Social Interaction and Market Reaction to Earnings News

David Hirshleifer    Lin Peng    Qiguang Wang *

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Abstract

Using Facebook Social Connectedness Index to identify the network centrality of a firm based on its headquarter location, we study how information propagates through social network and affects asset prices. We find that earnings announcements made by central firms attract more attention from both retail and institutional investors, generate stronger immediate reactions in prices, trading volume and return volatility, and weaker post announcement drifts. In addition, these announcements are followed by less persistent volatility but more persist investor attention and volume, especially disagreement-driven volume. Our evidence suggests a dual role of social interaction: it promotes information efficiency by facilitating public information diffusion, but also induces investor disagreement and excess trading volume.

KEYWORDS: Facebook, Social Network, Earnings Announcement, Information Diffusion, Investor Disagreement

*David Hirshleifer, Paul Merage School of Business, University of California, Irvine, david.h@uci.edu; Peng Lin, Zicklin School of Business, Baruch College, City University of New York, lin.peng@baruch.cuny.edu; Qiguang Wang, Hong Kong Baptist University, qiguangw@hkbu.edu.hk. We appreciate helpful comments and discussions from Jie Gao, Chong Huang, Danling Jiang, Philippe Jorion, Qin Li, Lin Sun, Zheng Sun, Lu Zheng, Youqing Zhou, and seminar participants at University of California, Irvine (UCI).
I. Introduction

One of the most important pieces of information for a firm is its earnings announcements. There have been extensive analyses that substantiate the impact of earnings announcements on securities prices. (Ball and Brown (1968); Beaver (1968); Bernard and Thomas (1989)). How agents in financial markets process and react to earnings information, though, has not been well studied. We investigate how such information propagates through social network and determine trading behavior and asset prices.

One of the major challenges in studying the social influence of information processing is to measure investor networks. 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)). These studies focus on cross-firm social connections and the method is only feasible for networks with manageable sizes. In contrast, we are interested in social interactions among a firm’s investor base and how network connectivity affects investors’ reaction to a firm’s disclosures.

In this paper, we use the Facebook Social Connectedness Index (SCI) to construct the county-to-county social network and identify the network centrality of a firm based on its headquarter location. Following Banerjee et al. (2013, 2019), who provide empirical evidence that information spreads faster when seeded from central nodes in the network, we test whether earnings announcements by firms located in central counties also diffuse more efficiently. In other words, we hypothesize social interaction as an effective diffusion channel for public news to travel from its source to the entire network, and test whether disclosures originated from the more central nodes are followed by more efficient market reactions.

We find that firms located in the central counties 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 attention and trading volume. These findings collectively suggest that social interaction expedites the diffusion of public information but also stimulates greater investor disagreement and noise trading 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)), suggesting that the public signal is gradually propagated in the market. The results in this paper indicate that the signal diffuses much more quickly when it is seeded to investors who are collectively more central in the network.

One explanation is that investors in central counties are collectively more attentive to
the firm’s financial disclosure. Central investors either are constantly at the center of the
information flow in the network or become information hub themselves from whom the
information flows out. Being in such positions accustom them to be attentive to the in-
formation even before it is publicly announced (ex-ante attention). Alternatively, even if
investors in central counties are equally attentive to the news as those in the peripheral
counties, central investors are positioned in the network to be more effective at spreading
information through word-of-mouth communication. The first explanation is based on the
positive association between centrality and ex-ante attention, and hence predicts a positive
effect of network centrality on the centralized information diffusion of the public news. We
find that centrality is positively associated with google search activities as well as Bloomberg
news clicks, lending support to this explanation. The second predicts a positive effect of
centrality on decentralized information diffusion, a prediction supported both theoretically
and empirically by Banerjee et al. (2013, 2019) among others.

The second explanation is also consistent with the negative association between social
interaction and volatility persistence. In the decentralized diffusion model of Walden (2018),
the speed at which the information transmits across the population through social interac-
tion is determined by the strength of investor connections. In a closely connected network
where everyone shares signals with their direct and indirect neighbors, information dissemi-
nates quickly and the effect of information shock on prices is short-lived, leading to less
persistent volatility. While Walden models the diffusion of private information and studies
the relation between network-level centrality and volatility dynamics, we develop a model of
public information diffusion in which news spread from different subgraphs within a network.
We show that a similar prediction also holds in our case – information shock is short lived if
it is originated from central subgraphs.

We next study volume reactions and find that trading activities react to earnings news
differently than prices. We find that while firms in central counties experience higher volume
reactions in the announcement window, these firms also experience highly persistent trading
activities for an extended period. This is difficult to reconcile with rational learning models,
such as Walden (2018) and the model we develop, in which information shock usually leads
to similar price and volume reactions.

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, we 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. Garfinkel and Sokobin (2006) use the second component upon the earnings announcement as a proxy for investor different opinion. We find that country centrality is positively correlated with this disagreement proxy.

We document that both components of trading volumes increase with county centrality during the announcement window. This indicates that social interaction stimulates efficient learning, which is in line with our earlier finding that investor connection is positively associated with price efficiency. Moreover, the results also imply that social interaction induces great investor disagreement.

But what kind of socially induced disagreement can lead to excessive and persistent trading activities? Disagreement can be endogenous in the sense that they disagree because of the inherent differences in their way of information processing. Alternatively, the very process of information transmission, or more generally social communication, can also trigger misinterpretations and rumors along the way, adding noises to the signal when transmitted from one person to another. We refer to this type as exogenous disagreement, since it does not require heterogeneous information processing.

Social interaction increases total endogenous disagreement by increasing the number of disagreeing investors who become informed of the news through interpersonal communications. However, this effect is very weak. In contrast, social interaction leads to exogenous disagreement in a more straightforward way, as the disagreement itself is the byproduct of the process of social interaction itself. Investors can also continue to discuss the news after they become informed of the signal. In addition, there is also evidence that social interaction exacerbates active trading (Han, Hirshleifer, and Walden (2017)), which greatly adds to the positive effect of social interaction on noise trading. Moreover, social interaction can also lead to persistent noise trading at the stock level. This is because the news quickly spreads from central nodes to the entire network, leading to a highly persistent dynamic of the percentage of noise traders, which, when combined with idiosyncratic noise trading at the individual level, results in an equally persistent aggregate noise trading.

Therefore, we conjecture that socially induced noise trading is the reason for the contrasting price and volume behaviors. To support our conjecture, we examine if centrality is also positively related to retail investor attention, as proxied by Google Search Volume Index (SVI), based on the notion that noise trading should be accompanied by investors’

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1Investors disagree when they possess differential abilities to interpret earnings news (Kim and Verrecchia (1994)), use different likelihood functions to update their beliefs (Kandel and Pearson (1995)) or different economic models (David (2008)), or just have differential priors and are subject to belief polarization and group polarization (Lord, Ross, and Lepper (1979), Isenberg (1986) and Brown (1986)).

2To see this, let \( \sigma^2 \) be the population variance of the investors’ posterior of the stock price, and \( \hat{\sigma}^2 \) be the variance of a sample of size \( n \) of informed investors through social interaction. Then, the expected value of the observed sample variance is \( E(\hat{\sigma}^2) = \frac{n-1}{n} \sigma^2 \), which only increases with \( n \) by the order of \( O(1/n^2) \).

3See equation (15) in Section VIII. for a proof.
search activities. We find that higher centrality is associated with higher average level (in both the announcement and post-announcement windows) as well as higher persistence of search activities. The results offer a possible explanation for the puzzling volume reaction – trading activities are high and persistent because retail investors’ attention is high and persistent.

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, we document a positive relation between social interaction and post-announcement returns. All these additional analyses supplement the main findings on trading volumes and lend support the notion that social interaction increases investor disagreement and noise trading.

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 and but also command higher expected returns in the post-announcement window.

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. Our 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 (2018).

Our 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 (2018)). Others, however, point out that social interaction can be detrimental to market efficiency by creating incentives to free ride on others’ signals, which in turn
discourages private information production \( (\text{Han and Yang (2013)}) \); by propagating rumors \( (\text{Andrei and Cujean (2016)}) \); and by inducing incorrect beliefs and preferences \( (\text{Han, Hirshleifer, and Walden (2017), Bali et al. (2018)}) \). We show that social interaction is positively associated with price efficiency after earnings announcements, but is also related to excessive trading volumes.

Finally, the result that social interaction positively predicts trading volumes and its persistence in the post-announcement window highlights the role of difference of opinion in driving excessive and persistent trading activities \( (\text{Karpoff (1986); Kim and Verrecchia (1994); Kandel and Pearson (1995); Banerjee and Kremer (2010)}) \). Most existing empirical studies investigate trading volumes around earnings announcement in a relatively static setting. In contrast, we analyze volume dynamics and how that social interaction can affect its persistence.

II. Theoretical Motivation and Predictions

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

A. Investor Attention

Attention is a scarce cognitive resource \( (\text{Kahneman (1973)}) \). 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 \( (\text{Hirshleifer and Teoh (2003); Hirshleifer, Lim, and Teoh (2011)}) \), asset price co-movement due to \textit{categorical learning} \( (\text{Peng and Xiong (2006)}) \), the \textit{ostrich effect} – the tendency for investors to pay more attention to their finances after good news than bad news \( (\text{Karlsson, Loewenstein, and Seppi (2009); Sicherman et al. (2016)}) \), and so on.

There is also empirical evidence of investor limited attention to earnings news. \text{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. \text{DellaVigna and Pollet (2009)} document that Friday announcements are associated with less pronounced market reactions. Both studies attribute their findings to investor inattention.

There are many ways of which social interaction can increase investor attention to local firms’ earnings news:
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 have in common. Therefore, frequent social interaction increases investor familiarity and attentiveness to the stocks that they hold.

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.

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, county centrality and social interaction shall be associated with higher investor attention, motivating the following predictions on attention:

**Hypothesis 1** *Firms located in central counties experience greater investor attention to earnings news;*

on price responses:

**Hypothesis 2a** *Firms located in central counties experience stronger announcement price reactions to earnings news;*

**Hypothesis 2b** *Firms located in central counties exhibit weaker post-announcement price continuations;*

and on volume reactions:

**Hypothesis 3a** *Firms located in central counties experience higher announcement abnormal trading volumes;*

**Hypothesis 3b** *Firms located in central counties exhibit lower post-announcement trading volumes.*

**B. Decentralized Information Diffusion**

Our postulation that information diffusion is faster from central counties is based on two important studies of Banerjee et al. (2013, 2019). In Banerjee et al. (2013), the authors show that the information of microfinance loans spreads more efficiently when it is seeded from central individuals. Banerjee et al. (2019) provide corroborating evidence for the diffusion of gossip and adoption of immunization.
Information network and decentralized information diffusion combined are able to generate rich price and volume dynamics. 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 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 increases trading volumes. Thus, their model yields the same prediction as Hypotheses 2a and 3a, 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 Hypotheses 2a and 3a should follow. Walden (2018) 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.

