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Social Interaction and Market Reaction to Earnings News

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Social Interaction and Market Reaction to Earnings News

DISSERTATION

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DOCTOR OF PHILOSOPHY

in Management

by

Qiguang Wang

Dissertation Committee:
Professor David Hirshleifer, Chair
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2017

DEDICATION

To my parents and my wife

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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ABSTRACT OF THE DISSERTATION

Social Interaction and Market Reaction to Earnings News

By

Qiguang Wang

Doctor of Philosophy in Management

University of California, Irvine, 2017

Professor David Hirshleifer, Chair

This study documents strong effects of social interaction on investors' attention and interpretations of earnings news. I estimate the firm-level investor social network and find that higher connectedness increases the announcement price reaction, reduces post-announcement drift, and decreases the long-run impact of the news on return volatility. I also find that social interaction triggers persistent disagreement-driven volume during and after the announcement. The evidence combined highlights the dual role of social interaction: It facilitates public information diffusion and thereby increases price efficiency, but also spawns investor disagreement and causes excessive trading volume that does not contribute to market efficiency.

Chapter 1

Introduction

Information processing of public signals has long been considered as an individual process, wherein investors interpret the news independently and identically and peer effects play no role. To the contrary, I document in this paper the significant effects of investor social network on the dynamic behaviors of price and volume during and after the public information disclosure. The evidence shows that social interaction not only influences investors' attention to the news but also impacts their interpretations of the signal.

I estimate investor social connections based on their spatial proximity and find that firms with strongly connected investors experience (1) stronger immediate price reactions during earnings announcements and weaker post-announcement drifts, (2) higher disagreement-driven trading volumes both during and after announcements, and (3) short-lived volatility but persistent trading volume. These findings collectively suggest that social interaction expedites the diffusion of public information but also stimulates greater investor disagreement along the way.

First, the evidence on price reactions and volatility dynamics suggests that social interaction enhances public information diffusion and improves price efficiency. While the neoclassic models usually assume that investors have infinite attention to financial news and react instantaneously, empirical studies find that the market usually underreacts to earnings announcements and stocks exhibit continued return reactions, i.e., post-earnings-announcement drift (PEAD) (Bernard and Thomas (1989)), which suggests that the public signal is gradually propagated in the market. The results in this paper indicate that the signal diffuses much more quickly when investors are well connected.

There are two ways through which social interaction improves public information diffusion: through centralized channels (press release and news article) and through decentralized channels (*word-of-mouth communication*). The former mechanism is due to investor attention effect. When two investors of the same stock communicate with each other, they are more likely to discuss the stocks that they both own than other stocks. During these conversations, inattentive investors can also be reminded of the scheduled earnings announcements. Either way, social interaction enhances the ex-ante level of investor attention to the news of the stocks that they hold in their portfolios, which in turn indicates more efficient centralized diffusion. The second mechanism occurs as the news spreads from attentive investors to their inattentive social peers after the announcement is made. In other words, social interaction also increases investors' ex-post attention upon earnings announcements and thereby contributes to the decentralized diffusion of the public signal.

The negative association between social interaction and volatility persistence implies that there exist decentralized diffusion channels such as word-of-mouth communications. In the theoretical model of Walden (2016), the speed at which the information diffuses across the population through social interaction is determined by the strength of investor connections. When investor networks exhibit high levels of connectedness, information disseminates quickly and the effect of information shock on prices is short-lived, leading to less persistent volatility. However, investors' ex-ante attention can also yield the same prediction. That is, when investors are more attentive to earnings news, the information will be quickly impounded into prices, rendering the effect of the information shock rather transient.

Therefore, to evaluate the second mechanism that social interaction improves the decentralized diffusion of the public signal after the announcement, I explore a quasi-natural experiment. Specifically, by utilizing the exogenous negative shock to social interaction through the statewide enforcements of distracted driving laws aimed to limit drivers' cell communication during driving, I document a weakened association between social interaction and announcement price reaction. For this analysis, the sample is truncated until the first release date of iPhone in 2007 to make sure that cell phones are mostly used for calling and texting rather than web browsing during the sample period. As a result, the constraint on cell use impacts social communications but does not affect investors' direct access to centralized news sources. The muted correlation between social interaction and immediate price reaction highlights the role of investor communication and strongly supports the hypothesis that social interaction increases investors' ex-post attention.

Second, the evidence reveals that trading activities react to earnings news differently than prices. While social interaction increases volume reactions in the announcement window, it also leads to highly persistent trading activities for an extended period. This is difficult to reconcile with rational learning models, in which information shock usually leads to similar price and volume reactions (Walden (2016)).

The literature documents that excessive trading volumes can be generated by investor disagreement (Kandel and Pearson (1995)). To verify whether the discrepant behaviors of price and volume can be explained by investor disagreement, I follow Kim and Verrecchia (1997) and Garfinkel and Sokobin (2006) to decompose the daily trading volume into two components: (1) the component that can be explained by concurrent price changes and (2) the component that cannot be explained. The first component represents the trading due to rational learning, whereas the second reflects investors' differential interpretations of the news.

I find that both components of trading volumes increase with social interaction during the announcement window. This indicates that social interaction stimulates efficient learning, which is in line with the previous finding that investor connection increases price efficiency. Moreover, the results also highlight that social interaction induces great investor disagreement.

The two components also differ in dynamic dependence. The learning component is on average much less persistent than the disagreement-driven component. Cross-sectionally, firms with strong investor connection experience much short-lived learning-driven volumes but more persistent disagreement-driven trading activities. The negative relation between social interaction and the persistence of learning component of volumes echoes the similar relation documented between social interaction and volatility persistence, supporting the positive role of social interaction in public information diffusion.

The positive association, on the other hand, between social interaction and the persistence of the disagreement-driven component implies that major disagreement not only arises through social interaction during the announcement but also persists and continues to drive trading volumes after the announcement (Banerjee and Kremer (2010)).

One possibility under which such persistent disagreement can be induced by social interaction is when investors hold heterogeneous interpretations of public news and agree to disagree, a setting modeled by Banerjee and Kremer (2010). As social interaction expedites the diffusion of the public news, more and more investors with different opinions begin to process the signal. For a given (non-degenerate and unbounded) belief distribution, an increase in the number of agents who become aware of the announcement (i.e., an increase in the belief sample size) implies greater likelihood for extreme opinions to exist in the market.

Therefore, disagreement surges after the announcement and generates trading continually until investors' opinions converge as they learn other resources.

Additionally, social interaction can also directly contribute to investor belief divergence. The literature on *belief polarization*[1] suggests that two people with opposing prior beliefs both strengthen their opinions after observing the same evidence. Therefore, social interaction, by spreading the signal from one to another and thereby subjecting the conversation participants to the same signal, may even further exacerbate their belief divergence. Furthermore, the empirical regularities on *group polarization*[2] indicate that individuals with similar prior beliefs, after discussing with each other, tend to become more aligned and more extreme in the direction of their pre-deliberation tendencies. It suggests that, even though social interaction reduces within-group differences, it polarizes cross-group opinions and can greatly increase investors disagreement at the aggregate level.

However, endogenous opinion difference is not the only source of disagreement. The very process of information transmission, or more generally social communication, can also trigger misinterpretations and rumors along the way. The resulting disagreement should be higher when investors interact more often with each other.

Different opinions triggered by conversations may or may not persist. On the one hand, erroneous beliefs formed during one conversation may well be carried over to other conversations by the same person. On the other hand, due to the fact that such disagreement is specific to each conversation, it could be idiosyncratic in nature, suggesting that the corresponding trading volumes should be independent. Moreover, strong investor connection predicts more frequent conversations, implying that average disagreement-driven trading volumes should be higher. I conduct empirical test and find that firms with strong investor connections also experience higher disagreement-driven

[1] A class study in this area is Lord, Ross, and Lepper (1979).

[2] For reviews, see Isenberg (1986) and Brown (1986).

volume in the post-announcement, lending support to the second possibility.

Moreover, in line with the view that investor disagreement and noise trading activities expose market participants to additional trading risk and therefore command risk premium, I document a robust positive relation between social interaction and post-announcement returns. All these additional analyses supplement the main findings on trading volumes and confirm the notion that social interaction increases investor disagreement.

Implicit in the above arguments of investor disagreement as well as its implications for trading volume and expected return is the assumption that investors will act upon their beliefs, which is possible if investors trade actively instead of passively. Han and Hirshleifer (2015) show that *self-enhancing transmission bias*, which occurs when investors recount their investment successes more often than failures and listeners do not fully take into account this asymmetry in updating their beliefs, leads to investors' preference toward active trading strategies over passive ones. Social interaction exacerbates this bias. This indicates that the effect of social interaction on trading volumes and subsequent returns will be even stronger, since well-connected investors not only disagree more at the first place but also trade more aggressively on their beliefs.

To sum up, the empirical findings in this paper suggest that, on the one hand, social interaction facilitates both the centralized and decentralized information diffusion of public signals, leads to strong immediate price and volume reactions, reduces the long-run impact of information shock on volatility, and thereby improves price efficiency. On the other hand, however, increased attention also induces strong disagreement, which in turn contributes to excessive trading activities that not only persist for a long time and but also command higher expected returns in the post-announcement window.

One of the biggest challenges in conducting social network analysis is to measure investor connection. Prior studies infer social networks of executives and directors from their education and employment ties (Cohen, Frazzini, and Malloy (2008); Engelberg, Gao, and Parsons (2012); Schmidt (2015); Fracassi (2016)). Moreover, the emphasis of these studies is on cross-firm social connections, which is different from the focus of this paper.

To measure social connection within a firm's investor base, I rely on geographical proximity. Specifically, I use *Spatial Social Network* models to estimate social network structure for each firm's local population. This type of models capitalizes on the negative empirical relation between social tie and spatial proximity and uses the geographical distance between two individuals to predict their friendship probability.

I apply these models to the estimation of social interaction among the local residents in the neighborhood of a firm's headquarter. To account for the differential friendship probability at a given distance for two individuals located in dense metropolitan cities such as the New York city and for two individuals in less populated rural areas, I adjust the connection probability by local population density. To gauge investor network connectedness for each firm, I then compute high-order mean degrees, which measure how many social contacts an average investor in the network can be connected to with no more than a specific number of steps.

The reasons that I choose to estimate connections of local residents to proxy for social interaction of the entire investor base are threefold. The first and the obvious reason is the data constraint. Constructing the investor-base network requires the identification of all existing investors. With the lack of these data, I rely instead on a firm's local investors and proxy their connectedness by the average per-household connections in the same neighborhoods. Second, there is evidence that investors exhibit strong preferences towards local investment (Coval and Moskowitz (1999), Ivković and Weisbenner (2005), and Seasholes and Zhu (2010)). The so-called *local bias* then implies that the shares of a stock should be disproportionately held by local investors. Third, the inverse relation between tie probability and geographical distance implies that social links among non-local investors and across non-local and local investors are much weaker than connections among local investors. Combined, these two effects guarantee that the geographic distribution of investor-base connections should be clustered at local areas and that local social interaction should have stronger impact on stock prices.

This paper contributes to the literature on investor attention. Prior studies document a number of determinants of investor attention, including characteristics of the stimulus (Fiske and Taylor (1991); Kahneman and Tversky (1973); Nisbett and Ross (1980)), bounded rationality (Gabaix and Laibson (2005)), rational attention allocation(Sims (2003); Kacperczyk, Nieuwerburgh, and Veldkamp (2014, 2016)), and exogenous distraction (Hirshleifer, Lim, and Teoh (2009); DellaVigna and Pollet (2009)). However, how attention can be modulated by social factors is poorly understood. This paper fills this gap and shows how investor attention to a firm's announcement can be reinforced through social interaction.

This paper is one of the very few studies that empirically test the impact of investor network on price dynamics. My findings provide a new test of the prediction of Han and Yang (2013) that investor social connection increases price efficiency when the information shock is exogenous. Furthermore, the negative relation documented between volatility persistence and investor connection is consistent with Walden (2016).

My study also contributes to the debate of whether social interaction improves or hurts market efficiency. Theoretical models that combine rational learning with decentralized information diffusion channels such as word-of-mouth communication, *information percolation*, and information network hold that strong investor connection leads to efficient information diffusion and thus improves market efficiency (Colla and Mele (2010); Ozsoylev and Walden (2011); Walden (2016)). Others, however, point out that social interaction can be detrimental to market efficiency by creating incentives to free ride on others' signal, which in turn discourages private information production (Han and Yang (2013)); by propagating rumors (Andrei and Cujean (2016)); and by inducing incorrect beliefs and preferences (Han and Hirshleifer (2015)). I show that social interaction increases price efficiency after earnings announcements, but also causes excessive trading volumes.

Finally, the result that social interaction positively predicts disagreement-driven trading volumes and its persistence in the post-announcement window highlights the role of difference of opinion in driving excessive and persistent trading activities (Karpoff (1986); Kim and Verrecchia (1994); Kandel and Pearson (1995); Banerjee and Kremer (2010)). Most existing empirical studies investigate trading volumes around earnings announcement in a relatively static setting. In contrast, I test volume dynamics and uncover the spike in investor disagreement and subsequent gradual opinion convergence as predicted by the theoretical model of Banerjee and Kremer (2010).

