appendix Table A1.7, *Target Investor* now takes the value of one if an investor holds the target stock one year prior to the M&A announcement. *Target Neighbor* takes the value of one if an investor lives within three miles of such a target investor. It is implausible that retail investors could forecast M&As one year in advance. Yet, we find that all our main results hold under this alternative specification.

[11] In Online Appendix Tables A2.1–A2.5, we provide descriptive evidence regarding the extent to which trading activity spills over varies with (1) social characteristics of the investors including measures of "sociability," length of residency and population density, (2) levels of market uncertainty and sentiment, (3) the presence of non-financial extraneous events ("distractions"), and (4) M&A deal characteristics.

5. The Rate of Communication

To estimate the rate of communication for our particular type of financial information and to study how much the rate varies with characteristics of the underlying investor population, we propose a "dynamic" estimation procedure drawn from research that examines the contagion rate of diseases (Kermack and McKendrick, 1927, 1932).

The figure below contrasts our previous "simple" difference-in-differences analysis with the new dynamic design. Each dot represents an investor in the neighborhood. Dark dots represent investors with abnormal trading in the acquirer industry; grey dots represent investors with no such abnormal trading activity. Investor 1 is a target investor.



Our earlier difference-in-differences analysis captures the degree to which target neighbors become "infected" over a given period of time. The difference-in-differences analysis cannot capture whether any such "infection" is coming straight from the target investor or another "infected" neighbor. For instance, in the left panel, it is unclear whether Investor 5 becomes "infected" through Investor 1 or whether abnormal trading in the acquirer industry first spills over from Investor 1 to Investors 2 and 4, who, in turn, infect Investor 5.

If the goal is to establish that financial information is contagious, such differentiation is not material. However, such differentiation becomes crucial when trying to estimate the rate of communication and the degree to which the rate varies with characteristics of the sender and receiver of the information because, for that, we need to know—at any given point—who the sender is and who the receiver is. In subsection 5.1 we describe our attempt to track how trading activity in the acquirer industry percolates from investor to investor, as illustrated in the right panel in the figure above.

5.1 Methodology

Following the completion of each cross-industry stock-financed M&A, we estimate a transmission matrix that quantifies how views and opinions percolate through the investor population from one period to the next. We then examine how the pairwise communication rate from investor j (the sender) to investor i (the receiver) varies with characteristics of both investors.

Specifically, we estimate the following transmission matrix with K investors:

$$\begin{pmatrix} X_{1,t+1} \\ X_{2,t+1} \\ \vdots \\ X_{k,t+1} \end{pmatrix} = \begin{pmatrix} \beta_{1,1}, \beta_{1,2}, \ldots, \beta_{1,k} \\ \beta_{2,1}, \beta_{2,2}, \ldots, \beta_{2,k} \\ \vdots \\ \beta_{k,1}, \beta_{k,2}, \ldots, \beta_{k,k} \end{pmatrix} * \begin{pmatrix} X_{1,t} \\ X_{2,t} \\ \vdots \\ X_{k,t} \end{pmatrix}, \tag{3}$$

where $X_{i,t}$ is the abnormal trading activity of investor i in the acquirer industry in period t and $X_{i,t+1}$ is her trading activity in the acquirer industry in period t+1. The diagonal terms, $\beta_{i,i}$, capture the persistence in investor i's trading behavior. For simplicity, we assume that the persistence is a constant for all investors. The off-diagonal terms, $\beta_{i,j}$, capture how much trading in the acquirer industry spills over from investor j to investor i.

In vector form and over p periods, we have:

$$\begin{aligned} X_{t+1} &= B * X_t \\ X_{t+2} &= B * X_{t+1} \\ &\cdots \\ X_{t+p} &= B * X_{t+p-1}. \end{aligned} \tag{4}$$

The advantage of the dynamic setting is that it enables us to explicitly and dynamically account for "third-party ties." That is, our setting allows for the possibility that investor j transmits her view to investor i through a third party (or a chain of third parties) without being in direct contact with investor i, which, in turn, enables us to quantify how the social distance between any two investors affect the communication rate between these two investors.

Compounding the transmission matrix in (4) over p periods, we have

$$X_{t+p} = B * X_{t+p-1} = B^2 * X_{t+p-2} = \cdots = B^p * X_t, \tag{5}$$

where t is the M&A completion date and p is the number of periods after the completion of the M&A.

If the set of X_{t+p}s satisfied the exogeneity condition, we could simply estimate a vector auto-regression based on $X_{t+p} = B * X_{t+p-1}$ by stacking our observations both across M&As and across periods within each M&A event. Of course, the exogeneity condition does not hold in our setting; we therefore instrument the right-hand side in each of these equations by the initial portfolio shocks induced by the cross-industry stock-financed M&As. In other words, we jointly estimate the following set of equations:

$$\begin{aligned} X_{t+1} &= B * \widehat{X_t} + e_{t+1} \\ X_{t+2} &= B^2 * \widehat{X_t} + e_{t+2}, \\ &\cdots \\ X_{t+p} &= B^p * \widehat{X_t} + e_{t+p}, \end{aligned} \tag{6}$$

where $\widehat{X_t}$ is the instrumented trading activity in the acquirer industry immediately after M&A completion.

Estimating this set of equations is computationally challenging as the set contains powers of an unknown 70,000 × 70,000 matrix (we have roughly 70,000 investors in our sample). To get around this technical complexity, we employ a three-stage approach.

In our first stage, we instrument the set of X_{t+p}s using portfolio shocks experienced by target investors at the M&A completion date. Specifically, we estimate regression equations of investor i's trading activity in the acquirer industry in each period t+p on *Target Investor*$_i$, which equals one if investor i is a target investor and zero otherwise. Trading activity in the acquirer industry is the total number (or total dollar value) of trades in the acquirer industry (excluding the acquirer firm) divided by the total number (or total dollar value) of trades across all industries.

In the second stage, we estimate how trading activity in the acquirer industry in period *t*+*p* (X_{t+p}) relates to the *fitted* trading activity in the acquirer industry in the previous period *t*+*p*-1 ($\widehat{X_{t+p-1}}$), calculated from the first-stage regression:

$$
\begin{aligned}
X_{t+1} &= B * \widehat{X_t} + e_{t+1} = B * \widehat{X_t} + e_{t+1} \\
X_{t+2} &= B^2 * \widehat{X_t} + e_{t+2} = B * \widehat{X_{t+1}} + e_{t+2} \\
&\dots \\
X_{t+p} &= B^p * \widehat{X_t} + e_{t+p} = B * \widehat{X_{t+p-1}} + e_{t+p}.
\end{aligned} \tag{7}
$$

If we were to stop here, our estimates of the B matrix would be unbiased (to the extent that our instruments are exogenous). However, we lose efficiency as we do not impose the following condition in the estimation: $\widehat{X_{t+p}} = B * \widehat{X_{t+p-1}} = \cdots = B^p * \widehat{X_t}$.

