News Diffusion in Social Networks and Stock Market Reactions

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Abstract

We study how the social transmission of public news influences investors' beliefs and securities markets. Using an extensive dataset to measure investor social networks, we find that earnings announcements from firms in higher-centrality locations generate stronger immediate price and trading volume reactions. Post announcement, such firms experience weaker price drifts but higher and more persistent volume. This evidence suggests that while greater social connectedness facilitates timely incorporation of news into prices, it also triggers opinion divergence and excessive trading. We provide a model of these effects and present further supporting evidence with granular data based on StockTwits messages and household trading records.

JEL Codes: G1, G4

Keywords: Social Networks, Information Diffusion, Earnings Announcement, Investor 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 observed in markets. 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."

How social interactions propagate information and influence investor beliefs and decisions remains an open question. In models of rational learning with social information transmission, social interactions improve trading decisions and improve market efficiency. However, social interactions can generate information cascades in which individuals do not make use of their private signals, giving rise to free-riding incentives in information sharing. Furthermore, in models with imperfectly rational investors, social interactions can propagate incorrect beliefs or naïve trading strategies, reducing information efficiency.[1]

We study here how social networks influence the dissemination of a crucial type of public news— corporate earnings announcements. An extensive literature finds that stock prices do not incorporate this news in a timely fashion, leaving a substantial portion of the news to be absorbed over the next several months (e.g., Ball and Brown 1968). The leading explanation for this phenomenon is that information frictions, such as limited investor attention to the news, prevents the timely incorporation of the news by a broad set of investors.[2] This paper explores how social transmission of this news among investors affects the speed of information diffusion, investors' opinions and trading decisions, and asset prices.

Motivated by Banerjee et al. (2013, 2019), who provide evidence that information transmits faster when signals are seeded at central nodes of a network, we postulate that earnings news transmits faster through the social network when the senders reside in high-centrality locations in the network of investors. Our premise is that investors are more attentive to news about local firms.[3] We therefore expect that earnings news attracts the attention of

[1] For rational learning models, see, for example, Ellison and Fudenberg (1995) and Colla and Mele (2010). For models of information cascades and free-riding incentives see Bikhchandani, Hirshleifer, and Welch (1992), Banerjee (1992), Han and Yang (2013), and Goldstein, Xiong, and Yang (2021). For models with imperfectly rational investors, see DeMarzo, Vayanos, and Zwiebel (2003) and Hirshleifer (2020).

[2] See, for example, Hirshleifer, Lim, and Teoh (2009) and DellaVigna and Pollet (2009).

[3] For evidence that local investors are more likely to hold the stocks of local firms and are more attentive to news about the firm, see, for example, Coval and Moskowitz (1999), Feng and Seasholes (2004), Ivković

local investors first, and then this news disseminates across the network of investors via word-of-mouth discussion. In consequence, earnings announcements made by firms based in locations with greater investor social network centrality tend to diffuse more quickly. To capture this, 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.

Consistent with our hypothesis, we find that earnings announcements by firms based in high-centrality locations tend to generate stronger immediate stock price, volatility, and trading volume responses. Notably, however, for such firms, the post-announcement volume remains high and persistent, whereas post-announcement returns exhibit weaker drift and faster volatility decays.

The striking contrast is not explained by classic frameworks, which would suggest a faster decay in both volatility and trading volume for such announcements. These findings raise the question of why greater social interactions lead to heavier trading but less post-announcement drift. As shown by Odean (1999), retail investors as a group tend to trade excessively, suggesting losses from behavioral biases. There is also evidence that investors are imperfectly rational in their responses to news. This suggests that there may be biases in investor responses to information gleaned from discussions with other investors. Different discussions may trigger different belief updates among different investors, causing disagreements to shift. This possibility is plausible in view of survey evidence of 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. The authors further suggest that "models that explicitly feature heterogeneous agents with different beliefs are likely to offer a fruitful starting point for future work" (p. 1484).

To understand more deeply how social interactions contribute to belief divergence and trading, we develop a model of information diffusion through a social network and belief updating when investors have limited attention. In the model, while the social transmission of earnings news brings this information to investors' attention, thereby promoting the incorporation of earnings information into price, this transmission also triggers persistent fluctuations in their disagreement in firm valuations. We show that the model offers a unified explanation for the contrasting dynamics of return, volatility, and trading volume. To evaluate the model, we use granular data based on StockTwits messages and household

and Weisbenner (2005, 2007), Seasholes and Zhu (2010), and Chi and Shanthikumar (2017).

trading records together with information about Google search activities. We provide evidence consistent with the predictions of the model about how social connectedness affects the dynamics of investor attention, belief formation, and trading.

More specifically, our empirical measure of the social network of investors uses the newly available Social Connectedness Index (SCI), provided by Bailey et al. (2018b), which captures the strength of social ties between investors across different U.S. counties. The measure corresponds to the aggregated and anonymized number of Facebook friendship links between two counties. As the world's largest online social networking service, Facebook's scale and the relative representativeness of its user body make the SCI a comprehensive measure of the geographic structure of U.S. social networks.[4] The centrality of a firm is therefore the centrality of its headquarters county in the matrix of SCIs between county pairs.

We first focus on price dynamics: short-term returns immediately after the announcement, post-announcement return drift, and the persistence of return volatility post-announcement. We find that earnings announcements of more centrally located firms are associated with greater immediate price reactions and weaker post-announcement drift. Compared to announcements made by firms located in the lowest degree centrality decile, announcements by firms located in the highest decile are associated with 28.6% stronger immediate price reactions, 20.1% weaker post-announcement drifts, and 11.0% lower volatility persistence, all relative to their respective sample averages. These results suggest that earnings news from more centrally located firms is more rapidly incorporated into their stock prices. Hence greater centrality in the social network may help facilitate the dissemination of relevant information and improve the information efficiency of asset prices.

We next turn to the implications of network centrality for the dynamics of trading volume. As with the tests on price dynamics, we examine volume immediately after the announcement, during the post-announcement period, and the post-announcement volume persistence. The transmission of earnings news between investors changes their opinions about asset valuation and thereby induces trading.[5] To the extent that news from firms that are

[4]Facebook had 243 million active users in the U.S. and Canada as of the end of 2018. A 2018 survey showed that 68% U.S. adults use Facebook, that roughly three-quarters of them visit the site daily, and that users span across a wide range of demographic groups (except for those 65 and older) (Smith and Anderson 2018). In addition, Duggan et al. (2015), Bailey et al. (2018a, 2019, 2020a,b) and Chetty et al. (2022) provide strong evidence that friendships observed on Facebook are a good proxy for real-world social connections and reflect long-run historic ties such as those due to migration of people and borders of historic empires.

[5]The arrival of news may trigger trading when investors have heterogeneous priors (Karpoff 1987, Kim and Verrecchia 1991) or different interpretations of the news (Harris and Raviv 1993, Kim and Verrecchia

more centrally located reaches more investors more quickly, we expect stronger immediate volume responses to that news. Consistent with this prediction, we find that earnings news from firms that are more centrally located on average generates stronger immediate trading volume responses than news from firms located in low-centrality regions. An increase in centrality from the lowest decile to the highest decile increases the immediate volume reaction to earnings news by 11.90% relative to the sample mean.

Post announcement, however, we find a striking positive relation between centrality and the level and the persistence of trading volume. An increase in centrality from the lowest decile to the highest decile is associated with a 14.7% increase in post-announcement volume and a 10.3% increase in volume persistence, relative to their respective sample mean. The pattern contrast sharply with the negative relation between centrality and post-announcement returns and volatility persistence. The results suggest that more-intense social transmission of important public news may generate excessive and persistent trading of the stock.

The striking contrast in how centrality is associated with price reaction and volume reaction poses a challenge to traditional models in which investors either have homogeneous beliefs or static heterogeneous beliefs. These models would predict that earnings announcements from higher-centrality locations, as the news is diffused more rapidly across a broader set of investors, should be associated with lower post-announcement return drift and trading volume, as well as less persistent volatility and volume.

To address this challenge, we explore a unique feature of social transmission of news, which is that discussions may continue to influence people's beliefs even in the absence of new information, and extend the static heterogeneous beliefs model to incorporate stochastic belief formations. In the model, social interactions accelerate the transmission and cognitive processing by investors of information. However, social interactions also amplify investor disagreement and generate persistent fluctuations in the disagreement, which leads to excessive and persistent trading. We show that the model offers a unified explanation for the divergent effects of centrality on price and volume dynamics documented in our tests. We describe the model intuition in the text and provide detailed proofs in the appendix.

