News Diffusion in Social Networks and Stock Market Reactions

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April 1, 2023

Abstract

We study how the social transmission of public news influences investors' beliefs and securities markets. Using data on investor social networks, we find that earnings announcements from firms in higher-centrality locations generate stronger immediate price, volatility, and trading volume reactions. Post announcement, such firms experience weaker price drift and faster volatility decay but higher and more persistent volume. This evidence suggests that greater social connectedness promotes timely incorporation of news into prices, but also opinion divergence and excessive trading. We propose the *social churning hypothesis* and present supporting evidence with granular data from StockTwits messages and household trading records.

JEL Codes: G1, G4

Keywords: Information Diffusion, Social Churning, Earnings Announcements, Limited Attention, Disagreement, Social Finance

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1 Introduction

In classic models of information in asset markets, people learn from others only indirectly through observation of market prices or quantities. There is growing evidence that more direct forms of social interaction, such as conversation, also affect investment decisions. As emphasized by Shiller (1989, p. 7), "[I]nvesting ... is a social activity. Investors spend a substantial part of their leisure time discussing investments, reading about investments, or gossiping about others' successes or failures in investing."

Past theoretical analysis suggests that social interactions can have both beneficial and deleterious effects on investor behavior. On the one hand, they can disseminate valuable information and lead to superior decisions and efficient prices. On the other hand, social interactions can also propagate incorrect beliefs and naïve trading strategies, thereby reducing information efficiency.[1]

To better understand the role of social networks on information transmission, our study focuses on the social dissemination of a crucial type of public news: corporate earnings announcements. Past research has shown that stock prices do not incorporate this news promptly, leading to predictable abnormal returns over several months after the event date (e.g., Ball and Brown 1968, Bernard and Thomas 1989).

The leading explanation for this delay is that not all investors are immediately attentive to earnings news owing to to limited cognitive processing abilities (see, e.g., Bernard and Thomas 1989, Hirshleifer and Teoh 2003). When there are inattentive investors, attention to earnings news may spread through social networks. Accordingly, this paper explores how investor social transmission networks influence the speed of news diffusion, beliefs, trading behavior, and asset prices.

Our approach is motivated by the findings of Banerjee et al. (2013, 2019) that information about microfinance or immunization spreads faster when signals are seeded at central nodes in a network. In the stock market context, there is extensive evidence that investors favor local firms and are more attentive to news about such firms.[2] We therefore hypothesize that

[1] Several models have explored the impact of social interactions on decision-making and efficiency, highlighting potential benefits (Ellison and Fudenberg 1995, Colla and Mele 2010, Özsöylev and Walden 2011). However, other studies have shown that social interactions can also lead to the spread of rumors and amplify behavior biases (DeMarzo, Vayanos, and Zwiebel 2003, Hirshleifer 2020, Han, Hirshleifer, and Walden 2021) and trigger information cascades (Bikhchandani, Hirshleifer, and Welch 1992, Banerjee 1992) and free-riding incentives (Han and Yang 2013).

[2] Evidence that investors favor investing in and trading stocks of nearby companies is provided by Coval

earnings news first captures the attention of local investors and then disseminates through the network of investors via word-of-mouth.

Consequently, we predict that the information content of earnings announcements made by firms located in counties with greater centrality in the social network of investors tends to diffuse more quickly. This implies stronger immediate volume and return responses to earnings news and higher immediate return volatility. In other words, higher centrality opposes the usual sluggishness of market responses to earnings news. We therefore predict less post-earnings announcement drift and a more precipitous post-event drop in return volatility.

To test for such effects, we define a firm's local investor base as the set of investors from its headquarters county and its centrality as the centrality of its local investor base in the social network of its potential investors in the United States. We find that earnings announcements by firms based in high-centrality locations tend to generate stronger immediate stock price, volatility, and trading volume responses for the two-day window around the announcement, [0, 1]. Notably, however, for such firms, the 60-day post-announcement period ([2, 61] window) volume remains high and persistent, whereas the returns exhibit weaker drift and faster decay of volatility.

More specifically, our proxy for network centrality builds upon the newly available Social Connectedness Index (SCI), which measures the connectedness between U.S. counties (Bailey et al. 2018a,b, 2019, 2020a) using data from Facebook, a social network with about a quarter of a billion users in the United States and Canada. The centrality of a firm is measured as the centrality of its headquarters county in the matrix of SCIs between county pairs.

Compared to announcements made by firms in the lowest decile of degree centrality, announcements by firms in the highest decile are associated with 28.6% stronger immediate price reactions during the [0,1] window and 20.1% weaker post-announcement drift (PEAD) and 11.0% faster decay in volatility during the [2, 61] window, all relative to their respective sample averages. These results indicate that earnings news from firms that more centrally located is more rapidly incorporated into their stock prices. Therefore, network centrality is associated with greater dissemination and price efficiency.

The same increase in centrality increases the immediate volume reaction to earnings news

and Moskowitz (1999), Hong et al. (2014), Ivković and Weisbenner (2005, 2007), Massa and Simonov (2006), Seasholes and Zhu (2010). Chi and Shanthikumar (2017)) find that local investors pay closer attention to news about local companies.

by 11.90% relative to the sample mean. Surprisingly, for the [2, 61] window, we also find a positive relation between centrality and the level and persistence of trading volume—the increase in centrality is associated with a 14.7% increase in volume and a 10.3% increase in volume persistence. The pattern contrasts sharply with the negative relation between centrality and post-announcement returns and volatility persistence. This evidence indicates that more-intense social transmission of earnings news is associated with greater and *more* persistent trading of stocks.

The striking contrast in these findings poses a challenge to traditional frameworks that would typically predict a faster decay in both volatility and trading volume for announcements that promote faster diffusion of information.[3] The findings therefore raise the question of why greater social interactions lead to persistently heavier post-announcement trading but less post-announcement drift and faster volatility decay.

A starting point for reconciling this evidence is the fact that there is extensive disagreement among retail investors. In a large panel survey, Giglio et al. (2021) find strong evidence that investors have large and persistent differences in beliefs. As the authors suggest, "models that explicitly feature heterogeneous agents with different beliefs are likely to offer a fruitful starting point for future work" (Giglio et al., 2021, p. 1484).

We propose a "social churning hypothesis" to explain the observed persistence in disagreement and the contrasting dynamics of return, volatility, and trading volume. As investors converse with different sets of acquaintances, they update their beliefs differently, causing the distribution of beliefs across investors, and investor disagreement, to shift.[4] Idiosyncratic fluctuations in disagreement need not hinder the incorporation of news into stock prices, but they do imply persistent volume of trade. Thus, greater network centrality reduces post-earnings announcement drift and is followed by fast-decaying volatility, but can make volume more persistent for a while.[5]

We evaluate the social churning hypothesis using granular data based on StockTwits

[3] Previous studies (Karpoff 1986, Kim and Verrecchia 1991, Harris and Raviv 1993, Kim and Verrecchia 1994, Kandel and Pearson 1995, Scheinkman and Xiong 2003, Banerjee and Kremer 2010) suggest that news arrival can trigger trading when investors have diverse beliefs or different interpretations of the news. If we interpret higher connectedness in the social network as promoting faster information diffusion, these models suggest that higher news centrality will be associated with faster decay in both volatility and volume. Our empirical findings for volume oppose this implication.

[4] Such shifts in beliefs can derive from imperfect rationality and biases in the social transmission of beliefs and behaviors between investors (Hirshleifer 2020) and from signal mutation and transmission failures along communication chains (Jackson, Malladi, and McAdams 2021).

[5] In the Internet Appendix, we provide a theoretical model to illustrate this mechanism.

messages and household trading records together with information about Google search activities. Our evidence is consistent with the predictions about the effects of social interactions and centrality on investor attention, belief formation, and trading.

Our first set of tests is based on a sample of more than 10 million messages on StockTwits, a popular social media platform for investors to share their investment opinions.[6] We classify StockTwits messages into two categories: New Messages, which corresponds to the number of initial mentions of a stock in a message thread, and Replies, which refers to the number of replies to the initial messages. We use New Messages to proxy for the number of newly informed investors and Replies to proxy for the intensity of subsequent discussions on StockTwits. To assess changes in message activity after earnings announcements compared to pre-announcement levels, we calculate Abnormal New Messages and Abnormal Replies.

We find that announcements by firms in more-central counties experience a larger initial increase in Abnormal New Messages than less-central firms, by 9.95% (relative to the sample mean), during the [0, 1] window. Furthermore, the news of high-centrality firms is associated with a larger drop in Abnormal New Messages for the [2, 61] window, which ends up close to the baseline preannouncement level. In contrast, centrality increases both the [0, 1] and [2, 61] Abnormal Replies by approximately 35%. These results are consistent with the prediction of the social churning hypothesis that high-centrality news quickly disseminates across different investors, but that the news also continues to attract investor attention and generate persistent intense discussions among investors for a substantial period post-announcement.

We then test whether stronger social interactions induce more-persistent disagreement. We apply textual analysis to StockTwits messages to construct a daily measure of disagreement in message sentiments. We find that earnings announcements of high-centrality stocks are associated with greater divergence of beliefs across investors, by 4.7% and 5.7% for the [0, 1] and [2, 61] windows, respectively, relative to the corresponding sample mean. This finding is consistent with the social churning hypothesis, which states that greater social news transmission contributes to more-persistent belief heterogeneity.

We also use an alternative centrality measure constructed directly from StockTwits data, defining "influencers" as users with high centrality in the social network of StockTwits users. We find that earnings announcements that receive more initial mentions by influencers gener-

[6]The data have been used to study the effect of social networks on investor belief formation (Cookson and Niessner 2020, Cookson, Engelberg, and Mullins 2023).

ate more Replies and greater disagreement among investors for the [2, 61] window. Such news is also associated with less-persistent volatility but more-persistent volume, all of which is consistent with the social churning hypothesis. These findings also provide an out of sample validity check for the Facebook-based centrality measures.

We also apply a more representative, albeit less granular, measure of retail investor attention: Google searches of stock ticker symbols (Da, Engelberg, and Gao 2011). We find that announcements made by firms from high-centrality areas elicit a greater increase in abnormal Google searches and that these increases are more persistent than the announcements made by low-centrality firms. As with the StockTwits findings, these tests are consistent with the hypothesis that news from high-centrality locations attracts more-persistent attention from investors. This is also consistent with our evidence for earnings news at such locations with high disagreement and persistent volume of trade.

We then test whether investors who reside in counties with stronger social connections to a firm's county are more likely to trade on the firm's earnings announcements using individual account-level data from a large U.S. discount brokerage (Barber and Odean 2000). We find that an increase in social connectedness (from the 10^{th} percentile to the 90^{th} percentile) increases the likelihood of household trading by 8.4% and 9.4% for the [0, 1] and [2, 61] windows, respectively, relative to their respective means. Findings are similar for the number of trades and relative trade size. Furthermore, higher social connectedness is associated with greater household trading losses, by 16.6% relative to the sample mean. The evidence suggests that the greater trading of connected households is excessive, presumably owing to erroneous beliefs.

Overall, the evidence based on stock returns, StockTwits messages, Google searches, and household trading activities provides support for the social churning hypothesis from various types of behaviors (trading, writing of text, Google searches), outcomes (volume, mean returns, volatility of returns, the persistence of these variables, and trading profitability) and datasets. These finding are consistent with social interactions directing investor attention to relevant news announcements but also generating persistent disagreement and excessive trading.

The use of granular message-level data in the StockTwits test and household-level data in the trading test allows us to include a broad range of household characteristics and apply firm and household fixed effects. Including these controls and fixed effects assists in accounting for omitted factors and helps us to rule out the possibility that our findings are purely driven by county, firm, or household characteristics that impact firm visibility or information access.

To provide additional evidence about causality, we exploit an exogenous shock to social interactions triggered by Hurricane Sandy. Sandy caused widespread power outages and disruptions to internet access for millions of individuals in the Mid-Atlantic region from October 22, 2012, to November 1, 2012. This resulted in a disturbance of information flow between the affected areas and the rest of the country.

We find that during the Sandy period, the association between network centrality and the responsiveness of returns and trading volume to earnings announcements weakened substantially for firms based in counties with a high connection to the affected region, relative to firms in low-connection counties. This evidence confirms the conclusions of the earlier analyses of a positive relation between centrality and rapid price reaction to firms' release of earnings.

We provide several additional robustness checks. These indicate that the results are not affected by analyst or media coverage of the firm, nor the social proximity of the headquarters county to institutional investor capital (Kuchler et al. 2022). Furthermore, our findings remain robust after excluding firms located in the U.S. tri-state area of New York, New Jersey, and Connecticut, or firms with geographically dispersed subsidiaries. We also use alternative persistence measures and analyze different sample periods, and the conclusions of the analysis remain unchanged.

Overall, these results provide, to the best of our knowledge, the first evidence that social network structure helps explain a rich set of asset price and trading volume dynamics around the arrival of public news. These patterns are not explained by traditional models; the social churning hypothesis provides a plausible explanation.

We are not the first to apply social networks data to study how social interactions affect investment decisions. We make use of the relatively comprehensive Facebook social networks data as well as investing-focused StockTwits data. Many previous studies of social networks have focused on more-specialized sets of participants and their individual decisions.[7] Recent

[7]Evidence that social interactions affect investment decisions is provided in Kelly and O'Grada (2000), Duflo and Saez (2002, 2003), Hong, Kubik, and Stein (2004, 2005), Brown et al. (2008), Cohen, Frazzini, and Malloy (2008), Shive (2010), Kaustia and Knüpfer (2012), Pool, Stoffman, and Yonker (2015), Heimer (2016), Ahern (2017), Crawford, Gray, and Kern (2017), Maturana and Nickerson (2018), Hong and Xu (2019), Ouimet and Tate (2020), and Huang, Hwang, and Lou (2021). One channel through which social interactions can trigger excessive trading is status concerns driven by Keeping-Up-with-the-Joneses preferences (Hong et al. 2014). There is also research on social interactions and managerial decision-making (Shue 2013), the performance of sell-side financial analysts (Cohen, Frazzini, and Malloy 2010), the sale of lottery tickets

studies have used Facebook data to explore how social networks affect firm-level outcomes such as valuation and liquidity (Kuchler et al. 2022) and aggregate outcomes such as international trade (Bailey et al. 2021). Our paper differs from these studies in that we examine the effects of social connectedness on information transmission and return and volume dynamics.

A growing literature explores the role of beliefs in explaining economic outcomes, as reviewed by DellaVigna (2009) and Benjamin (2019). The importance of beliefs is documented by Giglio et al. (2021) using survey evidence from a large panel of wealthy retail investors. Recent studies have also shown that social interactions shape expectations and decisions in the housing market (Bailey et al. 2018a, Bailey et al. 2019) and contribute to disagreement and "echo chambers" (Cookson and Niessner 2020, Cookson, Engelberg, and Mullins 2023). Our paper contributes to this literature by demonstrating that social interactions are associated with persistent disagreement following the release of public news and by providing a unified explanation for the sharply contrasting dynamics of return and volume responses to earnings announcements

Our paper also contributes to the literature on investor attention. Previous studies have analyzed the determinants of attention (Kahneman 1973, Fiske and Taylor 1991, Gabaix and Laibson 2005, Hirshleifer, Lim, and Teoh 2009, DellaVigna and Pollet 2009), the rational allocation of attention (Sims 2003, Peng 2005, Peng and Xiong 2006, Kacperczyk, Nieuwerburgh, and Veldkamp 2014, 2016), and the consequences of limited attention (Klibanoff, Lamont, and Wizman 1998, Hirshleifer and Teoh 2003, Barber et al. 2022). Our findings indicate that attention is socially transmitted and that this affects investor and market responses to earnings announcements.

2 Data and Variables

Our sample consists of all common shares (SHRCD = 10 and 11) traded on the NYSE, AMEX, NASDAQ, and NYSE Arca. We use the SEC Edgar 10-K header file, available in electronic form since May 1996, to obtain the headquarters county location of a firm based on its historical headquarters address. We obtain quarterly earnings and earnings forecast data from Compustat and IBES, stock data from CRSP, and other accounting and

(Mitton, Vorkink, and Wright 2018), and the relative contribution of mass media versus word-of-mouth news transmission in explaining return and volume (Choi et al. 2022). In addition, Cookson et al. (2022) compare social media attention and sentiment from three major platforms to analyze retail trading and returns.

financial statement variables from the merged CRSP-Compustat database. County-level demographics are obtained from the U.S. Census and American Community Survey. The final merged sample consists of 238,195 unique firm-quarter observations from 1996 through 2017.

2.1 Social Network and Centrality Measures

This subsection outlines the method used to construct empirical proxies for social network connections and characteristics.

We measure investor social connectedness between U.S. counties using the Social Connectedness Index (SCI) (see, e.g., Bailey et al. 2018a,b, 2019, 2020a). This measure is based on the number of Facebook friendship links between two counties and was created using anonymized information on the universe of friendship links between U.S.-based Facebook users as of April 2016.

Facebook's scale and the relative representativeness of its user body make the SCI a useful proxy for real-world friendships. There is strong evidence that friendships observed on Facebook reflect long-run historic connections between people.[8] As noted by (Chetty et al., 2022, p. 108), "The Facebook friendship network can therefore be interpreted as providing data on people's real-world friends and acquaintances rather than purely online connections."

We use a weighted adjacency matrix, $S = \{s_{ij}\}_{N\times N}$, to represent the social network of investors, where N is the number of counties and $s_{ij} = \mathrm{SCI}_{ij}$. We then measure the centrality of a firm as the centrality of its headquarters county in the matrix S. We construct three commonly used centrality measures in graph theory: degree centrality (DC), eigenvector centrality (EC), and information centrality (IC). DC is the number of direct neighbors, EC accounts for longer paths and indirect interactions, and IC uses all paths to summarize centrality based on informational distance. We normalize all three measures to a maximum value of 100.[9]

[8] Facebook became available after 2004 and had 243 million active users in the United States and Canada as of 2018. A 2018 survey showed that 68% of U.S. adults use Facebook, that roughly three-quarters of them visit the site daily, and that users span a wide range of demographic groups (except for those 65 and older) (Smith and Anderson 2018). Facebook social connectedness has been shown to be related to migration of people, borders of historic empires, and upward income mobility (Jones et al. 2013, Duggan et al. 2015, Bailey et al. 2018a, 2019, 2020a,b, Chetty et al. 2022).

[9] See Bonacich (1972), Stephenson and Zelen (1989), and Borgatti (2005) for more details. Banerjee et al.