Chapter 2

Theoretical Motivation and Predictions

I now lay out the theoretical foundations of the social interaction hypotheses, with the emphasis on the interplays of social interaction with investor attention, information diffusion, and investor disagreement. I then discuss the implications for price and trading volume.

2.1 Investor Attention

Attention is a scarce cognitive resource (Kahneman (1973)). Attention to financial information, in particular, requires not only substituting cognitive resources from other tasks but also extra mental effort to process the information. In contrast to the classic finance theories that assume infinite attention and instantaneous response, there is ample evidence consistent with investors' limited attention in various economic settings, including inattention to accounting variables (Hirshleifer and Teoh (2003); Hirshleifer, Lim, and Teoh (2011)), asset price co-movement due to *categorical learning* (Peng and Xiong (2006)), the *ostrich effect* – the tendency for investors to pay more attention to their finances after good news than bad news (Karlsson, Loewenstein, and Seppi (2009); Sicherman et al. (2016)), and so on.

There is also empirical evidence of investor limited attention to earnings news. Hirshleifer, Lim, and Teoh (2009) find that immediate price reactions to earnings news are weaker when there are a large number of same-day announcements. DellaVigna and Pollet (2009) document that Friday announcements are associated with less pronounced market reaction. Both these studies contribute their findings to investor inattention.

Following the same line, I argue that social interaction increases investor attention to local firms' earnings news both before and after the announcement. There are several ways in which social interaction is associated with higher ex-ante investor attention:

(i) The tendency for the common interest to direct social conversations (Fast, Heath, and Wu (2009)) implies that investors discuss more about the assets they both own than the assets that they do not own. Therefore, frequent social interaction increases investor familiarity and attentiveness to the stocks that they hold.

(ii) Social interaction also induces strong stock co-ownership (Hong, Kubik, and Stein (2004), Ivković and Weisbenner (2007), and Brown et al. (2008)). When investors exhibit local bias, social interaction increases local ownership, which in turn leads to more attention because investors should be more familiar with local firms.

(iii) Investors can also be reminded of the scheduled earnings announcement through social communication, so they are more attentive before earnings news is released.

Upon announcement, social interaction can also increase ex-post attention to news by sharing the signal and spreading the cognizance of the news. Both ex-ante attention and ex-post attention increase the stock market reaction to the news (DellaVigna and Pollet (2009)).

Strong social interaction then leads to higher attention prior to the announcement as well as during the announcement window, motivating the following predictions on price responses:

> **Hypothesis 1a** *Firms with higher investor connection experience stronger announcement price reactions to earnings news;*
>
> **Hypothesis 1b** *Firms with higher investor connection exhibit weaker post-announcement price continuations;*

and on volume reactions:

> **Hypothesis 2a** *Firms with higher investor connection experience higher announcement abnormal trading volumes;*
>
> **Hypothesis 2b** *Firms with higher investor connection exhibit lower post-announcement trading volumes.*

2.2 Decentralized Information Diffusion

Information network and decentralized information diffusion combined are able to generate rich price and volume dynamics.[1] Among the theoretical work that incorporates information networks, there are two studies closely related to the research questions proposed in this paper. Han and Yang (2013) investigate of whether strong investor connection necessarily leads to more efficient prices. The authors point out that the incentive to free ride both on others' signals and on the informative price significantly reduces private information production, leading to less efficient market prices. However, when the information shock is exogenous, such as earnings announcement, investor connection improves price efficiency and

[1]See Andrei (2013) for volatility persistence; Andrei and Cujean (2016) for price momentum and reversal; and Walden (2016) for a holistic discussion.

increases trading volumes. Thus, their model yields the same prediction as Hypotheses 1a and 2a, i.e., social interaction leads to more responsive immediate price and volume reactions.

Given the static nature of Han and Yang (2013)'s model, predictions concerning the post-announcement price and volume reactions are not directly available. However, if price eventually converges to the public signal, more immediate reaction means less delayed reaction, and the complements of Hypothesis 1a and 2a should follow. Walden (2016) confirms this conjecture in his multi-period model. Walden studies a dynamic information diffusion process in which agents share their signals with their direct neighbors, the neighbors of their neighbors, and so on, as time passes. In equilibrium, prices and volumes are determined by the sequence of average high-order degrees, which measure the number of neighbors to whom an average agent can be connected within a given number of links. If investor connection is strong, a large part of price and volume reactions will occur in the first few trading rounds. If connection is weak, then prices and volumes experience more delayed reactions.[2]

In addition, Walden (2016) shows that the effect of information shock on volatility and volume should be short-lived when investors are closely connected. The persistence of the shock depends on the speed at which the information is distributed in the population. When the network exhibits high level of connectedness, efficient information sharing leads to more aggressive trading and the shock is quickly absorbed. Therefore, considering the role of social interaction as decentralized diffusion channel, I test the following predictions on volatility and volume dynamics:

> **Hypothesis 3** *Firms with higher investor connection experience less persistent volatility after the announcement.*

[2] Walden (2016) focuses on the dissemination of private information, but the setting can be easily extended to study the diffusion of public signals. In particular, if investors only receive noisy versions of the public signal, the equilibrium should be identical to the original setting.

Hypothesis 4 *Firms with higher investor connection exhibit less persistent trading volume after the announcement.*

2.3 Investor Disagreement

There is a disparity between the price and trading volume reactions observed during the earnings announcement, which is hard to reconcile with standard rational expectation models in which agents share common priors and the same interpretation of the signal (Bamber, Barron, and Stevens (2011)). Such irregularities have motivated researchers to study investor disagreement as a distinct source of excessive trading activities. Kim and Verrecchia (1991) consider a rational learning setting where investors disagree with each other before the earnings news. The release of the public information decreases investor pre-disclosure disagreement and generates trading even if investors interpret the signal identically. Kim and Verrecchia (1994) argue that investors possess differential private information that can only be used jointly with the public signal and consequently their beliefs diverge upon announcement. Kandel and Pearson (1995) show that, if investors use different likelihood functions to update their beliefs with the public signal, large trading volume can be generated without price changes. Kondor (2012) show that when investors have differential private signals, the release of public information reduces disagreement regarding the fundamental value of the stock but increases the differences in opinions of higher-order expectations (opinions about the opinions of others)[3].

Therefore, trading volume upon public announcements derives from rational learning as in Kim and Verrecchia (1991) as well as from differential interpretations of the news as in Kim and Verrecchia (1994) and Kandel and Pearson (1995). And there is empirical evidence consistent with both. Moreover, combining both, Kim and Verrecchia (1997) and Banerjee

[3] The condition for the disagreement to arise is that the correlation between private information among investors is sufficiently low.

and Kremer (2010) study the joint effects of rational learning and disagreement on price and volume.

In particular, Banerjee and Kremer (2010) highlight that, in a multi-period trading game consisting of players who interpret public news differently and agree to disagree, returns are determined by shifts in the average investor opinion whereas volumes are driven by changes in belief dispersion. The authors argue that trading volumes should be positively autocorrelated if the public announcement triggers major disagreement. This happens because the disagreement slowly dissipates as investors acquire addition signals and converge in belief, and therefore, the disagreement-driven volume should be persistent.

Theoretically, social interaction can both increase and decrease investor disagreement. On the one hand, if individuals share common priors and are Bayesian, their posteriors beliefs also converges after observing the same information (Blackwell and Dubins (1962)). If investors posses additional conditional signal, such as in Kim and Verrecchia (1994) and Kondor (2012), common knowledge of rationality and Bayesian updating guarantee that disagreement disappears after individuals share their beliefs (Aumann (1976); Geanakoplos and Polemarchakis (1982)). This indicates that social interaction reduces disagreement associated with differential private information.

On the other hand, there is also evidence of belief polarization, such as Lord, Ross, and Lepper (1979), Kinder and Mebane (1983), and Westen et al. (2006). In these studies, individuals with different priors disagree with each other even more when they observe the same piece of evidence. Explanations include confirmatory bias (Rabin and Schrag (1999)), ambiguity aversion (Baliga, Hanany, and Klibanoff (2013)), and memory constraints (Wilson (2014)). Under these explanations, sharing beliefs does not eliminate investor disagreement. In fact, transmission of public signals through social interaction subjects individuals to the same piece of information and therefore increases chances of belief polarization resulted from alternative preference and bounded rationality.[4]

Moreover, individuals with similar priors collectively shift towards more extreme posteriors after group deliberation, which the literature calls group polarization. Stoner (1968) first documents this phenomenon. The first type of explanations relies on information aggregation (Bordley (1983); Roux and Sobel (2015)), which suggests that group discussion efficiently aggregate information and lead to group polarization under certain conditions. Festinger (1954)'s *social comparison theory* is also used to explain group polarization, which holds that, in order to gain support, individuals support the group's beliefs by expressing a belief that is similar to everyone else's but slightly more extreme.

The evidence of *homophily* (McPherson, Smith-Lovin, and Cook (2001)), which refers to the homogeneous nature of personal network with regards to sociodemographic, behavioral, and other inttrapersonal characteristics, suggests that social interaction is more likely for individuals with similar beliefs. Therefore strong social interaction increases the likelihood of group deliberation with members of similar beliefs (i.e., group polarization due to information aggregation) but also reinforce the incentive to obtain group acceptance (i.e., social comparison theory). Through social interaction, group members become more aligned in their belief and shift further apart in opinions from other groups.

In a nutshell, social interaction can contribute to both belief divergence and convergence. If social interaction induces convergence via information sharing and learning, price and volume dynamics should follow Hypotheses 1-4. In contrast, if social interaction triggers disagreement and investors agree to disagree, volume dynamics should exhibit persistence as suggested by Banerjee and Kremer (2010). A competing prediction to Hypothesis 4 therefore follows:

[4] There is exception to this prediction. For example, under rational explanations of belief polarization, such as multi-dimensional information structure (Andreoni and Mylovanov (2012)), communications of private signals and conditional information largely eliminates belief divergence.

Hypothesis 5 *If investors have differential interpretations of the earnings news, then firms with higher investor connection experience more persistent trading volumes after the announcement.*

In this section, I only discuss theoretical motivations behind these major predictions. Additional and supporting analyses – to distinguish ex-post attention from ex-attention, for example – are deferred to each section.

Chapter 3

Identification Strategy and Data

In this section, I outline the methodology used to construct empirical measures of social network. I include all information that is required to reproduce these measures. For those who are interested in the background development and technical details, please see Wang (2016) for a thorough introduction.

The approach that I propose overcomes the typical data constraint problem for most stock-level investor network studies. The strategy relies on identifying potential local investors of a firm. For this purpose, I use a firm's headquarter location and include all households within 20 km radius as a firm's local potential investors. The threshold of 20 km is a trade-off between computational capacity and the intention to encircle all potential local investors.

3.1 Spatial Social Network Models

For each firm, I construct network structure for its local investors using *Spatial Social Network Models* that explore the impact of the geographical variability in population distribution on the structure of social networks. In particular, these models are based on the well-established result from empirical network studies that the marginal probability of social tie between two individuals declines with geographic distance (see McPherson, Smith-Lovin, and Cook (2001) for a review). Spatial distance is often considered the single most important predictor for social friendship in many social network studies. And spatial models have been successful in explaining several social behaviors (see, e.g., Hipp et al. (2013) on crime rates and Almquist and Butts (2015) on regional self-identifications).

The effect of geographic variability on social network can be easily implemented with the spatial Bernoulli graphs, which are essentially an extension of Erdös-Rényi random graph model with spatial distance as the determinant of network connections. Let G be the n by n adjacency matrix, whose (i,j)th element G_{ij} takes value of 1 if node i and node j are connected and 0 otherwise. The spatial graph can then be characterized by the probability mass function (pmfs)

$$\Pr\left(G = g|D\right)) = \prod_{i,j} B\left(G_{ij} = g_{ij}|\mathcal{F}(D_{ij},\theta)\right), \tag{3.1}$$

where D is the matrix of pairwise geographical distances, B is the Bernoulli pmf that takes value of $\mathcal{F}(D_{ij},\theta)$ if $g_{ij} = 1$ and $1-\mathcal{F}(D_{ij},\theta)$ otherwise, $\mathcal{F}$ is the *spatial interaction function* that defines the tie probability between two randomly selected individuals at a given distance of D_{ij} through parameter vector θ.

The above model is implemented through simulation for each firm with its local households. Households are randomly placed within its census block boundaries. This process assigns each household with a unique pair of latitude and longitude, which is essential for pairwise household distance calculation. The number of people in each household is also simulated according to the household size distribution provided by the U.S. census at the block group level. Ceteris paribus, family size should positively affect household connections. To reflect the multiplicative effect of family sizes on cross-household ties, I calculate social connection probability between two households as follows:

$$\mathcal{F}(d) = \frac{\theta_1}{(1+\theta_2 d)^{\theta_3}}, \tag{3.2}$$

$$\mathcal{F}^H(d, m_i, m_j) = 1 - [1 - \mathcal{F}(d)]^{m_i \times m_j}, \tag{3.3}$$

where $\mathcal{F}(d)$ is the social interaction function at individual level, d is the distance, m is the family size. For the social interaction function $\mathcal{F}(d)$, I use the power law function with parameter vector $\theta = (0.533, 0.032, 2.788)$, which is calibrated by Butts (2002) using the data from Festinger, Schachter, and Back (1950). However, these estimates are based on individual data. In (3.3), I assume independent friendship formation between members across two households and calculate household ties based on individual friendship probabilities.