We then dive deeper and provide direct tests of the key implications of the model. In the first test, we measure social interactions of investors by using a sample of more than 10 million messages on StockTwits. StockTwits is a popular social media platform for investors

1994, Kandel and Pearson 1995, Scheinkman and Xiong 2003).

to share their investment opinions. Recent papers have applied StockTwits data to provide granular evidence on the effect of social networks on investor belief formation (Cookson and Niessner 2020, Cookson, Engelberg, and Mullins 2022).

We classify StockTwits messages into two categories. New Messages corresponds to the number of initial message mentions of a stock in a thread; Replies refers to the number of replies to the initial messages. We argue that New Messages proxies for the number of newly informed investors, whereas Replies proxies for the intensity of subsequent discussions on StockTwits.

To illustrate, consider two firms, BOFI Holding and Univest. BOFI is a savings bank located in San Diego County in California, which is one of the top-ten-centrality counties. Univest is a similar-sized savings bank, but it is located in a low-centrality county, Montgomery, Pennsylvania. The two banks shared similar characteristics and experienced comparable earnings surprises during our sample period. Figure 1 displays the dynamics of New Messages and Replies around the earnings announcements. The figure shows that New Messages and Replies both surge higher immediately upon the release of earnings news for BOFI compare to Univest. However, for the rest of the 60 day period post the BOFI announcement, New Messages quickly decays whereas Replies remain elevated.

Our statistical analysis confirms the patterns illustrated in our example of BOFI and Univest. Announcements by firms located in more-central counties trigger a larger initial increase in New Messages than announcements by less-central firms. Furthermore, for high-centrality news, the initially larger increase in New Messages is followed by a more precipitous drop, whereas Replies remains elevated throughout the post-announcement period. Specifically, an increase in centrality from the lowest to the highest decile increases New Messages by 7.8% in the announcement window but reduces the post-announcement New Messages by a substantial 90% relative to the corresponding sample mean. For Replies, the same change in centrality increases the Replies in both the announcement and the post-announcement window, by 12.1% and 12.0%, respectively. These results are consistent with a key implication of the model that, while earnings news from high-centrality firms quickly disseminates across different investors, the news continues to attract more investor attention and generate more-persistent intense discussions among investors post announcement.

We then test the second key implication of the model: social interactions contribute to persistent disagreement. We conduct textual analysis to each StockTwits message and then construct a daily measure of belief divergence at the stock level as the daily range of the message sentiments. Our regression analysis shows that, compared to earnings announcements by low-centrality stocks, the high-centrality announcements are associated with significantly more-divergent beliefs across investors, by 6.12% and 6.76% for the announcement and post-announcement period, respectively, relative to the corresponding sample mean. These findings therefore support the model's mechanism of social-based belief heterogeneity.

We complement the StockTwits-based findings with an additional analysis using the more representative, albeit less granular, measure of retail investor attention—Google searches of a stock's ticker symbols (Da, Engelberg, and Gao 2011). We find that announcements made by firms from high-centrality areas trigger a greater increase in abnormal Google searches, by 29.0% and 18.9% in the announcement and the post-announcement window, respectively. These increases are more persistent than the announcements made by low-centrality firms. These tests further support our hypothesis that news from high-centrality locations attracts more attention and more persistent attention from investors than news from low-centrality locations.

We next test the third key implication of the model, which is that investors from counties that have stronger social ties with a firm's county are more likely to trade on the firm's earnings announcements. To test this, we follow Barber and Odean (2000) and use individual account-level data from a large discount brokerage in the U.S. and find strong support for this implication. An increase in the social ties between the locations of a household and that of an announcing firm from the 10^{th}percentile to the 90^{th} percentile increases the household trading likelihood by 8.8% and 8.5% for the announcement and post-announcement windows, respectively, relative to the respective means. The corresponding increases in the number of trades are 10.4% and 14.6%. Similarly, the increases in relative trade size are 18.4% and 25.4% for the two windows.

Last, we examine the profitability of households' trading following earnings announcements. Barber and Odean (2000) show that individual households tend to lose money on their trades. We find that the households in counties sharing stronger social ties with the county of the announcing firm suffer greater losses post announcement. An increase in the social ties from the 10^{th}percentile to the 90^{th} percentile increases trading losses by 16.6% relative to the sample mean. The evidence is consistent with the implication of the model that excessive trading reflects investors' incorrect beliefs.

The granularity of the household-trade level data allows us to control for a multitude of household characteristics and enables the use of firm and household fixed effects. These controls and fixed effects are therefore helpful in accounting for omitted factors that may contribute to our findings (see, e.g., Altonji, Elder, and Taber 2005, Oster 2019).

Overall, the evidence based on the analysis of StockTwits messages, Google searches, and household trading activities provides strong support for the mechanisms outlined in our model. That is, social interactions help overcome information frictions and direct investor attention to important news announcements, but these interactions also generate persistent belief divergence and therefore lead to excessive trading.

To further address causality, we exploit an exogenous shock, Hurricane Sandy, which resulted in interruptions to social interactions that differed across investors. Sandy, the second-costliest hurricane in U.S. history, whose landfall in the Mid-Atlantic region on October 22, 2012, resulted in $71.4 billion in damages, led to major flooding in New York City's transportation systems, destroyed thousands of homes, and left six million people without power. The storm therefore disrupted information flow between the affected areas and the rest of the country. We focus on earnings announcements made during the storm period by firms located in areas that were not directly affected by Sandy. We measure the degree to which the counties of firms' headquarters were connected to the affected areas based on the number of friendship links those counties have with the Mid-Atlantic states. We find that, during the Sandy period, during which social information flow was disrupted, the association was substantially weakened for firms headquartered in high-connection counties relative to firms in low-connection counties. This result suggests that the positive relation between centrality and more swift price reactions upon earnings releases is likely driven by the social transmission of news rather than omitted county characteristics.

We provide several additional robustness checks. We show that our results are robust to alternative persistence measures. The results are not driven by media coverage nor by the geographical dispersion of a firm's subsidiaries. Our findings are also robust with respect to excluding firms located in the U.S. tri-state area of New York, New Jersey, and Connecticut. We further examine a residual investor social network centrality measure by orthogonalizing with respect to a set of county-level characteristics. The conclusions of the analysis are unchanged. In addition, the effect is not subsumed by measures of local bias, nor by spatial network centrality based on geographical distance across regions.

Overall, these results provide—to the best of our knowledge—the first evidence that social network structure can help explain a rich set of asset price and trading volume dynamics around the arrival of public news. These patterns are difficult to explain with traditional models.

The relatively comprehensive nature of the newly available Facebook social networks dataset permits addressing new questions about social interactions and individual decisions. Earlier studies of social networks focus on specific sets of participants.[6] The Facebook based measure of social networks allows researchers to address the issue of whether social networks affect aggregate outcomes. For example, Kuchler et al. (2020) find that an area's social proximity to institutional providers of capital increases the valuations and stock liquidity of companies located in the area. Bailey et al. (2021) find that social connectedness predicts international trade. Chetty et al. (2022) use data on the social networks of Facebook users to provide insight about the relationships between upward income mobility and racial segregation, poverty rates, and inequality. Our paper differs from these studies in examining the effects of social connectedness on the dynamics of market-level financial beliefs, pricing, and trading.

A growing literature explores the role of beliefs in explaining economic outcomes as reviewed by DellaVigna (2009) and Benjamin (2019). Several recent papers study how social networks shape investor beliefs. Bailey et al. (2018a) and Bailey et al. (2019) find that social interactions affect people's housing market expectations and decisions.[7] More recently, Cookson, Engelberg, and Mullins (2022) show that social networks can trigger "echo chambers" in investor opinion formation and contribute to higher volume. As discussed earlier, Giglio et al. (2021) find strong survey evidence that retail investor have large and persistent belief differences.

Our paper adds to the emerging literature in two ways. First, it shows that social interactions play an important role in belief formation, including the generation of disagreement after public news arrival. Second, it shows that social mechanisms offer a unified explanation for why the dynamics of return versus volume responses to earnings announcements are so different.

[6]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). In addition, there is research on social interactions and managerial decision making (Shue 2013), on the performance of sell-side financial analysts (Cohen, Frazzini, and Malloy 2010), and on lottery sales (Mitton, Vorkink, and Wright 2018).