2.2 Other Variables

Earnings Surprises We use a random walk model to calculate standardized unexpected earnings (SUE) (Foster 1977). Specifically, SUE is the decile rank of the standardized unexpected earnings, which is defined as the split-adjusted actual earnings per share minus the same quarter value from one year before, scaled by the standard deviation of this difference over the previous eight quarters.[10]

Returns and Trading Volume CAR[0, 1] and CAR[2, 61] represent the cumulative buy-and-hold returns for the periods [0, 1] and [2, 61], respectively, and are adjusted by size, B/M, and momentum following Daniel et al. (1997) (DGTW).[11] Daily log abnormal volume is defined as the difference between the logarithm of the number of shares traded on a given day and its pre-announcement average during the [–41, –11] window. LNVOL[0, 1] and LNVOL[2, 61] correspond to the average log abnormal volume during the announcement and the post-announcement periods, respectively.[12]

Controls We control for an extensive list of firm and county characteristics to account for factors that have been used in the literature to study price and volume reactions to earnings news. We summarize these variables below and present the detailed definitions in Appendix Table A1.

For firm-level variables, we estimate size (Size) and book-to-market ratio (B/M) following Fama and French (1992). Following Hirshleifer, Lim, and Teoh (2009), we include the following stock and earnings characteristics: earnings persistence (EP), earnings volatility (EVol), idiosyncratic volatility (IVOL), reporting lag (RL), and industry fixed effects. To further control for visibility and familiarity controls, we include a retail indicator (Retail)

(2013, 2019) use *diffusion centrality* to study microfinance program participation and the spread of rumors. It measures how widely information from a node i diffuses over a period T. Diffusion centrality is proportional to DC when $T = 1$ and to EC when $T \to \infty$. We find that using diffusion centrality produces similar results to EC for T from 1 to 60 days.

[10] To ensure the accuracy of announcement dates, we compare the dates in Compustat with those in IBES. When they differ, we take the earlier date following DellaVigna and Pollet (2009), who show that the earlier date is usually the actual announcement date, while the later date is that of the information's publication in the *Wall Street Journal*. Deflating unexpected earnings by quarter-end closing price yields similar results.

[11] The post-announcement window, [2, 61], refers to the period between day two of an announcement to five days before the next announcement.

[12] As trading volume is highly skewed, following Ajinkya and Jain (1989) and Bamber, Barron, and Stober (1997), a logarithmic transformation is used to better approximate normality.

that equals one if a firm operates in the retail sector, and zero otherwise (Chi and Shanthikumar 2017), an S&P 500 constituent indicator (S&P) that equals one if the firm belongs to the S&P 500 index, and zero otherwise (Ivković and Weisbenner 2005), and advertising expenditure (XAD) (Lou 2014). In addition, we include proxies for investor attention distractions, such as the number of same-day announcements (NA) (Hirshleifer, Lim, and Teoh 2009) and time dummies for year, month, and day of the week to account for time variations in investor attention (DellaVigna and Pollet 2009).

At the county level, we define an urban indicator that equals one if the county contains one of the ten largest U.S. cities, and zero otherwise (Loughran 2007). To proxy for the amount of information that local investors have access to, we measure the percentage of the local workforce in the same industry of the firm (SIW). We follow Bailey, Kumar, and Ng (2011) and include average age (AvgAge), retirement ratio (Retire) and educational attainment (Edu). We include median household income (Income) following Mankiw and Zeldes (1991) and Calvet, Campbell, and Sodini (2007). In addition, we include population density (PopDen) and the length of household tenancy (MoveIn).[13]

2.3 Summary Statistics

We present the summary statistics in Table 1. Panel A shows that the three centrality measures have different means and standard deviations and vary in skewness.[14] To make results comparable across different centrality measures, we use the decile ranks of the centrality measures in our empirical analysis.

Panel B reports the correlation coefficients between the decile rank of the centrality measures and all other variables. The centrality rank measures are highly correlated amongst each other, with correlations ranging from 0.885 to 0.971, but their correlations with firm characteristics are relatively small. The centrality measures are positively correlated with population density and negatively correlated with average age, the percentage of the retired population, and average length of tenancy, which collectively suggests that central counties are usually densely populated with young and mobile residents. We control for all these

[13]We obtain data on local demographics and socioeconomic status from the following sources: the 2000 and 2010 Censuses, the Census Decennial estimate, Census SAIP, and the American Community Survey for the years of 2009–2016. Missing years are interpolated.

[14]EC is more positively skewed than DC because EC assigns extra importance to a node if it is connected to the nodes that are themselves important.

variables in our subsequent analysis.

[Insert Table 1 here]

Figure 1 shows a heat map of the eigenvector centrality across U.S. counties as of June 2016. Darker colors correspond to higher centrality. The counties that have the highest centrality are counties in California (Los Angeles, Orange, San Bernadino, San Diego, Riverside), Illinois (Cook), Arizona (Maricopa), New York (New York), Nevada (Clark), and Texas (Harris), consistent with the correlation between centrality and county characteristics shown earlier. More importantly, the plot shows large cross-sectional variations in centrality and that even adjacent counties can have very different centralities. Such variation will help us distinguish between the effects of physical proximity and social proximity.

[Insert Figure 1 here]

3 Centrality and Price Dynamics

We start by investigating the relationship between investor social network centrality and stock market reactions to earnings news. As mentioned earlier, previous research documents short-run price underreaction to earnings announcements, followed by post-announcement return drift that is most pronounced for about three months. We therefore examine whether the social transmission of information is associated with greater diffusion of earnings news.

If information emanating from central counties quickly spreads to the rest of the network, thus bringing earnings news to the attention of more investors, then we expect more timely incorporation of earnings news. This implies that firms located in central counties should experience stronger immediate price reactions to earnings news, weaker post-announcement drift, and less-persistent volatility.

3.1 Announcement Returns and Post-Announcement Drift

We use the following panel regression specification to test the relationship between the social network centrality of a firm and its return responsiveness to earnings announcements:

$$\mathrm{CAR}_{it} = \alpha + \beta_1 \mathrm{SUE}_{it} + \beta_2(\mathrm{SUE}_{it} \cdot \mathrm{CEN}_i) + \beta_3 \mathrm{CEN}_i + \gamma X_{it} + \epsilon_{it}. \quad (1)$$

Here the dependent variable, CAR, is either the abnormal two-day earnings announcement return, CAR[0, 1], or the post-announcement cumulative abnormal return, CAR[2, 61]. SUE is the earnings surprise decile rank; CEN is the decile rank of one of the county-level centrality measures. The control vector X consists of the extensive list of lagged firm- and county-level control variables described in Section 2.2 and their interactions with SUE.[15] The key coefficient of interest is β_2, which captures the relationship between a firm's headquarters centrality and return responsiveness to its earnings announcements.

[Insert Table 2 here]

Table 2 presents the results, with Panels A and B corresponding to CAR[0, 1] and CAR[2, 61], respectively. Table 2, Panel A, column (1) presents the baseline specification for DC. The coefficient on SUE is positive and significant, consistent with the previous literature that stock prices tend to react positively to positive earnings surprises and vice versa.

Turning to the variable of interest, SUE·CEN, the coefficient β_2 is 0.00737, which is statistically significant at the 1% level. For column (2), we introduce firm- and county-level controls. The β_2 coefficient remains similar at 0.00673. Economically, compared to announcements made by firms located in centrality decile 1 (lowest) counties, announcements from firms located in decile 10 (highest) counties have a 0.061 ($= 0.00673 \times 9$) higher earnings announcement response coefficient, or 13% of the sample mean of 0.46 ($= 0.423 + 0.00673 \times 5.5$).

Column (3) further controls for all the interaction terms of the form Control·SUE. The β_2 coefficient remains positive, at 0.0152, and is even more strongly significant. In terms of economic magnitude, an increase of degree centrality from the lowest to the highest decile is associated with a sensitivity increase of 0.137 ($= 0.0152 \times 9$), or 28.6% of the sample average marginal effect of 0.479.[16]

The results are similar for the other two centrality measures, presented in columns (4)–(9): the coefficients of SUE·CEN are 0.0149 and 0.0172, respectively, with all controls and

[15] As noted in Collins and Kothari (1989), firm characteristics and the information environment affect the sensitivity of the return response to earnings news. The inclusion of interactive variables controls for such effects.

[16] To assess the mean return sensitivity to SUE in the full specification, we follow Williams (2012) and include all interaction terms of SUE, including SUE·CEN and SUE·controls. Regarding the relation of CEN and returns, CEN's net marginal effect is determined jointly by the coefficients of CEN and SUE·CEN. For example, based on the coefficient estimates in column (3), the effect of CEN on CAR[0, 1] for an average earnings announcement (i.e., SUE = 5.5) is $5.5 \cdot 0.0152 - 0.0909 = -0.0073$ and insignificant.

interactive controls included. Economically, announcements made by firms located in counties with decile 10 centrality have earnings response sensitivities that are 28.0% and 32.3% higher relative to the sample average.

Turning to post-earnings announcement drift, Table 2, Panel B shows that the β_2 coefficients are negative for all three centrality measures and statistically significant for EC. The results suggest that announcements by firms headquartered in high-centrality counties experience substantially less post-announcement drift. Based on the full model, a similar calculation on the economic magnitudes reveals that the post-announcement drift for firms located in counties with the highest centrality is lower than that of firms in the lowest centrality counties by 15.6% to 29.0% relative to the sample mean.

A comparison of the estimated coefficients across the three specifications indicates that the explanatory power of SUE·CEN is unlikely to be driven by CEN's correlation with controlled firm and county characteristics. To formally assess the robustness of our findings to omitted variable bias, we adopt the approach suggested by Altonji, Elder, and Taber (2005) and Oster (2019). The estimates for δ, the parameter of proportional selection, range from -0.40 to -0.35 (with R_{max} set to 1.3R as recommended). This suggests that the presence of omitted variables biases against our observed relationship (Satyanath, Voigtländer, and Voth 2017).[17]

In sum, we find that earnings announcements from more centrally located firms are associated with stronger immediate price reactions and weaker post-announcement drifts. This evidence suggests that social network centrality facilitates the dissemination of relevant information and improves the informational efficiency of asset prices.

3.2 Volatility Persistence

We next turn to the relationship between a firm's headquarters centrality and the dynamics of return volatility following the firm's earnings announcements. We have seen that earnings announcements from firms that are more centrally located generate stronger immediate price reactions and weaker post-announcement drift, potentially consistent with the faster resolution of uncertainty. We therefore expect to see faster decay in the volatility reactions to earnings surprises in the post-announcement period. Consequently, we analyze the relationship between the social network centrality of the announcing firm and the volatility

[17] Attenuation bias also explains why, as we control for more variables and interactive effects in Table 2, the coefficient on SUE·CEN actually becomes stronger.

persistence of its stock returns.

Following Bollerslev and Jubinski (1999), we estimate the volatility persistence parameter, $d_{|R|}$, by applying the autoregressive fractionally integrated moving average (ARFIMA) model to $|R|$, which is the daily absolute returns from the day of the announcement to five days before the next announcement. The estimated fractional integration parameter, d, when bounded between zero and one, captures the long memory of a process, with a higher value corresponding to a more persistent effect of shocks. For our sample, the $d_{|R|}$ estimate has a mean of 0.05 and a standard deviation of 0.14.

We regress $d_{|R|}$ on the centrality measure and other variables:

$$d_{|R|_{it}} = \alpha + \beta_1 \mathrm{CEN}_i + \beta_2 |\mathrm{SUE}|_{it} + \gamma X_{it} + \epsilon_{it}, \tag{2}$$

where |SUE| is the decile rank of absolute SUE to control for the magnitude of earnings surprises, and X is the list of lagged control variables described in Section 2.2. Since $d_{|R|}$ is scale-free, there is no compelling reason to believe that the size of |SUE| affects the CEN–persistence relation. Hence we do not include |SUE|· CEN in the regression.

Table 3 presents the results. Centrality is significantly and negatively associated with volatility persistence: the coefficients of CEN in columns (2), (4), and (6) (multiplied by 100) range from −0.072 to −0.059 across all three centrality measures. In terms of economic magnitudes, the volatility persistence for earnings announcements by the most centrally located firms (decile 10) is lower than that of firms from the least central locations (decile 1), by 0.005 to 0.006, or 11% to 13% of the sample mean. This shows that the effect of an earnings news shock on volatility is shorter-lived for firms in more-central locations.

[Insert Table 3]

Along with the results that announcements from high-centrality firms trigger stronger immediate price reactions and weaker post-earnings announcement drift, the volatility-based results provide support for our hypothesis that social interactions facilitate the dissemination of earnings information and improve the information efficiency of asset prices.

4 Centrality and Volume Dynamics

We next examine the trading behavior of investors following firms' earnings announcements. Theoretical models predict that the arrival of news triggers trading (see, e.g., Kim and

Verrecchia 1991, Harris and Raviv 1993, and Kandel and Pearson 1995). To the extent that news from more-centrally located firms reaches investors more rapidly, we expect such firms to have stronger immediate volume responses. If such news also helps investors more rapidly resolve their opinion differences, we also expect volume dynamics to be less persistent and the level of volume for the [2, 61] window to be lower for such firms. On the other hand, if social interactions generate persistent opinion differences regarding the news, it could instead result in persistent excess trading. To investigate the relationship between centrality and the sensitivity of trading volume at different dates to earnings news, we analyze three characteristics of volume dynamics: immediate volume responses, post-announcement volume responses, and the persistence of volume responses.

4.1 Immediate and Post-Announcement Volume Responses

The abnormal volume measures tend to be highly skewed. We therefore apply a log transformation following Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009). We first examine immediate volume reactions to earnings news by estimating the following regression:

$$\text{LNVOL}_{it} = \alpha + \beta_1 \text{CEN}_i + \beta_2 |\text{SUE}|_{it} + \gamma X_{it} + \epsilon_{it}, \tag{3}$$

where the dependent variables, LNVOL[0, 1] and LNVOL[2, 61], are the average abnormal log volume during the [0, 1]] and the [2, 61] period, respectively. |SUE| is the absolute earnings surprise decile rank, CEN is the county-level centrality measure, and X consists of all lagged control variables mentioned in Section 2.2. Given the log-linear specification, the variable of interest here is β_1, the coefficient on CEN.

[Insert Table 4 here]

Table 4, columns (1)–(3) presents the [0, 1] volume reactions immediately after the earnings announcement. These indicate that earnings news from the more centrally located firms triggers stronger immediate volume increases than news from the less central firms. The coefficients of CEN (multiplied by 100) are positive and significant across all centrality measures. In terms of economic magnitudes, a change in the centrality from the lowest to the highest decile increases the LNVOL[0, 1] by 0.076 to 0.091, an increases of 11.90% to 14.31% relative to its sample mean.

Evidence about the [2, 61]] volume dynamics are presented in Table 4, columns (4)–(6). The coefficients of CEN are positive and significant across all three centrality measures. Economically, a change in centrality from the lowest to the highest decile increases LNVOL[2, 61] by 14.68% to 30.79% relative to the sample average.[18]

This finding is in sharp contrast to the *negative* relationship between centrality and post-announcement returns that we document earlier. This contrast suggests that the effect of discussions of news on investor belief heterogeneity differs from their effects on prices. To provide further insight into volume dynamics in the longer run, we next examine post-announcement volume persistence.

4.2 Volume Persistence

We measure volume persistence with the persistence parameter, d_{VOL}, by applying an ARFIMA model to the daily abnormal log volume series for the time window of [0, 61]. The estimated d_{VOL} has a sample mean of 0.27, which is significantly higher than the mean of 0.05 for daily return volatility $d_{|R|}$. This suggests that post-announcement volume is substantially more persistent.

We then analyze the relationship between centrality and volume persistence using Equation (2) and replacing $d_{|\text{R}|}$ with d_{VOL}. Table 4, columns (7)–(9) present the results. The coefficients of CEN are positive and highly significant across all three centrality measures. Economically, an increase in centrality from decile 1 to decile 10 is associated with a 10.3% to 12.3% increase in volume persistence relative to the sample mean. This shows that announcements made by firms in high-centrality counties generate a volume response that is substantially more persistent than those from low-centrality counties.

The results provide a sharp contrast to the negative association between centrality and volatility persistence. This suggests that social interactions may contribute to excessive and persistent trading. The effects we identify suggest that social networks influence investor beliefs and trading in a more subtle way than is implied by the aforementioned models.

[18] As in our earlier tests and as suggested by Oster (2019), our analysis indicates that omitted variables are unlikely to drive our findings. In the LNVOL[0, 1] regression, the δ estimate ranges from 6.7 to 13.3, far exceeding the recommended threshold of 1. Similarly, in the LNVOL[2, 61] regression, the estimated δ ranges from -1.35 to -0.33, indicating that the omitted variables actually bias against observing the relationship that we find.

5 A Framework for Information Diffusion via Social Interactions

The striking contrast between the dynamics of the reactions of prices versus trading volumes to earnings news presents a puzzle. In the next subsection we offer a possible explanation. We then perform tests of further implications of our hypothesis. We present the hypothesis intuitively; as mentioned in the introduction, a formal model is provided in the Internet Appendix. The Internet Appendix also present stylized models that indicate that our findings pose challenges for several traditional frameworks.

5.1 The Social Churning Hypothesis

Consider a setting in which there is a social network of investors who are connected both within and across geographical locations. At the initial date, earnings news is first received by investors residing in the county of the firm's headquarters. These investors then spread the news to their network neighbors, both within and across counties, via word-of-mouth communication.

In each period, newly informed investors transmit the news to their network neighbors. As a result, the news diffuses socially, with higher-centrality counties experiencing faster transmission rates. In this setting, for a high-centrality area, the number of investors who are aware of the news at first grows more rapidly than for a low-centrality area. However, for a high centrality area the number of unaware investors declines more quickly, so the rate of growth in the number of aware investors falls more precipitously than for a low-centrality area.

When investors talk, they do not just convey the earnings surprise; they convey their opinions and interpretations. Such discussion after the arrival of earnings news further triggers changes in investor beliefs and disagreement about asset valuation, and hence trading. Investors beliefs fluctuate continually as a result of social interactions. As discussion continues, there is continuing fluctuation in investor beliefs and disagreement for a substantial period of time.[19] These belief fluctuations produce trading volume. However, the fluctua-

[19]This is motivated by theories in which word-of-mouth communication in social interactions can spread rumors, incorrect beliefs, or naïve trading strategies (Shiller 2000, Han, Hirshleifer, and Walden 2021, Hirshleifer 2020). Even for rational individuals, Jackson, Malladi, and McAdams (2021) demonstrate that message relaying can introduce “mutations" and increase transmission failures that become more pronounced as com-

tions are mostly idiosyncratic, limiting their contribution to price movements, and therefore to the persistence of return variance.