The last adjustment I make to the tie calculation is to account for population density. This is necessary because there is a great deal of variation in firms' headquarter locations as well as their local population distribution. When comparing firms' local network in cross sections, the methods that rely on distance alone simply assume that two individuals, one mile apart from each other for example, would be as likely to know each other when they live in New York City as when they are in Nebraska. The problem with the aforementioned approach is that it ignores the impact of the size of potential friendship candidates – friendship decreases not only with distance, but also with the total number of potential friends within that distance.

Capitalizing on this observation, Liben-Nowell et al. (2005) develop the famous *rank-based friendship* model to explain the well-known *small-world phenomenon*, which holds that two randomly selected individuals from a large social network can be connected with only a few links. Their model highlights that the probability with which i befriends j at the distance d_{ij} is inversely proportional to the total number of i's neighbors with distance less than d_{ij}. The total number of people within a given distance is proportional to ρd^2, where ρ

is the population density and d is the distance. Rank-based models effectively adjust the geographical distance by the square root of local population density (i.e., the distance d essentially enters the model pre-multiplied by $\sqrt{\rho}$). Therefore, instead of working with raw distance, I normalize distance d_{ij} used in (3.3) as

$$\tilde{d}_{ij} = d_{ij} \times \sqrt{\frac{\max(popdens_i, popdens_j)}{\text{median}(popdens)}}, \tag{3.4}$$

where $popdens_i$ is population density of the census block to which individual i belongs, and median($popdens$) is the median density across all census block groups used in my sample.

3.2 Network Connection Measures

To gauge network connectedness, I use (high-order) mean degrees. The degree of a node is the total number of distinct and direct ties that originate from it. Let v_i^1 denote the degree of node i, then

$$v_i^1(g) = \#\{j : g_{ij} = 1\} = \sum_j g_{ij}.\text{[1]} \tag{3.5}$$

The mean degree of the network is the average degree of all nodes. Let v^1 be the mean degree, then $v^1 = \sum v_i^1/n$. The mean degree is also considered as the first-order degree, since it only counts one-step connections. The concept of the degree, however, can be easily generalized to high-order connections that require several steps to establish the link. As such, I compute m^{th} *order degree* of node i, v_i^m, which measures the total number of nodes to which i can reach with nor more than m links. In other words, it counts not only neighbors at distance with exact m links, but also those less than m links. Using matrix algebra, it follows

$$v_i^m = \sum_{j \neq i} \mathbb{1}\left(s_{ij}^m\right), \tag{3.6}$$

where $\mathbb{1}(x)$ is the indicator function that equals 1 if $x > 0$ and 0 otherwise, and $s^m = g^1 + g^2 + \cdots + g^m$ is the matrix whose elements count the number of walks with length m between any two nodes. i and j are connected with no further than m steps if $s_{ij}^m > 0$.

In the multi-period asset pricing model with information network, the process $\{v^m : m = 1, 2, \ldots, T\}$ usually characterizes the information flow as well as the dynamic process of investor average opinion and determines equilibrium price and volume dynamics (Walden (2016)). Given its theoretical importance, I focus on mean-degree process up to the third order. The calculation of the high-order degrees requires matrix multiplication up to the m^{th} order, and the third order is the highest feasible order given the computing constraint.

For each firm in the sample, I calculate v^1, v^2, and v^3 as the network connection measures. There are in total $4,606$ distinct headquarter zip codes identified with 10-K header files from all U.S. firms. Figure 1 plots their latitude and longitude coordinates on the U.S. map.

In Table 1 Panel A, I report summary statistics for these connection measures along with the total number of local households for each firm. The mean degree across all local networks averages at 17, which is the number of households to which an average family is connected in the sample. High-order mean degrees reveal that the average household is connected to roughly 400 and $2,100$ other households through two and three links respectively. These numbers seem high from the perspective of individual friendship, but are in fact reasonable considering households are connected as long as any two members cross the households are socially connected.

Moreover, due to distance normalization, mean degrees are only mildly correlated with local population. This has two crucial implications. First, the effects of these connection measures on the market reaction to earnings announcement, if any, do not simply reflect the population effect. Second, the low correlation suggests that the documented results of social interaction are unlikely to be explained by local bias, at least to the extent that local bias can be proxied by the total number of households in the neighborhood of a firm's headquarter.

3.3 Data

The household data required to estimate social interactions are from the U.S. Census 2000. Stock returns, prices, and trading volumes are from CRSP, institutional holdings are from Thomson Reuters 13F database, and quarterly earnings and accounting variables are obtained from Compustat. To ensure the accuracy of announcement dates, I cross compare the dates in Compustat with those in I/B/E/S. When they differ, I take the earlier date following DellaVigna and Pollet (2009), who show that earlier date is usually the actual date of announcement while the later date is that of publication in the *Wall Street Journal*. Historical headquarter addresses are parsed from 10-K header files from SEC Edgar system.[2] Newspaper contact information is purchased from Media Contacts Pro. The sample is from 1994 to 2010, mainly constrained by the availability of SEC electronic filling. The final merged sample consists of 233,048 unique firm-quarter observations.

I use the random walk model to calculate SUE. For each firm-quarter, I calculate SUE as follows:

$$\mathrm{SUE}_{i,q} = \frac{e_{i,q} - e_{i,q-4}}{\sigma_{i,q}}, \tag{3.7}$$

where $e_{i,q}$ is the split-adjusted actual earnings per share for firm i in fiscal quarter q, $e_{i,q-4}$

[2]The data is made available at Bill MacDonal's website at http://www3.nd.edu/ mcdonald/10-K_Headers/10-K_Headers.html

is the earnings per share of the same quarter one year ago, and the deflator $\sigma_{i,q}$ is the standard deviation of unexpected earnings, $e_{i,s} - e_{i,s-4}$, over the previous eight quarters.[3] The random walk model assumes that investors simply extrapolate future earnings from same-season earnings in the previous year.

An alternative way to estimate earnings surprises is based on analyst forecasts. Instead of simple time-series forecast, this method assumes that investors rely on the consensus of analyst forecasts, which are supposedly more informative, to form expectations of future earnings. However, there is evidence that these two different measures of earnings surprises are associated with underreaction of different types of investors. Ayers, Li, and Yeung (2011) document that small (large) traders react more to seasonal random-walk- (analyst-) based unexpected earnings during announcement and continue to trade in the same direction in post-announcement window. Given that the empirical social network in this paper is constructed with household data, the associated connection measures should capture social interaction among retail investors who are usually considered to be small traders.

Working with the random walk model also means that the sample size will be much larger, which is especially desirable for analyses such as double portfolio sorting. In my sample, the drift, estimated as the spread of decile portfolios sorted by random-walk-based SUE, is 6.39% for all firms, which is also comparable to the drift based on analyst forecasts, 5.71%, for firms with analyst following. For all these reasons, I use random-walk-based earnings surprises throughout this paper.[4]

Following the literature, I calculate the cumulative abnormal return (CAR) of the announcement and post-announcement windows as the difference between the buy-and-hold return of the stock and that of its benchmark portfolio over the window [0, 1]

[3]Deflating unexpected earnings by quarter-end closing price yields almost identical results for most of the tests in this paper.

[4]The cumulative abnormal return in this comparison is DGTW-adjusted return; see the following paragraph for details.

and [2, 61] in trading days relative to the announcement date. While previous studies often use size and book-to-market (B/M) portfolios as benchmark, the empirical evidence in Novy-Marx (2015) suggests that including momentum portfolios into the benchmark increases the measured CARs in the post-announcement window.[5] For this reason, I use the 125 triple-sort portfolios on size, B/M, and momentum following Daniel et al. (1997) as benchmark[6] and define CARs as follows:

$$
\begin{aligned}
\text{CAR}[0,1]_{i,q} &= \prod_{s=t}^{t+1}(1+R_{i,s}) - \prod_{s=t}^{t+1}(1+R_{b,s}) \\
\text{CAR}[2,61]_{i,q} &= \prod_{s=t+2}^{t+61}(1+R_{i,s}) - \prod_{s=t+2}^{t+61}(1+R_{b,s}),
\end{aligned}
\tag{3.8}
$$

where t is the adjusted announcement date[7]. $R_{i,s}$ is stock return of firm i on day s, and $R_{b,s}$ is the return of the matching size-B/M-momentum portfolio.

[Insert Table 1 here]

Table 1 reports the summary statistics of key variables for portfolios sorted by the third-order mean degree v^3. The results show that firms with high degree of connection tend to be big firms with large market capitalization, high institutional ownership, and high share turnover. Additionally, high-connection firms are also associated with more persistent earnings, greater earnings volatility, and larger reporting lags. There is mixed evidence on whether investor network connection is related to the timing of earnings announcements that exploits investor limited attention. Both high-news days (days that have a large number of announcements) and Fridays are associated with a greater level of market inattention (Hirshleifer, Lim, and

[5] See Figure 3 of Novy-Marx (2015). The author find that the current earnings news predicts stock returns during future earnings announcements by forming long-and-short strategy based on most recent SUE. Moreover, the author find these strategies perform better if stock momentum (past one-year return) is controlled. These conditional strategies first assign stocks into momentum portfolios and then buy stocks with the most positive SUE and short ones with the most negative SUE within each momentum portfolio.

[6] The empirical results in this paper are not sensitive to any particular choice of benchmarks. Using 25 size and B/M portfolios as benchmark portfolios yields very similar results.

[7] If the announcement occurs on a non-trading day or after 4:00 p.m. ET, t will be the next trading day.

Teoh (2009); DellaVigna and Pollet (2009)). However, announcements for high-connection firms tend to occur on high-news days but are less likely to fall on Fridays. There is no significant difference in book-to-market ratios and earnings surprises between the highest and lowest connection deciles.

Most of the characteristics vary monotonically with v^3 ranks, with the exception being size, which shows great nonlinearity for middle- and high-rank portfolios. Given the significant correlations identified in this table, I employ these firm and announcement attributes as controls in regression analyses.

Chapter 4

Immediate and Delayed Return Responses

A number of previous studies attribute PEAD to market underreaction to earnings news in the announcement period (Bernard and Thomas (1989)). There is also consistent evidence that market underreaction is related to investor limited attention. DellaVigna and Pollet (2009) and Hirshleifer, Lim, and Teoh (2011) model the stock-level investor inattention as the fraction of investors that pay attention to the public signal and show that immediate (delayed) price response to the news increases (decreases) with the percentage of attentive investors. While previous research mostly studies time-series shifts in investor attention, I examine, in this section, whether social connection can also effectively lead to different aggregate levels of investor attention in cross sections.

4.1 Portfolio Approach

I construct double-sorted portfolios to test the effect of social interaction on price reaction to earnings announcement. In each calendar quarter, stocks are independently ranked from 1 to 10 based on the network connection measures (CXN) of stocks' local population and earnings surprises (SUE) as defined in (3.7), and are then assigned into $10 \times 10 = 100$ groups. Within each CXN decile, I calculate the mean announcement period (CAR[0, 1]) and post-announcement period (CAR[2, 61]) cumulative abnormal returns for the most positive (SUE10) and the most negative (SUE1) earnings surprise deciles and the difference in these returns between the two extreme earning surprise deciles.

If investors are fully attentive, they react to the news quickly. Stocks in the two extreme SUE deciles will experience, respectively, substantial positive and negative return responses during the announcement period, creating a large spread in announcement-day returns. Since the public signal is fully impounded into price during announcement, there will be no difference between firms with good earnings news and firms with bad earnings news in post-announcement performance.

On the other hand, if information is slowly incorporated into the prices, initial return reactions will be weak and delayed reactions will be strong, yielding a smaller spread in announcement returns and a larger spread in subsequent price changes. Therefore, the magnitude of the spread of announcement returns assesses the strength of investor immediate reactions and the magnitude of the spread in post-announcement returns measures the degree of delayed responses.

The social interaction hypothesis predicts that stocks with stronger investor connection experience strong investor attention, and therefore a larger $\mathrm{CAR}[0, 1]$ spread (stronger announcement-day reaction) and a smaller $\mathrm{CAR}[2, 61]$ spread (weaker post-announcement drift). Table 2 reports the results of the mean portfolio returns and spreads. For brevity, I only show the results based on the two-way sorts of v^3 (third-order mean degree) and SUE. Results for other network measures such as v^1 and v^2 are quantitatively similar.

[Insert Table 2 here]

Table 2 shows that investors' reactions to earnings surprises during announcement days are more responsive to the news for stocks with highly connected investors. For the lowest connection decile (VRANK = 1), the mean spread in 2-day abnormal announcement returns between stocks with the most positive earnings surprises and stocks with the most negative earnings surprises is 3.10%, compared to the mean spread of 4.13% between two groups of extreme earnings news firms for the highest connection decile (VRANK = 10). The difference in the spread between the highest and lowest investor connection deciles is 1.03%, which is significant at 1% level. This difference is also economically meaningful, representing roughly 30% of the full-sample mean spread across all connection deciles (3.47%). This indicates that connections among investors increase social attention and cause more immediate reactions to earnings news.