In addition, Walden (2018) 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 a high level of connectedness, efficient information sharing leads to more aggressive trading and the shock is quickly absorbed.

Since Walden (2018) does not specifically model the diffusion of public news, we develop a dynamic model that is tailored to our setting in the appendix. We show that similar predictions, when applied to the relation between the centrality of a particular node/subgraph and persistence of information shock, also hold. Therefore, considering the role of social interaction as decentralized diffusion channel and county centrality as the measure for how effective this role is, we test the following predictions on volatility and volume dynamics:

**Hypothesis 4** Firms located in central counties experience less persistent volatility after the announcement.

**Hypothesis 5** Firms located in central counties exhibit less persistent trading volume

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4 See Andrei (2013) for volatility persistence; Andrei and Cujean (2016) for price momentum and reversal; and Walden (2018) for a holistic discussion.
C. 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 prior to the earnings announcement. 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) shows 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)\(^5\).


Theoretically, social interaction can either increase or decrease investor disagreement. On the one hand, if individuals share common priors and are Bayesian, their posterior beliefs also converge after observing the same information (Blackwell and Dubins (1962)). If investors possess 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,\(^5\)

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\(^5\)The condition for the disagreement to arise is that the correlation between private information among investors is sufficiently low.
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. Rather, 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.\(^6\)

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 aggregates information and leads 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 regard to sociodemographic, behavioral, and other interpersonal 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 reinforces the incentive to obtain group acceptance (i.e., social comparison theory). Through social interaction, group members become more aligned in their beliefs but shift further apart in opinions from other groups.

Last but not least, information sharing on social network also picks up noises along the way (Stephenson and Zelen (1989)). Through social interaction, investors can continue to discuss earnings news and there can be misinterpretations being generated during the process. As such, social interaction can give rise to persistent noise tradings. The higher frequency at which investor talks to each other, the more persistent the induced noise trading. When the information is emanated from central investors, the number of informed investors and the incidence of social interaction during which the earnings news is discussed spike very quickly and remain at a high level for an extended period after the announcement, leading to a highly persistent noise trading dynamic when aggregated at the stock level.

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 2-5. In contrast, if social interaction triggers

\(^6\)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 eliminate belief divergence.
conversation-related disagreement and investors agree to disagree, volume dynamics should exhibit persistence. A competing prediction to Hypothesis 5 therefore follows:

**Hypothesis 6** If social interaction stimulates noise trading, then firms located in central counties experience more persistent trading volumes after the announcement.

### III. Identification Strategy and Data

In this section, we outline the method used to construct empirical measures of social network. The primary data we employ are Facebook friendship connections. The data provides *Social Connectedness Index* (SCI) for each county-to-county pair in the U.S.. SCI is calculated based on the total number of friendship ties as of April 2016 and has the maximum value of 1,000,000, which is assigned to Los-Angeles-to-Los-Angeles county pair. For a detailed introduction of the data, see Bailey et al. (2018).

Bailey et al. (2018) show that pairwise SCIs are positively related to regional trade flows, patent citation, and migration. Our emphasis is different in that we are not focusing on county-to-county connections but instead on measures county centralities with SCIs. To do so, we first construct the weighted county-to-county network with SCIs as connection weight between two counties. This network is essentially U.S. Facebook friendship network with friendship ties aggregated at the county level. We represent the structure of this network by a matrix $S = \{s_{ij}\}_{N \times N}$, known as *weighted adjacency matrix*, where $N$ is the number of counties and $s_{ij} = \text{SCI}_{ij}$. With $S$, we can identify central counties based on different measures.

#### A. County Centrality Measures

Centrality measures the importance of a node in a network. Different centrality measures have been proposed in the literature, including degree centrality, closeness centrality, betweenness centrality, eigenvector centrality, and information centrality. To measure the influence of a node, these measures make different implicit assumptions about the manners in which traffic flows – either through walks or paths – in the network. As a result, the calculation of these measures are either based on the counts of pairwise paths or walks (Borgatti (2005)). A walk is a sequence of links and nodes, where each link’s endpoints are the two nodes adjacent to it. A path is a walk in which all links and nodes are distinct. For example, closeness and betweenness assume the traffic flows along the shortest path from one node to another. Since information diffusion in the social network does not always follow the shortest path, we eliminate these two measures.

The first measure we choose is degree centrality, which measures the total number of
direct neighbors of a particular node. A node is central if it is directly connected to a large number of other nodes in the network. Since it only considers paths/walks of length of one, degree centrality is a measure of immediate effects – of what happens between time $t$ and $t + 1$. Hence, it is suited to study immediate effect of information diffusion.

To study long-term effect of information diffusion on price and volume dynamics, we need a measure that can account for transmission of signals along longer paths and walks. For this purpose, we choose another popular measure, eigenvector centrality (Bonacich (1972)). Eigenvector centrality is defined as the principle right eigenvector of the adjacency matrix characterizing the network:

$$\lambda v = Av,$$

where $A$ is the adjacency matrix, $\lambda$ is the largest eigenvalue of $A$, and $v$ is the eigenvector corresponding to $\lambda$. Eigenvector centrality of a node is proportional to the average centrality scores of its direct neighbors, lending itself to the interpretation that a node is central if it is adjacent to nodes which are themselves central.

It can also be shown that eigenvector is proportional to row sum of matrix $K$ formed by summing up all powers of the adjacency matrix, weighted by the inverse of the corresponding powers of the largest eigenvalue:

$$K = \sum_{t=1}^{+\infty} (\lambda^{-1} A)^t.$$

Since the $k^{th}$ power of the adjacency matrix gives the number of walks of length $k$ between any two nodes, eigenvector centrality score of node $i$ counts the number of walks of all lengths that connects node $i$ to every other node.

Eigenvector centrality is also closely related to diffusion centrality, which is initially proposed by Banerjee et al. (2013) to study diffusion of microfinance loans and is later used by Banerjee et al. (2019) to identify individuals who are best seeded to diffuse information. Diffusion centrality is defined as the row sum of the matrix $K(q, T) = \sum_{t=1}^{T} (qA)^t$ for $q \in (0, 1]$, of which eigenvector centrality is a special case when $q = 1/\lambda$ and $T \to +\infty$. When $q$ is treated as the probability that node $i$ broadcasts the information in each period, then $(i,j)^{th}$ element of $K(q, T)$ gives the expected number of times, in the first $T$ periods, that node $j$ receives the information emanating from node $i$. The diffusion centrality score of node $i$ is the expected total number of times that the information originated from $i$ is heard by any of the other nodes in the network during the first $T$ periods.

Following Banerjee et al. (2013, 2019), we also calculate diffusion centrality $K(\lambda^{-1}, T)$ for different values of $T$ ranging from 1 to 61. Since these alternative measures lead to very similar results, we choose only to tabulate the results using eigenvector centrality.

The third centrality measure we use is information centrality proposed by Stephenson
and Zelen (1989). Compared to eigenvector centrality, information centrality uses all paths, instead of walks, emanating from each node, summarizing the centrality of each node with harmonic mean of its “informational” distance to the others. A short “informational” distance between two nodes indicates that they are connected by paths with fewer distinct links on average. Thus, a central node can spread information to other nodes with just a few steps.

Taken together, we calculate degree centrality (DC), eigenvector centrality (EC), and information centrality (IC) for the Facebook county-to-county network:

\[ DC_i = \sum_{j=1} S_{ij}, \quad EC_i = \nu_i, \quad IC_i = \left( \frac{1}{n} \sum_{j \neq i} \frac{1}{I_{ij}} \right), \]

where \( \nu \) is principal eigenvector of the adjacency matrix \( S \) and \( I_{ij} \) is the reciprocal of the topological “informational” distance \( d_{ij} \) between node \( i \) and node \( j \). For adjacency matrix \( S \), if \( D \) is the diagonal matrix of the degree of each node and \( J \) a matrix with all elements equal to one, then \( d_{ij} \) is obtained by inverting the matrix \( B = D + S - J \):

\[ d_{ij} = (B^{-1})_{ii} + (B^{-1})_{jj} - 2(B^{-1})_{ij}. \]

B. Data

Firms are matched to each county in the SCI network based on their historical headquarter addresses, which are parsed from 10-K headers using SEC Edgar. Geographic and local demographic data are from U.S. Census 2000 & 2010 and American Community Survey. 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, we cross compare the dates in Compustat with those in I/B/E/S. When they differ, we 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. Newspapers contact information is purchased from Media Contacts Pro. The sample is from 1996 to 2017, mainly constrained by the availability of SEC electronic filling. The final merged sample consists of 238,195 unique firm-quarter observations.

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

\[ SUE_{i,q} = \frac{e_{i,q} - e_{i,q-4}}{\sigma_{i,q}}, \quad (1) \]
where $e_{i,q}$ is the split-adjusted actual earnings per share for firm $i$ in fiscal quarter $q$, $e_{i,q-4}$ 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.\footnote{Deflating unexpected earnings by quarter-end closing price yields almost identical results for most of the tests in this paper.}

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 relying on simple time-series forecast, this method assumes that investors rely on the consensus of analyst forecasts to form expectations of future earnings. However, there is evidence that these two different measures of earnings surprises are associated with under-reaction 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. As we use Facebook data, the connection measure should capture social interaction among retail investors who are usually considered to be small traders.