[7]In addition, Bailey et al. (2020c) find that individuals' beliefs and behaviors concerning the coronavirus are influenced by their social network exposure to COVID-19 cases.

Our paper also contributes to the literature on investor attention. Previous studies proposed a number of determinants of attention, including characteristics of the stimulus (Kahneman 1973, Fiske and Taylor 1991), bounded rationality (Gabaix and Laibson 2005), rational allocation (Sims 2003, Peng 2005, Peng and Xiong 2006, Kacperczyk, Nieuwerburgh, and Veldkamp 2014, 2016), and exogenous distraction (Hirshleifer, Lim, and Teoh 2009, DellaVigna and Pollet 2009). Barber et al. (2021) show that fintech brokerages influence retail attention and induce excessive trading. Our findings suggest that attention is also socially transmitted, so that the investor social network centrality of a firm is positively associated with investors' attention to its 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 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) first introduced by Bailey et al. (2018b). This measure is the number of Facebook friendship links between two counties[8] and was created using anonymized information on the universe of friendship links between U.S.-based Facebook users as of April 2016. According to a 2018 survey of social media use (Smith and Anderson 2018), Facebook is the primary social media platform for most Americans across a

[8]The maximum value of the measure is 1,000,000, which is assigned to the Los Angeles-to-Los Angeles county pair.

wide range of demographic groups: 68% of U.S. adults report that they are Facebook users, whereas the rates are 25% and 24% for LinkedIn and Twitter, respectively. A 2015 survey by the Pew Research Center shows that a substantial number of Facebook users in the United States use the platform to communicate with their real-world friends and acquaintances (Duggan et al. 2015).[9] Compared to other online platforms where unidirectional links to non-acquaintances are common, networks formed on Facebook more closely resemble real-world social networks.[10]

We represent the structure of the investor social network by a matrix $S = \{s_{ij}\}_{N\times N}$, known as the *weighted adjacency matrix*, where N is the number of counties and $s_{ij} = \mathrm{SCI}_{ij}$. In general, centrality measures the prominence or importance of a node within a network. We construct three network centrality measures that have been commonly used in graph theory to characterize the extent to which a firm is in a highly connected position in the information transmission network of its potential investors.

The first measure, *degree centrality* (DC), measures the total number of neighbors associated with a particular node:

$$\mathrm{DC}_i = \sum_j s_{ij}. \tag{1}$$

Since DC only considers paths/walks of length of one, it is a measure of direct effects.

The second measure, *eigenvector centrality* (EC), accounts for the transmission of signals along longer paths and walks (Bonacich 1972, Borgatti 2005). Specifically, the EC of a node i is the ith element of the principal right eigenvector of the adjacency matrix. A node's EC is also proportional to the average centrality scores of its direct neighbors; a node is more central if it is adjacent to nodes that are themselves highly central. In contrast to DC, EC allows fully for indirect as well as direct social interactions.[11]

The third centrality measure is *information centrality* (IC), which was proposed by Stephenson and Zelen (1989). Like EC, IC allows for indirect social interactions. How-

[9] The survey shows that 93% of Facebook users say they are Facebook friends with family members (other than parents or children), 91% and 87% say that they are connected to current and past friends, respectively, 58% are connected to work colleagues, and 36% are friends with neighbors.

[10] See Bailey et al. (2018a,b, 2019, 2020a) on these points.

[11] Banerjee et al. (2013, 2019) employ a closely related measure, *diffusion centrality*, to study the participation in a microfinance program and the spread of rumors. Diffusion centrality captures how widely information from a given node i diffuses for a given period T. Diffusion centrality is proportional to DC when $T = 1$ and to EC when $T \to \infty$. We find that using diffusion centrality yields similar results to those of EC for a wide range of T ranging from 1 through 60 days.

ever, IC uses all paths to summarize the centrality of each node with the harmonic mean of its "informational" distance to the others. A short informational distance between two nodes indicates that they are connected by paths with fewer distinct links on average. Thus, a central node can spread information to other nodes with just a few steps. More specifically,

$$\mathrm{IC}_i = \left(\frac{1}{n} \sum_{j \neq i} d_{ij} \right)^{-1}, \tag{2}$$

where d_{ij}, the topological "informational" distance between node i and node j, is calculated as $(B^{-1})_{ii} + (B^{-1})_{jj} - 2\,(B^{-1})_{ij}$, where $B = (D + S - J)^{-1}$, S is the adjacency matrix, D is the diagonal matrix of the degree of each node, and J is a matrix of ones. We normalize the three centrality measures to have a maximum value of 100.

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.[12]

Returns and Trading Volume We define CAR as the cumulative buy-and-hold abnormal returns following earnings announcements, with the abnormal returns adjusted by size, B/M, and momentum following Daniel et al. (1997) (DGTW). CAR[0, 1] corresponds to the two-day announcement return and CAR[2, 61] corresponds to the cumulative buy-and-hold returns for the post-announcement period.[13] We define log abnormal volume (VOL) as the logarithm of the ratio between the average daily log number of shares traded for a given period and its pre-announcement average for the window of [–41, –11]. VOL[0, 1]

[12] 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.

[13] We define the post-announcement window ([2, 61]) as the period between day two of an announcement to five days before the next announcement. We obtain similar results for size-and B/M characteristics-adjusted abnormal returns.

and VOL[2, 61] correspond to the log abnormal volume during the announcement and the post-announcement period, respectively.[14]

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 B.

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) 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 advertisement 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 measure the amount of information that local investors may 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).[15]

[14] It's well documented that trading volume is highly skewed (see, e.g., Ajinka and Jain 1989, Bamber et al. 1997), hence log transformation helps to alleviate the variable's problematic departure from normality.

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

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.[16] 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 suggest that central counties are usually densely populated with young and mobile residents. We control for all these variables in our subsequent analysis.

[Insert Table 1 here]

Figure 2 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 2 here]

3 Centrality and Price Dynamics

We begin our empirical analysis by investigating the relationship between investor social network centrality and stock market reactions to earnings news. As mentioned, a large literature documents short-run price underreaction to earnings announcements, followed by post-announcement return drift that is most pronounced for about three months. We therefore

[16] 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.

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, 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 Drifts

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:

$$\text{CAR}_{i,t} = \alpha + \beta_1 \text{SUE}_{i,t} + \beta_2(\text{SUE}_{i,t} \times \text{CEN}_i) + \beta_3 \text{CEN}_i + \gamma X_{i,t} + \epsilon_{i,t}. \quad (3)$$

Here the dependent variable, CAR, is either the abnormal two-day earnings announcement returns (CAR[0, 1]) or the post-announcement cumulative abnormal returns (CAR[2, 61]). As discussed in Section 2, 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 firm- and county-level control variables described in Section 2.2 and their interactions with SUE.[17] 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

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

controls. The β_2 coefficient remains similar, 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.[18] A comparison of the estimated coefficients across the three specifications suggests that the explanatory power of SUE×CEN is unlikely to be driven by CEN's correlation with the list of firm and county characteristics that we control for.

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 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 (PEAD), 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.

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

[18] 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 $5.5 \times 0.0152 - 0.0909 = -0.0073$ and insignificant.

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 more centrally located firms generate stronger immediate price reactions and weaker post-announcement drift, potentially consistent with faster resolution of uncertainty. We therefore expect to see faster decay in the volatility reactions to earnings surprises in the post-announcement period. We therefore analyze the relationship between the social network centrality of the announcing firm and the volatility 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 $|R|$, the daily absolute returns from the day of the announcement to five days before the next announcement.[19] 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:

$$d_{|R|_{i,t}} = \alpha + \beta_1 \mathrm{CEN}_i + \beta_2 |\mathrm{SUE}|_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \tag{4}$$

where $|\mathrm{SUE}|$ is the decile rank of absolute SUE to control for the magnitude of earnings surprises, and X is the list of control variables described in Section 2.2.[20]

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

[19] Similarly, Da, Engelberg, and Gao (2014) apply the ARFIMA model to estimate the effect of the FEARS index on the volatility persistence of daily market returns. In Subsection 6.2, as a robustness check, we use an alternative measure of volatility persistence based on the AR(1) coefficient of daily absolute returns and obtain similar findings.