In our third stage, we improve the efficiency of our estimates of the *B* matrix using a recursive method. Specifically, in each iteration, we use the *B* matrix estimated from the previous round to re-estimate a new set of $\widehat{X_{t+p}}$s. That is, we start with the instrumented $\widehat{X_t}$ and then calculate $\widehat{X_{t+1}} = B * \widehat{X_t}$, $\widehat{X_{t+2}} = B * \widehat{X_{t+1}}$, etc. We then re-estimate the set of Eq. (7) using $\widehat{X_{t+1}}$, $\widehat{X_{t+2}}$, ..., $\widehat{X_{t+p}}$ to derive a new B. We initialize the process with the B matrix estimated from the second stage and stop the process when we find a fixed point for B.

To reduce computational complexity, we impose two restrictions. First, for each M&A event, we track only the trading activity of investors who live within a 30-mile radius of a target investor. This restriction is motived by our earlier result that there is negligible contagion between investors residing more than 15 miles away from any target investor. Second, we set $\beta_{i,j}$ in the transmission matrix to zero if the distance between investors *i* and *j* is greater than three miles. That is, we assume that direct communication takes place only if the two investors live sufficiently close to one another.

Finally, in our estimation, we define each period as one quarter, as the average retail investor in our sample trades once a quarter. We study the four quarters after each M&A completion, so p ranges from 1 to 4. We restrict ourselves to four quarters as we find in our earlier difference-in-differences analysis that M&As no longer have a discernible impact on target neighbors' trading activity in years two and three after M&A completion. Again, trading in the acquirer industry is based either on the number of trades or the dollar value of trades.

5.2 The Overall Rate of Communication

In our baseline estimation, we assume that $\beta_{i,j}$ is a constant for all investor-pairs. For ease of interpretation, in our estimation we aggregate all neighbors of investor i into a representative "average" neighbor j. For example, if only one of the K neighbors of investor i were "infected," the representative neighbor would have a value of $1/K$. We then estimate the overall communication rate from this representative neighbor j to investor i.

Given our earlier finding that once "infected," investors exhibit similarly abnormal trading activity in the acquirer industry as "patient zero," we can interpret our communication rate as the probability that investor i becomes "infected" in the next period if all her neighbors are "infected." If only one of the K neighbors is "infected," the probability that investor i becomes "infected" in the next period is simply our communication rate multiplied by $1/K$.

Alternatively, we can think of the communication rate as reflecting the average number of new "infections" generated by a single "infective" investor in the neighborhood, akin to the reproduction number in the epidemiology literature: Consider again the case in which only one of the K investors in the neighborhood is "infected." The expected number of new infections—out of the K investors—naturally is the product of the number of investors, K, and the probability that any one of the "susceptible" investors becomes "infected," which, as described in the preceding paragraph, is simply our communication rate multiplied by $1/K$. In other words, the expected number of new "infections" generated by a single "infective" investor is simply our communication rate.

We report the results in Panel A of Table 4. As shown in Column (1), if trading is measured through the number of trades, our estimate of the overall rate of communication is 0.32 with a 95% confidence interval of 0.17 to 0.46. If trading is measured through the dollar value of trades (Column (6)), our estimate becomes 0.34 with a 95% confidence interval of 0.17 to 0.50. Our results suggest that one "infected" investor, on average, "infects" 0.32 or 0.34 of her neighbors. That is, financial information *is* contagious. At the same time, since all our estimates are substantially below one, we can infer that any contagion dies out on its own without intervention. Our results perhaps agree with casual observations that financial information is rarely so contagious that it triggers an outright "epidemic."

5.3 Variation tied to Differences in Age, Income, and Gender

Our next analysis considers how much the communication rate varies with distances in investor characteristics. To facilitate the computation of the transmission matrix, we impose a linear structure on the off-diagonal terms, $\beta_{i,j}$. That is, we conjecture that the change in communication rate between any two investors i and j is a linear function of the distances in investor characteristics. Specifically, we assume that $\beta_{i,j}$ is a function of the absolute differences in age, income and gender:

$$\beta_{i,j} = b_0 + b_1 * |Age_i - Age_j| + b_2 * |Income_i - Income_j|$$

$$+b_3 * |Gender_i - Gender_j| + \varepsilon_{i,j} \ \ (i \neq j). \tag{8}$$

$\varepsilon_{i,j}$ captures unobserved determinants of $\beta_{i,j}$. b_0 reflects the communication rate with all social distances set to zero. Scaling our estimates of b_1, b_2, and b_3 by our estimate of b_0 yields the percentage change in the communication rate as a function of social distances. As before, we take the average of all nearby investors to i and calculate the rate of communication from this representative neighbor to investor i. The coefficient estimate b_0 can thus be interpreted as the analog of the reproduction number when all social distances are set to zero; the estimates b_1, b_2, and b_3 measure variations in the zero-social-distance communication rate. For consistency, we employ the same estimation procedure for all subsequent tests discussed in this section.

We report the results in Panel B of Table 4. Several observations are worth noting. First, as shown in columns (5) and (10), our estimates of b_0 are 0.470 (*t*-statistic = 5.22) and 0.487 (*t*-statistic = 6.01) depending on whether we consider the number of trades or the dollar value of trades. That is, when all social distances are set to zero, the communication rate rises from its previous 0.32 and 0.34 to 0.47 and 0.49, respectively.

Second, when considering the number of trades, the estimates of b_1, b_2, and b_3 are -0.004, -0.012, and -0.056, respectively. All estimates are statistically significant at the 1% level. Our estimates suggest that a ten-year difference in age, a one-category difference in income, and being of another gender lowers the communication rate by 0.04, 0.012, and 0.056, or, by 9%, 3%, and 12%, respectively.[12] In other words, age and gender represent higher barriers to communication than differences in economic backgrounds. The results are similar when considering the dollar value of trades.[13]

Since our empirical design allows us to pinpoint the sender and the receiver, we can assess whether the communication rate varies *asymmetrically* with differences in social characteristics. That is, we can examine whether the communication rate differs between (1) the sender's being ten years *younger* than the receiver and (2) the sender's being ten years *older* than the receiver. Empirically, instead of estimating one slope for the absolute distance in a social characteristic, we now estimate two slopes, one for "positive differences" and another for "negative differences." Positive differences denote cases in which the receiver is older than the sender, the receiver has higher income than the sender, and the receiver is male and the sender is female. Negative differences denote cases in which the receiver is younger than the sender, the receiver has lower income than the sender, and the receiver is female and the sender is male.

The results, presented in column (1) of Table 5, show that, when considering the number of trades, the estimates of $|Age_i - Age_j|^+$ and $|Age_i - Age_j|^-$ are -0.006 and -0.003, respectively. These estimates are statistically different from each other at the 1% level. To interpret these estimates, consider a sender who is 40 years old. The communication rate is maximized if the receiver is also 40 years old. Our estimates

[12] The calculations are as follows: 9% (= (10*0.004) / 0.470), 3% (= 0.012 / 0.470), and 12% (=0.056 / 0.470).
[13] Online Appendix Tables A3.1 and A3.2 present results of various robustness checks.

suggest that if the receiver is older than the sender, the communication rate declines by 0.006 per one-year age gap. If the receiver is younger than the sender, the communication rate declines by 0.003. That is, the communication rate declines more slowly when the receiver is younger than the sender. We can thus infer that, relatively speaking, younger investors are more likely to act on older investors' views than the other way around. The results are similar when considering the dollar value of trades.