In addition, greater post-announcement drift is also observed for the lowest connection decile compared to the highest connection decile. For firms with the lowest level of investor connection, the post-announcement cumulative abnormal return spread between extreme earnings surprise deciles is 5.49%, whereas, for high-connection firms, the spread is only 3.06%. The difference, 2.43%, is 38% of the full-sample mean drift (6.39%). Combined, the evidence is consistent with the social interaction hypothesis that stocks with sparse investor information networks experience much weaker immediate price reactions, and consequently exhibit greater post-earnings-announcement drift.

There are noticeable nonlinear relations between investor connection and the return spread between the two extreme earnings surprise deciles for both time windows. This non-monotonicity could stem from the nonlinear correlation between investor connection and firm size as reported in Table 1. It is therefore useful to perform regression analyses with size and other controls.

4.2 Regression Analysis

To account for the significant correlations between investor connection measures and various variables in Table 1 and to confirm the portfolio sorting results, I conduct regression analysis in this section. The objective is to control for possible determinants of both announcement and post-announcement abnormal returns. Following the literature, I use earnings surprise decile ranks instead of the level measure in the regression to control for the well-documented nonlinear relation between SUE and stock returns (Kothari (2001)). Also, to prevent extreme values from dominating the regression, size, B/M ratio, and all empirical network measures are logged.

To test both immediate and delayed price reactions, I regress announcement-window abnormal returns CAR[0, 1] and post-announcement cumulative abnormal returns CAR[2, 61] on the earnings surprise decile rank (SUE), investor network connection measures (CXN), the interaction term SUE×CXN, and control variables, which are also interacted with SUE ranks, as follows:

$$\begin{aligned}\text{CAR} = {} & \alpha_0 + \alpha_1 SUE + \alpha_2 CXN + \alpha_3 (SUE \times CXN) \\ & + \sum_{i=1}^{n} \beta_i Control_i + \sum_{i=1}^{n} \gamma_i (SUE \times Control_i) + \epsilon.\end{aligned} \tag{4.1}$$

Return response to earnings news is captured by the slope, or the first-order derivative, of CAR as a function of SUE in the above regression, and therefore is equal to $\alpha_1 + \alpha_2 CXN + \sum_{i=1}^{n} \gamma_i Control_i$. The expression of this slope then clearly shows that, in order to control for the confounding effect of alternative variables on return reaction to news, their interactions with earnings surprise rank SUE must be included in the regression.

A positive α_3 in the regression of CAR[0, 1] indicates that investor connection leads to stronger immediate price reactions, whereas a positive α_3 in the regression of CAR[2, 61] implies stronger delayed price reactions. α_3 is also directly comparable to the difference in extreme earnings surprise spread (SUE10-SUE1) between the highest connection decile and lowest connection decile in Table 2. Therefore, if the regression analysis is consistent with the portfolio approach, I expect $\alpha_3 > 0$ for announcement-period returns and $\alpha_3 < 0$ for post-announcement drifts.

[Insert Table 3 here]

To make sure that the results from the regression are robust to the inclusion of stock and earnings characteristics, I add a set of control variables into the regression. To start with, I include the common firm attributes such as market beta, size, and book-to-market ratio. Motivated by the previous research that shows the significant effect of investor clientele and earnings announcement characteristics on investor reactions to the news, I further include institutional ownership, earnings persistence, earnings volatility, and share turnover. Studies also show that investors become more distracted to earnings news when there are a great number of concurrent announcements (Hirshleifer, Lim, and Teoh (2009)) or when earnings are announced on Fridays (DellaVigna and Pollet (2009)). As a result, the number of same-day announcements and day-of-week dummy variables are also added to the regression. Finally, to control for time-series trends and industry effects, I add indicator variables for year, month, and Fama-French 10 industry classification.

Apart from above-mentioned controls, I also include local population density, measured as the log of total number of local households within 20 km of a firm's headquarter. The purpose is to show that results are not simply due to density effect. In the untabulated results, I replicate the most tests with population density in place for social connection measures and find that it fails to support the same empirical prediction as outlined earlier.

The estimated α_3 in the regression model (1) is positive and significant at 1% level for all network measures. These coefficients are also economically meaningful. For example, one-standard-deviation change in the first-order mean degree measure (logged) v^3 (0.34) is associated 5.4% increase in the sensitivity of immediate responses relative to the mean sensitivity of announcement returns to earnings news.[1] For post-announcement returns, the interaction term (CXN×SUE) shows up negative and statistically significant for all network connection measures. A similar calculation reveals that a one-standard-deviation change in v^3 decreases the sensitivity of post-announcement price reactions to the public signal by 17%.

To compare the economic significance of network measures with that of the control variables, I follow Hirshleifer, Lim, and Teoh (2009) to run standardized regressions where all continuous variables are all standardized by subtracting mean and then dividing by standard deviation. Coefficients then represent the change in the dependent variable due to a one-standard-deviation change in the independent variables.

Judging from the absolute value of these coefficients (unreported), size is the strongest predictor for the sensitivity of both immediate and delayed price reactions to earnings news. In the announcement window, network measures come in third with smaller impact than book-to-market ratio but larger effect than all other controls. In the post-announcement window, only institutional ownership and share turnover are statistically significant in addition to size, and network measures have stronger influence on delayed reactions than share turnover but weaker influence than institutional ownership. Population density is significant in both windows but shows up with positive coefficients. In fact, network measures are the only variables with significant coefficients of different

[1]The mean sensitivity of announcement returns to earnings news equals 0.43, estimated from univariate regression of CAR[,1] on SUE.

signs across the both time windows.

4.3 Investor Clientele

Previous studies suggest that market reactions to earnings announcements may depend on the type of firms' investor clientele. For example, Bernard and Thomas (1989) find that the post-earnings announcement drift is stronger for small firms and suggest that investor naïvetè may drive the drift. There is evidence that retail investors are responsible for the return continuation after the announcement. Bartov, Krinsky, and Radhakrishnan (2000) find that PEAD decreases with the level of institutional ownership, providing a degree of support to Bernard and Thomas (1989)'s conjecture. Ayers, Li, and Yeung (2011) find small traders continue to trade in the same direction of random-walk-based earnings surprises after earnings announcements and the drift attenuates when these small traders react more thoroughly to the news, suggesting that retail investors are likely to be culprit.

Given that my empirical networks are based on local household data, the empirical effects of investor connection on return reactions documented in previous sections should also be driven by retail investors. And the previous findings are consistent with the notion that retail investors underreact to the news. To further support this hypothesis, I perform subsample analysis and test whether the effects of social interaction on investor attention are more pronounced for firms with a lot of retail investors.

[Insert Table 4 here]

I choose three proxies for retail investor clientele: size, institutional ownership, and idiosyncratic volatility of stock returns. At each calendar quarter, I divide all firm-announcement observations into two groups based on each of these three variables. For size groups, NYSE size median is used as the cutoff point. For institutional ownership and idiosyncratic volatility, the threshold is the sample median. The results for the subsample analyses are reported in Table 4. For brevity, I only report the results for the third-order mean degree v^3. The evidence is consistent with the above prediction for market reactions in the announcement window. The effect of social interaction on announcement price reactions is much stronger in the retail subsamples. The differences for post-announcement price reactions are, however, insignificant.

In sum, the empirical evidence is consistent with naïvetè hypothesis of Bernard and Thomas (1989). The effect of investor connection on stock's immediate price reactions is stronger for stocks that are small, with low institutional ownership, and exhibit large idiosyncratic volatility.

4.4 Local Bias

The network measures gauge the level of social interaction and the speed of public information transmission from one to another in the local area. How much local investors' connection impact stock markets as reflected in stock returns, however, depends on how much these households contribute to the trading market and how heavily they are invested in the local stocks. In other words, market reactions increase with both social interaction and local ownership. As a result, the regression coefficients in Table 3 therefore measure the joint effect of both contributing factors.

One concern is that social connection and local bias are positively correlated, not only because of peer effect on stock ownership (Hong, Kubik, and Stein (2004), Ivković and Weisbenner (2007), and Brown et al. (2008)), but also due to the specific method used to construct the network measures.

Specifically, there exists a mechanical effect that induces positive correlation between network connection measures such as high-order mean degrees and network size (the total number of nodes). This imposes a concern because local population is positively correlated with local ownership. Consider an extreme example of the m^{th}-order degree where m goes to positive infinity. Let v^∞ denote this measure. v^∞ then counts all possible friends to whom an average individual can be linked regardless of the number of steps. This number cannot exceed the total number of nodes in the network. In fact, v^∞ equals the size of the largest subgraph of the network (or the size of the network if it is a connected graph). As m goes up, so is the correlation between v^m, the m^{th}-order mean degree, and the network size. This pattern is evident in the growing correlations of v^1, v^2, and v^3 with the number of local households.

Network size, or the total number local households, should be positively associated with the level of local bias for the firm for two reasons. If stock ownership is an individual and independent decision, then an increase in the sample size of potential candidates implies an increase in the ex-post number of stock owners. However, as the peer effect literature suggest, stock participation and purchase are social decisions impacted by one's peers, which would further aggravate the relation between local population and local bias. It implies that the effect of social interaction on price reactions may be driven by its correlation with local population, especially when investor connection is measured by the third-order mean degree v^3, which exhibits highest correlation with local population among the three measures.

It is important to point out that local bias by itself does not impose a challenge to the documented social interaction effect. Examining two explanations for local bias: *local information advantage* (Ivković and Weisbenner (2005); Ivković, Sialm, and Weisbenner (2008)) and *familiarity bias* (Huberman (2001)), Chi and Shanthikumar (2016) argue that both reasons imply weaker market reaction to earnings news during the announcement window. This is due to the pre-event information in the case of local information advantage and behavioral biases in the case of familiarity bias. In both, local investors rely less on the public information. Therefore, firms with higher local bias react more weakly to earnings news.

Collectively, Chi and Shanthikumar (2016) support their hypotheses by showing that local ownership, proxied by geographical distribution of Google Search, is associated with higher pre-event stock return reaction, lower announcement-window market response, and higher post-earnings-announcement drift. In contrast, I find that network measures predict no pre-announcement return reactions (untabulated), stronger announcement-window reaction, and lower post-event drift. The opposite empirical findings suggest that the documented social interaction effect is not likely to be confounded by local bias on its own.

As such, although I control for local ownership in this section, the purpose is not to entertain local bias as a competing hypothesis to the social network effect. Rather, the goal is to account for the level of stock ownership of local investors, eliminate any mechanical relation between local bias and network connection measures, and in turn highlight social interaction effect on price reactions.

I choose several variables in addition to local population to control for local bias, which include local mean age, retirement ratio, and average household income. Bailey, Kumar, and Ng (2011) use age and retirement status as measures for trading experience and intelligence. A number of studies such as Mankiw and Zeldes (1991), Calvet, Campbell, and Sodini (2007), and Briggs et al. (2015) find compelling evidence of wealth effect on stock market participation. I also compute the ratio of local workforce in the same industry as the firm based on the first two digits of *North American Industry Classification System* (NAICS) classifications.

Last, I also include the social capital measure from Rupasingha, Goetz, and Freshwater (2006)[2]. Community resources not only enhance social interaction but also develop the

[2]The measure is the first principal component of the following five variables: the total number of community clubs/associations (1st factor), voter turnout, census response rate, the number of non-profit organizations. The first factor counts religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical

sense of social belonging and the support for the local business among its residents. Thus, it introduces a distinct channel through which the network measures can also be positively related to market reaction to earnings news: Highly connected neighborhoods may also happen to be those with greater support for and higher involvement in its local firms, therefore these communities react more strongly to earnings news of local firms. Including social capital not only controls for local bias induced by community resources but also helps disentangle community effect from social interaction effect.

Including all these controls only mildly reduces the size and the significance of the return reaction coefficient (CXN×SUE). Model (2) in Table 3 shows that social interaction still predicts strong announcement price reactions and weak post-announcement drifts, indicating that social interaction also increases market reaction.

4.5 Centralized v.s. Decentralized Diffusion

The positive relation between social interaction and immediate price reactions to the announcement suggests that social interaction expedites public information diffusion. However, investor connection contributes to the centralized diffusion as well as the decentralized diffusion of the public signal. In other words, social interaction boosts investor attention in two different ways. First, social communication increases investors' familiarity with local firms. The performance of local firms and the related news are likely to be a major topic for casual conversations among local peers. Moreover, through social interaction, investors can also be reminded of the scheduled earnings announcements. That is, social interaction raises investors' ex-ante attention to news.

Second, social interaction can also lead to higher ex-post attention after the announcement.

fitness facilities, public golf courses, and sport clubs/managers/promoters. The analysis is conducted at for each county for the year 1997, 2005, and 2009.

Investors who does not pay attention to the news will become aware of it when they talk to their friends. Thus, social interaction can contribute to additional investor attention on top of its ex-ante level by spreading the news through interpersonal communications. I use "ex-post attention" to indicate the extra investor attention derived from social interaction during the earnings announcement.

Both the ex-ante and ex-post attentions (within the announcement window) increase price reactions to earnings news. To separate the latter from the former and, therefore, to highlight the role of decentralized information channel, require controlling for ex-ante investor attention. In the following, I explore variables related to investor attention and firm exposure as potential controls to single out the ex-post attention effect. In addition, I also conduct a quasi-natural experiment to further disentangle these two channels.