[20] Since $d_{|R|_{i,t}}$ is a measure of the volatility decay rate, not a measure of volatility, $|\mathrm{SUE}|_{i,t}$ here is just a control; there is no strong reason to expect an interaction between $|\mathrm{SUE}|_{i,t}$ and CEN_i.

earnings news shock on volatility is shorter-lived for firms in more-central locations.

[Insert Table 3]

Together 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 when investors have different priors or different interpretations of news (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 the post-announcement volume 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 how centrality is associated with the reactions of trading volume to earnings news, we analyze three characteristics of volume dynamics: immediate volume responses, post-announcement volume, and volume persistence.

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:

$$\mathrm{VOL}_{i,t} = \alpha + \beta_1 \mathrm{CEN}_i + \beta_2 |\mathrm{SUE}|_{i,t} + \gamma X_{i,t} + \epsilon_{i,t}, \tag{5}$$

where the dependent variables, VOL[0, 1] and VOL[2, 61], are the log abnormal volume during the announcement and the post-announcement period, respectively. |SUE| is the absolute earnings surprise decile rank, CEN is the county-level centrality measures, and X consists of all control variables mentioned in Section 2.2.

[Insert Table 4 here]

Table 4, columns (1)–(3) presents the two-day volume reactions immediately after the earnings announcement. These indicate shows 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 VOL[0, 1] by 0.076 to 0.091, or increases of 11.90% to 14.31% relative to its sample mean.

Evidence about the post-announcement 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 the centrality from the lowest to the highest decile increases VOL[2, 61] by 14.68% to 30.79% relative to the sample average.

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. We discuss a proposed explanation in Section 5. First, to provide more insights 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 post-announcement volume persistence using Equation (4) and replacing $d_{|\mathrm{R}|}$ with d_{VOL}. The results are presented in Table 4, columns (7)–(9). 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 an 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 of centrality and volatility persistence and 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. We next discuss the existing models and propose a new framework that jointly explains the price and volume dynamics in response to news.

5 A Framework of Information Diffusion via Social Interactions

In this section, we explore the mechanisms underlying the striking contrast between the dynamics of the reactions of prices versus trading volumes to earnings news. We first provide a framework of social network–based diffusion of news and consider three types of investor belief formation processes: 1) identical interpretation of news, 2) static disagreement, and 3) stochastic disagreement. We analyze how prices and volume reacts to news under each setting and show that the stochastic disagreement setting provides a unified explanation for our findings. We then provide additional empirical analysis to test key additional implications of the third setting.

5.1 The Model

We next offer a framework of gradual information diffusion via word-of-mouth social communications. We describe the model's setup and main intuition in the main text and present the technical details and proofs in the Appendix.

The model features a single risky asset with an uncertain terminal payoff and risk averse investors with quadratic utility functions. Investors are connected to each other in a social network and can be categorized into subnetworks that correspond to their geographic locations. At date 1, earnings news first reaches the subnetworks of investors that reside in the firm's headquarters county, who then broadcast the news to the investor's direct neighbours via word-of-mouth communications.[21] At each subsequent period, the newly informed investors transmit the news to their network neighbours. In this way, news socially diffuses from local investors to other investors. We further show that news transmits faster for announcements by firms located in higher-centrality locations—the number of investors who become aware of such news grows more rapidly initially, with the rate of growth falling more precipitously soon after, relative to lower centrality areas. The intuition is analogous to that of Banerjee et al. (2013, 2019), who show that news seeded from more-central nodes tend to transmit faster.

We then model the behavior of investors who react to news by updating their beliefs. We consider three possible assumptions. In the first case, investors update their beliefs using the earnings signal, following Bayes rule, and have identical interpretations of news.[22] We refer to this case as the baseline case. In this case, the faster diffusion of information from high-centrality locations results in faster incorporation of news, faster resolution of uncertainty, and faster volatility decay, followed by less-pronounced post-announcement return drifts. Similarly, the news from high-centrality locations triggers stronger immediate trading responses as investors rapidly update their beliefs upon receiving the news, followed by lower trading activities and less-persistent volume post announcement. The prediction of a negative relation between centrality and the persistence of both volume and volatility is at odds with our findings.[23]

In the second case, 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. Based on the belief update, investors take trading positions that reflect the extent to which they disagree. There are two components to the trading volume: the first component is the baseline volume as in case one and the second component is due

[21] As mentioned in the introduction, the assumption is based on extensive evidence of local bias in investors attention and stockholding.

[22] We assume that the investors do not learn from prices.

[23] Using an alternative setup in which informed traders share their private signals in an information network, Walden (2019) shows a similar negative relation between network connectedness and the persistence of return volatility and trading volume.

to disagreement.

In this case, 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 case 1).

These predictions are not supported by our finding that higher centrality of a firm's location is associated with more-persistent trading. Therefore, traditional models of information networks with either homogeneously informed agents (as in case 1) or agents with static disagreement about the earnings news (as in case 2) cannot explain our empirical findings.

In the third case, we extend the second case by considering a setting of *stochastic disagreement*. Earnings news does not just triggers initial investor disagreement about the asset value. Disagreement between different investors continues to fluctuate as a result of social interactions. An investor's opinions can change each time the investor discusses the news with others, resulting in continuing irrational belief fluctuations. We postulate that the sustained discussions last for a period of up to 61 trading days. As in the second case, trading volume thus has two components, with one corresponding to the baseline volume and one related to disagreement. But in contrast with the second case, the second component increases with the number of investors that have received the news. Over time, as more investors have received the news, the first component diminishes, and the second component increases and comes to dominate. Hence, sustained discussions generate continuing shifts in disagreement between different investors, resulting in persistent trading volumes for the post-announcement window of [2,61]. This persistence increases with the centrality of the firm.

This setup is motivated by theories in which word-of-mouth communication in social interactions propagates rumors, incorrect beliefs, or naïve trading strategies (Shiller 2000, Han, Hirshleifer, and Walden 2021 and Hirshleifer 2020). Experimental evidence from psychology indicates that group decisions tend to become more extreme than the average opinions of the group's individual members.[24] Cookson, Engelberg, and Mullins (2022) provide strong

[24]See Stoner (1968) and Schkade, Sunstein, and Kahneman (2000) for experimental evidence and Isenberg

evidence that investors selectively expose themselves to information that tends to be confirmatory of their views about stocks in the StockTwits social network. This effect is especially strong around earnings announcements, and the resulting disagreement is accompanied by high trading volume. Furthermore, Jiao, Veiga, and Walther (2020) find that social media coverage predicts increases in the volatility and turnover of individual stocks, consistent with investors interpreting repeated signals disseminated by social media as new information.[25]

These belief fluctuations have a strong impact on trading volume. However, they are to some extent idiosyncratic, which limits their contribution to equilibrium prices and to the persistence of return variance. Indeed, since more rapid dissemination of information resolves uncertainty more quickly, the model implies that prices converge to the true firm value faster for news that originates from a high-centrality node.

Overall, the stochastic disagreement setting offers a unified explanation for the observed relationship between social network centrality and the dynamics of prices and trading volume after earnings announcements. On the one hand, more-intense social interactions accelerates the transmission of earnings news and investors' processing of that news, which results in faster incorporation of the news into asset prices. So return volatility is initially high but has low persistence. On the other hand, following the announcement, social interactions among investors continue to attract investor attention and to generate shifts in disagreement, which lead to high and persistent trading volumes for the next three months.

In the subsections that follow, we directly test the microfoundations of the model 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 our model 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 hypotheses with a dataset of 10.9 million of messages on StockTwits, a

(1986) for a review of the earlier literature. Glaeser and Sunstein (2009) provide a model to explain this phenomenon.

[25]The social media coverage is defined as the number of words and phrases referring to a stock from social media platform such as internet forums, finance-specific tweets, chat rooms, public Facebook posts, blogs, micro-blogs, etc.

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 (2022), 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 sensibly relate to market-level trading volume (Cookson and Niessner 2020; Giannini, Irvine, and Shu 2019).

Our sample consists of messages posted by 79,176 unique users from 2009 to 2013, covering 9,131 distinct symbols. 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.[26] 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 the Abnormal New Messages, ANM[0, 1] and ANM[2, 61], as the difference between the average New Messages for the announcement and the post-announcement windows respectively, relative to its per-announcement average ([–41, –11]). Similarly, Abnormal Replies (ARM[0, 1], ARM[2, 61]) is the difference between the average Replies for the corresponding window relative to the pre-announcement average. Matching the messages to stocks, our final sample consists of 35,940 unique firm-announcement observations.