Applying the same logic to income and gender, we find that, relatively speaking, lower-income investors are slightly more likely to act on higher-income investors' views than vice versa and that male investors are more likely to act on female investors' views than female investors are to male investors' views. One possible explanation of these asymmetries is that investors perceive information conveyed by older, wealthier, female investors as more credible and, thus, are more likely to act on any views transmitted by such investors.

5.4 Variation tied to Investors' Recent Trading Performances

We next examine how communication rates vary with senders' and receivers' recent trading performances. Kaustia and Knüpfer (2012), Heimer and Simon (2015), and Escobar and Pedraza (2019) find evidence that investors are more likely to share their investment experiences when their portfolios have performed well in the past. Our dynamic setting allows us to quantify the performance effects of both senders and receivers.

For each M&A event, we sort investors into halves based on their recent investment performances in the year prior to the M&A announcement. Investment performances are either portfolio returns in excess of the risk-free rate or market-adjusted portfolio returns. We then estimate the following linear function:

$$\beta_{i,j} = b_0 + b_1 * I_{HH} + b_2 * I_{LH} + b_3 * I_{HL} + \varepsilon_{i,j} \;\; (i \neq j). \tag{9}$$

I_{HH} is a dummy variable that equals one if both the sender and receiver belong to the "high-performing" group and zero otherwise. I_{LH} is a dummy variable that equals one if the receiver belongs to the "low-performing" group and the sender belongs to the "high-performing" group and zero otherwise. I_{HL} is a dummy variable that equals one if the receiver belongs to the "high-performing" group and the sender belongs to the "low-performing" group and zero otherwise. The counterfactual represents cases in which both the sender and the receiver reside in the "low-performing" group.

Below, we discuss the results when considering the number of trades and measuring performance as the portfolio return in excess of the risk-free rate. We arrive at the same conclusions when considering the dollar value of trades and market-adjusted portfolio returns.

The results presented in Table 6 show that the communication rate is the lowest, 0.289, when both the sender and the receiver reside in the low-performance group. The communication rate is the highest, 0.439 (= 0.289 + 0.150), when both investors reside in the high-performance group.

When there is a performance wedge between the sender and the receiver, we see an asymmetric effect. The coefficient estimate of I_{LH} suggests that when the receiver is in the low-performance group and the sender is in the high-performance group the pairwise communication rate equals 0.371 (= 0.289 + 0.082). In comparison, the coefficient estimate of I_{HL} suggests that when the receiver is in the high-performance group and the sender is in the low-performance group the communication rate equals 0.324 (= 0.289 + 0.035). The difference between 0.371 and 0.324 is significant, both economically and statistically, and suggests that investors with poor investment records are more likely to act on positively performing investors' views than the other way around. This asymmetry echoes our earlier suggestion that investors are more likely to act on views transmitted by investors seen as more competent and knowledgeable.

The results reported in Table 6 also show clearly that the communication rate is a function of not only the sender's recent performance but also the receiver's. The economic significance of the receiver's effect is substantial. Specifically, the difference in the communication rate between (1) pairs in which both investors are in the high-performance group and (2) pairs in which the sender is in the high-performance group and the receiver is in the low-performance group is 0.07 (0.439 – 0.371 = 0.068). Compared with the estimates reported in Table 4, such a 0.07 drop in the communication rate is equivalent to a drop in the communication rate generated by an 18-year age gap or a seven-category difference in income; it is larger than a drop generated by a difference in gender.

Overall, we make the novel observation that the communication rate strengthens not only with the recent investment performance of the sender but also with that of the receiver. The economic significance of this effect is substantial. One possible explanation is that receivers avoid discussing investment ideas when their portfolios perform poorly, as any such discussion would re-access negative emotional experiences tied to their investment failures. We also uncover another asymmetry: investors with poor investment records are more likely to act on positively performing investors' views than the other way around.

5.5 Variation tied to Differences in Lifestyle and Geography

Our final set of characteristics relate to similarities (or differences) in lifestyle and state of residence. We capture similarity in lifestyle through (1) same-type-of-unique-vehicle ownership and (2) same marital or parental status. In particular, we consider whether both the sender and the receiver own a truck (or not), an RV (or not), or a motorcycle (or not). We also consider whether the sender and the receiver have the same marital status (married or single) or the same parental status (with children or without children). Our data coverage for vehicle ownership and for marital and parental status is sparse. Our results in this subsection should thus be interpreted with caution.

As shown in Online Appendix Tables A3.3 and 3.4, we find that the communication rate is highest when the sender and the receiver own the same type of unique vehicle. If the sender owns a truck and the receiver does not, or, if the receiver owns a truck and the sender does not, the communication rate drops by around 0.11. The corresponding declines for RVs and motorcycles are around 0.09 and 0.07, respectively.

We detect no variation tied to differences in marital or parental status. One interpretation of this non-result is that when initiating and reciprocating on investment-related conversations, investors do not discriminate based on marital and parental status. The alternative perspective is that, given the sparsity in data coverage, our tests lack power.[14]

[14] The data coverage for marital and parental status is lower than that for vehicle ownership.

To examine the communication rate by state of residence, we estimate state fixed effects in the communication rate after controlling for observable social characteristics. Figs. 2 and 3 plot the average communication rate by state. Online Appendix Table A3.5 reports the data used to create Figs. 2 and 3. We observe strong regional differences. The Spearman's rank correlation coefficient between our communication rate based on the number of trades (dollar value of trades) and a state-level measure of sociability drawn from Putnam (2000)[15] is as high as 0.39 (0.43), suggesting that financial information is more contagious in regions in which individuals are more sociable.[16]

6. Dissemination of Value-Relevant Information or Merely Spreading Noise?

Do investors in our setting transmit unique and value-relevant news or simply spread noise? If any newly acquired views about the acquirer industry transmitted through social interactions represent unique and value-relevant information, stocks bought by target investors and their neighbors in the acquirer industry ("long leg") should subsequently outperform stocks sold by target investors and their neighbors in the acquirer industry ("short leg"). On the other hand, if views about the acquirer industry represent mere noise, we should observe no performance differential between the long leg and the short leg.

We experiment with three portfolio construction schemes: (a) For each stock in the acquirer industry traded by target investors and their neighbors from months 7 through 18 after the M&A is announced, we compute the total number of shares bought by target investors and their neighbors minus the total number of shares sold. The long leg contains stocks of which target investors and their neighbors are net buyers; the short leg contains stocks of which they are net sellers. The long and short legs are weighted by the net total number of shares that are bought (sold) across target investors and their neighbors and are held for one month. (b) We repeat the above exercise but now consider the dollar value of shares rather than the number of shares. (c) For each stock in the acquirer industry traded by target investors and

[15] Putnam (2000) surveys individuals regarding the frequency with which they visit their friends. The state-level measure of sociability is a dummy ranging from 1 through 6 indicating how strongly people agree with the statement that they spend a lot of time visiting friends (6 being definitely agree and 1 being definitely disagree).

[16] Ivković and Weisbenner (2007) and Brown, Ivković, Smith, and Weisbenner (2008) make a similar suggestion.

their neighbors from months 7 through 18 after the M&A is announced, we compute the average change in a stock's weight in the portfolios of target investors and their neighbors. The long leg contains stocks that experience a weight increase; the short leg contains stocks that experience a decrease. The long and short legs are weighted by the corresponding stock's portfolio weight change, and they are held again for one month.