Based on this account, we propose the social churning hypothesis as a unified explanation for the observed relationship between social network centrality and the dynamics of prices and trading volume after earnings announcements. This hypothesis predicts that greater intensity of social interactions accelerate the transmission of earnings news and the processing of that news by investors, leading to faster incorporation of the news into asset prices. This results in initially high return volatility but low persistence. In contrast, the hypothesis further predicts that following the announcement, greater social interactions among investors results in continuing investor attention and churning of beliefs and shifts in disagreement. This results in high and persistent trading volumes for a substantial length of time.

In the subsections that follow, we test the key implications of the social churning hypothesis using granular data based on StockTwits messages by individual users and household account-level trading records, and Google search activities at the stock level.

5.2 Evidence from StockTwits

The first two key implications of the social churning hypothesis are: 1) high-centrality earnings news attracts greater investor attention; and 2) more-intense discussions of earnings news generates more divergent asset valuations among investors.

We test these implications with a dataset of 10.9 million of messages on StockTwits, a popular social media platform for investors to share opinions and ideas. On the platform, users can directly mention a security in the message through "cashtags" by placing a dollar sign before its ticker (e.g., \$APPL for Apple). As shown by Cookson, Engelberg, and Mullins (2023), StockTwits users include a wide range of market participants, ranging in experience from novice, intermediate, to professional, with nearly 20% self-identified as professionals who work in finance or hold financial certifications such as a CFA. The dispersion of opinions expressed on StockTwits has been shown to be positively related to market-level trading volume (Cookson and Niessner 2020).

Our sample consists of messages posted by 79,176 unique users from 2009 to 2013, covering 9,131 distinct symbols. In the subsequent tests, we analyze the messaging activities and the divergence of beliefs as reflected in the messages following an earnings announce-

munication chains grow longer.

ment. We also examine the role of StockTwits influencers in information dissemination. The StockTwits data enable us to construct an alternative, time-varying measure of social network centrality and to include firm fixed effects. These additional findings serve as a validation check that complements our earlier analysis using Facebook's SCI measures.

Messaging Activities For each stock and for a given day, we define New Messages as the number of initial message mentions of a stock in a thread; we define Replies as the the number of replies to the initial messages.[20] New Messages therefore serves as a proxy for the number of newly informed investors, whereas Replies captures the intensity of subsequent discussions on StockTwits.

We define daily log abnormal new messages as the difference between the logarithmic of New Messages and its pre-announcement $[-41, -11]$ mean. We denote the averages of daily log abnormal new messages for the [0, 1] and [2, 61] windows as ANM[0, 1] and ANM[2, 61], respectively. Similarly, we calculate the averages of daily abnormal replies for the corresponding windows in the same manner and denote them as ARM[0, 1] and ARM[2, 61]. Matching the messages to stocks, our final sample consists of 35,940 unique firm-announcement observations.

We first find that earnings news generates a significant increase in daily New Messages and Replies about a stock, as evidenced by the higher mean values for ANM[0, 1] and ARM[0, 1] at 0.38 and 0.30, respectively. Following announcements, the number of New Messages drops back to pre-announcement levels, with ANM[2, 61] almost reaching zero, but Replies remains high, with ARM[2, 61] remaining at 0.39. These divergent trends in New Messages and Replies surrounding earnings announcements offer initial indications that investor discussions of news continue long after the initial news arrives.

[Insert Table 5 here]

We then formally examine the relation between the centrality of the announcing firm and StockTwits messaging activities. We estimate Equation (3), replacing the dependent variable

[20] For a given stock, we classify a message as an initial message if it satisfies all of the following three conditions: 1) it contains the stock's ticker symbol, 2) it does not mention another user, and 3) it is not labeled as a reply by the StockTwits platform (labels became available in our sample starting in 2013). A message is defined as a reply if it satisfies at least one of the following conditions: 1) it mentions another user who posted a message about the stock, or 2) it is labeled as a reply to an earlier message about the stock by the StockTwits platform (available starting in 2013).

with ANM or ARM. Table 5, Panel A reports the results for Abnormal New messages and columns (1)–(3) correspond to the announcement window of [0, 1]. The coefficient for CEN (multiplied by 100) is positive and significant, indicating that high-centrality announcements trigger a more pronounced increase in Abnormal New Messages immediately following the announcement. For Abnormal Replies, Panel B indicates that higher centrality is also associated with a greater number of replies on StockTwits, suggesting more discussions of the stock upon announcement.

We illustrate the economic magnitudes using the eigenvector centrality measure (EC). The coefficient of 0.42 for CEN in Panel A, column (2) indicates that news from the highest centrality decile triggers 0.0378 (=0.0042×9) more ANM during the [0, 1] window, a 9.95% increase from the sample mean of 0.38. Similarly, the coefficient of 1.16 for CEN in Panel B, column (2) indicates that news from the highest centrality decile triggers 0.1044 (=0.0116×9) more ARM[0, 1], a 34.8% increase from the sample mean of 0.30.

For the [2, 61] window, Panel A of Table 5, columns (4)–(6), show a negative and significant association between centrality and Abnormal New Messages, indicating a rapid reduction in new message activities. In sharp contrast, the CEN coefficient of 1.51 for Panel B, column (2) indicates that the same increase in CEN increases ARM by 34.85% (=0.0151×9/0.39). This suggests that high-centrality announcements attract more discussion of the news and that these discussions are, on average, substantially more persistent than the new mentions. The evidence is consistent with the first key implication of the social churning hypothesis.

Disagreement The next key implication of the hypothesis is that social interactions drive persistent disagreement. To test this, we measure the sentiment of each message on StockTwits and construct a daily stock-level measure of sentiment dispersion.[21] To do this, we use a convolutional neural network for textual classification, as described by Kim (2014), with Tensorflow to calculate the probability (in %) that each message conveyed positive sentiment.[22] We then determine a daily measure of opinion differences for each stock, calculated

[21]We do not use the self-reported sentiment by StockTwits users because the variable is only available for 10% of the messages in our sample.

[22]The Convolutional Neural Network (CNN) is a widely used model for sentiment analysis in artificial neural networks and has been shown to outperform 14 alternative models in sentiment classification (Kim 2014). To implement the model, we first use self-labeled bullish/bearish indicators as the training sample to train a CNN model. Next, we validate the model for out-of-sample accuracy using a ten-fold cross-validation method. We then use the trained model to classify all tweets. The package required to implement Kim's

as the standard deviation of the probability of positive sentiment across all messages related to that stock.

We obtain DO[0, 1] and DO[2, 61], the average opinion differences over the announcement and post-announcement windows, respectively. The sample averages of the two variables are 20% and 19%, suggesting that disagreements do not dissipate over time. The standard deviations of DO[0, 1] and DO[2, 61] are 9% and 5%, respectively.

We then run regression tests as in Equation (3), replacing the dependent variable with either DO[0, 1] or DO[2, 61]. Table 6, Panel A presents the results. Columns (1)–(3) show that the coefficients of CEN are positive and significant for all three centrality measures. This indicates that earnings announcements by high-centrality stocks are associated with greater disagreements among investors. Furthermore, these greater disagreements do not dissipate over time in the post-announcement window, as shown by the significant coefficient on CEN in columns (4)–(6).

In terms of economic magnitudes (based on eigenvector centrality), columns (2) and (5) show that the announcements from the highest centrality stocks exhibit substantially more investor disagreement than those from the lowest centrality locations, by 0.94 (= 0.104×9) for the announcement window and 1.09 (= 0.121×9) for the post-announcement period, respectively. These magnitudes correspond to 4.7% and 5.7% of the sample means and 10.4% and 21.8% of the sample standard deviations. Moreover, columns (7)–(10) show that d_{DO}, the persistence of disagreement estimated with the ARFIMA model discussed earlier, also increases significantly with centrality.

To gain additional insights into whether disagreements among StockTwits users are attributable to within-group or across-group differences, we examine Replies for the [2, 61] window and decompose the daily variances in sentiments into two components: a within-thread DO, which represents the average standard deviation of sentiments for messages in a given thread, and an across-thread DO, which corresponds to the standard deviation of average sentiments across threads. Across-thread DO is associated with disagreements that accompany with the wider dissemination of news, while within-thread DO reflects disagreements arising from discussions initiated by the same initial post in the thread.

We run regression tests as in Equation (3), replacing the dependent variable with the decomposed DO measures and report the results in Table 6, Panels B and C, respectively. The coefficients of CEN are positive and significant for both the level (DO[2, 61]) and the

model is available at https://github.com/dennybritz/cnn-text-classification-tf.

persistence of the disagreement (d_{DO}) for both panels and across all centrality measures. The results indicate that high-centrality news triggers greater disagreement and more-persistent disagreement both within-threads and across-threads. The findings suggest that both the dissemination of news and the more discussions of news via social interactions contribute to disagreement about stock valuations. Together, the positive effects of centrality on the level and persistence of investor disagreement provide direct support to the second key implication of the social churning hypothesis.

[Insert Table 6 here]

Influencers Lastly, we examine the role of StockTwits influencers on information dissemination. The social churning hypothesis implies that earnings news spreads faster and generates more and more long-lasting discussion if the news is initially mentioned by influencers. The hypothesis also predicts that such news would also trigger greater and more-persistent disagreement among StockTwits users.

To test these implications, we measure the influence of a user by the user's degree centrality, ω_i, which is defined as the logarithm of the number of followers the user has on StockTwits.[23] To measure the extent to which the announcement has attracted the messaging activities of influencers, we denote INFL[0, 1] as the average sender centrality of new messages posted during the [0, 1] window. Specifically, INFL[0, 1] is the ratio of the sum of the ω_i weighted number of new messages across all users over the total number of new messages.

If an earnings announcement attracts greater messaging activities by influencers during the [0, 1] window, we expect such an announcement to trigger a greater number of follow-up messaging activities, which we measure with ARM[2, 61], the abnormal replies during the post-announcement period as we defined earlier. We then test the prediction by estimating the following panel regression:

$$\mathrm{ARM}[2,\, 61]_{it} = \beta_1 \mathrm{INFL}[0,\, 1]_{it} + \beta_2 \mathrm{ANM}[0,\, 1]_{it} + \beta_3 |\mathrm{SUE}|_{it} + \gamma X_{it} + \epsilon_{it}, \tag{4}$$

where ANM[0, 1] is the average daily abnormal new messages immediately after an earnings announcement as defined before, |SUE| is the decile rank of absolute SUE, and X is the full

[23] We use a logarithmic transformation because the distribution of the number of followers is highly skewed. We obtain similar results if we use the alternative definition for ω_i as the raw number of followers a user has.

list of laggged firm and announcement characteristics and the characteristics of the firm's headquarters county as listed in Section 2.2. We also include firm fixed effects and hence are able to control for any omitted variables that are associated with the firm or the firm's location that can potentially contribute to the different messaging activities.

Table 7, column (1) presents the result. The coefficient of INFL[0, 1] is 0.019 and highly significant, indicating that a one standard deviation increase in INFL increases Replies by 4.4% relative to pre-announcement. The finding suggests that, all else being equal, earnings announcements that are discussed by StockTwits influencers generate more subsequent discussions on the platform.

[Insert Table 7 here]

The next implication of the social churning hypothesis is that more discussions among StockTwits users drive greater churning of beliefs and disagreement. Therefore, we expect that the initial mentioning of the stock by influencers triggers greater subsequent disagreement. We test this implication using the same regression as in Equation (4), replacing the dependent variable with DO[2, 61]. Table 7, column (2) presents the results, showing that the coefficient of INFL is 0.105 and highly significant. The result highlights the importance of influencers' activities during the earlier periods of discussion in triggering subsequent-period disagreements.

We next consider whether message activities by StockTwits users are associated with return and trading dynamics. The social churning hypothesis predicts that news that attracts the attention of influencers disseminates faster, resulting in faster volatility decay, but also generates more persistent trading volume. Table 7, columns (3) and (4), confirm this prediction using the same regression as in (4), with $d_{|R|}$ and d_{VOL} as dependent variables. The INFL coefficient is negative for the volatility persistence regression and positive for the volume persistence regression; both coefficients are statistically significant.

The evidence in this subsection provides support for the key implications of the social churning hypothesis about how investor social networks affect the transmission of earnings news and investor beliefs. Consistent with the hypothesis, we find that news transmitted by high-centrality users on the social network triggers more discussions and greater disagreement. A caveat to a causal interpretation is that the number of messages by influencers to an announcement may be endogenous.

5.3 Evidence from Google Searches

An advantage of the StockTwits analysis is that it offers detailed insights into investor conversations and opinion changes following earnings announcements. However, an open question is whether StockTwits investors are representative of the broader investor population. To address this, we examine investor attention dynamics using Google's daily search volume index (SVI) for individual stocks, which is a commonly used measure of retail investor attention. Previous research has established a strong correlation between SVI and stock returns and trading volume, (see, e.g., Da, Engelberg, and Gao 2011, 2014).

A key implication of the social churning hypothesis is that announcements made by firms from high-centrality areas are subject to continued intense discussions and therefore attract more-persistent investor attention. We define $\mathrm{ASV}[0,1]$ and $\mathrm{ASV}[2,61]$ as the log abnormal SVI during the [0, 1] and [2, 61] window, respectively, relative to the $[-41,-11]]$ pre-announcement window. Similar to before, we estimate the persistence parameter, d_{ASV}, with the ARFIMA model using daily ASV observations for the period [0, 61]. The SVI is available from 2004 onward.

We then estimate Equation (3), replacing the dependent variables with ASV-based measures. Table 8 presents the results for ASV in columns (1)–(3) and (4)–(6) for the [0, 1] and [2, 61] windows, respectively. In columns (7)–(9), we examine attention persistence. Across all columns, we find a positive and significant coefficient on CEN for all centrality measures, except for columns (4) and (6). This indicates that high-centrality news is associated with high and persistent levels of Google search volume. Columns (7)–(9) suggest that an increase in centrality from the lowest decile to the highest decile is associated with an increase in attention persistence of 19.1% to 23.7% relative to the sample mean. These magnitudes are also in line with the corresponding change in the persistence of trading volume, consistent with our hypothesis that persistent attention drives persistent trading volume.

[Insert Table 8 here]

These results complement the StockTwits-based findings and provide further support for our hypothesis that news from high-centrality locations triggers higher and more-persistent investor attention and more-intense discussions, and corresponds to greater and more-persistent opinion divergence among investors. Moreover, the results also provide external validation to the StockTwits–based analysis, confirming that the messaging activities on StockTwits are sensible proxies of the attention of market participants.

5.4 Evidence from Individual Investor Trading Data

Having established that firms located in high-centrality areas generate sustained attention and investor disagreement with their earnings announcements, we now examine the relations between centrality and investors' trading decisions and performance.

Trading Decisions We use individual account-level data from a large U.S. discount brokerage (Barber and Odean 2000). We conduct our analysis at the announcement–household level. For each earnings announcement, we examine the trading activities of households that have either held or traded the stock in the last 12 months. Our final sample consists of 3.9 million household-stock-announcement observations over the period of 1992–1996.[24] The sample encompasses 99,935 announcements made by 6,323 unique firms, with 40,835 unique households that contributed to a total number of 408,950 trades following the earnings announcements.

We define the relative social connectedness between the locations of firm i and household j, RSCI_{ij}, as the logarithm of the ratio of the total number of Facebook friendship ties between the two locations to the population of j's county. Thus, RSCI_{ij} measures the relative importance of i's county on the social network of household j's county, which proxies for the peer effect of investors in i's county on j.[25] To distinguish our findings from the well-documented local bias effect, we exclude observations for which the households reside in the same county as the headquarters of the announcing firm.

As discussed earlier, earnings news is likely to reach local investors first and then disseminate across the network of investors via discussions. Hence, the higher the RSCI_{ij}, the more likely household j, as well as j's same-county neighbors, receives earnings news and engages in discussions about these firms with its neighbours and social network peers. The social churning hypothesis therefore predicts that such discussions lead to persistent fluctuations in disagreement and excessive trading.As a result, household j engages in more trading and more-sustained trading of these stocks.

To investigate households' trading behavior following earnings announcements, we modify Equation (3) by replacing the centrality measure with RSCI and the dependent variable with

[24] We restrict our analysis to these households who are likely to be attentive to the stock. A full sample that includes all household-stock-announcement combinations would result in 7.8 billion observations and becomes computationally infeasible. We are grateful to Brad Barber and Terry Odean for kindly sharing their data.

[25] We take the logarithm transformation of RSCI for our subsequent analysis because it has a large skewness.

measures of household trading activity. We estimate the following regression model:

$$\text{Trade}_{ijt} = \alpha + \beta_1 \text{RSCI}_{ij} + \beta_2 |\text{SUE}| + \gamma X_{it} + \eta Z_{jt} + \epsilon_{ijt}, \tag{5}$$

where Trade_{ijt} denotes the trading activity for a given window, measured three ways: 1) an indicator variable that takes a value of one if a trade occurs, and zero otherwise, 2) the number of trades, or 3) relative trade size, which is the dollar amount traded scaled by the household's beginning-of-the-month stock portfolio balance.

As in our previous analysis, we consider the windows [0, 1] and [2, 61]. The vector X_{it} consists of firm-level controls, including the firm fixed effect and indicator variables for year, quarter, and day of the week. The vector Z_{jt} contains household fixed effects and other household characteristics.[26] The inclusion of these controls and fixed effects substantially reduces the likelihood that omitted factors may confound our findings.

[Insert Table 9 here]

Table 9, Panel A presents the results, with two-way clustered standard errors by firm and household. The coefficients on RSCI are positive and significant for all three measures of trading. Columns (1)–(2) indicate that households residing in locations that share strong social ties with the headquarters location of the announcing firm are more likely to trade both during the announcement period and during the three-month post-announcement period.[27] Economically, an increase in RSCI from the 10$^{\text{th}}$ percentile to the 90$^{\text{th}}$ percentile increases a household's trading likelihood by 8.4% and 9.4% for windows [0, 1] and [2, 61], respectively, relative to the corresponding sample average of 0.78% and 7.5%.