As expected, the average daily New Messages and Replies about a stock increase significantly, by 38% and 30%, respectively, in the two-day window upon the date of an earnings announcement, suggesting that the StockTwits-based measures are likely to be sensible proxies for investors' discussions of the news. After announcements, New Messages declines back to the pre-announcement level, whereas Replies is up to 39% higher relative to its pre-announcement average. The contrasting dynamics of New Messages and Replies around earnings announcements provide preliminary evidence that investors' discussions of news continue well past the initial arrival of the news.

[26]For a given stock, we classify a massage 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 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 within the last seven days, or 2) it is labeled as a reply to an earlier message about the stock by the StockTwits platform (available starting 2013).

[Insert Table 5 here]

We then formally test the model's key implications for the relation between the centrality of the announcing firm and StockTwits messaging activities. We estimate Equation (5), replacing the dependent variable 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 is positive and significant, indicating that high-centrality announcements trigger a more pronounced increase in 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 intense discussions of the stock upon announcement.

For the post-announcement window, Panel A of Table 5, Columns (4)–(6), show a negative and significant association between centrality and Abnormal New Messages. This is consistent with the implication of our model that social connections promote the timely dissemination of information. In consequence, new StockTwits mentions increase rapidly following the news as more investors receive the news faster, which reduces the number of investors who are unaware of the news and therefore reduces subsequent New Messages.

In sharp contrast, Panel B, columns (4)–(6) exhibit a positive and significant association between centrality and Abnormal Replies. This suggests that high-centrality announcements attract more-intense discussions of the news, and these discussions tend to be substantially more persistent than the new mentions. The evidence is consistent with the first key implication of the model.

The next key implication of the model is that social interactions drive persistent belief divergence. To test this, we first measure the sentiment of each StockTwits message, and then construct a daily stock-level measure of sentiment dispersion.[27] To measure sentiment for an individual message, we apply a convolutional neural network[28] of textual classification in Tensorflow (Kim 2014) and calculate the probability of positive sentiment (1 being extremely positive and 0 being extremely negative). We then construct a daily measure of opinion differences for a given stock as the range of the probability of positive sentiment across all messages related to the stock. DO[0, 1] and DO[2, 61] are then the average opinion

[27]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.

[28]Convolutional neural network (CNN) is a popular artificial neural network model for sentiment analysis. Kim (2014) benchmarks CNN against 14 alternative models and shows CNN has superior performance in sentiment classification.

differences over the announcement and the post-announcement windows, respectively. The sample average of DO[0, 1] and DO[2, 61] are 0.57 and 0.59 respectively. This suggests that disagreements do not dissipate over time. Instead, they slightly increase in the post-announcement window compared to the announcement window, although the increase is not statistically significant.

We then run regression tests as in Equation (5), replacing the dependent variable with either DO[0, 1] or DO[2, 61]. Table 6 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 disagreement among investors. Furthermore, these higher 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 e 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 6.12% (= 0.68%×9) for the announcement window and 6.75% (= 0.75%×9) for the post-announcement period, respectively. Moreover, columns (7)–(10) show that d_{DO}, the persistence of disagreement estimated with the ARFIMA model discussed earlier, also increases significantly with centrality. The positive effects of centrality on the level and persistence of investor disagreement provide direct support to the second key implication of our model.

[Insert Table 6 here]

5.3 Evidence from Google Searches

StockTwits analysis provides a much sharper and granular picture of the dynamics of investor conversations and opinion updating following earnings announcements. However, it is possible that StockTwits investors are not representative of investors at large. We next analyze the investor attention dynamics using a widely used attention measure, Google's daily search volume index (SVI) for individual stocks. This stock-level measure is a popular proxy for general retail investor attention. It has been shown to be strongly associated with stock returns and trading volume (see, for example, Da, Engelberg, and Gao 2011, 2014).

To capture the variations in retail investor attention to a stock relative to its past mean (and possible time trends), we define abnormal search volume (ASV) for day t as the difference between $\log(1 + \mathrm{SVI}_t)$ and its average over the pre-announcement window [–41, –11].

We define ASV$[0, 1]$ as the two-day average ASV around an earnings announcement and ASV$[2, 61]$ as the average ASV of the post-announcement window. Similarly, we estimate the persistence parameter, d_{ASV}, with the ARFIMA model using daily ASV observations for the period [0, 61]. SVI is available from 2004 onward.

A key implication of our model is that announcements made by firms from high-centrality areas are subject to continued intense discussions and therefore attract more persistent investor attention. For example, investors who have received the news are likely to acquire other information about the firm through their Google searches over subsequent weeks. We therefore predict that news from high-centrality locations will be associated with stronger and more persistent investor attention. To test this, we estimate Equation (5), replacing the dependent variables with ASV-based measures. Table 7, columns (1)–(3) present results for the announcement period [0, 1]. In this period there is a significant positive association between centrality and Google search activity. Columns (4)–(6) report the results for the post-announcement period [2,61]. In this period the coefficient on CEN is positive for all centrality measures and significant for eigenvector centrality. This indicates Google search volume is increasing with centrality. Columns (7)–(9) examine attention persistence. In these tests, the coefficients on CEN are positive and highly significant for all three centrality measures, ranging from 0.297 to 0.368. Quantitatively, 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 of d_{ASV}. The effects documented here are of similar magnitudes to the corresponding change in the persistence of trading volume.

[Insert Table 7 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, 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

We next consider the third key implication of our model that social connection drives excessive trading that can potentially be harmful to retail investors. We test the hypothesis by following Barber and Odean (2000) and use individual account-level data from a large discount brokerage in the United States from 1991 to 1996.[29] The data include trading and position records for households' investments, and demographic information and ZIP codes for the residence for a subset of the households.

We conduct our analysis at the announcement–household level. For each earnings announcement by stock i, 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.[30] 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.[31] 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 neighbours, receives earnings news about stock i by a given date. Our model therefore predicts that household j is more likely to engage in discussions, or more extensive discussions, about these firms with its neighbours and social network peers, and consequently, become more attentive to the stock. As a result, household j engages in more intense and more sustained trading of these stocks. In addition, 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.

We then analyze households' trading activities following earnings announcements using a modified version of Equation (5), replacing the dependent variable with measures of household trading activities and the centrality measure with RSCI. We estimate the following

[29]We are grateful to Bard Barber and Terry Odean for kindly sharing their data.

[30]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.

[31]This formulation of peer influences is consistent with the very popular DeGroot (1974) model of social learning. See Jackson (2010) for a review. We take the logarithm transformation of RSCI for our subsequent analysis since it has a large skewness.

regression:

$$\text{Trade}_{ijt} = \alpha + \beta_1 \text{RSCI}_{ij} + \beta_2 |\text{SUE}| + \gamma X_{it} + \eta Z_{jt} + \epsilon_{ijt}, \tag{6}$$

where Trade_{ijt} is the trading activity for a given window, measured three ways: (1) an indicator variable that equals one if there is a trade 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 before, we consider trading activities over the announcement window [0, 1] and the post-announcement window [2, 61]. X_{it} is the vector of firm controls, including the indicator variables for year, quarter, and day of the week. Z_{jt} is the vector of the household controls.[32] We also include firm and household fixed effects. These controls and fixed effects therefore go a long way in accounting for omitted factors that may contribute to our findings (see Altonji, Elder, and Taber 2005, Oster 2019).

[Insert Table 8 here]

Table 8 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 sharing strong social ties with the headquarters location of the announcing firm are more likely to trade both during the announcement and during the three-month post-announcement period.[33] Economically, an increase in RSCI from the 10$^{\text{th}}$ percentile to the 90$^{\text{th}}$ percentile increases an 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 show that the high-RSCI households not only make more trades immediately after the announcement but they also trade more post announcement.[34] In terms of economic magnitudes, an increase in RSCI from the 10$^{\text{th}}$percentile to the 90$^{\text{th}}$percentile increases the number of trades by 9.4%

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

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

[34]We also estimate these two models with Poisson regression and obtain quantitatively similar results. For ease of interpretation of the slope coefficients, we present the linear regression models.

and 14.5% for the announcement and the post-announcement windows, respectively, relative to the corresponding sample mean of 0.0083 and 0.096.

Last, column (5)–(6) present the effects of social ties on the relative trade size of households. A similar change in RSCI increases the relative trade size by 18.1% and 27.6% for the two windows, relative to the corresponding sample mean.