4.5.1 Controlling for Investor Attention

I start with exploring a number of firm characteristics that attribute to a company's exposure. I include advertisement expense, the log number of employees, the log number of shareholders, and urban indicator for whether the firm is located in one of the ten largest cities. The literature suggests that these variables should be positively related to firm visibility.

Also included is the log number of local firms within a 100 km radius from a firm's headquarter. Geographical firm clusters may create positive externality that induces investors to pay more attention to local corporate news. However, investors close to these clusters also have great number of firms to attend to. Therefore, their attention to each firm might be diluted. Which effect dominates is mostly an empirical question.

Similarly, I include the log number of local newspaper within 100 km radius to control for local investors' access to local news. The subsample analysis suggests that the social interaction effect is mostly driven by small firms whose earnings announcement are less likely to be covered by national newspaper. In addition, there is also empirical evidence that regional newspaper provides greater coverage of local firms and local investors rely substantially on local news media to get information (Miller and Shanthikumar (2010)).

Last, I include the lagged trading volume around the announcement as the proxy for investors' ex-ante attention. This is motivated by the "attention grabbing" hypothesis tested in Frazzini and Lamont (2007), who argues that large announcement trading volume attracts investor attention.

I present regression results with these additional attention controls in Model (3) of Table 3. The coefficients in front of the interaction term between network measures and SUE increase both in absolute value and statistical significance, suggesting that the social interaction effect cannot be explained by differences in firm visibility and investors' exposure to firm news.

4.5.2 Exogenous Shock to Social Communication

While attention controls are included in the previous section, they may not be sufficient to fully account for differences in firm-level investor attention. To separate the effect of decentralized diffusion from that of centralized diffusion, I explore a quasi-natural experiment where social communication is constrained but direct access to news are not affected. Specifically, the statewide *distracted driving law*, which restricts cell phone communication by drivers during driving, is imposed at different time for each state and can be used as a treatment to the firms located in areas where the law is enforced. Investors in these states experience limited mobile person-to-person communication as a result. The reduced social interaction should mainly affect ex-post attention, because these restrictions are more likely to be binding in a 2-day announcement window than in a long-term window where ex-ante attention is characterized and determined. Moreover, to ensure that the restrictions of cell phone usage does not necessarily affect investor attention to the news through direct and centralized information diffusion channel (i.e. mobile web browsing and trading app push notifications), the sample period is confined to pre-2007 period when the era of the widespread use of smartphones has yet to arrive.

If ex-ante attention alone drives the positive association between social interaction and price reactions, then this relation should not be impacted by the reduction in investor communication. On the other hand, if ex-post attention also contributes to the difference in price responses, the effect of social interaction on immediate price reactions would be muted when there is less social communication.

Using the state-by-state enforcement dates provided by Brown, Stice, and White (2015), I create a dummy variable, DDL, which equals 1 if the firm's local population are affected by the law in a given quarter. I then include the three-way interaction of earnings surprises, network connection, and the dummy variable DDL in the regression of announcement return CAR[0,1].

[Insert Table 5 here]

However, without further controls, a negative coefficient on the triple interaction may not indicate weaker social interaction effect. This is because of two confounding effects. First, only a handful of states implemented the laws in the sample. It is possible that for these states the interplay between social interaction and price response to earnings news are generally lower compared to other states, possibly due to cultural differences. In other words, DDL×CXN×SUE may just reflect the state-level differences for a subset of states compared to the rest. Second, the laws are enforced towards the end of sample period. The impact of geography on interpersonal communications is likely to exhibit a declining trend with the adoption of online social media and widespread use of smartphones. Therefore, the triple interaction may just capture this diminishing time effect.

To address these concerns, I include two triple interactions: State Dummies×CXN ×SUE and Year Dummies×CXN×SUE (double interactions of both dummies with SUE and CXN as well as the main effects are also included). Therefore, DDL×CXN×SUE now captures the before/after differences of cross-sectional social interaction effect for firms affected by the laws. Table 5 shows that its coefficient is negative and significant in all specifications regardless which network measure I use. The evidence suggests that limited investor communications negatively impact social interaction effect on market reactions, lending further support to the hypothesis that social interaction promotes decentralized information diffusion and increases ex-post attention.

Chapter 5

Volume Reactions

Based on theories of investor limited attention and decentralized information diffusion, investor social interaction should also be associated with more pronounced volume reactions during the announcement window.

I define daily abnormal dollar trading volume during announcement and post-announcement period as the difference between the log dollar volume on that day and the average of daily log dollar volume over days [-41, -11] relative to the announcement day:

$$\mathrm{VOL}[j] = \log(1 + \mathrm{V}_{t+j}) - \frac{1}{30} \sum_{k=t-41}^{t-11} \log(1 + \mathrm{V}_k), \tag{5.1}$$

where V is the log daily dollar volume.

By taking logarithm of the shares, the above definition calculates the percentage increase in trading volume around the announcement date. Benchmarking against pre-announcement trading volumes is necessary, given the evidence in Wang (2016) that stocks' daily and monthly trading volumes all increase with investors' social interaction. Taking the difference assures that the results will not be driven by the positive correlation between network connection and the general level of trading activity. I take the average of VOL[0] and VOL[1] as the measure for the abnormal trading activity during the 2-day announcement window, denoted by VOL[0, 1]. Similarly, VOL[2, 61], the abnormal trading volume in the 60-day post-announcement period, is calculated as the average of daily abnormal dollar trading volume over days [2, 61] relative to the announcement date.

To examine the effect of social interaction on abnormal trading volume, I regress VOL[0, 1] and VOL[2, 61] on network connection measures. All firm and announcement characteristics previously discussed are added as controls. In addition, I also include indicator variables for each decile rank of earnings surprises to account for heterogeneous volume reactions to different levels of earnings news. Last, to control for trading activity in the aggregate market, I include the market trading volume in the same period. The market trading volume on any given day is the average log dollar trading volume of all CRSP stocks on that day.

[Insert Table 6 here]

Table 6 Panel A shows that, for the regression of VOL[0, 1], the coefficient on network connection measures is positive and significant in all regression models, suggesting that stronger investor connection is associated with stronger immediate trading volume responses. If the decentralized channels propagate the public news in a firm's investor network, price and volume react swiftly during the announcement period; therefore, there should be less trading activity in the post-announcement window. Panel B displays the results for VOL[2, 61], and the evidence is, however, contrary to the expectation. Instead of the negative correlation as predicted by theories, social interaction positively predict post-announcement volume reactions.

Overall, the evidence is consistent with the notion that investor attention and decentralized information diffusion through investor social interaction lead to stronger immediate volume reactions. However, the prediction of the muted post-announcement trading volumes is largely rejected – a finding that I will revisit and explore more in the next few sections.

Chapter 6

Volatility and Trading Volume Dynamics

Social network also has implications for price and volume dynamics. Walden (2016) theoretically proves that the impact of information shock is short-lived in more central information networks. The intuition is that, with strong connections, the information quickly spreads through investor information network and its influence on return and trading volume dissipates rather quickly. However, if the network is relatively sparse, then the diffusion process is slow, suggesting that the shock can drive volatility and trading volume for an extended period of time. Walden accordingly derives related testable predictions: The more central the network is, the less persistent volatility and trading volume become. In other words, time-series data of volatility and trading volume after an information shock should exhibit short memory and rapidly decaying auto-correlations when the stock's investors are highly connected.

To measure persistence in time-series data of volatility and trading volume, I estimate the coefficient of fractional integration using *autoregressive fractionally integrated moving* *average* (ARFIMA) models. The ARFIMA model is designed to improve the power of early stationarity tests (e.g. unit root test) for time series embodying long-range dependence and frequent structure shift and is a natural choice for studying long memories in these series. Specially, for a process y_t with mean μ, the general ARFIMA(p, d, q) model takes the following form:

$$\Phi(L)(1-L)^d(y_t-\mu) = \Theta(L)\epsilon_t, \tag{6.1}$$

where L is the lag operator such that $L^j y_t = y_{t-j}$, $\Phi(L)$ is the autoregressive polynomial and equals $1-\rho_1 L - \rho_2 L^2 - \cdots - \rho_p L^p$, $\Theta(L)$ is moving average polynomial and equals $1-\theta_1 L - \theta_2 L^2 - \cdots - \theta_q L^q$, ϵ_t is an i.i.d. process with mean 0 and variance σ_ϵ^2, d is the fractional integration parameter, and $(1-L)^d$ is the fractional differencing operator defined by

$$(1-L)^d = \sum_{k=0}^{\infty} \frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)} \tag{6.2}$$

with $\Gamma(\cdot)$ denoting the (generalized factorial) gamma function.

To see what d represents, consider the simplest form ARFIMA$(0, d, 0)$

$$(1-L)^d(y_t-\mu) = \epsilon_t. \tag{6.3}$$

The fractionally integrated process $(1-L)^d(y-\mu)$ exhibits different levels of memory depending on the value of d. In general, the higher the value of d, the longer the memory of the process, and the higher the persistence of a shock. When $-0.5 < d < 0$, the process exhibits negative auto-correlations and is said to be anti-persistent. If $d = 0$, y_t is random walk with no memory. On the other hand, if $d = 1$, the process is integrated and the effect of shock persists indefinitely. In between these two extreme cases, the process is mean-reverting and the effect of shock will dissipate eventually. When $d > 1$, the effect of shock not only persists but also grows.

I follow Bollerslev and Jubinski (1999) and use ARFIMA$(0, d, 0)$ to estimate the coefficients of fractional integration $d_{|R|}$ for daily absolute return series and d_v for daily volume series. The estimation window is [0, 61] relative to the announcement date. $d_{|R|}$ and d_v will then be measures for volatility and trading volume persistence after the information shock of earnings announcement. If investors share the information of earnings news through social interaction, then I expect both $d_{|R|}$ and d_v to be positively related to network connection measures.

Daily absolute return series are $\{|R_{t+j}|, j = 0, 1, 2, \cdots, 61\}$, where R_{t+j} is the daily return in j^{th} day after the announcement date t. The estimated $d_{|R|}$ across all firm-announcement pairs falls in between -0.28 and 0.40. These estimates are lower compared to Bollerslev and Jubinski (1999)'s estimates for S&P 500 stocks. The reason is that the authors use the entire return series from 1962 to 1995 to estimate the coefficient for each stock; therefore, the fractional integration captures the memory effect of periodic arrival of latent information on stock returns, which tend to be long-lasting. In comparison, I estimate the coefficient for each firm-announcement combination using 62 days of return series during and after the earnings announcement. Thus, $d_{|R|}$ will only measure the persistence of the effect of earnings news on prices.

I then regress $d_{|R|}$ on network connection measures and control variables. The results in Table 7 Panel A are consistent with Walden (2016)'s prediction that the effect of the information shock on volatility is short-lived for more central networks. For most of the regression models, the network connection coefficient is negative and significant. It suggests that the information shock of the announcement is quickly absorbed via social interaction and its impact on volatility subsides very fast.

[Insert Table 7]

For volume dynamics, I define daily market-adjusted abnormal volume for days [0, 61] by

$$\Delta v_{i,t+j} = \hat{v}_{i,t+j} - \frac{1}{30}\sum_{k=t-41}^{t-11} \hat{v}_{i,k}, \tag{6.4}$$

where $\hat{v}_{i,k}$ is the market-adjusted trading volume calculated as the difference of log daily dollar volume of stock i on day k and the average log dollar volume of all CRSP stocks on the same day. In other words, I adjust volume by first subtracting the market component and then benchmarking against the pre-announcement volume. As Wang (2016) shows, the trading series for stocks with stronger investor connection tend to experience longer memory and higher co-movement with the market. The adjustment in equation (6.4) controls for these general patterns. It also ensures that the identified relation between d_v and network connection measures is not driven aggregate market movements. However, the results of the following test do not depend on these particular adjustments. Using raw volumes or abnormal volume without market adjustment yields very similar outcomes.

The estimated fractional integration parameters also confirm the prior finding that volatility declines much faster than volume after earnings announcements. The sample average of $d_{|R|}$ is only 0.052 whereas the average of d_v is 0.243. The difference is significant both economically and statistically.

Table 7 reports the cross-sectional regression of d_v on social interaction. From Panel B, the coefficient on the connection measures is positive across all the specifications and significant in all baseline models, indicating that the impact of earnings news on trading activity is surprisingly long-lived for highly connected investor networks. This positive relation is inconsistent with Walden (2016)'s prediction.

To sum up, the results for volatility persistence strongly support the hypothesis that social interaction promotes information diffusion. However, the contradictory findings on volume persistence, echoing the similar findings on post-event volume reaction, impose a challenge for the standard rational learning models.

Chapter 7

Dispersion of Investor Belief

7.1 The Role of Disagreement

Given the discrepant behaviors of return and trading volume in relation to social interaction documented in the previous section, I consider mechanisms under which this difference can happen. In fact, the literature has long observed the differential volume and price reactions to financial disclosure (Bamber, Barron, and Stevens (2011)), which in turn spurred researchers to study investor disagreement as a distinct determinant of trading volume. For example, Banerjee and Kremer (2010) model the differential interpretation of public information in a dynamic setting and provide the insight that changes in the dispersion of investor beliefs (both convergence and divergence of investor opinions) drive the trading volume whereas the changes in the average investor opinion determine the return dynamics.