Following the literature, we 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 return over the announcement window and the post-announcement window. Let $t_k$ be the $k^{th}$ announcement date for a firm, then the announcement window is defined as the $[t_k, t_k + 1]$ in trading days. Conventionally, $[t_k + 2, t_k + 61]$ is used as the post-announcement window. This definition assumes that firms make periodic earnings announcement every three months. If the next announcement is earlier (later) than scheduled, $[t_k + 2, t_k + 61]$ includes trading days in the next cycle of earnings news which should not have been included (omits the days which should have been included in the current cycle). Therefore, we define the post-announcement window as the trading days in $[t_k + 2, t_k + 1] - 5$. This window counts from the second trading day after the current announcement until the next announcement day, with 5-day gap to ensure that the current post-announcement window does not include the possible information leakage of the next quarterly earnings.\footnote{Using 10-day gap leads to very similar results.}

While previous studies often use size and book-to-market (B/M) portfolios as benchmark, recently Novy-Marx (2015) notes that the long-and-short strategy based on monthly calendar portfolios sorted on the most recent SUE performs better when stock momentum (past one-year return) is also controlled,\footnote{See Figure 3 of Novy-Marx (2015). 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.} suggesting that including momentum portfolios into the benchmark increases the measured CARs in the post-announcement window. For this
reason, we use the 125 triple-sort portfolios on size, B/M, and momentum following Daniel et al. (1997) as benchmark\textsuperscript{11} and define CARs as follows:

\[
\text{CAR}[t_k, t_k + 1]_{i,q} = \prod_{s=t_k}^{t_k+1} (1 + R_{i,s}) - \prod_{s=t_k}^{t_k+1} (1 + R_{b,s})
\]

\[
\text{CAR}[t_k + 2, t_k + 1 - 5]_{i,q} = \prod_{s=t_k+2}^{t_k+1-5} (1 + R_{i,s}) - \prod_{s=t+k+2}^{t_k+1-5} (1 + R_{b,s}),
\]

where \( t \) is the adjusted announcement date,\textsuperscript{12} \( R_{i,s} \) is the stock return of firm \( i \) on day \( s \), and \( R_{b,s} \) is the return of the matching size-B/M-momentum portfolio. To simplify notations, we use \([0, 1]\) as the announcement window and \([2, 61]\) as the post-announcement window. And we refer to the immediate and delayed price reaction defined in (2) as CAR\([0, 1]\) and CAR\([2, 61]\).

[Insert Table 1 here]

Table 1 reports the summary statistics of key variables for portfolios sorted by the firm’s own-county eigenvector centrality. The results show that the relationship between the centrality of a firm’s headquarter location and key characteristics has been non-monotonic. In particular, there is no significant difference in earnings surprises between firms belong to the highest and lowest centrality deciles.

**IV. Investor Attention**

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, we examine, in this section, whether social connection can also effectively lead to different aggregate levels of investor attention in cross sections.

Specifically, to provide a preliminary evidence for effect of information diffusion on market reactions, we test the hypothesis that whether the earnings news originated from a central county spreads more efficiently through social interaction and consequently draws greater

\textsuperscript{11}The empirical results in this paper are not sensitive to the particular choice of benchmarks. Using 25 size and B/M portfolios as benchmark portfolios yields very similar results.

\textsuperscript{12}If the announcement occurs on a non-trading day or after 4:00 p.m. ET, \( t \) will be the next trading day.
investor attention.

We use Google Search Volume Index (SVI) to measure retail investor attention. SVI is an index provided by Google to measure the search volume for a particular phrase or keyword relative to its maximum daily search activity in a specified time window. For each announcement date $t_k$, we define the daily abnormal SVI (ASVI) as

$$\text{ASVI}_t = \log(1 + \text{SVI}_t) - \frac{1}{31} \sum_{s=t_k-31}^{t_k-11} \log(1 + \text{SVI}_s),$$

(3)

where SVI$_s$ is the raw SVI data downloaded from Google. We then calculate the average of ASVI within the announcement window, ASVI[0, 1] as the retail investor attention upon earning announcement.

In addition, we also use Bloomberg Daily Maximum Readership (DMR) as a proxy for institutional investor attention. Bloomberg assigns a value of 0, 1, 2, 3, and 4 if the most recent 8-hour counts of news readership is below 80%, between 80% and 90%, 90% and 94%, 94% and 96%, and above 96% of the previous 30 days’ hourly counts. The hourly scores are then aggregated for each day. Since DMR is already relative measures, we define DMR[0, 1] as the two-day average of the daily DMR as the institutional investor attention measure.

We first regress both attention measures on decile ranks of firm’s county-level centrality measures and decile ranks of the absolute value of SUE. Following the literature, we use the random-walk-based SUE for SVI and the analyst-based SUE for DMR. Model (1)s in table 2 show that all centrality measures positively predict both the retail attention and institutional attention and their effects are statistically significant in most of the models. The coefficients range from 0.74 to 0.99. The evidence shows that announcements for more centrally located firms attracts greater attention from both retail and institutional investors, suggesting that network centrality corresponds to greater efficiency in information diffusion. Adding a number of variables that we use in the following sections to control firm and stock characteristics as well as local demographic and social-economic conditions does not change the results.

We next test whether the effect of social interaction on investor attention is asymmetric toward positive and negative news. We include an interaction term between centrality measure and an indicator variable that equals one if SUE is positive. Model (2)s display these results. We find a striking difference: social interaction promotes the spread of positive earnings news among retail investors but negative news among institutional investors. This finding is consistent with the self-enhancing transmission bias proposed by Han, Hirshleifer, and Walden (2017), which states that individual investors tend to transmit positive news leading to their personal investment successes more than negative news leading to losses. On the other hand, the results suggest that bad news spreads faster only among institutional
Last, we test whether attention to extreme positive news is also reinforced through social interaction, another prediction by Han, Hirshleifer, and Walden (2017), in model (3)s. In the baseline regression without additional controls, the coefficient in front of the interaction between centrality measures and an indicator variable that equals one if SUE is in the top 10% is positive and statistically significant. However, the coefficient becomes insignificant once controls are added.

V. Immediate and Delayed Return Responses

What determines the speed at which prices adjust to the earnings news? In this section, we provide evidence that social interaction plays an important role in facilitating information diffusion and speeding up the price reaction.

A. Regression Analysis

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

\[
\text{CAR} = \alpha_0 + \alpha_1 \text{SUE} + \alpha_2 \text{CEN} + \alpha_3 (\text{SUE} \times \text{CEN}) + \sum_{i=1}^{n} \beta_i \text{Control}_i + \sum_{i=1}^{n} \gamma_i (\text{SUE} \times \text{Control}_i) + \epsilon.
\]

(4)

Following the literature, we 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, we also rank centrality measures into deciles. 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 \(\alpha_1 + \alpha_2 \text{CEN} + \sum_{i=1}^{n} \gamma_i \text{Control}_i\). The expression of this slope then 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 \(\alpha_3\) in the regression of CAR\([0, 1]\) indicates that investor connection is associated with stronger price reaction, whereas a negative \(\alpha_3\) in the regression of CAR\([2, 61]\) implies social interaction is related to weaker delayed price reactions. If social interaction facilitates
diffusion of earnings news, we expect that $\alpha_3 > 0$ for announcement-period returns and $\alpha_3 < 0$ for post-announcement drifts.

To make sure that the results from the regression are robust to the inclusion of stock and earnings characteristics, we add a set of control variables into the regression. To start with, we 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, we further include institutional ownership, earnings persistence, earnings volatility, and share turnover. We also include a set of visibility and familiarity controls at the stock level, including retail dummy, S&P 500 constituent dummy, advertisement expenditure, and urban dummy if the firm is headquartered in one of the ten largest cities, and at the county level, including the number of local firms, the number of local newspapers, the percentage of the local workforce in the same industry, and population density. 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 fixed effect are also added to the regression. Finally, to control for time-series trends, we add indicator variables for year and month.

[Insert Table 3 here]

For the announcement window, the estimated $\alpha_3$ is positive and significant at 1% level for all centrality measures, regardless of whether the controls are added or not. These coefficients are also economically meaningful. For example, in Model (2), the decile spread in the eigenvector centrality is associated with 40% increase in the sensitivity of immediate return responses to earnings news relative to its sample average.\(^\text{13}\) For post-announcement returns, the interaction term ($\text{CEN} \times \text{SUE}$) shows up negative and is statistically significant for all network centrality measures. A similar calculation reveals that the same decile spread in eigenvector centrality decreases the sensitivity of post-announcement price reactions to the public signal by 65%.

Compared to other control variables, centrality measures, together with the percentage of workforce in the same industry, are the only variables with significant coefficients of different signs in front of the interaction with SUE across both the windows. Variables such as institutional ownership, share turnover, reporting lag, and the number of the same day announcement when interacted with SUE all have coefficient that are of different signs across

\(^{13}\)The mean sensitivity of announcement returns to earnings news equals 0.44 (0.42) for the announcement window (post-announcement window), estimated from univariate regression of CAR on SUE. Similar estimates can be obtained from Model (1)s in the table. For example, with EC as the CEN measure, the average SUE slope is $0.390 + 5 \times 0.00941 = 0.437$ ($0.579 + 5 \times (-0.0291) = 0.434$) for the announcement (the post-announcement) window. Decile spreads in EC then translates to 0.176 (0.272) changes in absolute value, or $0.176/0.44 = 40\%$ ($0.272/0.42 = 65\%$).
two windows but are only significant in one of the windows. All other variables have the same sign across the two windows, implying that these variables influence the total price reaction rather than the relative distribution of immediate vs delayed price reaction.

B. 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 naïveté 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 the culprit.

Given that our empirical networks are based on Facebook user connections, the empirical effects of county centrality on return reactions documented in previous sections should also be driven by retail investors, consistent with the notion that retail investors underreact to the news. To further support this conjecture, we perform subsample analysis and test whether the effects of social interaction on investor attention are more pronounced for firms with more retail investors.

We choose three proxies for retail investor clientele: size, institutional ownership, and idiosyncratic volatility of stock returns. At each calendar quarter, we divide all firm-announcement observations into two groups using sample median of NYSE stocks as cutoff points. The results for the subsample analyses are reported in Table 4. For brevity, we only report the results using eigenvector centrality.

The evidence is consistent with the above prediction. The effect of social interaction on announcement price reactions and subsequent drifts is much stronger in the retail subsamples. For example, relative to overall sample average, the decile spread in eigenvector centrality is associated with 53%, 44%, and 42% (66%, 75%, and 93%) change in immediate (delayed) return reaction for stocks with small size, low institutional ownership, and high idiosyncratic volatility, compared to only 6%, 15%, and 23% (46%, 22%, and 15%) for their non-retail counterparts.

In sum, the empirical evidence is consistent with naïveté hypothesis of Bernard and Thomas (1989). The effect of investor connection on stock’s immediate price reactions is stronger for stocks that are small, have low institutional ownership, and exhibit large id-
VI. Volume Reactions

Based on theories of investor limited attention and decentralized information diffusion, our model shows that investor social interaction should also be associated with more pronounced volume reactions during the announcement window and less volume reaction during the post-announcement window.

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

\[
\text{VOL}[j] = V_{t+j} - \frac{1}{31} \sum_{s=t_k-41}^{t_k-11} V_s,
\]

where \( V \) is the log daily volume.