The results are reported in Table 7. Irrespective of the portfolio construction scheme, we find that the long leg underperforms the short leg, albeit not statistically significantly so. These results do not support the notion that newly acquired views about firms in the acquirer industry reflect value-relevant information. Our results are similar to the observations made by Hvide and Östberg (2015), who also find evidence that financial information transmitted through social interactions does not improve investors' trading performances.

7. Conclusion

The question of how information becomes incorporated into prices lies at the heart of asset pricing and has motivated a significant body of research. Most such research examines how investors react to public news-and-opinion announcements, such as earnings announcements or releases of sell-side analyst recommendations. Kothari (2001) provides a review of this literature.

However, much of the information on which investors condition their behavior does not come "straight from the source" but, instead, reflects information obtained through word-of-mouth communication (Shiller and Pound, 1989). Compared with how extensively the accounting and finance literature has examined the way in which investors react to public news announcements, we know relatively little about how information travels "privately" through social interactions. Here, we provide an empirical strategy for studying the diffusion and contagion of financial information between investors. We use our setting to provide causal evidence that financial information is contagious. We also produce novel estimates of how contagious financial information is and how much such contagiousness varies with investor characteristics.

References

Anderson, R., 1982. Directly transmitted viral and bacterial infections of man. In: Anderson, R. (Ed.), The Population Dynamics of Infectious Diseases: Theory and Applications. Springer, Boston, pp.1-37.

Anderson, R., May, R., 1982. Directly transmitted infections diseases: control by vaccination. Science 215, 1053-1060.

Anderson, R., May, R., 1985. Vaccination and herd immunity to infectious diseases. Nature 318, 323-329.

Anderson, M., Magruder, J., 2012. Learning from the crowd: regression discontinuity estimates of the effects of an online review database. Economic Journal 122, 957-989.

Banerjee, A., Chandrasekhar, A., Duflo, E., Jackson, M., 2019. Using gossips to spread information: theory and evidence from two randomized controlled trials. Review of Economic Studies 86, 2453-2490.

Barber, B., Odean, T., 2001. Boys will be boys: gender, overconfidence, and common stock investment. Quarterly Journal of Economics 116, 261-292.

Barber, B., Odean, T., 2008. All that glitters: the effect of attention and news on the buying behavior of individual and institutional investors. Review of Financial Studies 21, 785-818.

Berger, J., 2014. Word of mouth and interpersonal communication: a review and directions for future research. Journal of Consumer Psychology 24, 586-607.

Berger, J., 2016. Contagious: Why Things Catch On. Simon and Schuster, New York.

Brown, J., Ivković, Z., Smith, P., Weisbenner, S., 2008. Neighbors matter: causal community effects and stock market participation. Journal of Finance 63, 1509-1531.

Cao, Z., Zhang, Q., Lu, X., Pfeiffer, D., Jia, Z., Song, H., Zeng, D., 2020. Estimating the effective reproduction number of the 2019-nCoV in China. MedRxiv, doi: 10.1101/2020.01.27.20018952v1.

Chen, H., Hwang, B., 2020. Listening in on investors' thoughts and conversations. Unpublished working paper. University of Hong Kong and Cornell University .

Delamater, P., Street, E., Leslie, T., Yang, Y., Jacobsen, K., 2019. Complexity of the basic reproduction number (R0). Emerging Infectious Diseases 25, 1.

Doucleff, M., 2014. No, Seriously, How Contagious Is Ebola. Public Health, National Public Radio, URL https://www.npr.org/sections/health-shots/2014/10/02/352983774/no-seriously-how-contagious-is-ebola (accessed 07.30.2020).

Duflo, E., Saez, E., 2003. The role of information and social interactions in retirement plan decisions: evidence from a randomized experiment. Quarterly Journal of Economics 118, 815-842.

Escobar, L., Pedraza, A., 2019. Active trading and (poor) performance: the social transmission channel. World Bank Policy Research Working Paper No.8767.

Flaxman, S., Mishra, S., Gandy, A., et al., 2020. Report 13 - Estimating the number of infections and the impact of non-pharmaceutical interventions on COVID-19 in 11 European countries. Imperial College London, doi: 10.25561/77731.

Giglio, S., Shue, K., 2014. No news is news: do markets underreact to nothing? Review of Financial Studies 27, 3389-3440.

Guerra, F., Bolotin, S., Lim, G., Heffernan, J., Deeks, S., Li, Y., Crowcroft, N., 2017. The basic reproduction number (R0) of measles: a systematic review. Lancet Infectious Diseases 17, e420-e428.

Han, B., Hirshleifer, D., Walden, J., forthcoming. Social transmission bias and investor behavior. Journal of Financial and Quantitative Analysis.

Heesterbeek, J., 2002. A brief history of R0 and a recipe for its calculation. Acta Biotheoretica 50, 189-204.

Heffernan, J., Smith, R., Wahl, L., 2005. Perspectives on the basic reproductive ratio. Journal of the Royal Society Interface 2, 281-293.

Heimer, R., Simon, D., 2015. Facebook finance: How social interaction propagates active investing. Federal Reserve Bank of Cleveland Working Paper No. 15-22.

Hirshleifer, D., 2020. Presidential address: social transmission bias in economics and finance. Journal of Finance 75, 1779-1831.

Hong, H., Kubik, J., Stein, J., 2005. Thy neighbor's portfolio: word-of-mouth effects in the holdings and trades of money managers. Journal of Finance 60, 2801-2824.

Hvide, H., Östberg, P., 2015. Social interaction at work. Journal of Financial Economics 117, 628-652.

Ivković, Z., Weisbenner, S., 2007. Information diffusion effects in individual investors' common stock purchases: covet thy neighbors' investment choices. Review of Financial Studies 20, 1327-1357.

Jackson, M., 2014. Networks in the understanding of economic behaviors. Journal of Economic Perspectives 28, 3-22.

Jackson, M., 2019. The Human Network: How Your Social Position Determines Your Power, Beliefs, and Behaviors. Pantheon Books, New York.

Kaustia, M., Knüpfer, S., 2012. Peer performance and stock market entry. Journal of Financial Economics 104, 321-338.

Keeling, M., Grenfell, B., 2000. Individual-based perspectives on R0. Journal of Theoretical Biology 203, 51-61.

Kermack, W., McKendrick, A., 1927. A contribution to the mathematical theory of epidemics. Proceedings of the Royal Society of London. Series A, containing papers of a mathematical and physical character 115, 700-721.

Kermack, W., McKendrick, A., 1932. Contributions to the mathematical theory of epidemics. II.—The problem of endemicity. Proceedings of the Royal Society of London. Series A, containing papers of a mathematical and physical character 138, 55-83.

Kothari, S., 2001. Capital markets research in accounting. Journal of Accounting and Economics 31, 105-231.

Lazarsfeld, P., Merton, R., 1954. Friendship as a social process: a substantive and methodological analysis. Freedom and Control in Modern Society 18, 18-66.