However, there is debate over whether investor opinions converge or diverge around earnings announcements. In the model of Kim and Verrecchia (1991), investors disagree with each other before the earnings announcement as they receive private information with differential precision. The public announcement, even though commonly interpreted, causes differential belief revisions among traders, which in turn generates trading. On the other hand, Kim and Verrecchia (1994) argue that traders may possess differential private signals that can only be used in conjunction with the public information released. Kandel and Pearson (1995) develop a model of Bayesian learning that allows investors to use different likelihood functions to update and interpret the public announcement. In both these models, investor opinions diverge after the public announcement.

There is empirical evidence supporting both convergence and divergence. Atiase and Bamber (1994) document a positive relation between investor pre-announcement disagreement and trading volume, which is consistent with convergence of investor beliefs and support Kim and Verrecchia (1991). Bamber, Barron, and Stober (1999) use analysts' revisions of annual earnings forecasts after the announcement of quarterly earnings as evidence of differential interpretations and find supportive evidence of the argument of Kandel and Pearson (1995) that large volumes coincident with small price changes reflect differential interpretations of the disclosure. The mixed evidence is in fact consistent with Banerjee and Kremer (2010) that trading volume arises from (1) belief convergence after differences in prior beliefs and (2) belief divergence driven by differential interpretations.

7.2 Trading volume: Convergence Driven v.s. Divergence Driven

To empirically separate these two effects, I rely on Kim and Verrecchia (1997), who combine both the differential precision of private pre-disclosure information and differential interpretations of the public signal into their model. A key result is that trading volumes associated with absolute price changes are driven by differential precision of private pre-disclosure information, whereas differential interpretations lead to trading that is unrelated to contemporaneous price reactions. This indicates that one can use the component of trading volumes not explained by absolute returns to proxy for differential interpretations.

I follow Garfinkel and Sokobin (2006)'s methodology to decompose trading volumes into two parts. For each firm-announcement observation, I regress daily log dollar volume on the daily absolute return in the benchmark period over the days [-41, -11] relative to the announcement date. I then use this model to adjust announcement trading volumes. Specifically,

$$V_{i,s} = \hat{\beta}_0 + \hat{\beta}_1 \max(R_{i,s}, 0) + \hat{\beta}_2 \min(R_{i,s}, 0) + e_{i,s} \tag{7.1}$$

$$\widehat{V}_{i,s} = \hat{\beta}_0 + \hat{\beta}_1 \max(R_{i,s}, 0) + \hat{\beta}_2 \min(R_{i,s}, 0) \tag{7.2}$$

$$SUV_{i,t+k} = \frac{V_{i,t+k} - \widehat{V}_{i,t+k}}{\hat{\sigma}(e)} \tag{7.3}$$

$$SEV_{i,t+k} = \frac{\widehat{V}_{i,t+k} - \hat{\beta}_0}{\hat{\sigma}(\hat{V})}, \tag{7.4}$$

where t is the announcement date, $s \in [t-41, t-11]$ represents the day in the benchmark window, V is log dollar volume, R is daily return, SUV is the standardized unexpected volume, $\hat{\sigma}(e)$ is the standard deviation of residuals in regression (7.1), SEV is the standardized expected volume, and $\hat{\sigma}(\widehat{V})$ is the standard deviation of the fitted value in the regression.

Garfinkel and Sokobin (2006) argue that $\hat{\beta}_0$ captures the liquidity trading, $\hat{\beta}_1 \max(R_{i,s}, 0) + \hat{\beta}_2 \min(R_{i,s}, 0)$ is equivalent to the trading component due to belief convergence (Kim and Verrecchia (1991)), and the residual $e_{i,s}$ measures the trading due to investor disagreement of the public signal (Kim and Verrecchia (1994); Kandel and Pearson (1995)). The variables of interest are SUV and SEV, which are convergence and divergence components of trading volumes scaled by their respective standard deviation in the estimation window.

As shown in Table 6, announcement abnormal trading volume increases with stock-level investor connection. However, it is unclear which component of the trading volume is driving this result. In other words, social interaction can induce convergence of beliefs, divergence of opinions, or both, all of which can generate abnormal trading volumes. Therefore, I start the exploration of the impact of social interaction on investor opinions by first investigating the reactions of the different components of trading volumes. I conduct the identical regression test as in Table 6 but with SUV[0, 1] and SEV[0, 1] as dependent variables, which are calculated as the average of SUV and SEV over the 2-day announcement window.

[Insert Table 8 here]

Decomposing the trading volume uncovers additional insight on the relation between social interaction and investor opinions. The results in Table 8 show that strong investor connection is associated with high convergence-driven volume as well as divergence-driven trading volumes during the announcement. It implies that, in addition to facilitating information diffusion and rational learning, social interaction also exacerbates investor disagreement due to differential interpretations of earnings news.

To verify and provide additional support for the above finding that social interaction aggravates the difference in opinions, I employ the alternative method used in Ahmed, Schneible, and Stevens (2003), which does not require explicit decomposition of trading volumes. In this alternative test, announcement abnormal trading volume is regressed on the absolute announcement abnormal return, investor connection, and the interaction between the two.[1] If social interaction stimulates disagreement, the slope coefficient on absolute price changes should decrease with network connectedness. As predicted, the coefficient on the interaction term between social interaction and absolute return is negative and significant at 1% level (Panel B in Table 8). Such a negative relation echoes the finding in Ahmed, Schneible, and Stevens (2003), who document that online trading increases earning announcement trading volumes that are unrelated to price change and

[1] Using unadjusted and trading volumes and raw returns does not change the result.

decreases the association between volume and absolute return.

7.3 Persistence of Volume

While the evidence suggests that social interaction encourages both belief convergence and divergence upon announcement, how persistent these effect are in the long run as reflected in the dynamics of their respective trading components remains uncertain. On the one hand, rational learning, either through direct social information sharing or by studying earnings reports once investors become aware of the news via social contacts, should occur rather efficiently if investor social attention is high, suggesting that trading volume associated with convergence of beliefs should be less persistent.

On the other hand, if social interaction evokes disagreement, the effect of different opinions as manifested in the trading volume dynamics, however, ought to depend on whether the disagreement is persistent. For this, I turn to the origin of investor disagreement. Investors disagree with each other when they have differential abilities to interpret earnings news (Kim and Verrecchia (1994)), if they use different likelihood functions to update their beliefs (Kandel and Pearson (1995)), and when they use different economic models (David (2008)). Under all these possibilities, disagreement stems merely from heterogeneous information processing at individual level, and social interaction only triggers these differential interpretations by increasing ex-ante investor attention and by spreading awareness to the news.

It follows from Banerjee and Kremer (2010) that this type of disagreement, when its magnitude is large, can lead to positively auto-correlated trading volumes. The intuition is that disagreement slowly declines as investors learn from additional resources; the larger the initial disagreement is, the longer it takes for the difference to disappear through rational learning, and the more persistent the trading volumes generated by the disagreement is. Therefore, social interaction should be positively related to the persistence of disagreement-driven volumes. To facilitate the discussion, I call the disagreement resulted from differential information processing as *information-processing disagreement*.

Alternatively, the very process of interpersonal communication might be able to spawn misinterpretations and other idiosyncratic errors along the way. Strong investor connection indicates more frequent interaction and hence more disagreement generated by social communication. However, since the inaccurate interpretations are caused by conversations themselves rather than by the transmitting of false beliefs from one to another, then the associated disagreement should be idiosyncratic and independent from one day to another. As such, the communication-triggered disagreement is associated with high volume in general but trading activities should be less auto-correlated as a result.

Moreover, social interaction, by spreading active investing strategies (Han and Hirshleifer (2015)), is able to induce more trading based on any given disagreement. If social interaction triggers disagreement, but investors all trade passively, there would be no visible effect on trading volumes. The more they trade actively, the stronger the association between social interaction and both disagreements that can be measured by volume dynamics. This implies an even stronger effect of social interaction on both the average and the persistence of volumes.

I repeat the persistence test as in the previous section with daily SEV and SUV series over [0, 61] days relative to the announcement. If SEV truly summarizes the trading originated from convergence of beliefs through rational learning when investors disagree in the pre-announcement period, it then fits better into the framework of Walden (2016). Therefore, social interaction should be negatively correlated with persistence parameter of SEV series. In contrast, the association between social interaction and the persistence of SUV could either be positive or close to zero, depending on whether investor disagreement is caused by disparate information assessment or triggered by social conversations.

Table 9 Panel A reveals a robust and significant negative relation between investor connection measure and persistence of SEV series. However, this result is not surprising given that social interaction is negatively associated with fractional integration parameter of absolute returns. Nonetheless, it provides support to the decentralized information diffusion hypothesis and the notion that strong network connection helps absorb information shock quickly. I next turn the attention to the dynamics of SUV. In Panel B, social interaction is positively correlated with fractional integration parameter for SUV across all the models. Recall that SUV is the portion of the trading volume that does not respond to price changes and hence gauges the magnitude of trading activities due to the difference in investor opinions. The evidence is therefore consistent with differential information processing causing disagreement.

To further distinguish disagreement resulted from information processing from that induced by conversations, I investigate the relation between social interaction and post-announcement trading volume SUV[2, 61]. Under both possibilities, social interaction gives rise to disagreement; however, the implications for the level of trading volume are distinct. Under the first scenario, strong social interaction predicts major disagreement that gradually declines with additional learning, whereas weak investor connection initiates small disagreement but continues to build more difference upon it. In other words, while social interaction may influence how information-processing disagreement arises and fades, it does not have a definite impact on the total level of disagreement and the associated trading volumes. Conversely, social interaction should predict a higher level of trading volumes if disagreement is due to recurrent social communication.

In panel C of Table 9, SUV[2, 61] is regressed on investor connection and other control variables. The coefficient of investor connection is positive and significant in all tests. In other words, the regressions accounting for firm attributes and investor ex-ante attention yield a positive and significant association between the post-announcement disagreement-driven volume and social interaction. This is consistent with the possibility that social conversations also generate idiosyncratic disagreement.

In the untabulated tables, I also perform the same test for the convergence component of trading volume SEV[2, 61]. The results show that the coefficient in front the network connection measures is either negative or insignificant depending on the model specification. Combined with the results of the regression of SUV[2, 61], this indicates that the positive association between social interaction and the total abnormal volume VOL[2, 61] as documented in Table 6 Panel B is entirely driven by the investor disagreement.

In sum, the differing results of SEV and SUV imply that the effect of social interaction on investor opinions is not fully explained by rational expectation models. On the one hand, the evidence is consistent with the notion that social interaction increases the attention to news and results in the short-lived effect of the public information shock on volatility and learning related volumes. On the other hand, social interaction also leads to differential interpretations of news and induces persistent disagreement-driven trading activities. Moreover, social interaction is also associated with a higher level of disagreement-driven trading volumes in the post-announcement window, which is consistent with the conversation-driven disagreement hypothesis.

7.4 Disagreement and Stock Returns

The evidence so far suggests social interaction induces disagreement. I next study whether the disagreement is associated with higher or lower subsequent returns. However, existing studies are divided on the relation between disagreement and expected stock returns.

One strand of the literature holds that difference in beliefs or opinions should lead to a positive risk premium. Varian (1985) models an Arrow-Debreu economy where agents have heterogeneous subjective probabilities. The equilibrium prices usually decrease with the dispersion of the probability beliefs as long as risk aversion is not too high. David (2008) studies an pure-exchange economy in which two types of agents use different models of economic fundamentals. In his model, investors face the adverse-selection risk that the market prices move more in line with the trading models of other agents than with their own and therefore demand premium for holding the asset. In a related paper, DeLong et al. (1990) argue that the unpredictability of noise traders' beliefs imposes risk on rational traders and therefore should be priced in equilibrium.

The only exception is Miller (1977), who postulates that difference in opinions can lead to lower expected returns when short sales are constrained. If short selling is not possible, market prices will only reflect the valuation of optimists. Empirical evidence is also mixed. There are studies supporting the Miller hypothesis, including Chen, Hong, and Stein (2002), Diether, Malloy, and Scherbina (2002), and Sadka and Scherbina (2007) among others. Other papers such as Garfinkel and Sokobin (2006), Boehme et al. (2009), Avramov et al. (2009), and Carlin, Longstaff, and Matoba (2014) all find opposite evidence.

In the context of earnings announcement, disagreement can impose substantial trading cost to each other due to adverse selection (David (2008)). Furthermore, since the network measures are derived from geographic variability in local household distribution, difference in opinions associated with social interaction should measure the extent of disagreement among the local retail investors, who are more likely to fit into the description of noise traders as in DeLong et al. (1990). Hence, the disagreement among local individual investors can also contribute to noise trading risk. As such, social interaction increases disagreement in the announcement window and should be associated with higher subsequent returns. Conversely, if there exists severe short-sale constraints during and after the announcement of earnings news, the Miller theory should apply, predicting that social interaction should be associated with lower subsequent returns.