Taking the difference assures that the results will not be driven by the positive correlation between county centrality and the general level of trading activity. We then define the abnormal trading volume in the announcement window and in the post-announcement window as

\[
\text{VOL}[t_k, t_k+1] = \frac{1}{2} \sum_{s=t_k}^{t_k+1} \text{VOL}[s],
\]

\[
\text{VOL}[t_k+2, t_k+1-5] = \frac{1}{t_{k+1} - t_k - 6} \sum_{s=t_k+2}^{t_{k+1}-5} \text{VOL}[s].
\]

To examine the effect of social interaction on abnormal trading volume, we regress these trading volumes on the county centrality measures. All controls variables previously discussed are added. In addition, we also include decile rank of absolute value of earnings surprises to account for the positive relation between the magnitude of earnings news and trading volume.\(^{14}\)

[Insert Table 5 here]

Table 5 Panel A shows that, for the announcement window volume reaction, the coefficients on the centrality measures are positive and significant in all regression models, suggesting that stronger central network positions are 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 quickly during the announcement period; therefore, there should be less trading activity in the post-announcement window. Panel B displays the results for the post-announcement window. However, the evidence is contrary to this prediction. Instead of the negative correlation as predicted by the rational model, social interaction positively predicts post-announcement volume reactions in all models and its effect is statistically significant for some specifications.

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 weaker post-announcement trading volumes is largely rejected – a finding that we will revisit and explore more in the next few sections.

VII. Volatility and Volume Persistence

We now turn to examine the impact of information diffusion on price and volume dynamics. Walden (2018) first shows that, in a information network where informed traders share their private signals, the impact of private information shock is short-lived in central networks. Walden accordingly derives related testable predictions: The more central the network is, the less persistent volatility and trading volume become. Our model shows that similar predictions also hold in our setting: the more central the positions from which the information is originated, the less persistent volatility and volume are. The intuition is that, when information is seeded from central positions, it quickly spreads through network and its influence on return and trading volume dissipates rather quickly. However, if the news is seeded from peripheral positions, then the diffusion process is slow, suggesting that the shock can drive volatility and trading volume for an extended period of time. In other words, time-series data of volatility and trading volume after an information shock should exhibit short memory (rapidly decaying auto-correlations) when the stock’s investors are highly connected.

To measure persistence, we follow Bollerslev and Jubinski (1999) and 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 $\mu$, the general ARFIMA$(p, d, q)$ model takes the following form:

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

where $L$ is the lag operator such that $L^jy_t = y_{t-j}$, $\Phi(L)$ is the autoregressive polynomial and equals $1 - \rho_1L - \rho_2L^2 - \cdots - \rho_pL^p$, $\Theta(L)$ is moving average polynomial and equals
$1 + \theta_1 L + \theta_2 L^2 + \cdots + \theta_q L^q$, $\epsilon_t$ is an i.i.d. process with mean 0 and variance $\sigma^2$, $d$ is the fractional integration parameter, and $(1 - L)^d$ is the fractional differencing operator defined by

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

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

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

$$(1 - L)^d (y_t - \mu) = \epsilon_t.$$ (9)

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.

We 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 $\{|R|\}$ and $d_v$ for daily log volume series $\{V\}$. The estimation window is $[t_k, t_{k+1} - 5]$. $d_{|R|}$ 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 we expect both $d_{|R|}$ and $d_v$ to be positively related to network connection measures. 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, which ranges from 0.15 to 0.57. 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 tends to be long-lasting. In comparison, we estimate the coefficient for each firm-announcement combination using on average 60 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.

We then regress $d_{|R|}$ on network connection measures and the control variables. The results in Table 6 Panel A are consistent with our model’s prediction that the effect of the earnings announcement changes with network connection measures.
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 6]

The estimated $d_v$ ranges from -0.16 to 0.62. Compared to $d_{|R|}$, we find that that volatility declines much faster than volume after earnings announcements. The sample average of $d_{|R|}$ is only 0.051 whereas the average of $d_v$ is 0.261. The difference is significant both economically and statistically. Table 6 reports the cross-sectional regression of $d_v$ on the county centrality measures. 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 at odds with Walden (2018)’s prediction and our model, both of which feature (bounded) rational learning.

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.

VIII. Dissecting Volume: Information v.s. Noise

Given the discrepant behaviors of return and trading volume in relation to social interaction documented in the previous section, we consider mechanisms under which this difference can occur. 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 generate 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 supports 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.

In the following, we test whether investor disagreement leads to the contrasting patterns in price versus volume reactions. We provide two pieces of evidence showing that social interaction is positively correlated with investor disagreement. Next, we ask the question of what is the source of this disagreement and how social interaction can give rise to such disagreement. We provide noise trading as possible solution and also provide additional supporting evidence.

A. Social Interaction and Volume Decomposition

Our first piece of evidence showing a positive relation between social interaction and belief divergence comes from trading volume decomposition. We 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.

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

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

(10)

\[ \hat{V}_{i,s} = \hat{\beta}_0 + \hat{\beta}_1 \max(R_{i,s}, 0) + \hat{\beta}_2 \min(R_{i,s}, 0) \]

(11)

\[ SUV_{i,t+k} = \frac{V_{i,t+k} - \hat{V}_{i,t+k}}{\hat{\sigma}(e)} \]

(12)

\[ SEV_{i,t+k} = \frac{\hat{V}_{i,t+k} - \hat{\beta}_0}{\hat{\sigma}(\hat{V})} \]

(13)

where \( t \) is the announcement date, \( s \in [t - 41, t - 11] \) represents the day in the benchmark window, \( V \) is raw log volume, \( R \) is daily return, \( SUV \) is the standardized unexpected volume, \( \hat{\sigma}(e) \) is the standard deviation of residuals in regression (10), \( SEV \) is the standardized expected volume, and \( \hat{\sigma}(\hat{V}) \) 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 5, announcement abnormal trading volume increases with county-level network centrality. 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, we start the analysis by first investigating the reactions of the different components of trading volumes. We conduct the identical regression test as in Table 5 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.

Decomposing the trading volume provides additional insight on the relation between social interaction and investor opinions. The results in Table 7 show that centrality is associated with high convergence-driven volumes 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, we employ the alternative method used in Ahmed, Schneible, and Stevens (2003), which argues that trading volumes that are related to prices
changes are more likely driven by informed trading, whereas noise trading can reduce the volume-absolute return sensitivity. They find that online trading increases earning announcement trading volumes that are unrelated to price change and decreases the association between volume and absolute return. In this alternative test, we regress announcement abnormal trading volume on the absolute announcement abnormal return, investor connection, and the interaction between the two.\textsuperscript{16} 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 7).

B. What Drives the Persistence of Volume

While we have demonstrated that social interaction is related to investor disagreement during the 2-day earnings announcement window, we have yet to show why disagreement can generate persistent trading volumes in the post-announcement window. For this, we 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)), when they use different economic models (David (2008)), and finally when they have differential priors and are subject to belief polarization and group polarization (Lord, Ross, and Lepper (1979); Isenberg (1986) and Brown (1986)).

Under the all four possibilities, disagreement stems merely from heterogeneous priors and/or differential information processing at individual level, and social interaction only triggers these differential interpretations by increasing ex-ante investor attention, by spreading awareness to the news, or by engaging individuals in discussions and group deliberations. However, social interaction’s effect on these types of investors disagreement, when measured at the stock level, is very minimal except for group polarization related disagreement.\textsuperscript{17}

Besides, these types of disagreement, when formed quickly, shall instead lead to fast decaying trading volumes. The intuition is that a larger part of disagreement-driven volume – the initial building up of the offsetting positions by investors – should occur rather quickly if the earnings news spreads quickly to individuals with different interpretations. Subsequently-informed investors enter into the market and trade against each other based on their different opinions. If their trading cannot be fully absorbed within themselves, they have to trade with early investors. However, since the portion of these late investors is small if the news has already reached a large part of the investor population, portfolio rebalancing by the early-informed investors also tends to be small, leading to fast-decaying, or less persistent.

\textsuperscript{16}Using unadjusted trading volumes and raw returns does not change the result.

\textsuperscript{17}See Footnote 2 for an illustration.
trading volume dynamics.

Banerjee and Kremer (2010) also study the similar type of disagreement but show that it can lead to positively auto-correlated trading volumes. This finding, however, does not contradict our argument. First, autocorrelation and persistence are two related but distinct measures of time-series data. Autocorrelation measures the extent of comovement before the current observation and its lags, whereas persistence measures how slow the autocorrelation decays over longer lags. Second, Banerjee and Kremer (2010) study a dynamic model in which investors receive public signals each period but have different interpretations of these signals. If disagreement surges in one period but regresses to normal levels in the subsequent periods, trading volume shall be positively autocorrelated following the disagreement surge. In this case, with less subsequent disagreement, investors beliefs converge gradually. And it is the gradual unwinding from their initial holding positions that leads to the positive autocorrelation in trading volume. In our study, we only focus on trading volume between two earnings announcements, and there is in general no periodical arrival of public announcements that can lead to investor belief convergence before the next earnings news. To facilitate the discussion, we 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, leading to noise trading. Strong social interaction indicates more frequent interaction and hence more disagreement generated by social communication, which leads to higher average volume in any time window. Since the inaccurate interpretations are caused by conversations themselves rather than by the transmitting of false beliefs from one to another, the associated disagreement should be idiosyncratic and independent from one day to another, hence leading to its name noise trading. We call this type of disagreement as noise-trading disagreement.

Although this noise-trading disagreement by nature is idiosyncratic, the number of noise traders is not independent over time. Information seeded from central counties transmits to the entire network quickly and therefore the percentage of induced noise traders becomes very large in day one and remain large for the entire period. As a result, the total noise trading volume can be very persistent.

To see this in detail, let $n_t$ be the number of noise traders on day $t$ and $v_{j,t}$ be the trading volume by noise trader $j$ on day $t$, which is independent across $j$ and across $t$. Aggregated stock-level noise trading volume on day $t$ becomes $V_t = \sum_{j=1}^{n_t} v_{j,t}$ and the correlation between volume on day $t$ and day $s$ is

$$\text{Cov}(V_t, V_s) = \mathbb{E}(\text{Cov}(V_t, V_s|n_t, n_s)) + \text{Cov}(\mathbb{E}(V_t|n_t, n_s), \mathbb{E}(V_s|n_t, n_s)) = \mathbb{E}(v)^2 \text{Cov}(n_t, n_s).$$

(14)
Combined with the fact that $E(V_t) = E(v)E(n_t)$, the autocorrelation between $V_t$ and $V_s$ is equal to the correlation between $n_t$ and $n_s$. Thus, a persistent $n_t$ dynamic can lead to an equally persistent volume dynamic.

Moreover, social interaction, by spreading active investing strategies (Han, Hirshleifer, and Walden (2017)), 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.

To this end, we have two competing hypotheses regarding the source of the disagreement – the information-processing disagreement and the noise-trading disagreement. The former predicts less persistent trading volumes and is ambiguous regarding the average value of the volume. The latter predicts both more persistent trading volumes and higher levels of average volumes for firms located in central counties, which are mostly consistent with the evidence so far. In addition, Table 8 shows that the persistence of daily $SUV$ series is also positively correlated with centrality measures, lending support to the noise-trading disagreement hypotheses.