Columns (3)–(4) focus on the number of trades by households and reveal that the high-RSCI households not only make more trades immediately after the announcement but they also trade more post announcement.[28] In economic terms, an increase in RSCI from the 10$^{\text{th}}$ percentile to the 90$^{\text{th}}$ percentile increases the number of trades by 9.4% and 14.5% for the [0, 1] and [2, 61], respectively, relative to the corresponding sample means of 0.0083 and 0.096.

[26]These characteristics include income, gender of the head of the household, marital status, number of stocks in the household's portfolio before the announcement, the number of trades in the last 12 months, and average monthly portfolio turnover of the household in the last 12 months.

[27]We obtain quantitatively similar results with logistic regression; however, we are unable to estimate the model with multiple fixed effects due to computational limitations.

[28]We also estimate these two models with a Poisson regression and obtain quantitatively similar results. However, to aid interpretation of the slope coefficients, we present the linear regression models.

With regard to relative trade size, columns (5)–(6) indicate that a similar change in RSCI increases the relative trade size by 18.1% and 27.6% for the two windows.

Overall, these results provide evidence consistent with the social churning hypothesis that earnings announcements trigger more sustained trading from households that reside in locations sharing stronger social ties with the headquarters of the announcing firm.

Household Performance We next investigate how the greater trading of high-RSCI households affects trading profits. Following Barber and Odean (2000), we compute Profit^{gross}, which is the gross profit of each trade following earnings announcements, before considering any transaction costs. Specifically, we define Profit^{gross} as $n_t P_t^{cl} \text{CAR}[t, 61]$, where n_t is the number of shares traded (positive for purchase and negative to sale), P_t^{cl} is the closing price on the day of the trade, and CAR$[t, 61]$ is the DGTW-adjusted cumulative abnormal return between days t and 61, based on the closing prices.[29] A positive Profit^{gross} refers to gains from the trade and a negative value implies losses.

Our measure of the cost of trade, Cost$_t$, includes the commission paid for the trade and the spread, $n_t P_t R_t^{cl}$, where P_t is the actual transaction price and R_t^{cl} is the intraday return between P_t and the same-day closing price.[30] We then define the net profit, Profit^{net}, as Profit^{gross} minus Cost. For each announcement and for a given household, we then aggregate the Profit and Cost measures seperately for the [0, 1] and the [2, 61] windows, respectively. To account for differences in wealth across across households, we scale a household's Profit and Cost measures by the market value of the household's portfolios at the beginning of the month prior to the earnings announcement.

We estimate the same regression as in Equation (5) with the scaled ($\times 10^4$) Profit and Cost measures for each household-announcement observations as the dependent variables. The results are reported in Table 9, Panel B. Columns (1) and (2) analyze the net and gross Profits for trades placed during the [0, 1] window. The coefficients of RSCI are negative but

[29] We use the closing price on day 61 as the liquidation price to focus on the profitability of trading in the 61-day period following an earnings announcement. Most households hold a stock for a considerable period. According to Barber and Odean (2000), the mean household portfolio turnover is 6.49%, which implies holding periods of 15.4 months. As such, considering the full holding period beyond the 61-day period is likely to introduce noise that is not related to the given earnings announcement. We obtain similar results with raw cumulative returns.

[30] We note that our definition of Cost does not incorporate the costs associated with liquidations beyond the 61-day period, and hence, it is a conservative estimate of the potential round-trip costs associated with excessive trading.

insignificant, suggesting that the tradings by the high-RSCI households immediately after the announcement do not generate significant Profit. Additionally, column (3) corresponds to Cost, and the positive coefficient of RSCI indicates that the high-RSCI households are subject to significantly higher transaction costs.

For the performances of households during [2, 61] window, column (4) presents the results for Profit^{net}. High-RSCI households incur significantly more losses for trades placed during this window relative to other households. The coefficient of -0.151 indicates that an increase in RSCI from the 10$^{\text{th}}$ percentile to the 90$^{\text{th}}$ increases the trading loss by 16.6% relative to the household-announcement sample average.[31]

The remaining columns identify the sources of trading losses for the high-RSCI households. In column (5), for Profit^{gross}, the coefficient of RSCI is insignificant, indicating that the high-RSCI households do not underperform before transaction costs. In contrast, in column (6), for the total transaction costs these household pay, the coefficient is positive and highly significant. This result indicates that the trading costs are the primary contributor to the household's losses during this sample period.[32]

The evidence is consistent with the social churning hypothesis, which maintains that greater trading by better-connected households derives in part from incorrect beliefs that are triggered by social interactions. Together, our empirical analyses of StockTwits messages, Google searches, and household trading activities provide support from several angles for the social churning hypothesis. That is, social interactions direct investor attention to relevant news, but also promote churning of beliefs, persistent disagreement, and excessive trading. Finally, the inclusion of fixed effects in our analysis, both for the StockTwits and Google tests, as well as using both firm and household fixed effects for the household-level tests, suggest that our findings do not derive from county, firm, or investor characteristics.

[31]For an average household in our sample, with a total investment portfolio of $47,334 and for a given announcement, the household trades an average of $1,060 worth of the stocks during the post-announcement period and incurs an average loss of $19.4, or 1.8%. The losses are a conservative estimate because the Profit measure does not account for the transaction costs associated with liquidation.

[32]Similarly, Barber and Odean (2000) find that excessive trading and trading costs are responsible for the poor performance of households.

6 Additional Analysis and Robustness Checks

We next perform additional tests to further address endogeneity concerns and evaluate the robustness of our findings. First, we use an exogenous shock to the intensity of social interactions to demonstrate that the observed associations between centrality and price and volume reactions remain robust. Next, we perform various robustness checks. These include utilizing alternative measures and including additional controls, examining different sub-periods, considering a firm's media and analyst coverage, considering a county's social proximity to institutional investor capital, and using two separate samples that exclude firms with dispersed operations or tri-state firms, respectively.

6.1 Exogenous Shocks to Social Interaction

A possible concern for our conclusions is that the centrality of a firm's location may be associated with other variables that can also influence how investors and prices react to earnings news. To address this concern, we have incorporated a wide range of firm- and county-level controls in our return and volume tests and have performed tests that indicate that the presence of omitted variables is unlikely to explain our results (Altonji, Elder, and Taber 2005, Oster 2019). Additionally, we include firm fixed effects in our StockTwits and Google SVI analysis and firm and household fixed effects in the household-level tests.

To go further in establishing causality, we next perform a test using a quasi-natural experiment that resulted in interruptions to investors' social interactions. This experiment is based upon the temporary shock to the social interactions between East Coast–based investors with the rest of the country during Hurricane Sandy. Hurricane Sandy's landfall on October 22, 2012, affected power supplies for more than eight million residents, disrupted wireless and internet services, and severely affected ground and air transportation for the Mid-Atlantic region (NY, NJ, CT, DC, PA, DE, MD, VA, and WV).

Given the concentration of investors in the heavily affected areas, Hurricane Sandy presents a unique means of testing the causal effects of social network centrality. We hypothesize that Sandy caused a greater disruption to the information dissemination of firms that are more connected to the affected areas and therefore weakened the association between centrality and return responsiveness for such firms.

To avoid any spurious effects stemming from the hurricane's direct impact on firm fundamentals or variables that might affect investor behavior, our test focuses on earnings announcements from firms located outside the affected area. We measure a county's connectedness to the affected regions as the sum of all its friendship links with the Mid-Atlantic counties and define an indicator variable, HSS, as equal to one if the sum is above the sample median, and zero otherwise.

We begin by verifying that Sandy did not have a differential impact on the fundamentals of these firms. To do so, we regress changes in ROA and ROE (between the post-Sandy quarter and the corresponding values from the prior year's quarter) on the HSS variable. Appendix Table A2 presents the results and shows that the coefficient of HSS is insignificant. This indicates that the social ties of firms in unaffected areas with people in affected counties do not result in differential long-term accounting performance.

We then estimate the following difference-in-difference (DID) regression:

$$\begin{aligned}\text{CAR} = \ & \alpha + \beta_1\text{SUE} + \beta_2\text{CEN} + \beta_3\text{HSS} + \beta_4\text{Sandy} + \beta_5\text{SUE}\cdot\text{CEN} + \\ & \beta_6\text{SUE}\cdot\text{CEN}\cdot\text{HSS} + \beta_7\text{SUE}\cdot\text{CEN}\cdot\text{HSS}\cdot\text{Sandy} + \beta_8\text{SUE}\cdot\text{CEN}\cdot\text{Sandy} + \gamma X + \epsilon,\end{aligned} \tag{6}$$

where Sandy is an indicator variable that equals one for announcements made during the Sandy period, which spans from October 22, 2012, through November 1, 2012, and zero otherwise. X includes all county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2, their interactions with SUE, and all lower-order interactions and main effects that are not explicit in the equation. The DID sample period spans from October 12, 2012, through November 11, 2012.

[Insert Table 10 here]

Table 10, Panel A, columns (1)–(3) report the results for the [0, 1] window. As a basis for comparison, the triple interaction term SUE·CEN·HSS has a positive coefficient β_6, which is significant for eigenvector centrality. This shows that, during normal times, the effect of centrality on immediate price reaction is higher for high-HSS counties than for low-HSS counties. This implies that being located in a high-centrality location is more advantageous in facilitating information dissemination if the location is well-connected to the Mid-Atlantic region, which is home to major financial centers and many financial analysts.

The key variable of interest is the coefficient β_7, which captures the effect of the difference-in-difference. β_7 is negative across all three centrality measures and significant for two of them. This indicates that the hurricane weakened the association between centrality and price reactions more for firms highly connected to the affected areas than for those with low connectedness. In other words, being well-connected to Mid-Atlantic states intensifies the centrality effect in normal times, but such relation was dampened during the Sandy period, consistent with our hypothesis.[33]

Columns (4)–(6) present the DID tests for the [2, 61] window. The β_6 coefficients are negative, indicating that during normal times, announcements from high-centrality firms that are highly connected to the Mid-Atlantic region tend to have less PEAD. However, and more importantly, the coefficients of β_7 are all positive and significant, suggesting that this negative relation between centrality on PEAD weakened for high-HSS announcers during Hurricane Sandy.[34]

We next investigate whether Hurricane Sandy changes the effect of centrality on trading volume. To examine this, we estimate a modified version of the log-linear Equation (3) as follows:

$$\begin{aligned}\text{LNVOL} = \ & \alpha + \beta_1|\text{SUE}| + \beta_2\text{CEN} + \beta_3\text{HSS} + \beta_4\text{Sandy} + +\beta_5\text{CEN}\cdot\text{HSS} \\ & + \beta_6\text{CEN}\cdot\text{HSS}\cdot\text{Sandy} + \beta_7\text{CEN}\cdot\text{Sandy} + \gamma X + \epsilon.\end{aligned} \tag{7}$$

The results are reported in Table 10, Panel B. Columns (1)–(3) and (4)–(6) correspond to the [0, 1] and [2, 61] windows, respectively. As a basis for comparison, the coefficients of β_5 for the CEN·HSS term are positive across all columns and significant in column (4), indicating that the positive centrality–volume relation is mostly driven by high-HSS announcements. In contrast, the coefficient of interest, β_7, is negative and statistically significant across all columns, suggesting that the hurricane weakened this association for high-HSS firms.

[33]In addition, both the coefficient β_4 on Sandy and the β_8 coefficient for the term SUE·CEN·Sandy are both insignificant, confirming that Sandy did not significantly affect earnings announcement return responsiveness for firms located in unaffected areas.

[34]In unreported analysis, we consider two alternative channels through which Sandy may have affected either the nature of earnings announcements or the media coverage of the announcements. First, some firms may have strategically postponed their earnings announcements to avoid announcing during Hurricane Sandy. We already account for this possibility by including the reporting lag variable as a control. Additionally, if there was strategic postponement, the announcements made after Hurricane Sandy should show larger reporting lags. We test the difference in reporting lags before and after Sandy and find no significant difference. Second, media outlets may be concentrated in the Mid-Atlantic states, and if these outlets tend to cover firms located in the high-HSS areas, the hurricane may have disrupted the coverage of earnings news for those firms, resulting in slow incorporation of the news into financial markets. To account for this effect, we directly control for the log number of news articles within the announcement window and find very similar results.

Overall, our Hurricane Sandy tests provide additional confirmation that our earlier results on the association between centrality and earnings responsiveness are likely causal and are not a manifestation of omitted firm or county characteristics.

6.2 Robustness Checks and Alternative Explanations

We next conduct robustness checks with respect to alternative measures of key variables and discuss several alternative explanations.

The Geographical Dispersion of Firm Subsidiaries, Tri-State Firms Firms with geographically dispersed business operations are more likely to have investors with local exposure to relevant information (Bernile, Kumar, and Sulaeman 2015). As a result, when these firms announce earnings, it may trigger greater price and trading reactions.

To evaluate whether our results are driven by the geographic dispersion of a firm's economic footprint, we obtain firms' subsidiary locations from Dyreng, Lindsey, and Thornock (2013) and conduct robustness checks of our main results by excluding firms with subsidiaries located in more than three states.[35] Although this filter eliminates firms that belong to the top 25% dispersion group, Appendix Table A3 shows that the main results still hold. Our results are also robust if we directly control for the number of states in which a firm has a subsidiary (the results are available upon request).

In addition, we test whether our results are driven by firms located in the tri-state area (New York, New Jersey, and Connecticut), wihch is a region with a heavy presence of institutional investors and financial analysts who play important roles in information dissemination in financial markets. Appendix Table A4 shows that our key results remain robust when we exclude these firms. Hence, our findings are not driven by the geographical dispersion of a firm's business operations or restricted to firms located in financial centers.

Subperiod Analysis As previously discussed, Facebook friendship links are useful indicators of individuals' real-world friendships and activities such as international trade and historical migration. However, one might be concerned that this measure could be relatively noisy for the earlier sample period, although we note that such noise would likely bias against

[35] Dyreng, Lindsey, and Thornock (2013) collected this information using a text-search program on firms' regulatory filings with the Securities and Exchange Commission (SEC). We are grateful to the authors for sharing these datasets.

finding any relationships between firm centrality and stock market reactions. Nevertheless, we provide additional analysis by separating our sample into two subsample periods and repeat the main analysis for each period.

Our results, presented in Appendix Table A5, are consistent with those obtained using the full sample. Panels A and B correspond to the sample periods of 1996–2006 and 2007–2017, respectively. For brevity, we only present results with degree centrality, but the results are similar with eigenvector and information centrality measures.

We find that high-centrality earnings announcements trigger significantly stronger CAR[0, 1] and are followed by somewhat weaker, although insignificant, CAR[2, 61]. Such announcements also trigger stronger immediate changes in volume, although the [2, 61] abnormal volume is insignificant, possibly because of the reduced number of observations. More importantly, these announcements are associated with significantly less-persistent volatility but significantly more-persistent volume, consistent with the findings of the full sample. Therefore, the findings of the relationship between centrality and volatility and volume persistence are consistent in both earlier and later sample periods.

Alternative Persistence Measures We examine the robustness of our results with respect to alternative measures of volume and volatility persistence. To do this, we use an AR(1) model to fit the daily post-announcement observations for the [0,61] window and use the AR(1) coefficient as the persistence measure. We find that centrality's positive association with volatility persistence and negative association with volume persistence remain robust. Appendix Table A6 presents the results.

Media and Analyst Coverage, and Social Proximity to Capital In our final robustness check, we evaluate the extent to which our findings can be explained by alternative mechanisms. One possible alternative explanation for the positive relation between CEN and volume persistence is that high-CEN announcements may also receive greater analyst or media coverage during the [2, 61] window, which might trigger persistent trading. To address this possibility, we include analyst coverage (Analysts) and media coverage (Media) as additional control variables in our analysis.[36]

[36] Analysts is the (log) number of analysts following a stock, obtained using IBES. Media is the (log) number of news articles about a firm during the [2, 61] window, obtained from Ravenpack. Media has a mean and median of 3.67 and 2.45, respectively, and a standard deviation of 15.55.

Another possibility is that high-centrality firms may have better access to institutional investors and therefore receive more investor attention and faster information dissemination. To account for this channel, we control for the social proximity to capital measure (SPC) of Kuchler et al. (2022), which is defined as the SCI-weighted average of total assets under management of all fund families headquartered in a county.

We re-estimate Equations (2) and (3) including these three additional variables and report the results in Appendix Table A7. Columns (1)–(4) present the results for $d_{|R|}$, with columns (1)–(3) adding the variables one at a time to the baseline specification, and column (4) including all three variables. Similarly, columns (5)–(8) present the results for d_{VOL}. The results are similar to those we obtained in Tables 3 and 4. Across all specifications, the coefficients of CEN remain negative and significant for volatility persistence, but remain positive and significant for volume and attention persistence. We therefore conclude that the centrality-persistence relation that we document is not subsumed by analyst coverage, media coverage, or the county's social proximity to institutional capital.

7 Conclusion

The efficient markets hypothesis posits that the prices immediately reflect all available information. This suggests that the only time that investors need to trade based on public information is on its arrival date. We provide a different perspective by studying how social interactions among investors affect information transmission and belief formation and affect securities markets' reactions to earnings announcements.

Using a newly available firm-level investor social network centrality measure, we find that earnings announcements made by firms that are more centrally located generate stronger immediate reactions in stock prices, volatility, and volume, which are followed by weaker price drift. Moreover, these stocks also exhibit less-persistent volatility but substantially more-persistent trading volume that last up to three months after the announcement.

These findings pose challenges to the traditional theories of information diffusion and instead suggest that the arrival of earnings news triggers a process of discussion (which we measure using social network data) and belief updating via the social network, and that this communication process takes time. During this period, social media activity is elevated, different investors update their beliefs differently, and this updating triggers trading. We call our predictions about this process the social churning hypothesis. Using granular data based on StockTwits messages by individual users, household account-level trading records, and the Google search activities at the stock level, we provide support for this hypothesis.

These results suggest a dual role of social interactions in influencing trading and the information efficiency of financial markets. On the one hand, they facilitate the incorporation of important news into prices. On the other hand, they can induce churning of investor beliefs and shifting disagreement among investors, thereby triggering persistent excessive trading.

Our findings raise a number of issues that suggest future avenues of research. Survey evidence suggests that investors' beliefs have substantial and persistent heterogeneity, features that have not been incorporated into existing macro-finance models (Giglio et al. 2021). Therefore, it would be valuable to test for the effects of social interactions in response to the arrival of other types of public information (anticipated or unanticipated), private information, or even fake news.