Lerner, J., Malmendier, U., 2013. With a little help from my (random) friends: success and failure in post-business school entrepreneurship. Review of Financial Studies 26, 2411-2452.

Lovett, M., Peres, R., Shachar, R. , 2013. On brands and word of mouth. Journal of Marketing Research 50, 427-444.

Manski, C., 1993. Identification of endogenous social effects: the reflection problem. Review of Economic Studies 60, 531-542.

McPherson, M., Smith-Lovin, L., Cook, J., 2001. Birds of a feather: homophily in social networks. Annual Review of Sociology 27, 415-444.

Mitchell, M., Pulvino, T., 2001. Characteristics of risk and return in risk arbitrage. Journal of Finance 56, 2135-2175.

Odean, T., 1998. Are investors reluctant to realize their losses? Journal of Finance 53, 1775-1798.

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

Shiller, R., 2017. Narrative economics. American Economic Review 107, 967-1004.

Shiller, R., Pound, J., 1989. Survey evidence on diffusion of interest and information among investors. Journal of Economic Behavior and Organization 12, 47-66.

Shue, K., 2013. Executive networks and firm policies: evidence from the random assignment of MBA peers. Review of Financial Studies 26, 1401-1442.

Table 1. Summary Statistics

This table reports summary statistics for our various samples. Panel A presents statistics for the M&A sample. Stock-financed M&As are deals that are at least partially equity-financed; cash-financed M&As comprise 100% cash-financed deals. Firm size is the number of shares outstanding multiplied by the share price as of the month prior to an M&A. All observations are at the M&A level. Panel B shows investor and portfolio characteristics for our retail investor sample. We require that investors place at least one trade in either the one-year period prior to the M&A or the one-year period following the M&A. We further require that these households have no existing positions in the acquirer industry prior to the M&A announcement. Portfolio size is the dollar value of the stock holdings. Investor income is the annual income of the primary account holder. Investor gender is a dummy that equals one for male and zero for female. All observations are at the account/year-month level. Panel C shows demographic information for each zip code included in our sample. All observations are at the zip-code/year-month level.

	N	25%	Median	75%	Mean	Std. Dev.
Panel A: M&A Characteristics						
Stock-Financed M&As						
Acquirer Firm Size ($million)	316	216	952	2,969	2,754	5,503
Target Firm Size ($million)	316	31	72	250	654	2,396
Cash-Financed M&As						
Acquirer Firm Size ($million)	143	391	1,561	4,491	5,541	12,970
Target Firm Size ($million)	143	30	93	216	266	585
Panel B: Investor/Portfolio Characteristics						
Portfolio Size ($)	70,608	5,513	13,141	31,818	41,030	216,539
Number of Stocks Held	70,608	1.00	2.00	5.00	3.88	5.03
Number of Trades Each Month	70,608	0.00	0.00	0.00	0.47	1.76
Value of Trades Each Month ($)	70,608	0	0	0	5,679	76,056
Investor Age	70,608	36.00	46.00	56.00	42.02	21.44
Investor Income ($)	70,608	45,000	62,500	87,500	69,500	30,064
Investor Gender	70,608	1.00	1.00	1.00	0.90	0.30
Panel C: Zip Code Characteristics						
Basic Characteristics						
Population	42,057	785	2,777	11,960	8,965	13,134
No. Household Members	42,057	2.40	2.56	2.73	2.59	0.35
House Value ($)	42,057	58,200	82,900	122,300	105,359	89,589
Household Income ($)	42,057	29,779	36,250	45,750	39,631	16,243

Table 2. Trading in the Acquirer Industry after Stock-Financed M&As

This table reports coefficient estimates from regressions of investor trading in the acquirer industry on a target investor dummy (Panel A) or a target neighbor dummy (Panel B). The observations are at the M&A/brokerage account/year-month level, whereby we consider cross-industry stock-financed M&As only. The dependent variable in Columns (1)-(3) is the number of trades in the acquirer industry (excluding the acquirer firm) as a fraction of the total number of trades across all industries in months 7 through 18 after the M&A is announced. The dependent variable in Columns (4)-(6) is the dollar value of trades in the acquirer industry (excluding the acquirer firm) as a fraction of the total dollar value of trades across all industries in months 7 through 18 after the M&A is announced. We examine total trading behavior in months 7 through 18 after the M&A is announced since the exact completion date is missing for many M&As, and as, on average, it takes six months for an M&A to be completed (Giglio and Shue, 2014). *Target Investor* is an indicator, which equals one if an investor possesses shares of the target stock at the end of the month prior to the M&A announcement. *Target Neighbor* is an indicator variable that takes the value of one if an investor lives within three miles of a target investor. Investor-level controls include the account holder's income, number of children, number of family members, age, gender, and marital status. Zip-code-level controls include the zip-code population, fraction of male residents, average home value, average number of household members, and average household income. Standard errors, shown in brackets, are clustered at the zip-code- and the year-month-of-an-M&A-announcement level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	# Trades			$ Trades		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Target Investors' Trading in the Acquirer Industry						
Target Investor	0.0253*** [0.0047]	0.0233*** [0.0048]	0.0232*** [0.0048]	0.0227*** [0.0045]	0.0208*** [0.0047]	0.0208*** [0.0047]
Investor Controls	YES	NO	YES	YES	NO	YES
Zip Code Controls	YES	NO	YES	YES	NO	YES
M&A Fixed Effects	NO	YES	YES	NO	YES	YES
Adj. R^2	0.01%	1.65%	1.65%	0.01%	1.58%	1.59%
# Obs.	7,580,930	7,580,930	7,580,930	7,580,930	7,580,930	7,580,930
Panel B: Target Neighbors' Trading in the Acquirer Industry						
Target Neighbor	0.0046*** [0.0007]	0.0020*** [0.0007]	0.0022*** [0.0007]	0.0043*** [0.0008]	0.0018*** [0.0007]	0.0021*** [0.0007]
Investor Controls	YES	NO	YES	YES	NO	YES
Zip Code Controls	YES	NO	YES	YES	NO	YES
M&A Fixed Effects	NO	YES	YES	NO	YES	YES
Adj. R^2	0.01%	1.65%	1.65%	0.01%	1.58%	1.59%
# Obs.	7,578,642	7,578,642	7,578,642	7,578,642	7,578,642	7,578,642

Table 3. Trading in the Acquirer Industry after *Cash-Financed* M&As – Placebo

This table reports coefficient estimates from regressions of investor trading in the acquirer industry on a target investor dummy (Panel A) or a target neighbor dummy (Panel B). The regressions are identical to those in Table 2 except for that we now estimate regressions on a sample of cross-industry *cash-financed* M&As. Standard errors, shown in brackets, are clustered at the zip-code- and the year-month-of-an-M&A-announcement level. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	# Trades			$ Trades		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Target Investors' Trading in the Acquirer Industry						
Target Investor	0.0047 [0.0037]	0.0043 [0.0035]	0.0043 [0.0035]	0.0061 [0.0042]	0.0059 [0.0040]	0.0059 [0.0040]
Investor Controls	YES	NO	YES	YES	NO	YES
Zip Code Controls	YES	NO	YES	YES	NO	YES
M&A Fixed Effects	NO	YES	YES	NO	YES	YES
Adj. R^2	0.01%	2.36%	2.37%	0.01%	2.25%	2.25%
# Obs.	3,489,774	3,489,774	3,489,774	3,489,774	3,489,774	3,489,774
Panel B: Target Neighbors' Trading in the Acquirer Industry						
Target Neighbor	0.0017 [0.0012]	-0.0001 [0.0010]	0.0003 [0.0010]	0.0016 [0.0012]	-0.0002 [0.0010]	0.0003 [0.0010]
Investor Controls	YES	NO	YES	YES	NO	YES
Zip Code Controls	YES	NO	YES	YES	NO	YES
M&A Fixed Effects	NO	YES	YES	NO	YES	YES
Adj. R^2	0.01%	2.36%	2.37%	0.01%	2.25%	2.25%
# Obs.	3,489,054	3,489,054	3,489,054	3,489,054	3,489,054	3,489,054