In the following section, we provide additional evidence supporting the conjecture that social interaction leads to noise trading, which in turn contributes to the contrasting behaviors between price and volume reactions.

C. Noise Trading: Additional Evidence

C.1. Social Interaction and Retail Investor Attention

If frequent social interactions spawn noise trading, then retail investors’ attention, as reflected in the Google Search Volume, should be a byproduct of this process. We therefore expect that firms located in central counties should be subject to greater investor attention in both the announcement and the post-announcement periods as well as persistent search activity after the announcement.

[Insert Table 8 here]

We have already demonstrated that SVI is positively related to county centrality during the earnings announcement window. Hereby we show that the same positive relation also holds for the post-announcement window. We define the abnormal search activity in the post-announcement window, $ASVI[2, 61]$, as the average of daily ASVI over the trading days in the post-announcement window. Table 8 Panel B reveals a robust and significant relation between the post-announcement search activity and centrality measures. In Panel
C, we regress the persistent measure of daily ASVI series, $d_{SVI}$, on centrality measures. The results confirm our prediction, showing that news emanated from central counties leads to subsequent persistent search activities. Our results on the search actives match those on the trading volume both in terms of the average level and the long-range memory properties. Strong links between the SVI series and volume series as such, combined with the evidence that these trading volumes and search activities do not contribute to the price convergence, are consistent with the conjecture that social interaction stimulates repeated search activities that generate noise trading.

C.2. Noise Trading Risk Premium

The evidence so far suggests social interaction induces noise trading, which is manifested in persistent volume dynamics. We next study whether the disagreement is associated with higher or lower subsequent returns. Most of the theoretical works identify disagreement as a source of risk, and therefore predict that disagreement risk commands return premiums. 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 a 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, we regress cumulative abnormal returns CAR[2, 61] on centrality measures and display the coefficients in Table 9. 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, we also include SUV[0, 1] as control. 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 we find in model (2)s.

To summarize, in this entire section, we investigate the role of disagreement in explaining the differing dynamic patterns of return volatility and trading volume as documented in the previous section. We 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, both components of the trading activities increase with social interaction, 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, we turn to distinguish two alternative mechanisms through which social interaction can induce disagreement – information-processing disagreement and conversation-induced disagreement. We argue that the former type of disagreement is associated with less persistent trading volumes while the latter with volume dynamics that exhibit high persistence and high means. The evidence on the volume persistence strongly supports the second mechanism. The evidence shows that, social communication seems to induce misinterpretations and generate conversation-specific errors. Finally, we show that social interaction is associated with higher post-announcement returns, consistent with the notion that the induced disagreement/noise trading imposes additional trading risk.
IX. Conclusion

Various economic factors contribute to the price and volume behaviors around information events. In this paper, we study how information propagates through social network and its implications on investor behavior and information efficiency of financial markets. We propose a social interaction hypothesis, which holds that social interaction facilitate information diffusion, especially if the information is seeded from central locations in the network.

Using Facebook social connectivity index data to identify the network centrality of a firm based on its headquarter location, we empirically test the social interaction hypothesis. We find that earnings announcements made by central firms attract significantly higher attention from both retail and institutional investors. In addition, the central firms announcements generate stronger immediate reactions in prices, volume and volatility, followed by weaker price drifts. Moreover, these stocks also exhibit less persistent volatility after the announcement. These evidence suggest that social interaction improves price efficiency by increasing investor attentiveness to earnings news, and enabling the quick incorporation of information into prices.

On the other hand, we find that the announcement-driven trading volume is more persist for centrally located firms, a result inconsistent with the predictions of rational learning models. Motivated by theories which suggest that trading volume can be attributed to both the convergence of investor opinions through rational learning as well as the divergence of opinions via differential interpretations of the public news, we explore whether investor disagreement can explain the conflicting findings between price (volatility) and volume dynamics. We decompose trading volume into two components: one that is related to price changes and reflects rational learning, and the other that is unrelated to price changes and is likely to represent investor disagreement. We find that indeed both components increase with social interaction during the announcement window, and the disagreement component of trading volume exhibits a persistence that increases with network centrality. Furthermore, we show that retail attention following earnings announcement is highly persistent and is increasing in the network centrality of the announcement firms, suggesting that noise trading and the disagreement among the retail investors can be an contributing factor to the volume persistence.

Our findings highlight the dual role of social interaction in information efficiency of financial markets. On the one hand, it promotes rational learning and facilitates the incorporation of important news into prices, on the other hand, it can fuel noise trading and trigger disagreement among unsophisticated investors. Taken together, the evidence speaks strongly about the importance of studying the social aspect of investor attention and information processing.
References


Bamber, Linda Smith, Orie E. Barron, and Douglas E. Stevens, 2011, Trading volume around earnings announcements and other financial reports: Theory, research design, empirical


Bonacich, Phillip, 1972, Factoring and weighting approaches to status scores and clique identification, *The Journal of Mathematical Sociology* 2, 113–120.


Fracassi, Cesare, 2016, Corporate finance policies and social networks, Forthcoming, Management Science.


Han, Bing, David Hirshleifer, and Johan Walden, 2017, Social transmission bias and investor behavior, Working paper, University of Toronto.


Kondor, Peter, 2012, The more we know about the fundamental, the less we agree on the price, *The Review of Economic Studies* 79, 1175.


Novy-Marx, Robert, 2015, Fundamentally, momentum is fundamental momentum, Working paper, University of Rochester.


Table 1: Descriptive Statistics
This table reports the descriptive statistics for the main variables in the paper sorted by the decile rank of county-level eigenvector centrality. It displays the average, 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.

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<tr>
<th>EC Rank</th>
<th>Size</th>
<th>B/M</th>
<th>SUE</th>
<th>EP</th>
<th>EVOL</th>
<th>IO</th>
<th>RL</th>
<th>ST</th>
<th>NA</th>
<th>i.Fri</th>
</tr>
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<td>10.6%</td>
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</tr>
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<td>12.3%</td>
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<td>13.0%</td>
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<td>231</td>
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<td>0.23</td>
<td>0.23</td>
<td>1.20</td>
<td>53%</td>
<td>31.50</td>
<td>18.4%</td>
<td>227</td>
<td>21.5%</td>
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<td>10-1</td>
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<td>5.9%***</td>
<td>14.24***</td>
<td>1.9%***</td>
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</table>
Table 2: Multivariate Regression of Attention Reactions to Earnings News

This table reports the regression of abnormal investor attention on county-level centrality measures. Dependent variables are abnormal google search index (ASVI[0,1]) defined in equation (3) and Bloomberg Daily Max Readership (DMR[0,1]). Centrality measures (CEN) include degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Main variables include decile rank of absolute earnings surprises (Abs(SUE)), dummy variable for positive earnings surprise ($I_{SUE>0}$), and dummy variable for extreme positive earnings surprises ($I_{SUE=10}$). Random-walk based earnings surprises is used for Panel A and analyst-based earnings surprises are used for Panel B. Other controls include, size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. Sample period ranges from 2004-2016 for ASVI[0,1] regression and 2010-2016 for DMR[0,1] regression. Coefficients are multiplied by 100. 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 ASVI[0, 1]

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<th>Eigenvector Centrality</th>
<th></th>
<th>Information Centrality</th>
<th></th>
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</thead>
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<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>CEN</td>
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<td>0.66***</td>
<td>0.74***</td>
<td>0.99***</td>
<td>0.90***</td>
<td>0.98***</td>
</tr>
<tr>
<td></td>
<td>(3.70)</td>
<td>(3.23)</td>
<td>(3.67)</td>
<td>(4.47)</td>
<td>(3.98)</td>
<td>(4.43)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.36***</td>
<td>0.35***</td>
<td>0.36***</td>
<td>0.37***</td>
<td>0.36***</td>
<td>0.35***</td>
</tr>
<tr>
<td></td>
<td>(4.49)</td>
<td>(4.33)</td>
<td>(4.10)</td>
<td>(4.59)</td>
<td>(4.42)</td>
<td>(4.07)</td>
</tr>
<tr>
<td>CEN × $I_{SUE&gt;0}$</td>
<td>0.14**</td>
<td>-</td>
<td>0.16**</td>
<td>-</td>
<td>0.14**</td>
<td>-</td>
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<tr>
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<td></td>
<td>(2.28)</td>
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### Panel B: Regression of DMR[0, 1]

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<th>Eigenvector Centrality</th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
</tr>
<tr>
<td>CEN</td>
<td>1.40***</td>
<td>1.69***</td>
<td>1.40***</td>
<td>0.77</td>
<td>1.08*</td>
<td>0.77</td>
</tr>
<tr>
<td></td>
<td>(2.85)</td>
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<td>(1.37)</td>
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<td>(1.38)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.48**</td>
<td>0.62***</td>
<td>0.50**</td>
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<td>0.63***</td>
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</tr>
<tr>
<td></td>
<td>(2.07)</td>
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</tr>
<tr>
<td>CEN × $I_{SUE&gt;0}$</td>
<td>-0.49**</td>
<td>-</td>
<td>-0.53**</td>
<td>-</td>
<td>-0.54**</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(-2.16)</td>
<td></td>
<td>(-2.32)</td>
<td></td>
<td>(-2.36)</td>
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</tr>
<tr>
<td>CEN × $I_{SUE=10}$</td>
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<td></td>
<td>(-0.17)</td>
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<td>(-0.25)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td>X</td>
<td>X</td>
<td>X</td>
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<td>Obs.</td>
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<td>24,802</td>
<td>24,802</td>
<td>24,802</td>
<td>24,802</td>
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</tr>
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</table>
Table 3: Return Reactions to Earnings News

This table reports the multivariate regression of abnormal cumulative returns during announcement and post-announcement windows. Independent variables include earnings surprises rank (SUE), network centrality measures (CEN), and their interaction (CEN×SUE). The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. 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]

<table>
<thead>
<tr>
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<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>SUE</td>
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<td>1.498***</td>
<td>0.390***</td>
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<tr>
<td></td>
<td>(23.84)</td>
<td>(12.80)</td>
<td>(23.78)</td>
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<tr>
<td></td>
<td>(-4.03)</td>
<td>(-4.57)</td>
<td>(-5.17)</td>
</tr>
<tr>
<td>CEN×SUE</td>
<td>0.00896***</td>
<td>0.0172***</td>
<td>0.00941***</td>
</tr>
<tr>
<td></td>
<td>(3.25)</td>
<td>(4.89)</td>
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<tr>
<td>Obs.</td>
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<td>238,195</td>
</tr>
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</table>