To test these competing hypotheses, I regress cumulative abnormal returns CAR[2, 61] and cumulative raw returns R[2, 61] on network connection measures and display the coefficients in Table 10. The evidence is supportive of risk premium hypothesis that disagreement imposes additional risk and earns high subsequent returns. This finding is directly comparable with Garfinkel and Sokobin (2006), who find SUV[0, 1], which proxies for investor disagreement, predicts positive post-announcement returns and argue that this effect is consistent with the notion that disagreement induces risk premium. Motivated by their findings, I also include both VOL[0, 1] and SUV[0, 1] as controls variables. If social interaction triggers differential interpretations as described earlier, its positive effect on subsequent returns should remain robust after including announcement trading volumes, which is exactly what I find in model (4)s and model (5)s.

To summarize, in Section VII, I investigate the role of disagreement in explaining the differing dynamic patterns of return volatility and trading volume as documented in the previous section. I decompose the trading volume according to whether it is correlated with contemporaneous absolute price changes. The objective is to perform tests separately on opinion-convergence-driven and divergence-driven volumes. The evidence shows that, upon announcement, social interaction increases the components of the trading activities, suggesting that social interaction resolves pre-disclosure disagreement through information sharing while at the same time also leads to differential interpretations of the signal. The sensitivity of announcement trading volume to absolute return also decreases with social interaction, proving additional support that social interaction stimulates disagreement on earnings news.

Building on the evidence, I turn to distinguish two alternative mechanisms through which social communication can induce disagreement – information-processing disagreement and conversation-induced disagreement. I argue that the former type of disagreement is associated with highly persistent trading volumes while the latter with volume dynamics that exhibit low persistence but high means. The evidence on the volume persistence strongly supports the first mechanism. However, the positive relation between social interaction and post-announcement disagreement-driven trading volumes also lend support to the second mechanism. The evidence suggests that investors possess heterogeneous information processing skills or employ different economic models to update their beliefs, and these different interpretations are triggered once investors become aware of the news through social contacts. Meanwhile, social communication also seems to induce misinterpretations and generate conversation-specific errors. Finally, I show that social interaction is associated with higher post-announcement returns, consistent with the notion that the induced disagreement imposes additional trading risk.

Chapter 8

Conclusion

Various economic factors contribute to the price and volume behaviors around the announcement. In this paper, I propose to study these behaviors through stock-level investor network. I develop and test the social interaction hypothesis, which holds that strong investor social interaction leads to high investor attention both before and after the earnings announcement.

Consistent with the hypothesis, firms with strong investor connection are associated with stronger immediate price reactions and weaker delayed reactions, indicating that social interaction increases investor attentiveness to the news and improves price efficiency. Moreover, these stocks also exhibit less persistent volatility after the announcement, suggesting that the impact of the information shock is short-lived.

While the evidence on price reactions to earnings news and price dynamics is consistent with the notion that investor connection increases social attention and contributes to price efficiency, the results on trading volume are not consistent with the predictions of rational learning models. On the one hand, the announcement-window abnormal trading volume is positively correlated with investor connection, and therefore social interaction increases volume reaction. On the other hand, volume exhibits long memory and its persistence is positively associated with social interaction. It is a surprising result given the opposite finding with volatility dynamics, which implies that social interaction improves rational learning and close investor connections should absorb the information shock rather quickly.

Motivated by theories which suggest that the convergence of investor opinions through rational learning as well as the divergence of opinions via differential interpretations of the public news is able to generate trading volumes, I explore whether investor disagreement can explain the conflicting findings between price and volume dynamics. To start with, I decompose trading volume into two components depending on whether it is related to the concurrent price changes. The first component co-moves with the absolute price change and reflects the trading activity derived from rational learning. The second component is unrelated to the price change and represents investor disagreement. I then document that both components increase with social interaction during the announcement window, highlighting the dual role of social interaction in promoting rational learning and in triggering disagreement. The result that social interaction reduces the positive relation between announcement-period volumes and absolute price changes also confirms that social interaction increases investor disagreement.

The two components of the trading volume also exhibit different dynamics. Consistent with theories of Walden (2016), learning component is associated with short memory while the disagreement component is associated with long memory. Firms with strong investor connection experience less persistent learning-driven volumes but more persistent disagreement-driven volumes. The positive relation between social interaction and learning-driven volume persistence is fully compatible with rational learning models, which suggest that, in an economy without investor disagreement, the volume dynamics should echo price dynamics and exhibit less persistence if investors are well connected. The latter result is supportive of models of difference in opinions, which contemplates that major disagreement has a long-lasting effect on trading volumes.

The observation that volumes behave very differently from prices around the earnings announcement has stirred a great deal of research interest. In this study, I document the substantial impact of investor connection on cross-sectional price and volume behaviors and emphasize the role of social interaction not only in increasing investor attention and improving rational learning, but also in inducing greater investor disagreement. Taken together, the evidence speaks strongly about the importance of studying the social aspect of investor attention and information processing.

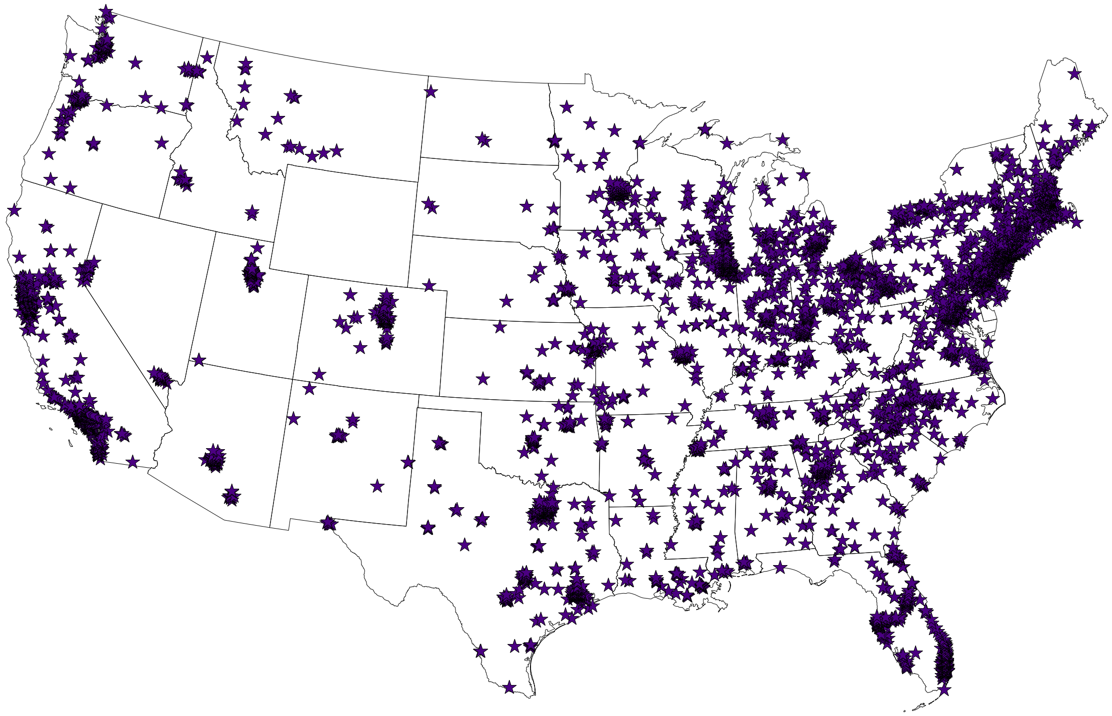

Figure 1: Geographic distribution of distinct U.S. firm locations, 1994-2010.

Table 1: Descriptive Statistics

This table reports the descriptive statistics for the main variables in the paper. Panel A displays mean, median, standard deviation, and percentiles at 10%, 25%, 75%, and 90% for total number of local households (# HH) and network connection measures including the mean degree (v^1), the second-order mean degree (v^2), and the third-order mean degree (v^3). Panel B displays the average Beta, Size, Book-to-market Ratio (B/M), Standardized Earnings Surprises (SUE), Earnings Persistence (EP), Earnings Volatility (EVOL), Institutional Ownership (IO), Reporting Lag (RL), Share Turnover (ST), the number of same-day announcements (NA), and Friday Dummy (i.Fri). *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Panel A: Network Connection Measures

	Mean	Median	Stdev.	10% Pctl.	25% Pctl.	75% Pctl.	90% Pctl.
v^1	16.95	16.28	4.14	14.19	15.07	18.32	20.26
v^2	402.29	392.90	79.36	331.43	353.99	445.80	494.65
v^3	2128.00	2157.71	514.97	1484.31	1844.95	2472.99	2776.49
# HH	564,013	393,813	714,639	64,226	197,115	604,329	1,033,915

Panel B: Sample Characteristics by VRANK

VRANK	Beta	Size	B/M	SUE	EP	EVOL	IO	RL	ST	NA	i.Fri
1	0.60	1056	0.82	0.37	0.16	0.31	31.4%	30.1	6.6%	110.2	14.6%
2	0.72	1149	0.82	0.38	0.17	0.57	38.6%	30.3	8.4%	113.6	13.1%
3	0.74	2794	0.81	0.37	0.16	0.52	42.4%	31.0	9.7%	116.2	12.4%
4	0.76	2508	0.76	0.42	0.16	0.66	41.7%	30.9	9.9%	115.8	11.3%
5	0.78	1817	0.81	0.38	0.18	0.51	41.2%	33.0	10.2%	111.4	12.8%
6	0.81	2365	0.80	0.34	0.18	0.68	40.5%	33.5	11.1%	114.2	12.3%
7	0.84	2179	0.76	0.37	0.17	0.89	39.9%	34.0	11.2%	112.6	12.2%
8	0.84	1804	0.80	0.36	0.20	0.73	42.3%	34.3	11.5%	113.2	12.1%
9	0.90	4166	0.77	0.37	0.16	0.81	41.8%	33.8	12.1%	112.8	11.4%
10	0.92	1876	0.79	0.36	0.21	0.86	42.5%	32.9	13.0%	115.8	11.3%
10-1	0.31***	819***	-0.03	-0.02	0.05**	0.55***	11.1%***	2.8***	6.4%***	5.6***	-3.4%***

Table 2: Double-Sorted Portfolio Returns

At each calendar quarter, stocks are sorted independently into 10 by 10 portfolios based on standardized earnings surprise and network connection measure (the third-order mean degree v^3). Then I calculate the average 2-day announcement cumulative abnormal returns (CAR[0, 1]) and 60-day post-announcement cumulative abnormal returns (CAR[2, 61]) for extreme earnings news deciles (SUE1: bad news, SUE10: good news) by the network connection deciles (VRANK). Standard errors are estimated using Newey-West estimator with 8 lags. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	Average CAR[0, 1] for Earnings Surprises Deciles 1 and 10			Average CAR[2, 61] for Earnings Surprises Deciles 1 and 10		
VRANK	SUE1	SUE10	SUE10-SUE1	SUE1	SUE10	SUE10-SUE1
1	−1.77%	1.33%	3.10%***	−4.82%	0.67%	5.49%***
2	−1.84%	1.70%	3.54%***	−3.34%	0.87%	4.21%***
3	−1.93%	1.39%	3.32%***	−2.26%	0.99%	3.25%***
4	−2.54%	1.49%	4.02%***	−3.31%	1.17%	4.48%***
5	−2.07%	1.66%	3.73%***	−3.78%	0.67%	4.45%***
6	−2.15%	1.34%	3.49%***	−2.90%	0.23%	3.13%***
7	−1.95%	1.80%	3.75%***	−2.65%	0.76%	3.41%***
8	−2.27%	2.11%	4.38%***	−3.20%	1.94%	5.14%***
9	−2.14%	1.69%	3.83%***	−3.32%	0.83%	4.15%***
10	−2.43%	1.70%	4.13%***	−1.49%	1.57%	3.06%***
10-1	−0.66%**	0.37%**	1.03%***	3.33%***	0.90%	−2.43%***

Table 3: Multivariate Regression of Return Reactions to Earnings News

This table reports the multivariate regression of abnormal cumulative returns during 2-day announcement and 60-day post-announcement windows. Independent variables include earnings surprises rank (SUE), network connection measures (CXN), and their interaction (CXN×SUE). The regression models are performed for all empirical network measures: the first-order mean degree (v^1), the second-order mean degree (v^2), and the third-order mean degree (v^3). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households. Local bias controls include mean age, retirement ratio, and same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. All control variables are also interacted with earnings surprises rank (SUE). Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Regression of Cumulative Abnormal Returns CAR[0, 1]

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
SUE	0.319***	-0.0965	0.541***	0.194	-0.265	0.410**	0.231*	-0.283	0.458***
	(3.04)	(-0.23)	(3.70)	(1.42)	(-0.59)	(2.32)	(1.80)	(-0.64)	(2.76)
CXN	-0.448***	-0.360**	-0.526***	-0.428***	-0.366**	-0.502***	-0.416***	-0.363**	-0.469***
	(-2.62)	(-2.04)	(-2.88)	(-2.74)	(-2.24)	(-2.99)	(-2.66)	(-2.23)	(-2.81)
CXN×SUE	0.0685***	0.0563**	0.0758***	0.0663***	0.0579**	0.0719***	0.0646***	0.0602**	0.0694***
	(2.71)	(2.24)	(2.90)	(2.83)	(2.43)	(2.92)	(2.72)	(2.48)	(2.82)
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Panel B: Regression of Cumulative Abnormal Returns CAR[2, 61]