Table 4. Overall Communication Rate and Variation in Communication Rate tied to Differences in Investor Characteristics

This table reports the results of a three-stage estimation of a transmission matrix. The estimation procedure is detailed in Section 5. In essence, we assess how trading activity in the acquirer industry percolates across investors from quarter to quarter (Panel A) and how any such "contagion rate" varies with differences in income, age and gender between the sender of acquirer-industry information and the receiver of acquirer-industry information (Panel B). The dependent variable is investor *i*'s actual trading in quarter *t*+1. $\widehat{Trade}_{i,t}$ is investor *i*'s own instrumented trading in quarter *t*; $\widehat{Trade}_{j,t}$ is the average instrumented trading across neighboring investors *j* in quarter *t*. Bootstrapped standard errors are shown in brackets. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	# Trades					$ Trades				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Overall Communication Rate										
$\widehat{Trade}_{i,t}$	0.598***					0.575***				
	[0.076]					[0.080]				
$\widehat{Trade}_{j,t}$	0.315***					0.335***				
	[0.076]					[0.082]				
# Obs.	2,076,790					2,076,790				
Panel B: Communication Rate and Differences in Investor Characteristics										
$\widehat{Trade}_{i,t}$		0.535***	0.560***	0.620***	0.556***		0.513***	0.542***	0.599***	0.539***
		[0.075]	[0.061]	[0.080]	[0.083]		[0.070]	[0.088]	[0.066]	[0.072]
$\widehat{Trade}_{j,t}$		0.449***	0.385***	0.307***	0.470***		0.472***	0.399***	0.326***	0.487***
		[0.082]	[0.060]	[0.080]	[0.090]		[0.074]	[0.092]	[0.067]	[0.081]
$\widehat{Trade}_{j,t} \times \lvert Age_i - Age_j \rvert$		-0.005***			-0.004***		-0.005***			-0.005***
		[0.001]			[0.001]		[0.001]			[0.001]
$\widehat{Trade}_{j,t} \times \lvert Income_i - Income_j \rvert$			-0.017***		-0.012***			-0.017***		-0.011***
			[0.005]		[0.005]			[0.005]		[0.004]
$\widehat{Trade}_{j,t} \times \lvert Gender_i - Gender_j \rvert$				-0.064***	-0.056***				-0.068***	-0.060***
				[0.017]	[0.018]				[0.016]	[0.018]
# Obs.		2,076,790	2,076,790	2,076,790	2,076,790		2,076,790	2,076,790	2,076,790	2,076,790

Table 5. Variation in Communication Rate tied to Differences in Investor Characteristics: Asymmetries

This table reports the results of a three-stage estimation of a transmission matrix. The estimation procedure is detailed in Section 5. The estimation procedure is identical to that in Table 4 except for that we now allow for differences in age, income, and gender to have a differential impact on the communication rate depending on whether the receiver of financial information is older, or younger than the sender of financial information; whether the receiver has higher income, or lower income than the sender; and whether the receiver is male and the sender is female, or the receiver is female and the sender is male. "Positive differences" below denote cases in which the receiver is older than the sender, the receiver has higher income than the sender, and the receiver is male and the sender is female. "Negative differences" below denote cases in which the receiver is younger than the sender, the receiver has lower income than the sender, and the receiver is female and the sender is male. Bootstrapped standard errors are shown in brackets. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	# Trades (1)	$ Trades (2)
$\widehat{Trade}_{i,t}$	0.480*** [0.058]	0.463*** [0.082]
$\widehat{Trade}_{j,t}$	0.516*** [0.062]	0.534*** [0.086]
$\widehat{Trade}_{j,t} \times \lvert Age_i\text{-}Age_j \rvert^{+}$	-0.006*** [0.001]	-0.007*** [0.001]
$\widehat{Trade}_{j,t} \times \lvert Age_i\text{-}Age_j \rvert^{--}$	-0.003*** [0.001]	-0.003*** [0.001]
$\widehat{Trade}_{j,t} \times \lvert Income_i\text{-}Income_j \rvert^{+}$	-0.018*** [0.007]	-0.017*** [0.006]
$\widehat{Trade}_{j,t} \times \lvert Income_i\text{-}Income_j \rvert^{--}$	-0.016*** [0.005]	-0.015*** [0.005]
$\widehat{Trade}_{j,t} \times \lvert Gender_i\text{-}Gender_j \rvert^{+}$	-0.018 [0.046]	-0.024 [0.043]
$\widehat{Trade}_{j,t} \times \lvert Gender_i\text{-}Gender_j \rvert^{--}$	-0.091*** [0.016]	-0.097*** [0.017]
# Obs.	2,076,790	2,076,790

Table 6. Variation in Communication Rate tied to Investors' Past Trading Performances

This table reports the results of a three-stage estimation of a transmission matrix. The estimation procedure is detailed in Section 5. In essence, we assess how trading activity in the acquirer industry percolates across investors from quarter to quarter and how any such "contagion rate" varies with recent trading performances of the sender of financial information and the receiver of financial information. The dependent variable is investor i's actual trading in quarter t+1. $\widehat{Trade}_{i,t}$ is investor i's own instrumented trading in quarter t; $\widehat{Trade}_{j,t}$ is the average instrumented trading across neighboring investors j in quarter t. In columns (1) and (3), investors' recent trading performances are the raw portfolio returns in excess of the risk-free rate in the year prior to the M&A announcement. In columns (2) and (4), investors' recent trading performances are the market-adjusted portfolio returns in the year prior to the M&A announcement. For each M&A event, we divide all investors into halves based on their recent trading performance. I_{HH} is a dummy variable, which equals one if both sender and receiver belong to the high-performance group, and zero otherwise. I_{LH} is a dummy variable, which equals one if the sender belongs to the high-performance group and the receiver belongs to the low-performance group, and zero otherwise. I_{HL} is a dummy variable, which equals one if the receiver belongs to the high-performance group and the sender belongs to the low-performance group, and zero otherwise. The counterfactual represents cases in which both sender and receiver reside in the low-performance group. Bootstrapped standard errors are shown in brackets. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	# Trades		$ Trades	
	Excess Return	Market-Adjusted Return	Excess Return	Market-Adjusted Return
	(1)	(2)	(3)	(4)
$\widehat{Trade}_{i,t}$	0.579***	0.582***	0.558***	0.560***
	[0.070]	[0.073]	[0.077]	[0.063]
$\widehat{Trade}_{j,t}$	0.289***	0.282***	0.306***	0.299***
	[0.074]	[0.070]	[0.085]	[0.064]
$\widehat{Trade}_{j,t} \times I_{HH}$	0.150***	0.162***	0.152***	0.162***
	[0.028]	[0.030]	[0.028]	[0.030]
$\widehat{Trade}_{j,t} \times I_{LH}$	0.082**	0.096**	0.086**	0.098***
	[0.035]	[0.042]	[0.035]	[0.034]
$\widehat{Trade}_{j,t} \times I_{HL}$	0.035	0.035	0.040	0.042
	[0.027]	[0.034]	[0.027]	[0.027]
# Obs.	2,019,064	2,019,064	2,019,064	2,019,064

Table 7. Does Word-of-Mouth Help Investors Make Better Investment Decisions?