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

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<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
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<td>(2)</td>
<td>(1)</td>
</tr>
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<td>(14.30)</td>
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<td>(15.72)</td>
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<td>0.296***</td>
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<tr>
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<td>-0.0163*</td>
<td>-0.0291***</td>
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<tr>
<td>Controls</td>
<td>X</td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>238,195</td>
<td>213,889</td>
<td>238,195</td>
</tr>
</tbody>
</table>
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. At each quarter, samples are divided based on the NYSE median of size, institutional ownership, and idiosyncratic volatility. The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC), however, this table only tabulates the results using EC. Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. 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]\]

<table>
<thead>
<tr>
<th></th>
<th>Size</th>
<th>Institutional Ownership</th>
<th>Idiosyncratic Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small (1)</td>
<td>Large (2)</td>
<td>Low (3)</td>
</tr>
<tr>
<td>SUE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.144***</td>
<td>0.00413</td>
<td>-0.121***</td>
</tr>
<tr>
<td></td>
<td>(-5.52)</td>
<td>(0.10)</td>
<td>(-4.82)</td>
</tr>
<tr>
<td>CEN</td>
<td>1.617***</td>
<td>1.345***</td>
<td>2.125***</td>
</tr>
<tr>
<td></td>
<td>(11.20)</td>
<td>(6.14)</td>
<td>(12.21)</td>
</tr>
<tr>
<td>CEN×SUE</td>
<td>0.0235***</td>
<td>0.00275</td>
<td>0.0197***</td>
</tr>
<tr>
<td></td>
<td>(4.93)</td>
<td>(0.45)</td>
<td>(4.27)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>149,100</td>
<td>63,984</td>
<td>162,137</td>
</tr>
</tbody>
</table>

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

<table>
<thead>
<tr>
<th></th>
<th>Size</th>
<th>Institutional Ownership</th>
<th>Idiosyncratic Volatility</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Small (1)</td>
<td>Large (2)</td>
<td>Low (3)</td>
</tr>
<tr>
<td>SUE</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.281***</td>
<td>0.180**</td>
<td>0.298***</td>
</tr>
<tr>
<td></td>
<td>(3.52)</td>
<td>(2.19)</td>
<td>(4.03)</td>
</tr>
<tr>
<td>CEN</td>
<td>2.241***</td>
<td>1.572***</td>
<td>2.721***</td>
</tr>
<tr>
<td></td>
<td>(5.06)</td>
<td>(2.91)</td>
<td>(5.26)</td>
</tr>
<tr>
<td>CEN×SUE</td>
<td>-0.0278**</td>
<td>-0.0194</td>
<td>-0.0317***</td>
</tr>
<tr>
<td></td>
<td>(-2.17)</td>
<td>(-1.63)</td>
<td>(-2.66)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>149,100</td>
<td>63,984</td>
<td>162,137</td>
</tr>
</tbody>
</table>
Table 5: Volume Reactions to Earnings News

This table reports the multivariate regression of average abnormal trading volume during the announcement window, VOL[0, 1], and the post-announcement window, VOL[2, 61], both of which are defined in (6). The main independent variable is network centrality (CEN) and the decile rank of absolute value of earnings surprise (Abs(SUE)). The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. 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.

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.0161***</td>
<td>0.0174***</td>
<td>0.0162***</td>
</tr>
<tr>
<td></td>
<td>(18.56)</td>
<td>(18.31)</td>
<td>(18.74)</td>
</tr>
<tr>
<td>CEN</td>
<td>0.00941***</td>
<td>0.0113***</td>
<td>0.0114***</td>
</tr>
<tr>
<td></td>
<td>(5.58)</td>
<td>(6.04)</td>
<td>(6.80)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>238,195</td>
<td>213,889</td>
<td>238,195</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.00857***</td>
<td>0.00897***</td>
<td>0.00857***</td>
</tr>
<tr>
<td></td>
<td>(19.37)</td>
<td>(17.97)</td>
<td>(19.38)</td>
</tr>
<tr>
<td>CEN</td>
<td>0.000232</td>
<td>0.000702</td>
<td>0.000380</td>
</tr>
<tr>
<td></td>
<td>(0.77)</td>
<td>(1.44)</td>
<td>(1.27)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>238,195</td>
<td>213,889</td>
<td>238,195</td>
</tr>
</tbody>
</table>
Table 6: Volatility and Volume Dynamics

This table reports the multivariate regression of $d_{|R|}$ and $d_v$, the persistence parameters of absolute returns series and daily log volume series over $[0, 61]$, on network centrality (CEN) and the decile rank of absolute earnings surprises. The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. Coefficients are multiplied by 100. 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.

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>-0.0973***</td>
<td>0.0231**</td>
<td>-0.0994***</td>
</tr>
<tr>
<td></td>
<td>(-8.80)</td>
<td>(2.07)</td>
<td>(-8.98)</td>
</tr>
<tr>
<td>CEN</td>
<td>-0.178***</td>
<td>-0.0482***</td>
<td>-0.189***</td>
</tr>
<tr>
<td></td>
<td>(-8.89)</td>
<td>(-2.78)</td>
<td>(-9.64)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>233,050</td>
<td>209,297</td>
<td>233,050</td>
</tr>
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</table>

Panel B: Regression of Persistence Parameter $d_v$

<table>
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<tr>
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<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.267***</td>
<td>0.0237*</td>
<td>0.267***</td>
</tr>
<tr>
<td></td>
<td>(16.32)</td>
<td>(1.65)</td>
<td>(16.32)</td>
</tr>
<tr>
<td>CEN</td>
<td>0.627***</td>
<td>0.233***</td>
<td>0.627***</td>
</tr>
<tr>
<td></td>
<td>(15.63)</td>
<td>(7.39)</td>
<td>(15.63)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>214,418</td>
<td>192,585</td>
<td>214,418</td>
</tr>
</tbody>
</table>
Table 7: Disagreement and Social Interaction

Daily volumes are decomposed into two components according to (10)-(13). 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, respectively. 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 centrality measure (eigenvector centrality, EC). 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]|), eigenvector centrality (EC), and the interaction between |CAR[0, 1]| (|R[0,1]|) and EC. Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. 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

<table>
<thead>
<tr>
<th></th>
<th>SUV[0, 1]</th>
<th>SEV[0, 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Abs(SUE)</td>
<td>0.0279***</td>
<td>0.00982***</td>
</tr>
<tr>
<td></td>
<td>(21.22)</td>
<td>(8.54)</td>
</tr>
<tr>
<td>EC</td>
<td>0.0243***</td>
<td>0.0135***</td>
</tr>
<tr>
<td></td>
<td>(8.76)</td>
<td>(5.47)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>244,674</td>
<td>219,722</td>
</tr>
</tbody>
</table>

### Panel B: Volume Reaction and Absolute Price Changes

<table>
<thead>
<tr>
<th></th>
<th>VOL[0, 1]</th>
<th>V[0, 1]</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>EC</td>
<td>0.00904***</td>
<td>0.0166***</td>
</tr>
<tr>
<td></td>
<td>(4.62)</td>
<td>(6.97)</td>
</tr>
<tr>
<td></td>
<td>CAR[0,1]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(32.81)</td>
<td>(33.30)</td>
</tr>
<tr>
<td>EC×</td>
<td>CAR[0,1]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-4.62)</td>
<td>(-4.44)</td>
</tr>
<tr>
<td></td>
<td>R[0,1]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(18.51)</td>
<td>(25.10)</td>
</tr>
<tr>
<td>EC×</td>
<td>R[0,1]</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(-9.17)</td>
<td>(-7.91)</td>
</tr>
<tr>
<td>Controls</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>244674</td>
<td>219,722</td>
</tr>
</tbody>
</table>
Table 8: Information-Processing Disagreement v.s. Conversation-Triggered Disagreement

Daily volumes are decomposed into two components according to (10)-(13). SUV represents disagreement-driven trading. Panel A, B, and C regress the fractional integration parameter $d_{SUV}$, the post-announcement abnormal search activity ASVI[2, 61], and the fractional integration parameter $d_{SVI}$ on county centrality measures (CEN) and the decile rank of absolute earnings surprises, respectively. The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. Coefficients are multiplied by 100. 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.

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Abs(SUE)</td>
<td>0.18***</td>
<td>-0.03**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(11.59)</td>
<td>(-2.19)</td>
</tr>
<tr>
<td></td>
<td>CEN</td>
<td>0.49***</td>
<td>0.16***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(14.36)</td>
<td>(6.08)</td>
</tr>
<tr>
<td></td>
<td>Controls</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>238,195</td>
<td>213,889</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Regression of Post-Announcement Attention ASVI[2, 61]

<table>
<thead>
<tr>
<th></th>
<th>Degree Centrality</th>
<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Abs(SUE)</td>
<td>0.68***</td>
<td>0.38***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(7.43)</td>
<td>(4.59)</td>
</tr>
<tr>
<td></td>
<td>CEN</td>
<td>1.69***</td>
<td>1.10***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(6.33)</td>
<td>(3.50)</td>
</tr>
<tr>
<td></td>
<td>Controls</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
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<td>213,889</td>
<td></td>
</tr>
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</table>

Panel C: Regression of SVI Persistence $d_{SVI}$

<table>
<thead>
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<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Abs(SUE)</td>
<td>0.11***</td>
<td>-0.03</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(2.80)</td>
<td>(-0.86)</td>
</tr>
<tr>
<td></td>
<td>CEN</td>
<td>0.49***</td>
<td>0.48***</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(4.71)</td>
<td>(3.64)</td>
</tr>
<tr>
<td></td>
<td>Controls</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Obs.</td>
<td>238,195</td>
<td>213,889</td>
<td></td>
</tr>
</tbody>
</table>
Table 9: Post-Announcement Return and Social Interaction

This table tests the relation between post-announcement return and social interaction. CAR[2, 61] is regressed on county centrality measures. CAR[2, 61] is the post-announcement cumulative abnormal return defined in (2). Decile rank of earnings surprises (SUE) and SUV[0,1] are also included. SUV[0, 1] is the disagreement-driven component of announcement trading volume as defined in (10)-(13). The regression models are performed for all empirical centrality measures: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). Controls include size, book-to-market ratio, institutional ownership, earnings persistence, earnings volatility, share turnover, idiosyncratic volatility, reporting lag, the number of same-day announcements, indicator variables for year, month, day of week, and S&P 500 constituent, population density, retail dummy, same-industry workforce percentage, the number of local newspapers, the number of local firms, and advertisement expenses. 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.