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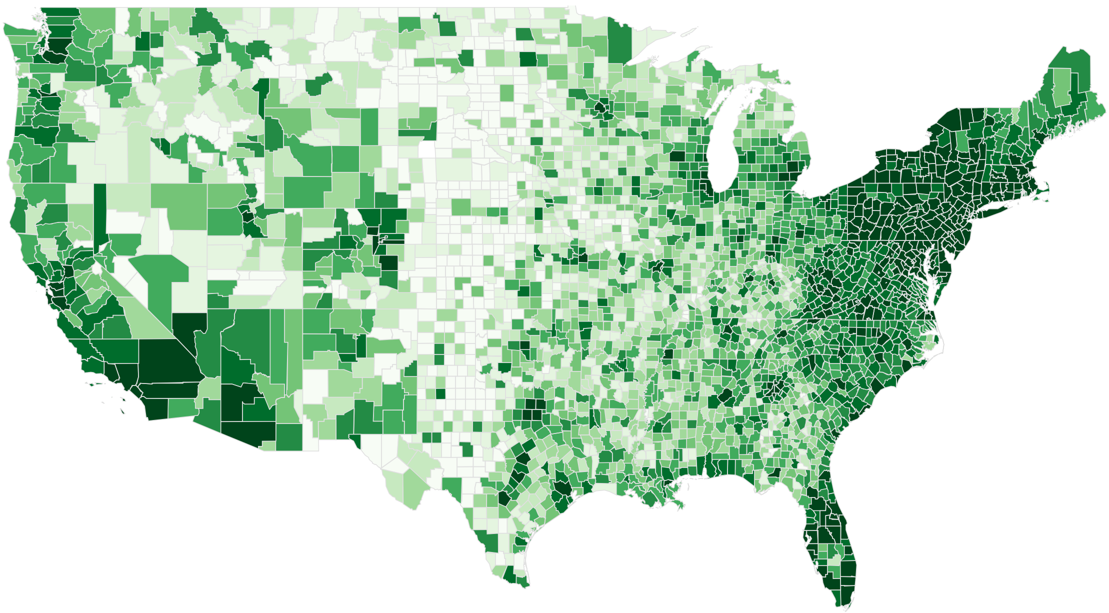

Figure 1: Heat Map of Eigenvector Centrality

This figure plots a heat map of eigenvector centrality across U.S. counties as of June 2016. Darker colors indicate higher values. The ten counties with the highest eigenvector centrality are Los Angeles (CA), Cook (IL), Orange (CA), San Bernardino (CA), San Diego (CA), Riverside (CA), Maricopa (AZ), New York (NY), Clark (NV), and Harris (TX). The ten counties with lowest eigenvector centrality are King (TX), McPherson (NE), Wheeler (NB), Slope (ND), Sioux (NE), Blaine (NE), Arthur (NE), Petroleum (MT), Thomas (NE), and Banner (NE).

Table 1: Descriptive Statistics

This table reports the summary statistics and correlation matrix for the main variables used in the paper. Panel A reports the mean, median, standard deviation, skewness, 10%, 25%, 75%, and 90% for each variable. The centrality measures, degree centrality (DC), eigenvector centrality (EC), and information centrality (IC) are scaled so that the maximum value of each is 100. Panel B reports time-series averages of cross-sectional correlations between the decile ranks of centrality measures against other variables. Variable descriptions are in Appendix Table A1.

Panel A: Descriptive Statistics

					Percentile			
Variable	Mean	Median	Stdev	Skewness	10%	25%	75%	90%
DC	18.84	13.14	21.73	2.29	2.11	6.01	20.85	40.15
EC	4.76	0.47	17.91	5.02	0.04	0.17	1.78	5.14
IC	97.90	99.26	4.62	-5.42	95.34	98.42	99.61	99.90
SUE	0.29	0.19	1.36	0.46	-1.41	-0.49	1.02	1.97
CAR[0, 1] (%)	0.02	-0.11	8.91	1.78	-8.81	-3.64	3.49	8.69
CAR[2, 61] (%)	-0.74	-1.73	26.98	12.23	-23.95	-11.69	7.88	20.24
LNVOL[0, 1]	0.64	0.61	0.99	-0.04	-0.38	0.13	1.14	1.75
LNVOL[2, 61]	0.04	0.02	0.59	0.35	-0.61	-0.27	0.32	0.70
Size	3.58	0.34	17.60	0.00	0.03	0.09	1.42	5.61
B/M	0.65	0.53	0.47	1.19	0.16	0.30	0.87	1.34
IVOL	0.03	0.02	0.02	1.95	0.01	0.01	0.03	0.05
EP	0.17	0.12	0.43	0.34	-0.34	-0.13	0.46	0.76
Evol	0.86	0.14	4.07	8.65	0.03	0.06	0.35	0.95
IO	0.50	0.51	0.31	0.15	0.07	0.22	0.76	0.91
RL	33.65	30.00	16.99	4.59	18.00	23.00	40.00	50.00
NA	219	204	136	0.61	46	111	304	420
PopDen	4647	1510	13356	4	237	676	2411	5452
SIW	0.09	0.08	0.06	1.37	0.03	0.04	0.12	0.17
Xad	30.60	0.00	233.70	17.34	0.00	0.00	0.91	18.05
AvgAge	37.03	36.65	3.37	0.64	33.10	34.57	39.15	41.42
Retire	0.14	0.13	0.04	1.32	0.09	0.11	0.16	0.19
Income	54.50	51.88	19.07	0.00	32.24	42.24	65.89	80.94
Edu	13.32	13.34	0.68	-0.20	12.50	12.83	13.83	14.17
MoveIn	7.17	7.00	2.49	0.34	4.00	5.39	9.00	10.00

Panel B: Correlation Structure			
	DC	EC	IC
DC	1.000		
EC	0.875	1.000	
IC	0.969	0.902	1.000
SUE	-0.035	-0.046	-0.036
CAR[0, 1] (%)	-0.005	-0.004	-0.005
CAR[2, 61] (%)	-0.006	-0.005	-0.006
LNVOL[0, 1]	0.005	0.023	0.008
LNVOL[2, 61]	0.004	0.005	0.005
Size	0.062	0.033	0.057
B/M	-0.036	-0.093	-0.056
IVOL	0.022	0.073	0.034
EP	-0.019	0.012	-0.013
Evol	-0.017	-0.021	-0.013
IO	0.014	-0.007	0.009
RL	0.037	0.039	0.049
NA	0.024	0.034	0.029
PopDen	0.309	0.313	0.353
SIW	-0.169	-0.100	-0.194
Xad	0.052	0.039	0.064
AvgAge	-0.245	-0.211	-0.225
Retire	-0.257	-0.317	-0.281
Income	-0.063	-0.059	-0.050
Edu	-0.165	-0.028	-0.109
MoveIn	-0.248	-0.210	-0.270

Table 2: Centrality and Returns Following Earnings Announcements

This table reports the regression of stock returns on the centrality of the announcing firm's headquarters location. The dependent variable, CAR, is the cumulative abnormal returns for the announcement period (CAR[0, 1]) or the post-announcement period (CAR[2, 61]). CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality, eigenvector centrality, or information centrality. SUE is the decile rank of unexpected earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 and their interactions with SUE are included. Standard errors are two-way clustered by firm and announcement date, and the resulting *t*-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: CAR[0, 1]

	Degree Centrality			Eigenvector Centrality			Information Centrality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SUE	0.405***	0.423***	1.386***	0.403***	0.425***	1.428***	0.402***	0.422***	1.413***
	(24.89)	(24.52)	(5.26)	(24.76)	(24.71)	(5.42)	(24.90)	(24.63)	(5.39)
SUE·CEN	0.00737***	0.00673**	0.0152***	0.00766***	0.00635**	0.0149***	0.00801***	0.00685**	0.0172***
	(2.78)	(2.42)	(4.68)	(2.90)	(2.29)	(4.39)	(3.02)	(2.45)	(5.06)
CEN	-0.0558***	-0.0430**	-0.0909***	-0.0723***	-0.0440***	-0.0933***	-0.0620***	-0.0412**	-0.0998***
	(-3.68)	(-2.51)	(-4.81)	(-4.76)	(-2.58)	(-4.81)	(-4.07)	(-2.38)	(-5.07)
Ctrls		X	X		X	X		X	X
SUE·Ctrls			X			X			X
Obs.	253,148	226,986	226,986	253,148	226,986	226,986	253,148	226,986	226,986
Adj. R^2	2.1%	2.5%	3.2%	2.1%	2.5%	3.2%	2.1%	2.5%	3.2%

Panel B: CAR[2, 61]

	Degree Centrality			Eigenvector Centrality			Information Centrality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
SUE	0.531***	0.547***	1.810**	0.566***	0.583***	1.859**	0.526***	0.540***	1.766**
	(13.72)	(13.22)	(2.35)	(14.62)	(14.23)	(2.49)	(13.98)	(13.39)	(2.31)
SUE·CEN	-0.0213***	-0.0227***	-0.00994	-0.0274***	-0.0292***	-0.0141*	-0.0203***	-0.0213***	-0.00726
	(-3.35)	(-3.40)	(-1.27)	(-4.12)	(-4.22)	(-1.77)	(-3.20)	(-3.18)	(-0.90)
CEN	0.186***	0.177***	0.106**	0.282***	0.265***	0.179***	0.183***	0.169***	0.0910*
	(4.34)	(3.91)	(2.07)	(5.78)	(5.39)	(3.28)	(4.24)	(3.69)	(1.71)
Ctrls		X	X		X	X		X	X
SUE·Ctrls			X			X			X
Obs.	252,184	226,106	226,106	252,184	226,106	226,106	252,184	226,106	226,106
Adj. R^2	0.2%	0.5%	0.7%	0.2%	0.5%	0.7%	0.2%	0.5%	0.7%

Table 3: Centrality and Volatility Persistence

This table reports the regression of volatility persistence on the centrality of the announcing firm's headquarters location. The dependent variable, $d_{|R|}$, is the persistence parameter of the absolute returns series over the [0, 61] window. CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality, eigenvector centrality, or information centrality. |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Degree Centrality		Eigenvector Centrality		Information Centrality	
	(1)	(2)	(3)	(4)	(5)	(6)
CEN	-0.178***	-0.059***	-0.193***	-0.072***	-0.174***	-0.061***
	(-9.15)	(-3.58)	(-9.96)	(-4.31)	(-8.89)	(-3.57)
|SUE|	-0.101***	0.015	-0.103***	0.014	-0.102***	0.014
	(-8.92)	(1.30)	(-9.09)	(1.25)	(-8.96)	(1.29)
Controls		X		X		X
Obs.	249,426	223,698	249,426	223,698	249,426	223,698
Adj. R^2	0.2%	6.8%	0.2%	6.8%	0.2%	6.8%

Table 4: Centrality and Trading Volume

This table reports the regression of trading volume on the centrality of the announcing firm's headquarters location. In columns (1)–(3) and (4)–(6) the dependent variables are LNVOL[0, 1] and LNVOL[2, 61], the average abnormal dollar trading volume during the announcement window and the post-announcement window, respectively. In columns (7)–(9), the dependent variable is d_{VOL}, the persistent parameter of the daily abnormal turnover for the post-announcement window. CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included and for columns (1)–(6), their interactions with |SUE| are also included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	LNVOL[0, 1]			LNVOL[2, 61]			d_{VOL}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN	0.846***	1.018***	1.014***	0.062*	0.130***	0.082**	0.308***	0.369***	0.344***
	(5.56)	(6.60)	(6.41)	(1.74)	(3.37)	(2.17)	(10.75)	(12.69)	(11.50)
|SUE|	1.602***	1.614***	1.608***	0.833***	0.836***	0.834***	0.027*	0.031**	0.028**
	(19.03)	(19.21)	(19.09)	(18.33)	(18.38)	(18.34)	(1.86)	(2.15)	(1.96)
Controls	X	X	X	X	X	X	X	X	X
Obs.	233,218	233,218	233,218	232,687	232,687	232,687	205, 779	205, 779	205, 779
Adj. R^2	4.4%	4.4%	4.4%	2.8%	2.8%	2.8%	17.6%	17.7%	17.6%

Table 5: Centrality and StockTwits Mentions

This table reports the regression of the StockTwits mentions on the centrality of the announcing firm's headquarters location. For each stock and for a given day, we define New Messages as the logarithm of the number of initial message mentions of a stock in a thread, and Replies as the logarithm of the number of replies to the initial messages. Abnormal New Messages, ANM[0, 1] and ANM[2, 61], is the differences (in logarithm) between the average New Messages for the announcement and the post-announcement window respectively, relative to its pre-announcement average. Similarly, the Abnormal Replies (ARM[0, 1], ARM[2, 61]) is the difference (in logarithm) between the average Replies for the corresponding window relative to the pre-announcement average. Panels A and B present results of regressions of ANM and ARM on the centrality of the firm's headquarters location, respectively. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Standard errors are two-way clustered by firm and announcement date and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

	Panel A: New Messages					
	ANM[0, 1]			ANM[2, 61]		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
CEN	0.34**	0.42**	0.40**	-0.07***	-0.09***	-0.07**
	(2.07)	(2.56)	(2.37)	(-2.82)	(-3.00)	(-2.51)
|SUE|	2.69***	2.70***	2.70***	0.44**	0.43**	0.44**
	(5.37)	(5.40)	(5.39)	(2.40)	(2.39)	(2.40)
Ctrls	X	X	X	X	X	X
Obs.	35,940	35,940	35,940	35,940	35,940	35,940
Adj. R^2	36.8%	36.8%	36.8%	9.7%	9.7%	9.7%
	Panel B: Replies					
	ARM[0, 1]			ARM[2, 61]		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
CEN	0.83***	1.16***	0.86***	1.08***	1.51***	1.18***
	(3.42)	(4.68)	(3.39)	(4.03)	(5.51)	(4.22)
|SUE|	1.97**	2.00**	1.97**	3.01***	3.06***	3.02***
	(2.27)	(2.31)	(2.28)	(3.35)	(3.40)	(3.36)
Ctrls	X	X	X	X	X	X
Obs.	34,326	34,326	34,326	34,326	34,326	34,326
Adj. R^2	27.1%	27.1%	27.1%	28.8%	28.9%	28.8%

Table 6: Centrality and StockTwits Disagreement

This table reports the regression of disagreement of StockTwits messages on the centrality of the announcing firm's headquarters location. DO[0, 1] and DO[2, 61] correspond to the average StockTwits opinion differences for the announcing stock over the announcement and the post-announcement window, respectively. d_{DO} is the persistence parameter of StockTwits opinion differences. In Panel A, the disagreement measures are constructed using all messages for the corresponding windows. The disagreement measures in Panels B and C are computed with Replies over the [2, 61] period and correspond to within-thread and across-thread disagreement measures. CEN is the decile ranking of the centrality of a firm's headquarters county based on the degree centrality (DC), eigenvector centrality (EC), or information centrality (IC), respectively. |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Message Disagreement

	DO[0, 1]			DO[2, 61]			d_{DO}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN	0.065**	0.104***	0.066**	0.099***	0.121***	0.107***	0.388***	0.490***	0.423***
	(2.11)	(3.35)	(2.06)	(4.63)	(5.39)	(4.82)	(3.67)	(4.51)	(3.87)
|SUE|	0.018	0.019	0.018	0.045***	0.045***	0.045***	0.058	0.060	0.059
	(0.78)	(0.81)	(0.78)	(3.49)	(3.52)	(3.50)	(0.82)	(0.85)	(0.82)
Obs.	21,528	21,528	21,528	30,185	30,185	30,185	26,562	26,562	26,562
Adj R^2	10.2%	10.2%	10.2%	20.7%	20.7%	20.7%	8.3%	8.4%	8.3%

Panel B: Reply Disagreement, Within-Thread

	DO[2, 61]			d_{DO}		
	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)
CEN	0.036**	0.041**	0.035*	0.164*	0.215**	0.200**
	(1.98)	(2.17)	(1.82)	(1.84)	(2.29)	(2.18)
|SUE|	0.033	0.033	0.033	-0.260	-0.255	-0.256
	(0.50)	(0.51)	(0.50)	(-0.69)	(-0.67)	(-0.68)
Obs.	16,286	16,286	16,286	16,025	16,025	16,025
Adj. R^2	23.4%	23.4%	23.4%	6.3%	6.3%	6.3%

Panel C: Reply Disagreement, Across-Thread						
	DO[2, 61]			d_{DO}		
	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)
CEN	0.038**	0.060***	0.041**	0.328***	0.371***	0.369***
	(2.34)	(3.51)	(2.49)	(3.49)	(3.98)	(3.87)
|SUE|	0.069	0.071	0.070	0.282	0.279	0.281
	(1.37)	(1.41)	(1.38)	(0.75)	(0.74)	(0.74)
Obs.	14,563	14,563	14,563	14,355	14,355	14,355
Adj. R^2	26.7%	26.8%	26.7%	6.1%	6.1%	6.1%

Table 7: Influencer Posts, Replies, and the Persistence of Volatility and Volume

This table reports results of regression analysis of StockTwits influencer posts and the subsequent messaging activities as well as volatility and volume persistence. The dependent variables for columns (1) and (2) are ARM[2, 61] and DO[2, 61], the abnormal number of replies and the average opinion differences of all messages in the post-announcement window of [2, 61]. For columns (3) and (4), the dependent variables are volatility persistence ($d_{|R|}$) and volume persistence ($d_{|VOL|}$), respectively. The independent variables are INFL[0, 1] and ANM[0, 1], the average sender centrality of new messages and abnormal new messages for the [0, 1] window, respectively, and |SUE|, the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and firm fixed effects are included. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1) ARM[2, 61]	(2) DO[2, 61]	(3) $d_{\|R\|}$	(4) d_{VOL}
INFL[0, 1]	0.019***	0.105***	-0.114*	0.662***
	(4.19)	(5.05)	(-1.86)	(9.45)
ANM[0, 1]	0.398***	0.115*	0.498**	0.900***
	(12.59)	(1.79)	(2.17)	(3.48)
|SUE|	0.005***	0.017	0.035	0.006
	(2.89)	(1.53)	(1.30)	(0.23)
Obs.	34,232	20,917	35,940	35,940
Adj. R^2	46.7%	42.8%	7.4%	13.2%