This table reports monthly returns of hedge portfolios that (1) go long acquirer-industry stocks bought by target investors and their neighbors ("long leg") and (2) go short acquirer-industry stocks sold by target investors and their neighbors ("short leg"). We experiment with three portfolio construction schemes: In Panel A, for each stock in the acquirer industry traded by target investors and their neighbors from months 7 through 18 after the M&A is announced, we compute the total number of shares bought by target investors and their neighbors minus the total number of shares sold. The long leg contains stocks of which target investors and their neighbors are net buyers; the short leg contains stocks of which they are net sellers. The long and short legs are weighted by the net total number of shares bought (sold) across target investors and their neighbors, and they are held for one month. In Panel B, we repeat the above but we now consider the dollar value of shares as opposed to the number of shares. In Panel C, for each stock in the acquirer industry traded by target investors and their neighbors from months 7 through 18 after the M&A is announced, we compute the equal-weighted average change in a stock's weight in target investors' and target neighbors' portfolios. The long leg contains stocks that experience an increase; the short leg contains stocks that experience a decrease. The long and short legs are weighted by the relevant stock's portfolio weight change, and they are held again for one month. *T*-statistics, shown in parentheses, are computed based on standard errors with Newey-West corrections of twelve lags. *, **, *** denote significance at the 10%, 5%, and 1% level, respectively.

	Excess Return (1)	CAPM Alpha (2)	Three-Factor Alpha (3)	Four-Factor Alpha (4)
Panel A: Returns to Portfolios Weighted by Shares Traded				
Buy-Sell	-0.35% (-1.01)	-0.24% (-0.53)	-0.15% (-0.42)	-0.13% (-0.29)
Panel B: Returns to Portfolios Weighted by Trading Value				
Buy-Sell	-0.36% (-0.73)	-0.13% (-0.23)	-0.16% (-0.28)	-0.02% (-0.04)
Panel C: Returns to Portfolios Weighted by Portfolio Weight Changes				
Buy-Sell	-1.14% (-0.90)	-1.29% (-1.01)	-0.69% (-0.69)	-0.33% (-0.29)

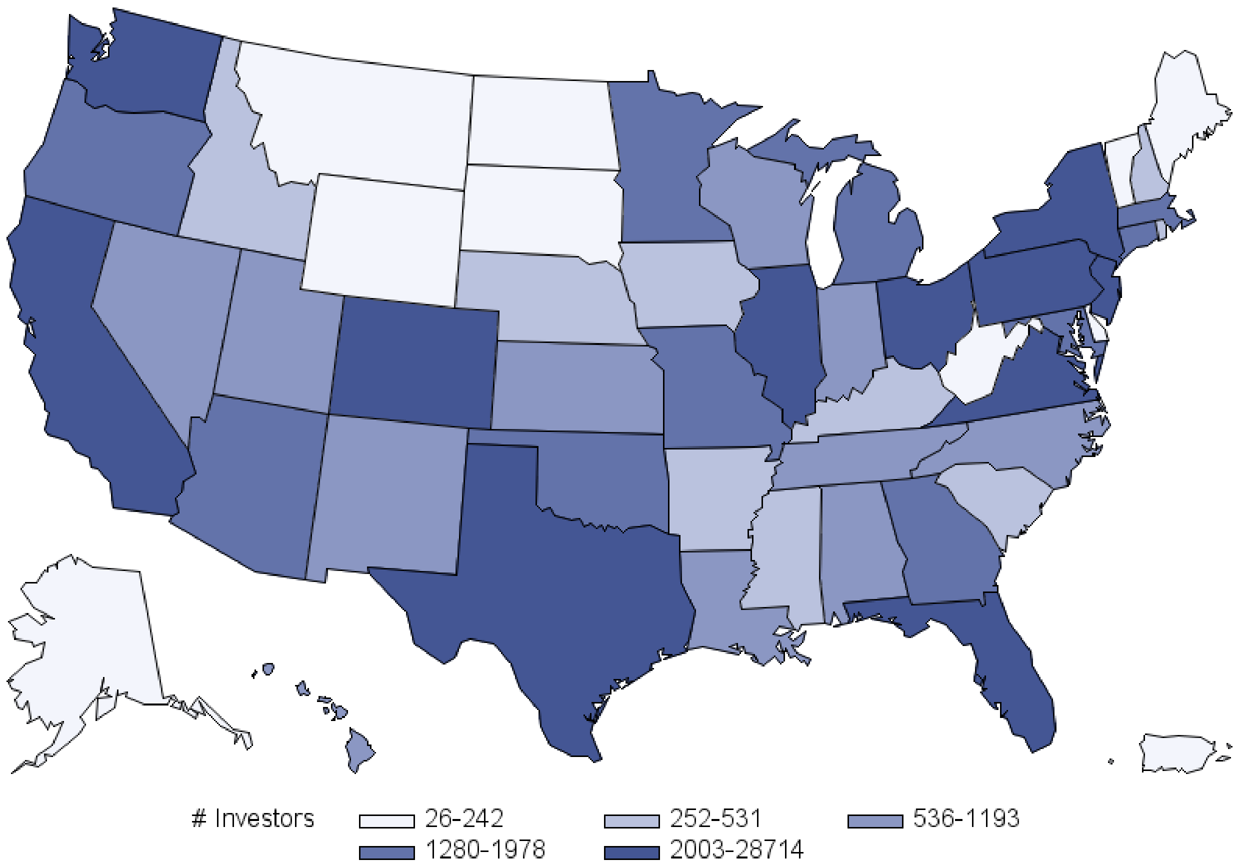


Fig. 1. Number of Investors in Each State

This figure shows the number of investors in each state in our sample. The darker the color of the block, the larger the number of investors in the corresponding state.