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

We next examine whether the excessive trading by the high-RSCI households is detrimental to their welfare. We follow Barber and Odean (2000) and first compute Profit^{gross}, the gross profit of each trade following earnings announcements before any transaction costs. Profit^{gross} is defined 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 $\text{CAR}[t, 61]$ is the DGTW-adjusted cumulative abnormal return between days t and 61, based on the closing prices.[35] A positive Profit^{gross} refers to gains from the trade and a negative value refers to losses. Next, we measure the cost of trade, Cost_t, as the commission paid for the trade plus 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.[36] The net profit, Profit^{net}, is then Profit^{gross} minus Cost.

For each announcement and for a given household, we then aggregate the Profit and Cost measures across all trades over the announcement window [0, 1] and the post-announcement window [2, 61], respectively. To compare across households and control for wealth heterogeneity, we scale a household's Profit and Cost measures by the beginning-of-month market value of all stocks held by the household before the announcement. We estimate the same regression as in Equation (6) with the scaled ($\times 10^4$) Profit and Cost measures for each household-announcement observations as dependent variables. The results are reported in

[35] 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 noises that are not related to the given earnings announcement. We obtain similar results with raw cumulative returns.

[36] We acknowledge that our definition of Cost may ignore the costs associated with liquidations beyond the 61-day period and hence is a conservative estimate of the potential round-trip costs associated with excessive trading.

Table 9, with columns (1)–(3) and (4)–(6) corresponding to the announcement and post-announcement windows, respectively.

[Insert Table 9 here]

Columns (1) and (2) analyze the net and gross Profits for trades placed during the announcement window. The coefficients of RSCI are negative but insignificant, suggesting that the tradings by the high-RSCI households immediately after the announcement do not generate significant net or gross Profit. Together with the finding of an increased trading volume during the announcement window by the high-RSCI households shown in Table 8, the result suggests that the increased trading immediately following the announcement does not deliver abnormal performance to the households. In addition, column (3) corresponds to Cost and the positive coefficient of RSCI indicates that the high-RSCI households are subject to significantly higher total transaction costs.

We next turn to the post-announcement window and test the distinctive implication of the model that persistent excess trading is driven by biased beliefs and reduce investor profits. Column (4) presents the results for Profit^{net} and shows that the high-RSCI households incur significantly more losses for trades placed during the [2,61] window relative to other households. The coefficient of -0.151 indicates that an increase in RSCI from the 10^{th} percentile to the 90^{th} increases the trading loss by 16.6% relative to the sample average of trading loss for a given household-announcement.[37] Further analyzing what contributes to the losses for the high-RSCI households, column (5) examines Profit^{gross} and finds the coefficient of RSCI to be insignificant. This suggests that the high-RSCI households do not underperform before transaction costs. In contrast, column (6) examines the total transaction costs these household pay and show the coefficient to be positive and highly significant. The result indicates that the trading costs are the main contributors to the household's losses during this sample period.[38]

The evidence is consistent with the model's implication that the excessive trading by households for the post-announcement period reflect their incorrect beliefs triggered by so-

[37]We consider an average household with a total investment portfolio of $47,334 and focus on the stocks that they have held or traded in the last 12 months prior to an earnings announcement as mentioned earlier. For a given announcement, the household trade an average of $1,060 worth of the stocks during the post-announcement period and incur an average loss of $19.4, or 1.8%. The losses are a conservative estimate because the Profit measure may ignore the transaction costs associated with liquidation.

[38]Similarly, Barber and Odean (2000) find that it is the excessive trading and the cost associated with the trading that is responsible for the poor performance of households.

cial interactions. Hvide and Östberg (2015) and Huang, Hwang, and Lou (2021) also find that information transmitted through social interactions does not improve investors' trading performances.

Overall, our empirical analyses of StockTwits messages, Google searches, and household trading activities provide direct support for the mechanisms outlined in our model. That is, social interactions direct investor attention to relevant news, but also promote persistent belief divergence and excessive trading.

6 Additional Analysis and Robustness Checks

In this section we provide additional analysis to address endogeneity concerns and to conduct further robustness checks. We first utilize an exogenous shock to the intensity of social interactions and show that the documented associations between centrality and price and volume reactions are likely causal. We then perform several robustness checks using alternative measures and additional controls, by accounting for the geographical dispersion of firm subsidiaries, and by considering a sample that excludes tri-state firms. In addition, we discuss the extent to which our results are attributable to local versus cross-state networks, the effect of local population on centrality measures, and spatial network centrality based on geographical distance across regions.

6.1 Exogenous Shocks to Social Interaction

Despite the rich set of firm- and county-level controls that we used, there may still be omitted variables that are positively related to county centrality that also affect price reactions to earnings news. For example, maybe places with high social network centrality tend to have more well-known firms, and high attention to such firms causes more rapid price reactions to earnings announcements. To address such possible endogeneity, we employ 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. For example, it has been used by Kuchler et al. (2020) to identify the effect of social proximity to institutional capital on stock liquidity. We hypothesize here that Sandy caused a greater disruption to the information dissemination of firms that are more connected to the affected areas and therefore weakens the association between centrality and return responsiveness for such firms. We focus our analysis on earnings announcements from firms located outside the affected area to avoid any spurious effects deriving from the hurricane's direct impact on firms' fundamentals or on the characteristics of their home counties.

To test the hypothesis, we measure a county i's connectedness to the affected areas to be the sum of all its friendship links with the Mid-Atlantic counties, and define an indicator variable, HSS_i, as equal to one if the sum is above the sample median, and zero otherwise. We estimate the following difference-in-difference (DID) regression:

$$\begin{aligned}\mathrm{CAR} = \; & \alpha + \beta_1 \mathrm{SUE} + \beta_2 \mathrm{SUE} \cdot \mathrm{CEN} + \beta_3 \mathrm{SUE} \cdot \mathrm{CEN} \cdot \mathrm{HSS} \\ & + \beta_4 \mathrm{SUE} \cdot \mathrm{CEN} \cdot \mathrm{Sandy} + \beta_5 \mathrm{SUE} \cdot \mathrm{CEN} \cdot \mathrm{HSS} \cdot \mathrm{Sandy} + \gamma X + \epsilon,\end{aligned} \tag{7}$$

where Sandy is an indicator variable that equals one for announcements made during the Sandy period, defined as October 22, 2012, through November 1, 2012,[39] and zero otherwise. X includes all county- and firm-level control variables 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 is a one-month window, starting ten days before Sandy formed and ending ten days after it dissipated, that is, from October 12, 2012, to November 11, 2012. The variable of interest is the coefficient β_5, which captures the effect of the difference-in-difference.

[Insert Table 10 here]

Table 10 Panel A reports the results. Columns (1)–(3) test the DID regression in Equation (7) for the immediate price reaction CAR[0,1]. There are several results. First, both the coefficient on Sandy and the β_4 coefficient for the triple=interaction term SUE·CEN·Sandy are insignificant, further supporting our evidence in Appendix B Table B2 that Sandy did

[39] We chose this date range to capture the period when travel in the tri-state region of NY, NJ and CT was substantially impacted by Sandy. See https://www.cnn.com/2013/07/13/world/americas/hurricane-sandy-fast-facts/index.html for details.

not significantly affect earnings announcement return responsiveness for firms located in unaffected areas.

The β_3 coefficient of the triple interaction term SUE·CEN·HSS is positive, and it 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. The result suggests that a high-centrality location is even more advantageous in facilitating information dissemination if the location is well-connected to the Mid-Atlantic region, which contains major financial centers and employs many financial analysts.

The key variable of interest is the quadruple term, SUE · CEN · HSS · Sandy, with the corresponding coefficient β_5 measuring the extent to which the hurricane mediates the triple-interaction term. β_5 is negative across all three centrality measures and significant for two of them. This indicates that the hurricane weakens 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 is dampened during the Sandy period, consistent with our hypothesis.

Columns (4)–(6) present the DID tests for the post-announcement window and show results that complement the findings over the announcement period. The coefficients of SUE·CEN·HSS in these columns are all negative, suggesting that during normal times, announcements from high-centrality firms that are highly connected to the Mid-Atlantic region tend to have less post-announcement drift. However, and more importantly, the coefficients of SUE · CEN · HSS · Sandy are all positive and significant, consistent with our hypothesis that the effect of centrality on PEAD is weaker for high-HSS counties during Hurricane Sandy.[40]

We next test how Hurricane Sandy changes the effect of centrality on trading volume.