Table 8: Centrality and Google Searches

This table reports the regression of investor attention on the centrality of the announcing firm's headquarters location. The dependent variable for columns (1)–(3) is ASV[0, 1], the abnormal Google searches for the announcing stock. The dependent variable for columns (4)–(6) is ASV[2, 61], the post-announcement abnormal Google searches. For columns (7)–(9), the dependent variable is d_{SVI}, the persistence of Google searches for the post-announcement period. CEN is the decile ranking of the centrality of a firm's headquarters county based on the degree centrality (DC), eigenvector centrality (EC), or information centrality (IC), respectively. |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ASV[0, 1]			ASV[2, 61]			d_{ASV}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN	0.280**	0.659***	0.366***	0.037	0.056**	0.039	0.368***	0.297**	0.356***
	(2.11)	(4.64)	(2.65)	(1.43)	(2.04)	(1.43)	(3.00)	(2.43)	(2.82)
|SUE|	0.130**	0.139**	0.132**	0.087***	0.087***	0.087***	-0.045	-0.044	-0.044
	(2.01)	(2.16)	(2.05)	(3.72)	(3.75)	(3.73)	(-1.28)	(-1.26)	(-1.26)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	115,452	115,452	115,452	113,512	113,512	113,512	111,871	111,871	111,871
Adj. R^2	1.8%	1.9%	1.8%	1.7%	1.7%	1.7%	11.9%	11.9%	11.9%

Table 9: Social Ties and Household Trading

This table analyzes households' trading activities and profits following earnings announcements. In Panel A, the dependent variable is the trading activity of a household on the announcing stock for a given window, measured three ways: 1) a trading indicator, 2) the number of trades, or 3) relative trade size. For Panel B, the dependent variable is the profit of a household from trading the announcing stock for a given window, with a negative value corresponding to a loss. Profit^{net} is the net profit for a household. Profit^{gross} is the profit before any transaction cost. Cost is the trading costs (e.g., commission and bid-ask spread). All Profit and Cost measures are scaled by the household's beginning-of-the-month stock portfolio value before the announcement and multiplied by 10^4. RSCI (in logarithm) is relative social connectedness between the locations of the firm and the household. |SUE| is the decile rank of absolute earnings surprises. We include time indicator variables, firm-level control variables (lagged) , household-level controls, and firm and household fixed effects. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and household, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Trading Activities						
	Trading Indicator		Number of Trades		Relative Trade Size	
	[0, 1]	[2, 61]	[0, 1]	[2, 61]	[0, 1]	[2, 61]
	(1)	(2)	(3)	(4)	(5)	(6)
RSCI	0.015***	0.162***	0.018***	0.321***	0.005***	0.143***
	(3.08)	(9.61)	(3.43)	(8.45)	(4.56)	(8.88)
|SUE|	0.056***	0.379***	0.063***	0.740***	0.011***	0.184***
	(4.19)	(6.13)	(4.18)	(5.17)	(4.55)	(5.42)
Ctrls	X	X	X	X	X	X
Obs.	3,916,866	3,916,866	3,916,866	3,916,866	3,916,866	3,916,866
Adj. R^2	1.1%	6.3%	1.2%	6.6%	1.5%	6.0%

Panel B: Trading Profits						
	[0, 1]			[2, 61]		
	Profit^{net}	Profit^{gross}	Cost	Profit^{net}	Profit^{gross}	Cost
	(1)	(2)	(3)	(4)	(5)	(6)
RSCI	-0.007	-0.002	0.005***	-0.151**	0.009	0.178***
	(-1.48)	(-0.45)	(2.79)	(-2.31)	(0.15)	(6.76)
|SUE|	-0.032**	-0.017	0.014***	-0.687***	-0.404***	0.254***
	(-2.42)	(-1.56)	(3.67)	(-3.71)	(-2.67)	(5.17)
Ctrls	X	X	X	X	X	X
Obs.	3,916,866	3,916,866	3,916,866	3,916,866	3,916,866	3,916,866
Adj. R^2	0.2%	0.1%	1.0%	1.4%	1.0%	3.8%

Table 10: Centrality and Security Market Reactions to Earnings News, Hurricane Sandy

This table reports the difference-in-difference regression results of the impact of Hurricane Sandy on the relationship between centrality and market reactions to a firm's earnings news. Panel A presents the reactions of stock prices. The dependent variables are CAR[0, 1] or CAR[2, 60], the cumulative buy-and-hold abnormal returns for the announcement and the post-announcement period, respectively. Panel B presents the reactions of trading volume, with dependent variables LNVOL[0, 1] and LNVOL[2, 61] correspond to the average abnormal volume during the announcement and the post-announcement window, respectively. CEN is the decile ranking of the centrality of the announcing firm's headquarters county, measured by degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). SUE is the decile rank of earnings surprises. HSS is an indicator variable that equals one if a county has above median social connectedness with Mid-Atlantic states. Sandy is an indicator variable that equals one during the affected period, defined as October 22, 2012, to November 1, 2012. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 and their interactions with (SUE) are included. The sample period ranges from October 12, 2012, to November 12, 2012. Standard errors are clustered by firm and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	Panel A: Price Reactions					
	CAR[0, 1]			CAR[2, 61]		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
SUE	1.579	1.944**	1.765*	2.314	2.456	2.294
	(1.62)	(1.97)	(1.82)	(1.01)	(1.07)	(1.00)
CEN	-0.0837	0.553	0.275	-1.034	-0.355	-1.610
	(-0.18)	(1.37)	(0.57)	(-0.82)	(-0.30)	(-1.18)
HSS	3.504	9.484**	3.649	-27.24**	-7.630	-29.11**
	(0.66)	(2.12)	(0.67)	(-2.32)	(-0.78)	(-2.44)
Sandy	-0.524	1.387	0.496	-0.106	3.212	-0.494
	(-0.26)	(0.61)	(0.24)	(-0.02)	(0.52)	(-0.08)
SUE·CEN	0.0246	-0.0890	-0.0516	0.139	0.0568	0.247
	(0.37)	(-1.44)	(-0.72)	(0.81)	(0.35)	(1.37)
SUE·CEN·HSS	0.0498	0.210*	0.0995	-0.783***	-0.380	-0.901***
	(0.41)	(1.93)	(0.78)	(-2.72)	(-1.43)	(-3.11)
SUE·CEN·HSS·Sandy	-0.137	-0.355**	-0.197	0.738**	0.255	0.881**
	(-0.92)	(-2.54)	(-1.29)	(2.11)	(0.72)	(2.41)
SUE·CEN·Sandy	-0.000	0.138	0.0724	-0.180	0.0284	-0.166
	(-0.00)	(1.53)	(0.79)	(-0.86)	(0.13)	(-0.75)
Controls (· SUE)	X	X	X	X	X	X
Obs.	1,407	1,407	1,407	1,404	1,404	1,404
Adj. R^2	3.2%	3.8%	3.2%	5.6%	5.5%	5.6%

Panel B: Volume Reactions						
	LNVOL[0, 1]			LNVOL[2, 61]		
	DC	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(6)
CEN	-0.00754	-0.0143	-0.00922	-0.00319	0.00148	0.00378
	(-0.27)	(-0.52)	(-0.29)	(-0.22)	(0.10)	(0.23)
|SUE|	0.0130**	0.0128*	0.0128*	0.00680*	0.00664*	0.00672*
	(1.99)	(1.95)	(1.96)	(1.79)	(1.74)	(1.76)
HSS	-0.379*	-0.258	-0.255	-0.291**	-0.242**	-0.217
	(-1.83)	(-1.31)	(-1.21)	(-2.21)	(-2.00)	(-1.58)
Sandy	-0.242*	-0.277*	-0.286*	-0.157**	-0.136*	-0.138*
	(-1.74)	(-1.92)	(-1.93)	(-2.16)	(-1.82)	(-1.79)
CEN·HSS	0.0573	0.0465	0.0422	0.0384*	0.0306	0.0246
	(1.61)	(1.33)	(1.10)	(1.81)	(1.51)	(1.09)
CEN·HSS·Sandy	-0.0935**	-0.103**	-0.0970**	-0.0577**	-0.0625**	-0.0461*
	(-2.07)	(-2.28)	(-2.01)	(-2.32)	(-2.54)	(-1.73)
CEN·Sandy	0.0532	0.0644*	0.0694*	0.0249	0.0192	0.0198
	(1.52)	(1.79)	(1.78)	(1.37)	(1.05)	(0.99)
Controls	X	X	X	X	X	X
Obs.	1,444	1,444	1,444	1,440	1,440	1,440
Adj. R^2	3.7%	3.6%	3.6%	4.3%	4.4%	4.1%

Appendix: Variables List and Additional Tests

List of Tables

Table A1: Description of Variables

Variable	Definition
SUE	Decile rank of standardized unexpected earnings. Standardized unexpected earnings is defined as the split-adjusted actual earnings per share minus the same quarter value one year before, scaled by the standard deviation of this difference over the previous eight quarters.
|SUE|	Decile rank of the absolute value of standardized unexpected earnings.
ASV	Abnormal daily Google search volume. Defined as the difference between $\log(1+\mathrm{SVI}_t)$ and its average over the pre-announcement window [-41, -11], where SVI is the Google search volume index for a stock's ticker symbol. ASV[0, 1] is the two-day average ASV around an earnings announcement.
CAR	Daily abnormal returns adjusted by size, B/M, and momentum following Daniel et al. (1997) (DGTW). CAR[0, 1] is the cumulative buy-and-hold abnormal announcement returns of the announcement window. CAR[2, 61] is the post-announcement cumulative buy-and-hold abnormal returns.
LNVOL	Daily abnormal log volume. Defined as the difference between the log volume for a given day and the average daily log volume over days $[-41, -11]$. LNVOL[0, 1] is the average abnormal log volume over the announcement window and LNVOL[2, 61] is the average for the post-announcement window.
$d_{\|R\|}$	Volatility persistence parameter, estimated with an $\mathrm{ARFIMA}(0, d, 0)$ model for daily absolute returns in the window of [0, 61].
d_{VOL}	Volume persistence parameter, estimated with an $\mathrm{ARFIMA}(0, d, 0)$ model for LNVOL in the window of [0, 61].
d_{ASV}	ASV persistence parameter, estimated with an $\mathrm{ARFIMA}(0, d, 0)$ model for ASV in the window of [0, 61].
HSS	An indicator variable for high social connectedness to Mid-Atlantic region that takes the value of one for county i if $\sum_{j\in \mathrm{MA}} \mathrm{SCI}_{ij}$ is above the sample median.
Sandy	An indicator variable that is equal to 1 for announcements made during the Sandy period, i.e., from October 12, 2012, to November 11, 2012.
Size	Stock's market capitalization in millions of dollars, rebalanced every June. Logged when used in regression tests.
B/M	Book-to-market ratio, rebalanced every June.
IVOL	Idiosyncratic volatility, calculated as the standard deviation of the residuals from Fama–French three-factor model with daily returns in the pre-announcement window.
EP	Earnings persistence, calculated as the first-order autocorrelation coefficient of quarterly earnings per share during the past four years.
EVol	Earnings volatility, calculated as the standard deviation in the previous four years of the difference between quarterly earnings and the one-year prior earnings.
IO	Institutional ownership, measured as the percentage of shares owned by institutions in the most recent quarter.
RL	Reporting lag, the difference in days between the fiscal quarter end and the earnings announcement day.
NA	The number of the same-day earnings announcements. Decile rank is used in regression test following Hirshleifer, Lim, and Teoh (2009).
S&P 500	An indicator variable for S&P 500 constituent stocks.

Variable	Definition
Urban	An indicator variable for firms headquartered in the ten most populous metropolitan areas of the United States in 2000: New York City, Los Angeles, Chicago, Washington DC, San Francisco, Philadelphia, Boston, Detroit, Dallas, and Houston.
Retail	An indicator variable if a firm is in the food products, candy and soda, retail, consumer goods, apparel, or entertainment industries according to the Fama–French 48 industry classification.
SCI	Number of Facebook friendship links between two counties.
DC	Degree centrality, calculated based on SCI. Normalized so that the maximum value is equal to 100 in Table 1. For all other tests, decile rank is used.
EC	Eigenvector centrality, calculated based on SCI. Normalized so that the maximum value is equal to 100 in Table 1. For all other tests, decile rank is used.
IC	Information centrality, calculated based on SCI. Normalized so that the maximum value is equal to 100 in Table 1. For all other tests, decile rank is used.
PopDen	Population density at the county level, measured as the number of residents per square mile.
SIW	The percentage of workforce in a firm's home county that is in the same industry as that of the firm, matched by the first two digits of the NAICS.
XAD	Advertising expenses in millions of dollars. Logged in the regression tests.
AvgAge	The average age of the population in the home county of firm i.
Retire	The percentage of the population over 65 years old in the home county of firm i.
Income	The median household income in the home county of firm i.
Edu	Educational attainment for the population in the home county of firm i, measured as the average years of education since primary school.
MoveIn	The median number of years since a household has moved into the county.

Table A2: Sandy and Firm Fundamentals

The table below displays the results of a regression analysis investigating the effects of Hurricane Sandy on firm fundamentals in the four quarters immediately following the storm. Columns (1) and (2) show the dependent variables ΔROA and ΔROE, respectively, which represent the difference between the post-Sandy quarter's return on assets (ROA) and return on equity (ROE) and the corresponding values from the prior year's quarter. HSS is an indicator variable that equals one if a county has above-median social connectedness with the affected Mid-Atlantic states. The sample includes, for each firm, four fiscal quarters after Hurricane Sandy. The coefficients are multiplied by 100. We cluster the standard errors by firm and report the corresponding t-statistics in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	ΔROA (1)	ΔROE (2)
HSS	0.029	-0.363
	(0.27)	(-0.79)
Controls	X	X
Obs.	14,153	14,152
Adj. R^2	11.6%	6.3%

Table A3: Robustness Checks: Excluding Firms with Dispersed Subsidiaries

This table reports robustness tests of our main results excluding firms with subsidiaries located in more than three states. Panels A and B correspond to the analyses of price and volume reactions, respectively. CAR[0, 1] and CAR[2,16] are the daily cumulative buy-and-hold abnormal announcement returns for the announcement and post-announcement periods, respectively. LNVOL[0, 1] and LNVOL[2,16] are the average abnormal volume for the announcement and post-announcement periods, respectively. $d_{|R|}$ and d_{VOL} are the post-announcement persistence parameters of return volatility and LNVOL, respectively. CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). SUE (|SUE|) is the decile rank of (absolute) earnings surprises. The controls for the CAR and LNVOL regressions are the same as in Table 2, and the controls for the d regressions are the same as in Table 3. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Price Reactions

	CAR[0, 1]			CAR[2, 61]			$d_{\|R\|}$		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
SUE·CEN	0.0184***	0.0183***	0.0211***	-0.0145	-0.0230**	-0.00924			
	(4.57)	(4.30)	(5.01)	(-1.34)	(-2.04)	(-0.84)			
CEN	-0.107***	-0.117***	-0.121***	0.179**	0.299***	0.152**	-0.0906***	-0.0994***	-0.0971***
	(-4.66)	(-4.84)	(-5.00)	(2.56)	(4.10)	(2.15)	(-4.96)	(-5.38)	(-5.14)
SUE	0.0907	0.0905	0.0755	0.257	0.302	0.226			
	(1.04)	(1.04)	(0.86)	(0.96)	(1.16)	(0.85)			
|SUE|							0.0150	0.0140	0.0146
							(1.10)	(1.03)	(1.07)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	147,077	147,077	147,077	146,430	146,430	146,430	143,227	143,227	143,227
Adj. R^2	3.4%	3.4%	3.4%	0.8%	0.8%	0.8%	7.1%	7.1%	7.1%

Panel B: Volume Reactions									
	VOl[0, 1]			LNVOL[2, 61]			d_{VOL}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
CEN	0.943***	1.145***	1.131***	0.089*	0.184***	0.113**	0.277***	0.308***	0.298***
	(5.05)	(6.11)	(5.86)	(1.88)	(3.67)	(2.23)	(8.57)	(9.53)	(8.86)
|SUE|	1.980***	1.994***	1.988***	0.927***	0.930***	0.928***	0.040**	0.044**	0.042**
	(17.04)	(17.20)	(17.12)	(15.11)	(15.16)	(15.12)	(2.14)	(2.32)	(2.23)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	151,476	151,476	151,476	151,079	151,079	151,079	131,001	131,001	131,001
Adj. R^2	4.3%	4.3%	4.3%	3.2%	3.2%	3.2%	10.3%	10.3%	10.3%

Table A4: Robustness Checks: Excluding Firms in the Tri-State Area

This table reports robustness tests of our main results, excluding announcements made by firms located in the tri-state (NY, NJ, and CT) area. Panels A and B correspond to the analyses of price and volume reactions, respectively. CAR[0, 1] and CAR[2,16] are the daily cumulative buy-and-hold abnormal announcement returns for the announcement and post-announcement periods, respectively. LNVOL[0, 1] and LNVOL[2,16] are the average abnormal volume for the announcement and post-announcement periods, respectively. $d_{|R|}$ and d_{VOL} are the post-announcement persistence parameters of return volatility and LNVOL, respectively. CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). SUE (|SUE|) is the decile rank of (absolute) earnings surprises. The controls for the CAR and LNVOL regressions are the same as in Table 2 and the controls for the d regressions are the same as in Table 3. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at 10%, 5%, and 1%, respectively.