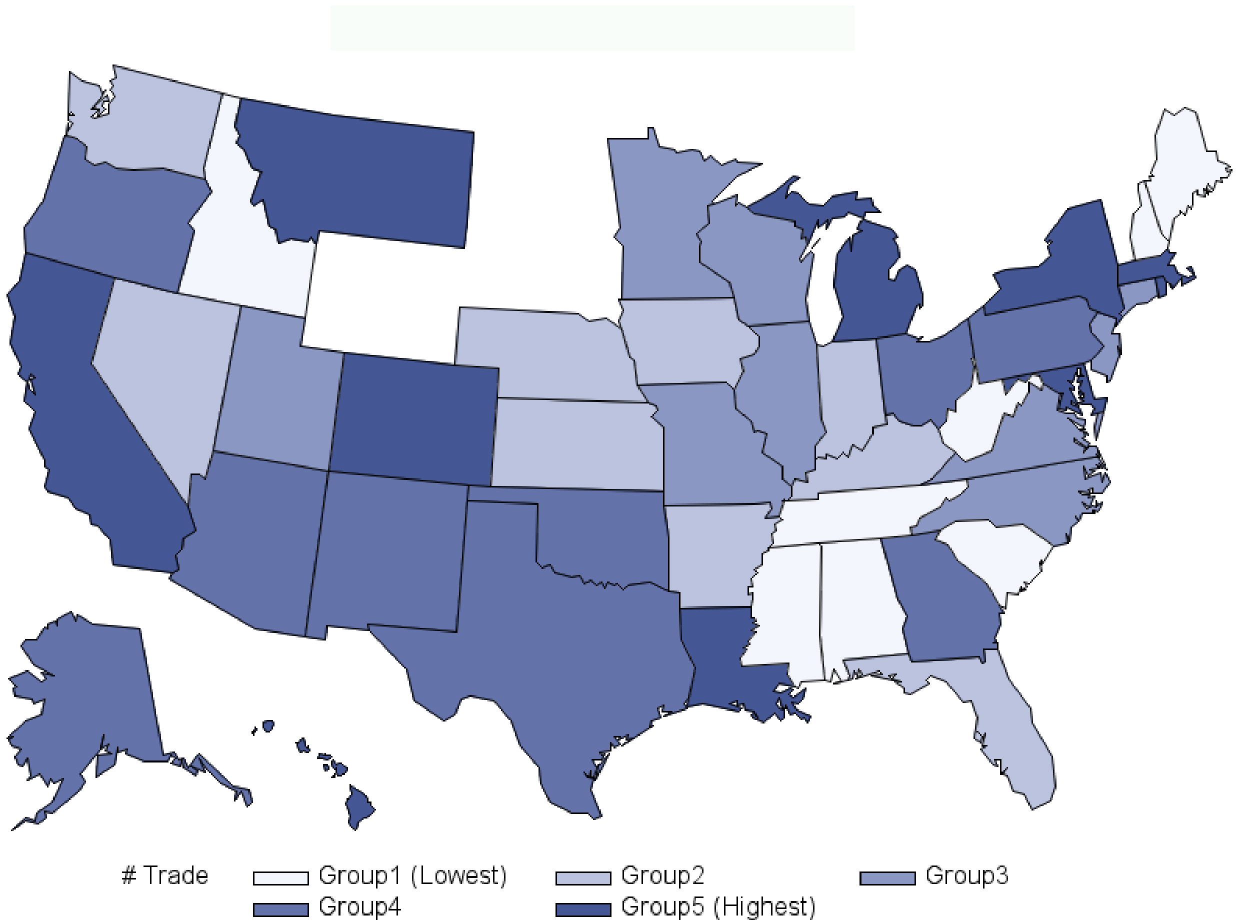


Fig. 2. Communication Rate in Each State (# Trades)

This figure shows the variation of communication rates across states. The darker the color of the block, the higher the average communication rate in the corresponding state. Trading is defined based on the number of trades.

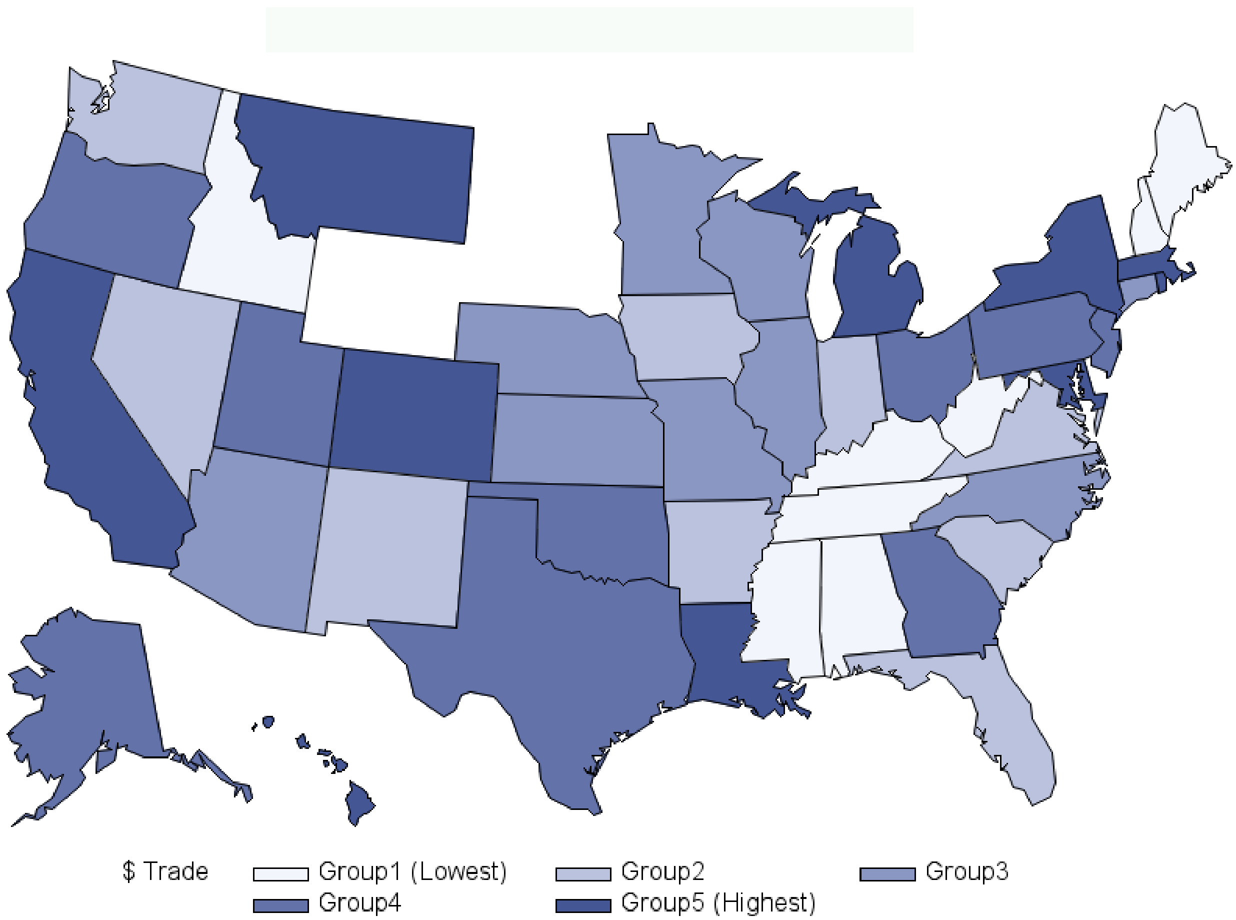


Fig. 3. Communication Rate in Each State ($ Trades)

This figure shows the variation of communication rates across states. The darker the color of the block, the higher the average communication rate in the corresponding state. Trading is defined based on the dollar value of trades.