[40] In unreported analysis, we consider two alternative channels through which Sandy may have affected either the nature of earnings surprises of firms in unaffected areas or the media coverage of these firms. First, certain firms may have strategically postponed their earnings announcements to avoid announcing during Hurricane Sandy. Our results already account for this possibility by including the reporting lag variable as a control. In addition, 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 once we control for firm and stock characteristics listed in Section 2.2. Second, media outlets may be concentrated in the Mid-Atlantic states. If these outlets tend to cover firms located in the high-HSS areas, the hurricane may have caused a greater disruption in the coverage of earnings news for those firms, resulting in slow incorporation of the news into financial markets. To account for the potential supply effect, we directly control for the log number of news articles within the announcement window and find very similar results.

If Sandy interrupts social interactions, we expect a weaker positive association between centrality and trading volume after the hurricane for high-HSS counties. To test this, we run the following regression:

$$\begin{aligned}\text{VOL} = \; & \alpha + \beta_1|\text{SUE}| + \beta_2\text{CEN} + \beta_3\text{HSS} + \beta_4\text{Sandy} + +\beta_5\text{CEN} \cdot \text{HSS} \\ & + \beta_6\text{CEN} \cdot \text{Sandy} + \beta_7\text{CEN} \cdot \text{HSS} \cdot \text{Sandy} + \gamma X + \epsilon.\end{aligned} \tag{8}$$

Table 10 Panel B reports the regression results, with columns (1)–(3) and columns (4)–(6) corresponding to the announcement- and the post-announcement windows, respectively. The coefficient of interest, β_7, is negative and statistically significant across all models, suggesting that the hurricane weakens the immediate and post-announcement centrality-volume relation much more for the high-HSS firms than low-HSS firms.

Overall, our Hurricane Sandy tests suggest 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.[41]

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.

Alternative 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. The results are presented in Appendix Table B3.

Media Coverage and Persistence. An alternative possible explanation for the positive relation between CEN and post-announcement volume persistence is that high-CEN announcements may also receive more persistent media coverage, which might trigger persis-

[41] As shown in Appendix B, Table B2, the coefficient of HSS is insignificant in explaining the annual differences in ROA and ROE, measured before and after the Sandy period. This suggests that firms' social ties with the affected regions do not result in differential long-term accounting performances.

tent trading. To address this possibility, we include media coverage (Media) as an additional control variable in the analysis of CEN and persistence and report the results in Appendix Table B4.[42] The coefficient of Media is positive across all three series, suggesting that media coverage does indeed contribute to persistent volatility and trading volume. More importantly, the coefficients of CEN remains negative and significant for volatility persistence, but remains positive and significant for volume and attention persistence. We therefore conclude that the centrality–persistence relation that we document is distinctly different from the effect of media coverage.

The Geographical Dispersion of Firm Subsidiaries, Tri-State Firms. If firms that have more geographically dispersed business operations enjoy greater investor recognition (Bernile, Kumar, and Sulaeman 2015), the earnings announced by such firms may generate 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 different states.[43] Although this filter eliminates firms that belong to the top 25% dispersion group, Appendix Table B5 show 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), a region with a heavy presence of institutional investors and financial analysts, who play important roles in information dissemination in financial markets. Appendix Table B6 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.

Residual Centrality. In our main tests, we account for a rich set of county-level characteristics by including them directly as control variables. To further address the possibility

[42] We define Media as (log) the number of news articles about a firm during the post-announcement window [2,61]. We obtain media coverage data from Ravenpack for 2000—2017. Media has a mean and median of 3.67 and 2.45, respectively, and a standard deviation of 15.55.

[43] 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 for the authors for sharing these datasets.

that our centrality measures may be correlated with these characteristics, we construct a residual centrality measure, extracted from a regression of centrality on the county characteristics. We then use the decile ranks of the residual centrality measures as the main variables in our analysis while still controlling for the county characteristics along with other control variables. The results, reported in Appendix Table B7, show that our results remain robust.

Local versus Cross-State Networks, and the Role of Local Population. It is possible that the centrality measures may simply reflect local bias or be driven by investors' connections with their nearby neighbors. To address this concern, we examine two alternative centrality measures that further exclude local influences. Specifically, we define DC_{across} and $\mathrm{DC}_{>100m}$ as the degree centrality based on the number of Facebook friendship links that concern only out-of-state friends and friends from counties located more 100 miles away, respectively.[44]

In addition, social transmission of information can be substantially affected by the population of the focal county (*pop*).[45] A large local population can be associated with a greater number of local investors who tend to be especially attentive to news about the firm. Such large local investor base contributes to a stronger social transmission of information to other investors both within the state and to other areas. Therefore, we also evaluate the extent to which the explanatory powers of DC_{across} and $\mathrm{DC}_{>100m}$ are attributable to population-driven connectedness by orthogonalizing the two centrality measures with respect to population and obtaining the corresponding residual centrality measures, $\log(\mathrm{DC}_{across})^{res}$ and $\log(\mathrm{DC}_{>100m})^{res}$.

We consider the relative importance of non-local connections and the effect of population by regressing CAR[0,1] on the logarithms of the three measures and their interactions with SUE while controlling for all other variables listed in Equation (3). Appendix Table B8, columns (1)–(3), show that DC_{across}, $\mathrm{DC}_{>100m}$, and *pop* are all positively associated with stronger immediate price reactions. Turning to residual centrality, columns (4)–(5) show

[44]We focus our analysis on DC because EC and IC are based on high-order links and therefore cannot be decomposed in this linear way.

[45]A large literature in urban economics and geography has shown that an area's population size is an important determinant of salient urban characteristics and socioeconomic activity, with more recent papers suggesting that the effect stems directly from the network of human social interactions. See, for example, Sveikauskas (1975), Glaeser and Sacerdote (1999), Bettencourt et al. (2007), Batty (2008), Bettencourt (2013), Pan et al. (2013), Schläpfer et al. (2014), Li et al. (2017), and O'Sullivan (2018).

that the coefficients of SUE and the residual centrality remain positive and significant. This evidence therefore confirms that our results on the relationship between centrality and the reactions of price to earnings news are not simply driven by local bias or attributable to the effect of the local population.

Spatial Network Centrality. Finally, we consider the spatial network centrality of firms based on physical proximity between regions. Spatial network centrality can contribute to social network centrality because regions that are physically close to each other also tend to share higher social ties as measured by SCI than those that are distant. Physical distance may also influence investors' access to information or familiarity about a firm and therefore affect trading and prices.[46] As a robustness check, we consider the extent to which the effects of social network centrality is attributable to spatial network centrality.

Specifically, we adopt a gravity model to measure the relative strength of the bond between two counties based on their geographical distance and define spatial network centrality ($\mathrm{DC}_{spatial}$) as the degree centrality of such bonds.[47] We examine the role of spatial centrality in relation to our social network centrality in Appendix Table B8, columns (6)–(9). Column (6) shows that the effect of spatial degree centrality on immediate price reaction is positive and significant. However, column (7) shows that the residual spatial degree centrality, $\log(\mathrm{DC}^{res}_{spatial})$, obtained by regressing $\log(\mathrm{DC}_{spatial})$ on log (pop), becomes insignificant, suggesting that the role of spatial centrality is largely attributable to local population size. Columns (8)–(9) consider spacial centrality, social network centrality, and population jointly. The coefficients for $\mathrm{SUE}\cdot\log(\mathrm{DC}^{res}_{across})$ and $\mathrm{SUE}\cdot\log(\mathrm{DC}^{res}_{>100m})$ remain strong and robust. The evidence therefore further confirms that our social network centrality measures capture an effect that is beyond the effect of local population and spatial network centrality.

[46] For example, previous literature has shown that investors are more likely to invest in nearby firms and are more attentive to news about such firms (Ivković and Weisbenner 2007, Feng and Seasholes 2004, Engelberg and Parsons 2011, Chi and Shanthikumar 2017).

[47] The gravity model was first used by Tinbergen (1962) to model trade between countries and has been used extensively in the trade literature (see, for example, Leamer and Levinsohn 1995, and Eaton and Kortum 2002. We define the relative strength of a bond between two counties, i and j, to be $\frac{pop_i \cdot pop_j}{distance^2}$. An alternative specification of the bond, $\frac{pop_i \cdot pop_j}{distance}$, also gives similar results.