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
SUE	1.247***	0.0173	2.142***	1.480***	0.279	2.409***	1.426***	0.285	2.296***
	(3.78)	(0.01)	(5.11)	(3.61)	(0.21)	(4.88)	(3.72)	(0.22)	(4.96)
CXN	2.377***	2.038***	2.214***	2.003***	1.646***	1.860***	2.043***	1.623***	1.899***
	(4.01)	(3.45)	(3.59)	(3.99)	(3.22)	(3.51)	(4.13)	(3.16)	(3.69)
CXN×SUE	-0.213***	-0.195**	-0.217***	-0.174**	-0.156**	-0.185**	-0.180**	-0.155**	-0.180**
	(-2.61)	(-2.38)	(-2.59)	(-2.42)	(-2.11)	(-2.48)	(-2.54)	(-2.07)	(-2.47)
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Table 4: Subsample Analysis: Investor Clientele

This table reports the multivariate regression of abnormal cumulative returns during 2-day announcement and 60-day post-announcement windows using subsamples based on size, insitutional owernship, and idiosyncratic volatility. Each quarter, samples are divided based on the NYSE size median, the sample median of institutional ownership, and the sample median of idiosyncratic volatility. Independent variables include earnings surprises rank (SUE), network connection measures (the third-order mean degree v^3), and their interaction ($v^3\times$SUE). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households. All control variables are also interacted with earnings surprises rank (SUE). Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Regression of Cumulative Abnormal Returns CAR[0, 1]

	Size		Institutional Ownership		Idiosyncratic Volatitlity	
	Small	Large	Low	High	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
SUE	0.813***	0.197	0.439*	0.809***	0.779***	0.555***
	(4.21)	(1.17)	(1.92)	(4.97)	(2.80)	(4.67)
v^3	-0.504**	0.154	-0.528**	0.127	-0.507*	-0.0356
	(-2.31)	(0.74)	(-2.15)	(0.55)	(-1.70)	(-0.25)
$v^3\times$SUE	0.0875**	-0.0224	0.0850*	-0.0172	0.0784	0.0111
	(2.25)	(-0.84)	(1.92)	(-0.56)	(1.40)	(0.52)
Firm Controls	X	X	X	X	X	X
Obs.	177,751	55,297	116,497	116,551	117,804	115,244

Panel B: Regression of Cumulative Abnormal Returns CAR[2, 61]

	Size		Institutional Ownership		Idiosyncratic Volatitlity	
	Small	Large	Low	High	High	Low
	(1)	(2)	(3)	(4)	(5)	(6)
SUE	2.610***	0.182	1.518***	3.020***	2.861***	1.249***
	(5.60)	(0.29)	(3.12)	(5.45)	(4.36)	(3.48)
v^3	2.434***	0.325	1.352**	2.626***	3.034***	0.671
	(4.33)	(0.39)	(2.23)	(3.15)	(3.82)	(1.27)
$v^3\times$SUE	-0.225**	-0.00579	-0.0940	-0.273**	-0.259*	-0.0587
	(-2.33)	(-0.05)	(-0.92)	(-2.51)	(-1.94)	(-0.81)
Firm Controls	X	X	X	X	X	X
Obs.	177,742	55,296	116,489	116,549	117,798	115,240

Table 5: Exogenous Variations in Social Communication

I test the impact of exogenous shock to social communications on the social attention effect of social interaction. The dummy variable DDL equals 1 if a firm i at quarter t is located in the area where the distracted driving law is enforced. This table reports the multivariate regression of abnormal cumulative returns during 2-day announcement and 60-day post-announcement windows. Independent variables include earnings surprises rank (SUE), network connection measures (CXN), distracted driving law dummy DDL, all two-way interactions among them (CXN×SUE, DDL×SUE, and CXN×DDL) , and the three-way interation (DDL×CXN×SUE). The regression models are performed for all empirical network measures: the first-order mean degree (v^1), the second-order mean degree (v^2), and the third-order mean degree (v^3). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. All control variables are also interacted with earnings surprises rank (SUE) for Panel A. In addition, whenever a tripple interaction is included, all its lower-order interactions and main effects are also included. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Regression of Cumulative Abnormal Returns CAR[0, 1]									
	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
DDL×CXN×SUE	-0.312**	-0.301**	-0.251*	-0.444***	-0.453***	-0.388***	-0.383***	-0.439***	-0.388***
	(-2.16)	(-2.10)	(-1.80)	(-3.09)	(-3.19)	(-2.78)	(-3.00)	(-3.40)	(-2.92)
i.State×CXN×SUE	X	X	X	X	X	X	X	X	X
i.Year×CXN×SUE	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	206,925	187,437	187,437	206,925	187,437	187,437	206,925	187,437	187,437

Table 6: Multivariate Regression of Volume Reactions to Earnings News

This table reports the multivariate regression of average abnormal trading volume during 2-day announcement window, VOL[0, 1], and 60-day post-announcement window, VOL[2, 61]. The abnormal dollar trading volume on a particular day is the difference between (log) dollar trading volume of that day and the average of the (log) dollar volume over days [-41, -11] relative to the announcement date (see equation (5.1)). The main independent variable is network connection (CXN). The regression models are performed for all empirical network measures: the first-order mean degree (v^1), the second-order mean degree (v^2), and the third-order mean degree (v^3). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households, and the aggregate trading volume over the same period, defined as the average VOL[0, 1] and VOL[2, 61] across all CRSP stocks. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Regression of Abnormal Volume VOL[0, 1]

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	0.0617***	0.0366*	0.0421**	0.0628***	0.0403**	0.0422**	0.0626***	0.0444**	0.0450***
	(3.38)	(1.90)	(2.49)	(3.58)	(2.11)	(2.55)	(3.43)	(2.27)	(2.63)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Panel B: Regression of Abnormal Volume VOL[2, 61]

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	0.0203***	0.0119**	0.0162**	0.0179***	0.0106*	0.0136**	0.0199***	0.0136**	0.0153**
	(3.28)	(2.01)	(2.40)	(3.16)	(1.83)	(2.12)	(3.37)	(2.29)	(2.36)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Table 7: Volatility and Volume Dynamics

I estimate the fractional integration coefficient $d_{|R|}$ and d_v for the absolute return series and abnormal turnover series over days [0, 61] relative to the announcement date. The daily abnormal trading volume is the difference market-adjusted turnover on that day with the average of market-adjusted turnover in the [-41, -11] pre-announcement window. This table reports the multivariate regression of $d_{|R|}$ and d_v on network connection (CXN). The regression models are performed for all empirical network measures: the first-order mean degree (v^1), the second-order mean degree (v^2), and the third-order mean degree (v^3). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households, and the aggregate trading volume over the same period, defined as the average VOL[0, 1] and VOL[2, 61] across all CRSP stocks. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Regression of Volatility Persistence $d_{\|R\|}$									
	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	-0.0055***	-0.0043*	-0.0042**	-0.0046**	-0.0035*	-0.0032*	-0.0031*	-0.0023	-0.0017
	(-2.67)	(-1.87)	(-2.00)	(-2.55)	(-1.70)	(-1.69)	(-1.74)	(-1.15)	(-0.93)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Panel B: Regression of Volume Persistence d_v									
	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	0.0059*	0.0031	0.0007	0.0075**	0.0046	0.0020	0.0068***	0.0038	0.0025
	(1.66)	(0.85)	(0.27)	(2.32)	(1.35)	(0.80)	(2.12)	(1.16)	(0.97)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Table 8: Disagreement and Social Interaction

Daily volumes are decomposed into two components according to (7.1)-(7.4). SUV represents disagreement driven trading and SEV the rational learning driven trading. SUV[0, 1] and SEV[0, 1] are the average of the SUV and SEV over the 2-day announcement window, repsectively. Panel A tests the decomposed volume responses to the news and displays the regression coefficients of SUV[0, 1] and SEV[0,1] on the network connection measure (the third-order mean degree v^3). Panel B regresses announcement abnormal trading volume VOL[0, 1] (raw volume V[0, 1]) on absolute abnormal cumulative return —CAR[0, 1]— (absolute raw return —R[0,1]—), network connection measure v^3, and the interaction between —CAR[0, 1]— (—R[0,1]—) and v^3. Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households, and the aggregate trading volume over the same period, defined as the average VOL[0, 1] and VOL[2, 61] across all CRSP stocks. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Disagreement-Driven and Learning-Driven Volume Reactions

	SUV[0, 1]			SEV[0, 1]		
	(1)	(2)	(3)	(1)	(2)	(3)
CXN(v^3)	0.0485***	0.0335**	0.0234	0.0389**	0.0137	0.0336*
	(3.04)	(2.05)	(1.55)	(2.12)	(0.73)	(1.95)
Indicator Variables for SUE deciles	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X
Local Bias Controls		X			X	
Attention Controls			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593

Panel B: Volume Reaction and Absolute Price Changes

	VOL[0, 1]			V[0, 1]		
	(1)	(2)	(3)	(1)	(2)	(3)
v^3	0.0805***	0.0776***	0.0703***	0.326***	0.299***	0.163***
	(4.07)	(3.68)	(3.60)	(6.08)	(5.43)	(5.08)
|R[0,1]|	0.149***	0.164***	0.130***			
	(8.78)	(8.77)	(7.74)			
$v^3\times$|R[0,1]|	-0.0135***	-0.0156***	-0.0111***			
	(-5.49)	(-5.76)	(-4.55)			
|CAR[0,1]|				0.300***	0.314***	0.189***
				(11.04)	(10.78)	(10.20)
$v^3\times$|CAR[0,1]|				-0.0342***	-0.0362***	-0.0196***
				(-8.78)	(-8.66)	(-7.36)
Indicator Variables for SUE deciles	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X
Local Bias Controls		X			X	
Attention Controls			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593

Table 9: Information-Processing Disagreement v.s. Conversation-Triggered Disagreement

Daily volumes are decomposed into two components according to (7.1)-(7.4). SUV represents disagreement driven trading and SEV the rational learning driven trading. Panel A and Panel B regress the fractional integration parameter d_{SUV} and d_{SEV}, both estimated with ARFIMA$(0, d, 0)$ models, on investor connection measures. Panel C regresses post-announcement disagreement-driven volume SUV[2, 61] on invsetor connection measures. Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households, and the aggregate trading volume over the same period, defined as the average VOL[0, 1] and VOL[2, 61] across all CRSP stocks. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Panel A: Regression of SUV Persistence d_{SUV}

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	0.0064***	0.0049*	0.0019	0.0076***	0.0059**	0.0026	0.0071***	0.0054**	0.0027
	(2.29)	(1.69)	(0.90)	(2.94)	(2.17)	(1.30)	(2.79)	(2.06)	(1.44)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Panel B: Regression of Volume Persistence d_{SEV}

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	-0.0048***	-0.0035	-0.0044**	-0.0042***	-0.0031**	-0.0035*	-0.0031*	-0.0023	-0.0024
	(-2.55)	(-1.64)	(-2.08)	(-2.59)	(-1.67)	(-1.88)	(-1.94)	(-1.28)	(-1.27)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Panel C: Regression of Post-Announcement Volume Reaction SUV[2, 61]

	v^1			v^2			v^3		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
CXN	0.0204***	0.0137**	0.0146**	0.0178***	0.0120**	0.0118*	0.0177***	0.0140**	0.0128**
	(2.85)	(2.09)	(1.02)	(2.95)	(2.04)	(1.86)	(2.99)	(2.40)	(2.05)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	233,153	233,048	211,593	233,153	233,048	211,593

Table 10: Post-Announcement Return and Social Interaction

This table test the relation between post-announcement return and social interaction. CAR[2, 61] is the post-announcement cumulative abnormal return defined in (3.8). VOL[0, 1] is the announcement abonormal trading volume defined in (5.1). SUV[0, 1] is the disagreement-driven component of announcement trading volume as defined in (7.1)-(7.4). Firm controls include stock beta, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, number of daily announcements, indicator variables for year, month, day of week, Fama-French 10 industry classifications, and number of local households, and the aggregate trading volume over the same period, defined as the average VOL[0, 1] across all CRSP stocks. Local bias controls include mean age, retirement ratio, same-industry workforce percentage, and social capital. Attention controls include urban dummy, number of local newspaper, number of local firms, advertisement expenses, number of employees, number of shareholders, and lagged announcement-window volume reaction. Standard errors are corrected for heteroskedasticity and two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance level at 10%, 5%, and 1%, respectively.

Returns and Social Interaction									
	CAR[2, 61]								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
v^3	0.949***	0.707***	0.849***	0.921***	0.695***	0.831***	0.919***	0.683***	0.833***
	(4.12)	(3.24)	(3.57)	(4.00)	(3.17)	(3.50)	(4.02)	(3.15)	(3.53)
VOL[0,1]				0.790***	0.746***	0.816***			
				(17.18)	(16.16)	(15.85)			
SUV[0,1]							0.732***	0.693***	0.656***
							(11.82)	(10.61)	(10.19)
Indicator Variables for SUE deciles	X	X	X	X	X	X	X	X	X
Firm Controls	X	X	X	X	X	X	X	X	X
Local Bias Controls		X			X			X	
Attention Controls			X			X			X
Obs.	233,153	233,048	211,593	211,593	211,593	233,153	233,048	211,593	211,593

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