Panel A: Price Reactions									
	CAR[0, 1]			CAR[2, 61]			$d_{\|R\|}$		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
SUE·CEN	0.0124***	0.0140***	0.0149***	-0.0113	-0.0120	-0.00912			
	(3.67)	(3.89)	(4.15)	(-1.36)	(-1.43)	(-1.07)			
CEN	-0.0759***	-0.0916***	-0.0882***	0.134**	0.192***	0.120**	-0.0765***	-0.0950***	-0.0851***
	(-3.83)	(-4.41)	(-4.21)	(2.50)	(3.53)	(2.18)	(-4.71)	(-5.82)	(-5.03)
SUE	0.244*	0.235*	0.231*	-0.165	-0.162	-0.176			
	(1.89)	(1.82)	(1.78)	(-0.45)	(-0.44)	(-0.48)			
|SUE|							0.0148	0.0137	0.0145
							(1.28)	(1.19)	(1.26)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	194,822	194,822	194,822	194,110	194,110	194,110	192,003	192,003	192,003
Adj. R^2	3.1%	3.1%	3.1%	0.7%	0.7%	0.7%	7.0%	7.0%	7.0%

Panel B: Volume Reactions									
	LNVOL[0, 1]			LNVOL[2, 61]			d_{VOL}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
CEN	0.755***	0.962***	0.922***	0.051	0.120***	0.060	0.274***	0.292***	0.297***
	(4.86)	(6.06)	(5.66)	(1.40)	(3.03)	(1.54)	(9.76)	(10.21)	(10.08)
|SUE|	1.590***	1.602***	1.595***	0.821***	0.823***	0.821***	0.058***	0.061***	0.059***
	(18.01)	(18.17)	(18.07)	(16.76)	(16.80)	(16.76)	(3.66)	(3.83)	(3.72)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	199,942	199,942	199,942	199,515	199,515	199,515	177,030	177,030	177,030
Adj. R^2	4.4%	4.4%	4.4%	2.8%	2.8%	2.8%	10.9%	10.9%	10.9%

Table A5: Subsample Analysis

This table reports the subsample regression of abnormal cumulative returns on the centrality of a firm's headquarters location. Panel A reports the results in the early sample period from 1996 to 2006. Panel B reports the results in the late sample period from 2007 to 2017. For columns (1) and (2), the dependent variable, CAR, is the cumulative abnormal returns for the announcement period (CAR[0, 1]), the post-announcement period (CAR[2, 61]). For columns (3) and (4), the dependent variables are LNVOL[0, 1] and LNVOL[2, 61]. For columns (5) and (6), the dependent variables are the persistence parameter of volatility and volume, respectively. CEN is the decile ranking of the degree centrality of a firm's headquarters county. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 and their interactions with SUE (when applicable) are included. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Sample Period 1996–2006						
	CAR[0, 1]	CAR[2, 61]	LNVOL[0, 1]	LNVOL[2, 61]	$d_{\|R\|}$	d_{VOL}
SUE·CEN	0.0172***	-0.00963				
	(4.34)	(-0.89)				
CEN	-0.0885***	0.148**	0.642***	0.166	-0.039*	0.242***
	(-3.84)	(2.04)	(3.20)	(0.31)	(-1.92)	(6.66)
Obs.	131,946	131,396	135,506	135,154	125,904	115,291
Adj. R^2	2.9%	0.7%	4.1%	3.6%	6.2%	16.5%
Panel B: Sample Period 2007–2017						
	(1)	(2)	(3)	(4)	(5)	(6)
	CAR[0, 1]	CAR[2, 61]	LNVOL[0, 1]	LNVOL[2, 61]	$d_{\|R\|}$	d_{VOL}
SUE·CEN	0.0111**	-0.00847				
	(2.21)	(-0.74)				
CEN	-0.0893***	0.0259	0.943***	-0.020	-0.072***	0.337***
	(-2.98)	(0.37)	(4.26)	(-0.38)	(-3.02)	(8.44)
Obs.	95,040	94,710	97,712	97,533	97,794	90,488
Adj. R^2	3.6%	0.9%	5.6%	2.2%	7.6%	17.1%

Table A6: Alternative Persistence Measures

This table reports robustness tests with alternative persistence measures. $\varphi_{|R|}$ and $\varphi_{\text{VOL}}$are post-announcement persistence measures defined as the AR(1) coefficient of the daily return volatility and abnormal volume, respectively. CEN is the decile ranking of the centrality of a firm's headquarters county, measured by degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Standard errors are two-way clustered by firm and announcement date, and the resulting *t*-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$\varphi_{\|R\|}$			φ_{VOL}		
	DC	EC	IC	DC	EC	IC
CEN	-0.065***	-0.083***	-0.071***	0.345***	0.438***	0.391***
	(-3.80)	(-4.84)	(-4.02)	(10.41)	(12.98)	(11.35)
|SUE|	0.011	0.010	0.011	0.017	0.022	0.018
	(0.87)	(0.79)	(0.85)	(1.07)	(1.41)	(1.18)
Ctrls	X	X	X	X	X	X
Obs.	233,531	233,531	233,531	233,531	233,531	233,531
Adj. R^2	6.9%	6.9%	6.9%	22.2%	22.3%	22.2%

Table A7: Robustness Checks for Persistence

This table reports robustness tests for the relationship between centrality and post-announcement persistence while controlling for analyst coverage, media coverage, and social proximity to capital. Analyst is the log number of analysts following the stock. Media is the log number of news articles about the firm for the post-announcement window. Social proximity to captial (SPC) for county i is calculated as $\sum_j \text{AUM}_{jt} \cdot \text{RFP}_{ij}$, where AUM_{jt} is the total assets under management of all fund families headquartered in county j, and RFP_{ij} equals the total Facbook friendship ties between county i and county j divided by the product of the population of i and j. $d_{|R|}$ and d_{VOL} are post-announcement persistence parameters for the daily return volatility and abnormal trading volume, respectively. CEN is the decile ranking of the degree centrality of a firm's headquarters county. |SUE| is the decile rank of absolute earnings surprises. All county- and firm-level control variables (lagged) and fixed effects listed in Section 2.2 are included. Standard errors are two-way clustered by firm and announcement date, and the resulting t-statistics are shown in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

	$d_{\|R\|}$				d_{VOL}			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CEN	-0.061***	-0.108***	-0.084***	-0.097***	0.285***	0.338***	0.315***	0.294***
	(-4.07)	(-4.54)	(-4.70)	(-4.04)	(10.23)	(8.75)	(10.05)	(7.77)
|SUE|	0.014	0.023	0.006	0.022	0.030**	0.024	0.036**	0.027
	(1.28)	(1.30)	(0.50)	(1.26)	(2.12)	(1.16)	(2.22)	(1.30)
Analysts	-0.917***			-1.070***	1.777***			1.771***
	(-15.87)			(-12.16)	(19.95)			(14.97)
Media		0.452***		0.395***		2.499***		2.093***
		(4.27)		(2.93)		(10.79)		(7.37)
SPC			0.151*	0.124			0.228*	0.240*
			(1.92)	(1.59)			(1.81)	(1.94)
Obs.	223,698	156,068	92,246	83,819	205,779	146,377	85,655	78,350
Adj. R^2	7.0%	7.0%	7.6%	6.9%	18.0%	15.2%	17.0%	16.8%

Internet Appendix: A Model of Information Diffusion, Price Formation, and Trading

In this appendix, we present a model of gradual information diffusion in a network setting. Motivated by Banerjee et al. (2013, 2019), We first introduce an explicit structure of investor social networks and show that the speed of information diffusion across the network is positively related to the centrality of the node where the information originated.

We then model the behavior of imperfectly rational investors who react to earnings announcements by updating their beliefs but do not learn from prices (see, e.g., Hirshleifer and Teoh 2003, DellaVigna and Pollet 2009, and Fedyk 2022). We investigate the relationship between centrality and the dynamics of price, volatility, and trading volume under three scenarios: 1) investors have identical priors and interpretation of the earnings news, 2) investors have heterogeneous priors and a static disagreement, and 3) social interactions triggers sustained fluctuations in disagreements. The third scenario corresponds to what we refer to as the "social churning hypothesis." We show that the first two scenarios imply that news seeded from high-centrality nodes leads faster decays in returns, volatility, and trading volume and are at odds with our empirical findings. We then demonstrate that the third scenario provided a unified explanation for the observed empirical findings.

Let t denote the trading dates: $t \in 0, 1, \ldots, T+1$. There is a single risky asset with terminal payoff R at date $T+1$ that is normally distributed with mean $\bar{R}$ and variance σ_R^2. At date 1, earnings news Y is announced, which is informative of R and takes the form of $Y = R + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. Date $T+1$ corresponds to the date of the next earnings announcement, so the model describes the dynamics of prices and trading volume for the time period between the announcements. There is also a risk-free bond with a zero interest rate. The per capita supply of the risky asset is fixed at X. Investors can borrow and lend freely.

We assume that investors are risk averse and exhibit quadratic utility with risk aversion γ_i. The i^{th} investor maximizes the expected utility of terminal wealth W_T^i:

$$\begin{aligned} &\max_{x_t^i} \mathbb{E}_{it}[W_T^i] - \frac{\gamma_i}{2}\mathrm{Var}_{it}[W_T^i] \\ &s.t. \quad W_T^i = W_t^i + x_t^i(R - P_t). \end{aligned} \tag{B.1}$$

For simplicity, we assume all investors have the same preference ($\gamma_i = 1$ for $\forall i$).

Centrality and Information Diffusion There are N investors in the market who are indexed by $i \in \{1, 2, \ldots, N\}$. 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 $\mathcal{E} \subseteq \mathcal{N} \cdot \mathcal{N}$ 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 $(i, i') \in \mathcal{E}$. In addition, each investor is connected to himself. Hence $\mathcal{E}(i, i) = 1$ for all $i \in \mathcal{N}$. Edges can be conveniently expressed by the *adjacency matrix* $A \in \{0, 1\}^{N \cdot N}$, whose $(i, i')^t$ element $(A)_{ii'} = 1$ if $(i, i') \in \mathcal{E}$, and $(A)_{ii'} = 0$ otherwise.

Denote $p(i, i')$ as the shortest path between two investors i and i'. A $p(i, i')$ value of one indicates that i and i' can be connected via one link, and a value of 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 a distance less than or equal to k from investors i. Hence, $\mathcal{D}_k^{(i)} = \bigcup_{j=1}^{k} \mathcal{S}_j^{(i)}$. We define $D_k^{(i)}$, the k^{th} degree of i, as equal to $|\mathcal{D}_k^{(i)}|$. Therefore, $D_1^{(i)}$ measures the total number of i's direct neighbors, and $D_k^{(i)}$ measures the total number of investors that can be connected to i with no more than k steps.

Investors are connected to each other in a social network and can be categorized into county-level subnetworks that correspond to their geographic locations. We partition graph $\mathcal{G}$ into M subgraphs, $\mathcal{G}^m = (\mathcal{N}^m, \mathcal{E})$, for $m = 1, \ldots, M$, 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 $\mathcal{D}_k^m = \bigcup_{i \in \mathcal{N}^m} \mathcal{D}_1^{(i)}$ as 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 k^{th} order degree of an individual node, we can define the k^{th} order degree of the subset of investors $\mathcal{N}^m$ as $D_k^m = |\mathcal{D}_k^m|$. Given that the $(i,i')^{th}$ element of the k^{th} power of the adjacency matrix A, $(A^k)_{ii'}$, equals 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*

$$D_k^m = \xi(\mathbf{I}'_{\mathcal{N}^m} A^k)\mathbf{I}, \tag{B.2}$$

where $\xi : \mathbb{R}^{+N \times N} \to \{0,1\}^{N \times N}$ is a matrix element-wise indicator function such that $(\xi(A))_{ij} = 1$ if $A_{ij} > 0$ and $(\xi(A))_{ij} = 0$ if $A_{ij} = 0$, $\mathbf{I}_{\mathcal{N}^m}$ is $N \times 1$ vector with $(\mathbf{I}_{\mathcal{N}^m})_i = 1$ if $i \in \mathcal{N}^m$ and $(\mathbf{I}_{\mathcal{N}^m})_i = 0$ otherwise, and $\mathbf{I}$ is $N \times 1$ vector of ones.

We next extend the concept of centrality for a node to the centrality of 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*

$$D_k^m \geq D_k^{m'}, \forall\, k = 1, 2, \ldots, \tag{B.3}$$

where strict inequality holds for at least some values of k.

We assume that a news announcement made by a firm first spreads to the local subgraph that the firm belongs to and then gradually diffuses to other subgraphs via investor social interactions. At date 0, the signal is leaked to local investor $I_0 \subset \mathcal{N}^m$.[37] At date 1, the public news arrives at subgraph $\mathcal{G}^m$, which is informative of R and takes the form of $Y = R + \epsilon$, where $\epsilon \sim \mathcal{N}(0, \sigma_\epsilon^2)$. Each investor $i \in \mathcal{N}^m$ becomes informed, and the investor starts to broadcast the news to each of his direct neighbors. At each subsequent time t, the newly informed investors from the previous period

[37] General diffusion processes in networks are usually difficult to characterize. To keep solutions tractable, we assume that $I_0 \subset \mathcal{N}^m$, that is, the information only occurs in a firm's home network $\mathcal{G}^m$.

$t-1$ broadcast the news to each one of their direct neighbors. This is similar to the information structure used in Walden (2019) to model private signal sharing. As the news diffuses over time, and at any given date t, the fractions of informed and uninformed investors are F_t and $1-F_t$, respectively, and we denote the corresponding investor population as I_t and U_t.

In our setting, the sequence of the total fraction of attentive investors at each date t, $\{F_t\}_{t=0,1,\ldots,T}$ characterizes the information diffusion process and determines the corresponding price and volume dynamics. Therefore, the percentage of the population that becomes informed (F_t) follows a deterministic process and is directly mapped to D_t^m, the centrality of the subgraph where the news originated:

$$F_t = D_t^m/N,\ t = 1, 2, \ldots, T. \tag{B.4}$$

We can further show that, if $\mathcal{G}$ is connected, that is, 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 $t \geq \hat{k}$. That is, F_t is increasing with t for a certain number of periods and obtains a value of one afterwards. The dynamics of prices and trading volume depend on the time-series properties of F_t. Given the mapping between F_t and D_t, we derive the relationship between centrality and price and volume dynamics below, in which we consider three scenarios of investor belief formation.

Scenario 1: Identical Interpretations of News

We first consider a benchmark case in which investors have homogeneous priors and share identical interpretation of news. Investors update their beliefs in a naïve Bayesian manner: they learn from their own signals but do not learn from prices. Given the previously described information diffusion process, we describe the price, volatility, and volume dynamics below.

Price and Volatility Dynamics Informed investors form posterior beliefs of R by conditioning on the signal Y, whereas uninformed investors do not update:

$$i \in I_t : \mathbb{E}_t^{(i)}[R] = \frac{\sigma_\epsilon^2 \bar{R} + \sigma_R^2 Y}{\sigma_\epsilon^2 + \sigma_R^2}; \quad \mathrm{Var}_t^{(i)}[R] = \frac{\sigma_\epsilon^2 \sigma_R^2}{\sigma_\epsilon^2 + \sigma_R^2}; \tag{B.5}$$

$$i \in U_t : \mathbb{E}_t^{(i)}[R] = \bar{R}; \quad \mathrm{Var}_t^{(i)}[R] = \sigma_R^2. \tag{B.6}$$

Given the price P_t, which will be determined through the market-clearing condition, investors' demand functions are as follows:

$$i \in I_t : x_t^{(i)} = \frac{\sigma_\epsilon^2(\bar{R} - P_t) + \sigma_R^2(Y - P_t)}{\sigma_\epsilon^2 \sigma_R^2}; \tag{B.7}$$

$$i \in U_t : x_t^{(i)} = \frac{\bar{R} - P_t}{\sigma_R^2}. \tag{B.8}$$

The total demands from both types 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:

$$F_t \frac{\sigma_\epsilon^2(\bar{R} - P_t) + \sigma_R^2(Y - P_t)}{\sigma_\epsilon^2 \sigma_R^2} + (1 - F_t)\frac{\bar{R} - P_t}{\sigma_R^2} = 0. \tag{B.9}$$

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

$$P_t = \frac{\sigma_\epsilon^2 \bar{R} + F_t \sigma_R^2 Y}{\sigma_\epsilon^2 + F_t \sigma_R^2}. \tag{B.10}$$

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

$$\Delta P_t = \frac{(F_t - F_{t-1})\sigma_R^2 \sigma_\epsilon^2 (Y - \bar{R})}{(\sigma_\epsilon^2 + F_t \sigma_R^2)(\sigma_\epsilon^2 + F_{t-1}\sigma_R^2)}; \quad \sigma_{\Delta P_t} = \frac{(F_t - F_{t-1})\sigma_R^2 \sigma_\epsilon^2 \sqrt{\sigma_R^2 + \sigma_\epsilon^2}}{(\sigma_\epsilon^2 + F_t \sigma_R^2)(\sigma_\epsilon^2 + F_{t-1}\sigma_R^2)}. \tag{B.11}$$

For simplicity, we assume that $\sigma_\epsilon^2 \ll \sigma_R^2$ for all three scenarios, that is, earnings news is informative such that the noise in the earnings signal is small relative to the variance of investors' prior beliefs about the asset payoff. The price changes can therefore be approximated as:

$$\Delta P_t \approx \frac{\Delta F_t \sigma_\epsilon^2}{F_t F_{t-1}} \times \frac{Y - \bar{R}}{\sigma_R^2}. \tag{B.12}$$

Next, we relate the topological properties of $\mathcal{N}^m$ to price reactions to the public news. Let $\hat{t}$ be the cutoff point such that $[0, \hat{t}]$ 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. Using Equation (B.11), the immediate price reaction is

$$\Delta P_{0,\hat{t}} = P_{\hat{t}} - P_0 = \frac{F_{\hat{t}} \sigma_R^2}{\sigma_\epsilon^2 + F_{\hat{t}} \sigma_R^2}(Y - \bar{R}), \tag{B.13}$$

which is increasing in $F_{\hat{t}}$ and, based on Equation (B.4), the subgraph centrality of the location where the news originated.

We then describe the relation between subgraph centrality and post-earnings announcement drift. Assume that $T \geq \hat{k}$ so that $F_T = 1$, that is, the news diffuses to the entire population by the end of the trading dates. We can calculate delayed price reaction as follows:

$$\Delta P_{\hat{t},T} = P_T - P_{\hat{t}} = \frac{\sigma_\epsilon^2 \sigma_R^2}{\sigma_\epsilon^2 + \sigma_R^2} \frac{1 - F_{\hat{t}}}{\sigma_\epsilon^2 + F_{\hat{t}} \sigma_R^2}(Y - \bar{R}). \tag{B.14}$$

Therefore, the delayed price reactions are decreasing in $F_{\hat{t}}$ and the subgraph centrality of the location where the news originated.

We now turn to the relationship between centrality and volatility dynamics. The total amount of volatility to be incorporated from 0 to T is $\sigma_R^2(\sigma_\epsilon^2 + \sigma_R^2)^{-1/2}$. The cumulative volatility of price changes from date 0 to date t is

$$\sum_{s=1}^{t} \sigma_{\Delta P_s} = \frac{F_t \sigma_R^2}{\sigma_\epsilon^2 + F_t \sigma_R^2} \sqrt{\sigma_\epsilon^2 + \sigma_R^2}. \tag{B.15}$$

Thus the amount of volatility yet to be incorporated at time t is

$$\sum_{s=t+1}^{T} \sigma_{\Delta P_s} = \frac{\sigma_\epsilon^2 \sigma_R^2}{\sqrt{\sigma_\epsilon^2 + \sigma_R^2}} \frac{1 - F_{\hat{t}}}{\sigma_\epsilon^2 + F_{\hat{t}} \sigma_R^2}. \tag{B.16}$$

It follows from Equation (B.16) that news from a more central subgraph is quickly absorbed into prices and leaves less residual volatility at each given point of time; therefore, the impact of news on volatility decays faster.