<table>
<thead>
<tr>
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<th>Eigenvector Centrality</th>
<th>Information Centrality</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(1)</td>
</tr>
<tr>
<td>CEN</td>
<td>0.0509*</td>
<td>0.143***</td>
<td>0.0587**</td>
</tr>
<tr>
<td></td>
<td>(1.93)</td>
<td>(4.88)</td>
<td>(2.12)</td>
</tr>
<tr>
<td>SUV[0,1]</td>
<td>0.403***</td>
<td>0.399***</td>
<td>0.402***</td>
</tr>
<tr>
<td></td>
<td>(8.78)</td>
<td>(8.72)</td>
<td>(8.80)</td>
</tr>
<tr>
<td>Firm Controls</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Obs.</td>
<td>214,693</td>
<td>214,693</td>
<td>214,693</td>
</tr>
</tbody>
</table>

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Appendix

A Model

In this section, we present a model of gradual information diffusion in a network setting. The basic setup is borrowed from Fedyk (2018), which is itself based on Hirshleifer and Teoh (2003) and DellaVigna and Pollet (2009). Let $t$ denote the trading dates: $t = 0, 1, \ldots, T + 1$. There is a single risky asset with terminal payoff $R$ at date $T + 1$ that is normally distributed with mean $\bar{R}$ and variance $\sigma^2_R$. There is also a riskless bond with zero interest rate. The per-capita supply of the risky asset is fixed at $X$. Investors can borrow and lend freely.

There are $N$ investors in the market who are indexed by $i \in \{1, 2, \ldots, N\}$. Investors are risk averse and exhibit quadratic utility with risk aversion $\gamma_i$. The $i^{th}$ investor maximizes the expected utility of terminal wealth $W^i_T$:

$$\max_{x^i_t} \mathbb{E}_{i,t}[W^i_T] - \frac{\gamma_i}{2} \text{Var}_{i,t}[W^i_T]$$  \hspace{1cm} (A.1)

$$s.t. \ W^i_T = W^i_t + x^i_t (R - P_t).$$

In order to highlight the trading due to gradual information diffusion, we set $\gamma_i = 1$ for $\forall i$ to eliminate the trading due to heterogeneous preferences.

Investors update their beliefs in a naive Bayesian manner: they learn from their own signals but do not learn from the price history. In other words, investors do not form rational expectations of information available to others. At each trading date $t$, let $F_t$ be the total fraction of investors who are informed of the public signal, and $1 - F_t$ the total fraction of uninformed investors. At date 0, investors form common priors of the asset’s payoff $R$. Meanwhile, there is pre-announcement information leakage so that a fraction $F_0$ of investors receives the public signal. At date 1, a public signal $Y$ arrives, which is informative of $R$ and takes the form of $Y = R + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \sigma^2_\epsilon)$. A fraction $F_1 - F_0$ of investors become newly informed of the signal and update their belief with $Y$. The remaining fraction $1 - F_1$ of investors are inattentive and only trade based on their priors. The public news diffuses over time, and at trading $t$, investors of mass $F_t$ are informed and investors of mass $1 - F_t$ remain uninformed. Denote $I_t$ the set of informed investors at time $t$ who receive the public signal either prior to or during period $t$. Similarly, denote $U_t$ the set of uninformed investors at time $t$.

A.1. Price and Volume

In our setting, a gradual information diffusion process is entirely characterized by the sequence of the total fraction of attentive investors at each trading date $t$, $\{F_t\}_{t=0,1,\ldots,T}$. And we show that the same sequence also characterizes the price and volume dynamics.

Given that investors are naively Bayesian, informed investors form posterior beliefs of $R$ by
conditioning on the signal $Y$ whereas uninformed investors do not update:

$$i \in I_t : \mathbb{E}_t^{(i)}[R] = \frac{\sigma^2_i \tilde{R} + \sigma^2_R Y}{\sigma^2_i + \sigma^2_R}; \quad \text{Var}_t^{(i)}[R] = \frac{\sigma^2_i \sigma^2_R}{\sigma^2_i + \sigma^2_R}; \quad \text{(A.2)}$$

$$i \in U_t : \mathbb{E}_t^{(i)}[R] = \tilde{R}; \quad \text{Var}_t^{(i)}[R] = \sigma^2_R. \quad \text{(A.3)}$$

Given the price $P_t$, which will be determined through the market clearing condition, investors’ demand functions are as follow:

$$i \in I_t : x_t^{(i)} = \frac{\sigma^2_i (\tilde{R} - P_t) + \sigma^2_R (Y - P_t)}{\sigma^2_i \sigma^2_R}; \quad \text{(A.4)}$$

$$i \in U_t : x_t^{(i)} = \frac{\tilde{R} - P_t}{\sigma^2_R}. \quad \text{(A.5)}$$

The total demands from both type of investors must be equal to the total supply $NX$. We set $X = 0$ to simplify notations. Then the equilibrium price $P_t$ must clear the market:

$$F_t \frac{\sigma^2_i (\tilde{R} - P_t) + \sigma^2_R (Y - P_t)}{\sigma^2_i \sigma^2_R} + (1 - F_t) \frac{\tilde{R} - P_t}{\sigma^2_R} = 0. \quad \text{(A.6)}$$

Solving the market clearing condition, we have the expression for $P_t$:

$$P_t = \frac{\sigma^2_i \tilde{R} + F_t \sigma^2_R Y}{\sigma^2_i + F_t \sigma^2_R}. \quad \text{(A.7)}$$

Per-period price change $\Delta P_t = P_t - P_{t-1}$ and its volatility $\sigma_{\Delta P_t}$ become

$$\Delta P_t = \frac{(F_t - F_{t-1}) \sigma^2_R \sigma^2_i (Y - \tilde{R})}{(\sigma^2_i + F_t \sigma^2_R) \sigma^2_i + F_t \sigma^2_R}; \quad \text{Var}_{\Delta P_t} = \frac{(F_t - F_{t-1}) \sigma^2_R \sigma^2_i \sqrt{\sigma^2_i + \sigma^2_i}}{(\sigma^2_i + F_t \sigma^2_R) \sigma^2_i + F_t \sigma^2_R}. \quad \text{(A.8)}$$

We next calculate the trading volume. We define the volume as the absolute difference from investors time $t$ demand and time $t-1$ demand averaged across all traders $V_t = \frac{1}{2N} \sum_{i=1}^N |x_t^{(i)} - x_{t-1}^{(i)}|$. $|\Delta x_t^{(i)}|$ depends on the $i$’s types across $t - 1$ and $t$:

$$\forall i \in I_{t-1} \cap I_t : \quad |\Delta x_t^{(i)}| = |x_t^{(i)} - x_{t-1}^{(i)}| = \frac{(F_t - F_{t-1}) \sigma^2_R (\sigma^2_i + \sigma^2_i)}{(F_t - F_{t-1}) \sigma^2_R + \sigma^2_i} (\frac{\sigma^2_i + \sigma^2_i}{F_t \sigma^2_R + \sigma^2_i}) |Y - \tilde{R}|;$$

$$\forall i \in I_{t-1} \cap U_t : \quad |\Delta x_t^{(i)}| = |x_t^{(i)} - x_{t-1}^{(i)}| = \frac{F_{t-1} (\sigma^2_R + \sigma^2_i) + (1 - F_t) \sigma^2_i}{F_{t-1} \sigma^2_R + \sigma^2_i} (\frac{\sigma^2_i + \sigma^2_i}{F_t \sigma^2_R + \sigma^2_i}) |Y - \tilde{R}|;$$

$$\forall i \in I_{t-1} \cap U_t : \quad |\Delta x_t^{(i)}| = |x_t^{(i)} - x_{t-1}^{(i)}| = \frac{(F_t - F_{t-1}) \sigma^2_i}{(F_t - F_{t-1}) \sigma^2_R + \sigma^2_i} (\frac{\sigma^2_i + \sigma^2_i}{F_t \sigma^2_R + \sigma^2_i}) |Y - \tilde{R}|.$$

Multiplying the fraction of each type of investors above with their trading volume and averaging,
we have the volume at $t$:

$$V_t = \frac{1}{2} (F_{t-1}|x_t^l - x_{t-1}^l| + (F_t - F_{t-1})|x_t^U - x_{t-1}^U| + (1 - F_t)|x_t^U - x_{t-1}^U|)$$

$$= (F_t - F_{t-1}) \frac{F_{t-1} (\sigma_R^2 + \sigma_e^2) + (1 - F_t) \sigma_e^2}{(F_{t-1}\sigma_R^2 + \sigma_e^2)(F_t\sigma_R^2 + \sigma_e^2)} |Y - \bar{R}|.$$  \hspace{1cm} \text{(A.9)}$

### A.2. Information Network

In this section we describe a gradual information diffusion process in an information network. Investors are connected by a graph $\mathcal{G} = (\mathcal{N}, \mathcal{E})$. $\mathcal{N} = \{1, 2, \ldots, N\}$ is the set of all investors and $|\mathcal{N}| = N$. The set of edges $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$ defines which investors are connected in the network. Specifically, two investors $i, i' \in \mathcal{N}$ are directly connected via an edge if and only if $(i, i') \in \mathcal{E}$. We further use the convention that each investor is connected to himself: $\mathcal{E}(i, i) = 1$ for all $i \in \mathcal{N}$. Edges can be conveniently expressed by the so-called adjacency matrix $A \in \{0, 1\}^{N \times N}$ whose $(i, i')^t$ element $(A)_{ii'} = 1$ if $(i, i') \in \mathcal{E}$ and $(A)_{ii'} = 0$ otherwise.

Denote $p(i, i')$ the shortest path between two investors $i$ and $i'$. $p(i, i') = 1$ indicates $i$ and $i'$ can be connected via one link, i.e., they are neighbors. $p(i, i') = k$ indicates that $i$ and $i'$ are not directly connected but can be indirectly connected via $k$ links. We define $\mathcal{S}_k(i) = \{i' : p(i, i') = k\}$ as the set of investors at distance $k$ from investors $i$ and $\mathcal{D}_k(i) = \{i', p(i, i') \leq k\}$ as the set of investors at distance less than or equal to $k$ from investors $i$. Hence, $\mathcal{D}_1(i) = \bigcup_{j=1}^k \mathcal{S}_j(i)$. $D_1(i) = |\mathcal{D}_1(i)|$ is called the $1^{st}$-order degree of $i$, which measures the total number of $i$'s direct neighbors. Similarly, $D_k(i) = |\mathcal{D}_k(i)|$ is called the $m^{th}$ degree of $i$, which measures the total number of investors that can be connected to $i$ with no more than $k$ steps.

We partition graph $\mathcal{G}$ into $M$ subgraphs $\mathcal{G}^m$ for $m = 1, \ldots, M$. When the firm announces its public news, the information first arrives in the subgraph where the firm belong and then gradually diffuses to other subgraphs via investor social interactions. These subgraphs can be considered as the networks of the subset of the firm’s investors who respond to the news immediately, and these investors could be characterized by their sophistication such as institutional investors or by familiarity such as local investors. We simply use the network partition to capture the idea that the news first hit a particular group of investors before it transmits to the rest of the population.