Volume Dynamics We next solve for trading volume. We first express trading volume for the informed and uninformed investors as the absolute changes in their holdings from the previous period, respectively:

$$\begin{aligned}
\forall i \in I_{t-1} \cap I_t : \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^I| = \frac{(F_t - F_{t-1})\left(\sigma_R^2 + \sigma_\epsilon^2\right)}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|; \\
\forall i \in U_{t-1} \cap I_t : \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^U| = \frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1 - F_t)\,\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|; \\
\forall i \in U_{t-1} \cap U_t : \quad & |\Delta x_t^{(i)}| = |x_t^U - x_{t-1}^U| = \frac{(F_t - F_{t-1})\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|.
\end{aligned}$$

The average trading volume at time t is therefore:

$$\begin{aligned}
V_t &= \frac{1}{2}\left(F_{t-1}|x_t^I - x_{t-1}^I| + (F_t - F_{t-1})|x_t^I - x_{t-1}^U| + (1 - F_t)|x_t^U - x_{t-1}^U|\right) \\
&= (F_t - F_{t-1}) \frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1 - F_t)\,\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|. \qquad \text{(B.17)}
\end{aligned}$$

As assumed earlier, if $\sigma_\epsilon^2 \ll \sigma_R^2$, volume can be approximated as:

$$V_t \approx \frac{\Delta F_t}{F_t} \times \frac{|Y - \bar{R}|}{\sigma_R^2}. \tag{B.18}$$

As mentioned earlier, as F_t is increasing with t for a certain number of periods and obtains a value of one afterwards, we can express F_t as $F(t)$, a cumulative distribution function where

$t = 0, 1, 2, \ldots, T$, $F(t) = F_t$ and $F(T) = 1$, we have:

$$F_t = \prod_{s=t+1}^{T} (1 - \lambda_s), \tag{B.19}$$

where $\lambda_t = \frac{\Delta F_t}{F_t}$ is the *reverse hazard rate*. The above equality implies a reverse relationship between F_t and subsequent λ_s with $s = t+1, \ldots, T$. That is, trading volume within $[0, \hat{t}]$ is determined by λ_s for $s = 1, \ldots, \hat{t}$, which can be expressed as:

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

Assume that $\lambda(s)$ is small, and we can approximate the above expression using Taylor expansion as: $\frac{F_0}{F_{\hat{t}}} = \exp\left(\sum_{s=1}^{\hat{t}} \log(1 - \lambda_s)\right) \approx \exp\left(-\sum_{s=1}^{\hat{t}} \lambda_s\right) = \exp\left(-\sum_{s=1}^{\hat{t}} \frac{\Delta F_s}{F_s}\right)$. Hence, $F(t)$ is positively associated with $\lambda(s)$ for $s = 1, \ldots, \hat{t}$.[38] Then the cumulative trading volume within $[0, \hat{t}]$ becomes

$$\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{\sigma_R^2} \log\left(\frac{F_{\hat{t}}}{F_0}\right) |Y - \bar{R}|. \tag{B.20}$$

Hence, the higher the value of $F_{\hat{t}}$, the stronger the immediate volume reactions.

Similarly, applying Taylor's expansion to Equation (B.19) and approximating the post-announcement period volume, we can show that post-announcement period volume tends to be weaker if $F_{\hat{t}}$ is large:

$$\sum_{s=\hat{t}+1}^{T} V_s \approx \frac{1}{\sigma_R^2} \log\left(\frac{1}{F_{\hat{t}}}\right) |Y - \bar{R}|. \tag{B.21}$$

Equation (B.21) further suggests that a higher F_t corresponds to a more rapid convergence of investor beliefs and lower residual trading volume at any point in time, which implies that volume is also less persistent.

We summarize the implications of Scenario 1 as below:

Scenario 1 Predictions *When investors have common priors and identical interpretation of news, then public news that diffuses from a more central subgraph generates:*

1. *stronger immediate price reactions and weaker post-announcement price;*

[38] This approximation holds exactly if $F(t)$ is continuous and admits a probability density function $f(t)$: $F(t) = \exp\left(-\int_t \lambda(s) ds\right)$, where $\lambda(s) = f(s)/F(s)$ is the reverse hazard rate for $F(t)$. When there is no pre-announcement leakage, that is $F_0 = 0$, then $V_1 = \frac{F_1(1-F_1)}{F_1 \sigma_R^2 + \sigma_\epsilon^2} |Y - \bar{R}| \approx \frac{1-F_1}{\sigma_R^2} |Y - \bar{R}|$. And when F_1 is large, $V_1 \approx -\log(F_1) \frac{1}{\sigma_R^2} |Y - \bar{R}|$. With this, we can rewrite Equation (B.20) as $\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{\sigma_R^2} log(F_{\hat{t}}) |Y - \bar{R}|$.

2. *less-persistent return volatility; and*
3. *stronger immediate volume reactions, followed by lower post-announcement volume that is also less persistent.*

Scenario 2: Heterogenous Prior and Static Disagreement

In the second scenario, we assume that earnings news triggers investor disagreement about the asset valuation. This can be either because investors have different priors about the valuation or, because they interpret information differently (see, e.g., Kim and Verrecchia 1991, Harris and Raviv 1993, Kandel and Pearson 1995, Scheinkman and Xiong 2003). This disagreement is static in the sense that investors perform a one-time belief update upon observing the news. The investors' beliefs, once updated, remain unchanged until the arrival of the next piece of news. We show that this setting, the relationship between centrality and price, volatility, and volume dynamics are very similar to those of Scenario 1.

Specifically, investor i believes that $R \sim \mathcal{N}(\bar{R}^{(i)}, \sigma_R^2)$. And $\bar{R}^{(i)}$ follows normal distribution $\mathcal{N}(\bar{R}, \eta)$. In addition, investors also interpret the public signal differently. Following Banerjee and Kremer (2010), we assume that investor i's belief of the public signal is given by

$$Y = R + \epsilon, \quad \epsilon \sim \mathcal{N}(e^{(i)}, \sigma_\epsilon^2),$$

where $e^{(i)}$ denotes investor i's idiosyncratic interpretation of the signal noise. For simplicity, we assume that $e^{(i)}$ follows the binary distribution of $(-\bar{e}, +\bar{e})$ with equal probabilities.

Price and Volatility Dynamics At $t = 0$, investors' demands are determined by their priors, and the price aggregates the heterogeneous prior means.

$$x^{(i)} = \frac{\bar{R}^{(i)} - P_0}{\sigma_R^2}, \tag{B.22}$$

$$P_0 = \bar{R}. \tag{B.23}$$

For $t \geq 1$, the demand function depends both on investors' priors as well as the differential interpretations of the news:

$$i \in I_t : x_t^{(i)} = \frac{\sigma_\epsilon^2(\bar{R}^{(i)} - P_t) + \sigma_R^2(Y - e^{(i)} - P_t)}{\sigma_\epsilon^2 \sigma_R^2}; \tag{B.24}$$

$$i \in U_t : x_t^{(i)} = \frac{\bar{R}^{(i)} - P_t}{\sigma_R^2}. \tag{B.25}$$

Imposing the market-clearing condition,

$$\int_{i \in I_t} \frac{\sigma_\epsilon^2(\bar{R}^{(i)} - P_t) + \sigma_R^2(Y - e^{(i)} - P_t)}{\sigma_\epsilon^2 \sigma_R^2} di + \int_{i \in U_t} \frac{\bar{R}^{(i)} - P_t}{\sigma_R^2} di = 0, \tag{B.26}$$

the price can be solved by

$$P_t = \frac{\sigma_\epsilon^2 \bar{R} + F_t \sigma_R^2 Y}{\sigma_\epsilon^2 + F_t \sigma_R^2}. \tag{B.27}$$

Note that the equilibrium price is identical to Equation (B.10) in scenario 1 with homogeneous priors and identical interpretation of news. This is because differences in investors' demands cancel each other and do not affect equilibrium prices. As such, investment disagreement does not change any of the predictions on the price reactions or volatility persistence.

Volume Dynamics Regarding trading volume, when the newly informed investors trade with the previously informed investors and the uninformed investors, their corresponding trading volume is:

$$\begin{aligned}
\forall i \in I_{t-1} \cap I_t: \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^I| = \frac{(F_t - F_{t-1})\left(\sigma_R^2 + \sigma_\epsilon^2\right)}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|; \\
\forall i \in U_{t-1} \cap I_t: \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^U| = \left| \frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1 - F_t)\,\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} (Y - \bar{R}) - \frac{e^{(i)}}{\sigma_\epsilon^2} \right|; \\
\forall i \in U_{t-1} \cap U_t: \quad & |\Delta x_t^{(i)}| = |x_t^U - x_{t-1}^U| = \frac{(F_t - F_{t-1})\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|.
\end{aligned}$$

Trading volume is otherwise identical to the baseline model except for the disagreement-driven component of volume, $e^{(i)}/\sigma_\epsilon^2$, which is due to the newly informed investors.

Total trading volume is thus

$$V_t = V_t^B + \max\left((F_t - F_{t-1}) \frac{\bar{e}}{2\sigma_\epsilon^2} - \frac{1}{2} V_t^B, 0 \right), \tag{B.28}$$

where V_t^B is the same as Equation (B.17) of Scenario 1, which corresponds to the component driven by information diffusion. The additional term, $\max\left((F_t - F_{t-1}) \frac{\bar{e}}{2\sigma_\epsilon^2} - \frac{1}{2} V_t^B, 0 \right)$, reflects the disagreement-driven volume component and leads to the decoupling of the price and volume relation.

Given the earlier assumption $\sigma_\epsilon^2 \ll \sigma_R^2$, we have $V_t^B \approx \frac{1}{\sigma_R^2} \frac{\Delta F_t}{F_t} |Y - \bar{R}|$. Suppose that disagreements are nontrivial, i.e., $\bar{e} > \frac{\sigma_\epsilon^2}{\sigma_R^2} \frac{1}{F_1}$ such that the second component in Equation (B.28) is always positive for all t. Then the volume becomes

$$V_t \approx \frac{1}{2\sigma_R^2} \frac{\Delta F_t}{F_t} |Y - \bar{R}| + \Delta F_t \frac{\bar{e}}{2\sigma_\epsilon^2} \quad t = 1, 2, \ldots, T, \tag{B.29}$$

and the volume–price relation is

$$V_t \approx \frac{F_{t-1}}{2\sigma_\epsilon^2} |\Delta P_t| + \Delta F_t \frac{\bar{e}}{2\sigma_\epsilon^2} \quad t = 1, 2, \ldots, T. \tag{B.30}$$

The immediate trading volume reactions for the period $[0, \hat{t}]$ and for the post-announcement period volume are therefore

$$\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{2\sigma_R^2} \log\left(\frac{F_{\hat{t}}}{F_0}\right) |Y - \bar{R}| + F_{\hat{t}} \frac{\bar{e}}{2\sigma_\epsilon^2}, \quad \text{and}$$

$$\sum_{s=\hat{t}+1}^{T} V_s \approx \frac{1}{2\sigma_R^2} \log\left(\frac{1}{F_{\hat{t}}}\right) |Y - \bar{R}| + (1 - F_{\hat{t}}) \frac{\bar{e}}{2\sigma_\epsilon^2}.$$

From the above equations, it is evident that there are two components to the trading volume: the first component is the baseline volume as in Scenario 1 and the second component is due to disagreement. News from the high-centrality node spreads to a broader set of investors more quickly, so opinion differences develop more quickly, resulting in larger immediate volume reactions. Also, the number of investors unaware of the news decreases more quickly, leaving less scope for opinion differences and trading activities for the future periods. In consequence, both components of the trading volume decay more rapidly when more investors receive the earnings news. Therefore, the higher the centrality, the more quickly the effects of news on both trading volume and volatility dissipate. So there is a negative relation between centrality and the persistence of volume and volatility (similar to Scenario 1).

We summarize the implications of Scenario 2 below:

Scenario 2 Predictions *When investors have heterogeneous priors and if their disagreement is static, then public news that diffuses from a more central subgraph generates:*

1. *stronger immediate price reactions and weaker post-announcement price drifts;*
2. *less-persistent return volatility; and*
3. *stronger immediate volume reactions, followed by lower and less-persistent post-announcement volume.*

Scenario 3: Social Churning and Fluctuating Disagreement

In the third scenario, we extend the second scenario and consider a setting in which social interactions generate stochastic disagreement among the investors. We show that this setting provides an unified explanation to the dynamics of prices and volume that we observe.

Specifically, we propose that investors who become aware of the public signal continue to discuss news with their social network friends and those conversations lead to idiosyncratic misinterpretations.[39] That is, for $i \in I_t$, his belief of the public signal at t is given by

[39] As mentioned earlier, this setup is motivated by theories that suggest social interactions can lead to disagreements (e.g., Shiller 2000, Han, Hirshleifer, and Walden 2021, Jackson, Malladi, and McAdams (2021). Furthermore, there is also evidence that investors respond irrationally to the republication of old news (Huberman and Regev 2001, Tetlock 2011, Gilbert et al. 2012, and Fedyk and Hodson 2022). Additionally, social interactions trigger echo chamber effects among investors (Cookson, Engelberg, and Mullins 2023).

$$Y = R + \epsilon_t, \quad \epsilon_t \sim \mathcal{N}(e_t^{(i)}, \sigma_\epsilon^2),$$

where $e_t^{(i)}$ denotes investor i's interpretation of the signal noise at time t. $e_t^{(i)}$ follows a random walk

$$e_t^{(i)} = e_{t-1}^{(i)} + \xi_t^{(i)}, \tag{B.31}$$

where $\xi_t^{(i)}$ is independent over time and across investors and follows a binary distribution $(-\bar{\xi}, +\bar{\xi})$ with equal probabilities. Essentially, $\xi_t^{(i)}$ corresponds to additional disagreement generated by social interactions. We postulate that the sustained discussions last for the post-announcement window and generate continuing shifts in investor disagreement.[40]

It can be easily shown that the stochastic disagreements cancel out in the market clearing process and leave the price identical to that of Scenarios 1 and 2. However, the trading volume of investors is distinctively different:

$$\begin{aligned}
\forall i \in I_{t-1} \cap I_t: \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^I| = \left| \frac{(F_t - F_{t-1})\left(\sigma_R^2 + \sigma_\epsilon^2\right)}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)}(Y - \bar{R}) - \frac{\xi_t^{(i)}}{\sigma_\epsilon^2} \right|; \\
\forall i \in U_{t-1} \cap I_t: \quad & |\Delta x_t^{(i)}| = |x_t^I - x_{t-1}^U| = \frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1 - F_t)\,\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)}|Y - \bar{R}|; \\
\forall i \in U_{t-1} \cap U_t: \quad & |\Delta x_t^{(i)}| = |x_t^U - x_{t-1}^U| = \frac{(F_t - F_{t-1})\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)}|Y - \bar{R}|.
\end{aligned}$$

The total trading volume becomes

$$V_t = V_t^B + F_{t-1} \max\left(\frac{\bar{\xi}}{2\sigma_\epsilon^2} - \frac{(F_t - F_{t-1})\left(\sigma_R^2 + \sigma_\epsilon^2\right)}{2\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)}|Y - \bar{R}|, 0 \right). \tag{B.32}$$

If social interactions generate substantially greater opinion divergence than the initial disagreement of investors (that is, $\bar{\xi}$ is large relative to σ_ϵ^2), then $\frac{\bar{\xi}}{\sigma_\epsilon^2}$ is large enough so that the second component in Equation (B.32) is positive for all t. Given the earlier assumption that $\sigma_\epsilon^2 \ll \sigma_R^2$, volume can be approximated as

$$V_t \approx \frac{1}{2\sigma_R^2}\frac{\Delta F_t}{F_t}|Y - \bar{R}| + F_{t-1}\frac{\bar{\xi}}{2\sigma_\epsilon^2} \quad t = 1, 2, \ldots, T, \tag{B.33}$$

[40] To match the horizon of our empirical analysis, we assume that there is sustained discussion in the post-announcement window. In reality, one would expect investors' attention to an announcement to decay over time owing, for example, to the occurrence of further unrelated events. This could be modeled by assuming exponential decay of attention. In such a model, we would still expect to see a similar positive relationship between news centrality and the persistence of trading volume for at least a substantial number of days before the eventual decay.

and the volume-price relation is

$$V_t \approx \frac{F_{t-1}}{2\sigma_\epsilon^2}|\Delta P_t| + F_{t-1}\frac{\bar{\xi}}{2\sigma_\epsilon^2} \quad t = 1, 2, \ldots, T. \tag{B.34}$$

The second components on the right-hand side of these two equations are the excessive trading volumes triggered by social interactions.

We now characterize the relation between subgraph centrality and volume dynamics. The cumulative volume for the two-day announcement period and for the post-announcement period are

$$\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{2\sigma_R^2}\log\left(\frac{F_{\hat{t}}}{F_0}\right)|Y - \bar{R}| + \sum_{s=1}^{\hat{t}} F_{t-1}\frac{\bar{\xi}}{2\sigma_\epsilon^2},$$
$$\sum_{s=\hat{t}+1}^{T} V_s \approx \frac{1}{2\sigma_R^2}\log\left(\frac{1}{F_{\hat{t}}}\right)|Y - \bar{R}| + \sum_{s=\hat{t}+1}^{T} F_{t-1}\frac{\bar{\xi}}{2\sigma_\epsilon^2}.$$

As investors continue to discuss the stock in their social interactions, their stochastic disagreements continue to cross and generate sustained trading activities that are strictly increasing in subgraph centrality. If this disagreement-driven component dominates, then news from high-centrality areas will generate both higher and more-persistent trading volume.

We summarize the implications of the social churning hypothesis below:

Scenario 3 Predictions *When social interactions trigger sustained investor attention and fluctuations in disagreement, then public news that diffuses from a more central subgraph generates:*

1. *stronger immediate price reactions and weaker post-announcement price drifts;*
2. *less-persistent return volatility; and*
3. *stronger immediate volume reactions, followed by higher and more persistent post-announcement volume.*