We represent the subgraphs $\mathcal{G}^m = (\mathcal{N}^m, \mathcal{E})$, where the subsets of investors $\mathcal{N}^m$ for $m = 1, \ldots, M$ are mutually disjoint subsets within $\mathcal{N}$. Let $N^m = |\mathcal{N}^m|$. The percentage of the total investors in $\mathcal{G}^m$ relative to all the investors in the network is given by $\lambda^m = \frac{N^m}{N}$, with $\sum_{m=1}^M \lambda_m = 1$. Denote $\mathcal{D}_1^m = \bigcup_{i \in \mathcal{N}^m} D_1(i)$ the set of investors that the investors in $\mathcal{N}^m$ can reach within no more than $k$ steps. Moreover, analogous to the concept of the $m^{th}$-order degree of an individual node, we can define the $m^{th}$-order of the subset of investors $\mathcal{N}^m$ as $D_k^m = |\mathcal{D}_k^m|$. Using the well-known property that $(i, i')^t$ element of the $k^{th}$ power of the adjacency matrix $A$, $(A^k)_{ii'}$ gives the total number of walks between $i$ and $i'$, we can calculate $D_k^m$ as follows:
Definition 1 The \( k \)-th order degree of investor subset \( \mathcal{N}^m \) is defined as
\[
D^m_k = \xi(\mathbb{1}^m_{\mathcal{N}} A^k) \mathbb{1},
\]
where \( \xi : \mathbb{R}^{+N \times N} \rightarrow \{0, 1\}^{N \times N} \) is a matrix element-wise indicator function such that \( (\xi(A))_{ij} = 1 \) if \( A_{ij} > 0 \) and \( (\xi(A))_{ij} = 0 \) if \( A_{ij} = 0 \). \( \mathbb{1}^m_{\mathcal{N}} \) is \( N \times 1 \) vector with \( (\mathbb{1}^m_{\mathcal{N}})_i = 1 \) if \( i \in \mathcal{N}^m \) and \( (\mathbb{1}^m_{\mathcal{N}})_i = 0 \) otherwise, and \( \mathbb{1} \) is \( N \times 1 \) vector of ones.

At trading date 0, the signal is leaked to investor \( i \in I_0 \). General diffusion process in networks are usually difficult to characterize. To keep solutions tractable, we assume that \( I_0 \subset \mathcal{N}^m \), i.e., the information only occur in a firm’s home network \( \mathcal{G}^m \). At trading date 1, the public news arrives at subgraph \( \mathcal{G}^m \). Each investor \( i \in \mathcal{N}^m \) becomes informed and he immediately broadcasts the information to each of his direct neighbor. At each subsequent time \( t \), the newly informed investors from the previous period \( t-1 \) broadcast the news to each one of their direct neighbors. This information sharing structure is similar to the one used in Walden (2018) to model private signal sharing in an information network. This treatment allows for tractable solutions and yields a deterministic process of percentage of informed population \( F_t \):
\[
F_t = D^m_t / N, \quad t = 1, 2, \ldots, T.
\]

If \( \mathcal{G} \) is connected, i.e., there is a path for every pair of investors, then \( F_t \geq F_{t-1} \) for all \( t \) and there exits a positive integer \( \hat{k} \) such that \( F_t = 1 \) if \( t \geq \hat{k} \).

A.3. Empirical Predictions

In this subsection we relate the topological properties of \( \mathcal{N}^m \) to price and volume reactions to the public news. It is useful to first define the concept of subgraph centrality. Such concept is an extension from the centrality notions defined for a node to that for a subgraph.

Definition 2 The topological position of subgraph \( \mathcal{G}^m \) in the entire graph \( \mathcal{G} \) is said to be more central than another subgraph \( \mathcal{G}^{m'} \) if
\[
D^m_k \geq D^{m'}_k, \quad \forall \ k = 1, 2, \ldots,
\]
where strict inequality hold for at least some values of \( k \).

To derive empirical predictions, Let \( \hat{t} \) be the cutoff point such that the \([0, \hat{t}]\) is the time window for which immediate price reaction is measured empirically and \((\hat{t}, T]\) is the time window for which delayed price reaction is measured. Without loss of generality, we assume that \( F_0 \) is sufficiently close to zero in following analyses. Using equation (A.8), the immediate price reaction is
\[
\Delta P_{0, \hat{t}} = P_{\hat{t}} - P_0 = \frac{F_\hat{t}\sigma_R^2}{\sigma^2 + F_\hat{t}\sigma_R^2}(Y - \bar{R}),
\]
which is increasing in $F_t$. In our settings, $F_t$ increases with subgraph centrality. And we have our first prediction.

**Prediction 1 (Immediate Price Reaction)** Public news that diffuses from a more central subgraph will be followed by stronger immediate price reaction to the news.

How does the delayed price reaction relate to subgraph centrality then? Intuitively, if the diffusion process started from central subgraphs is associated with stronger immediate price reaction, it should be followed by weaker delayed price reaction. To see this, assume that $T \geq \bar{k}$ so that $F_T = 1$, i.e., the news diffuses to the entire population by the end of the trading dates. We can calculate delayed price reaction as follows:

$$
\Delta P_{t,T} = P_T - P_t = \frac{\sigma^2}{\sigma^2 + \sigma^2_R} \frac{1 - F_t}{\sigma^2 + \sigma^2_R} (Y - \bar{R}),
$$

(A.14)

which is decreasing in $F_t$. This result confirms our intuition and we have our second prediction.

**Prediction 2 (Delayed Price Reaction)** Public news that diffuses from a more central subgraph will be followed by weaker delayed price reaction to the news.

Together, public information diffuses fast from a central subgraph and consequently the news is quickly absorbed into the asset prices. These results imply that price volatility resulted from the information shock to the market should also be short-lived if the news diffuses more efficiently. We check this prediction by calculating the cumulative volatility of price changes from date 0 to date $t$

$$
\sum_{s=1}^{t} \sigma^2_{\Delta P_s} = \frac{F_t \sigma^2_R}{\sigma^2 + \sigma^2_R} \sqrt{\sigma^2 + \sigma^2_R},
$$

(A.15)

which is the amount of volatility already incorporated in the prices up to time $t$. Note that the total volatility incorporated from 0 to $T$ is fixed at $\sigma^2_R (\sigma^2 + \sigma^2_R)^{-1/2}$. The amount of volatility yet to be incorporated at time $t$ is thus

$$
\sum_{s=t+1}^{T} \sigma^2_{\Delta P_s} = \frac{\sigma^2 \sigma^2_R}{\sqrt{\sigma^2 + \sigma^2_R}} \frac{1 - F_t}{\sigma^2 + \sigma^2_R},
$$

(A.16)

It follows from (A.16) that volatility after an information shock is less persistence with higher $F_t$ for $t = 1, 2, \ldots, T$, in the sense that at each date $t$ there is less residual volatility to impounded into prices. Therefore, subgraph centrality is directly related to volatility persistence.

**Prediction 3 (Volatility Persistence)** Public news that diffuses from a more central subgraph will be followed by less persistent price volatility.

We next study the volume reactions. To simplify the calculation, we assume that the noise in the signal is small relative to the variance of the asset payoff: $\sigma^2 \ll \sigma^2_R$, which we expect to be true for most public signals. Under this assumption, trading volumes can be approximated by:
\[ V_t \approx \frac{1}{\sigma^2} \frac{\Delta F_t}{F_t} |Y - \bar{R}|, \quad t = 1, 2, \ldots, T, \]  

(A.17)

where \( \Delta F_t = F_t - F_{t-1} \).

It is useful to consider \( F_t \) as a cumulative distribution function (CDF) \( F(t) \) define on \( t = 0, 1, 2, \ldots, T \), with \( F(t) = F_t \) and \( F(T) = 1 \). Then the ratio \( \lambda_t = \frac{\Delta F_t}{F_t} \) is known as reverse hazard rate. And the following equality between CDF and reverse hazard rate holds:

\[ F_t = \prod_{s=t+1}^{T} (1 - \lambda_s). \]  

(A.18)

The above equality implies a reverse relationship between \( F_t \) and subsequent \( \lambda_s \) with \( s = t + 1, \ldots, T \). Trading volume within \([0, \hat{t}]\) is determined by \( \lambda_s \) for \( s = 1, \ldots, \hat{t} \), which can be expressed using the above equality as:

\[ \frac{F_0}{F_{\hat{t}}} = \prod_{s=1}^{\hat{t}} (1 - \lambda_s). \]

Hence, the higher the value of \( F(t) \), the higher the values of \( \lambda(s) \) for \( s = 1, \ldots, \hat{t} \). To see this more clearly, assume that \( \lambda(s) \) is small and we can approximate the above expression using Taylor expansion:

\[ \frac{F_0}{F_{\hat{t}}} = \exp \left( \sum_{s=1}^{\hat{t}} \log(1 - \lambda_s) \right) \approx \exp \left( - \sum_{s=1}^{\hat{t}} \lambda_s \right) = \exp \left( - \sum_{s=1}^{\hat{t}} \frac{\Delta F_s}{F_s} \right). \]  

Using above approximation, the cumulative trading volume within \([0, \hat{t}]\) becomes:

\[ \sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{\sigma^2} \log \left( \frac{F_{\hat{t}}}{F_0} \right) |Y - \bar{R}|. \]

Hence, the higher the value of \( F_t \), the stronger the immediate volume reactions. This result leads to the following predication.

**Prediction 4 (Immediate Volume Reaction)** *Public news that diffuses from a more central subgraph will be followed by stronger immediate volume reaction to the news.*

Similary, we can apply Taylor’s expansion to (A.18) and approximate the delayed volume reac-

\[18\text{This approximation holds exactly if } F(t) \text{ is continuous and admits a probability density function } f(t): \]

\[ F(t) = \exp \left( - \int_t \lambda(s) ds \right), \text{ where } \lambda(s) = f(s)/F(s) \text{ is the reverse hazard rate for } F(t). \]
The above result suggests that delayed volume reaction tends to be weaker if \( F_t \) is large.

**Prediction 5 (Delayed Volume Reaction)** *Public news that diffuses from a more central subgraph will be followed by weaker delayed volume reaction to the news.*

Finally, we derive our last prediction on volume persistence. Note that (A.19) holds for any \( \hat{t} = 1, 2, \ldots, T - 1 \), which suggests that volume dynamics is less persistence with higher values of \( F_t \) since at any point in time there are less residual trading volumes due to investors’ belief convergence.

**Prediction 6 (Volume Persistence)** *Public news that diffuses from a more central subgraph will be followed by less persistent trading volumes.*