7 Conclusion

The Efficient Markets Hypothesis holds the prices immediately reflect all available information. This suggests that the only time that investors need to trade based on this 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. Our evidence instead suggests that the arrival of earnings news triggers a process of social media discussion (which we directly measure) 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 in different ways, and this updating triggers trading.

Furthermore, using a novel firm-level investor social network centrality measure, we find that earnings announcements made by more centrally located firms generate stronger immediate reactions in stock prices, volatility, and volume, followed by weaker price drifts. 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 models of information diffusion. To provide insight into the underlying mechanisms we provide a model that offers a unified explanation for the rich and complex dynamics of return, volatility, and trading volume. Using granular data based on StockTwits messages by individual users and household account-level trading records, and the Google search activities at the stock level, we provide direct support for the key implication of the model.

Our results thus suggest a dual role of social interactions in 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 disagreement among unsophisticated investors and trigger persistent excessive trading. Our findings raise a number of issues that suggest future avenues of continuing research. In particular, survey evidence suggests that investors' beliefs are characterized by large and persistent heterogeneity, features that have not been incorporated by the existing macro-finance models (Giglio et al. 2021). Therefore, it would be valuable to explore the extent to which social interactions influence investor beliefs and result in belief divergence in response to other types of public information, private information, or even fake news, and how the dynamics drive economic outcomes.

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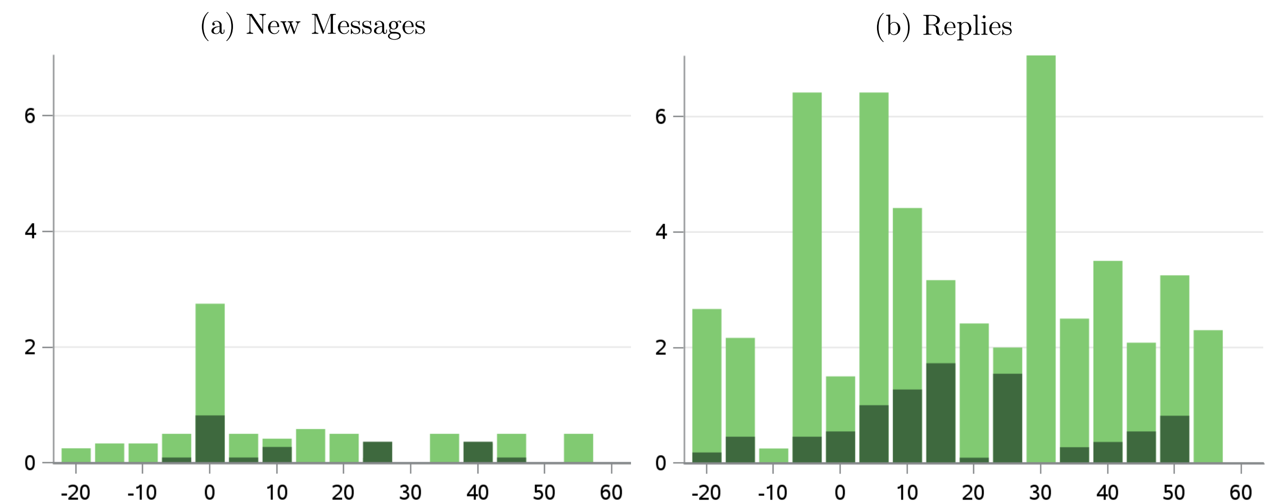

Figure 1: StockTwits Messages around Earnings Announcements

This figure plots daily StockTwits message activities for two firms, BOFI (in dark gray) and Univest (in light gray) for the [-20, 60] window around the firms' earnings announcements. Panels (a) and (b) present the numbers of New Messages and Replies of the corresponding stock on StockTwits. The numbers are averaged across all the announcements between 2010 and 2013 for the corresponding firm.

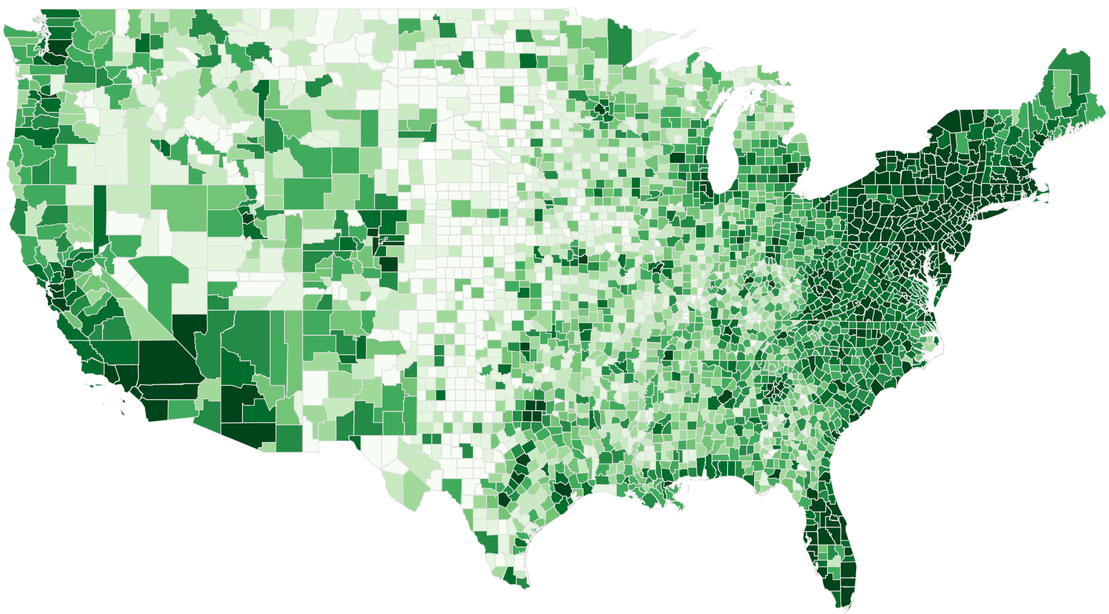

Figure 2: Heat Map of Eigenvector Centrality

This figure plots a heat map of eigenvector centrality across U.S. counties as of June 2016. Darker colors indicate higher values. Ten counties with 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). Ten counties with lowest eigenvector centrality are King (TX), McPherson (NE), Slope (ND), Sioux (NE), Blaine (NE), Arthur (NE), Petroleum (MT), Thomas (NE), and Banner (NE).

Table 1: Descriptive Statistics

The 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 B.

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
VOL[0, 1]	0.64	0.61	0.99	-0.04	-0.38	0.13	1.14	1.75
VOL[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
VOL[0, 1]	0.005	0.023	0.008
VOL[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 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 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 VOL[0, 1] and VOL[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 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.

	VOL[0,1]			VOL[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. The Abnormal New Messages, ANM[0, 1] and ANM[2, 61], are the difference between the average New Messages for the announcement and the post-announcement window respectively, relative to its per-announcement average. Similarly, the Abnormal Replies (ARM[0, 1], ARM[2, 61]) are the difference 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 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	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(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	EC	IC	DC	EC	IC
	(1)	(2)	(3)	(4)	(5)	(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. Columns (1)–(6) present DO[0, 1] and DO[2, 61], which correspond to the average StockTwits opinion differences for the announcing stock over the announcement and the post-announcement window, respectively. The dependent variable in columns (7)–(9) is d_{DO}, the persistence parameter of StockTwits opinion differences 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 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.

	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	0.48***	0.68***	0.52***	0.54***	0.75***	0.59***	0.43***	0.51***	0.49***
	(3.86)	(5.40)	(4.05)	(4.46)	(6.08)	(4.79)	(4.21)	(4.85)	(4.67)
|SUE|	0.68*	0.70*	0.68*	0.85***	0.88***	0.86***	0.42	0.43	0.43
	(1.75)	(1.81)	(1.75)	(2.60)	(2.69)	(2.62)	(1.04)	(1.06)	(1.05)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	21,528	21,528	21,528	21,143	21,143	21,143	20,598	20,598	20,598
Adj. R^2	28.0%	28.1%	28.0%	39.4%	39.6%	39.5%	7.1%	7.1%	7.1%

Table 7: 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 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 8: Social Ties and Household Trading

This table reports the regression of households' trading activities following earnings announcements. The dependent variable is the trading activity of a household on the announcing stock for a given window, measured three ways: 1) an indicator variable that equals one if there is at least one trade and zero otherwise, 2) the number of trades, or 3) relative trade size, which is the dollar traded scaled by the household's beginning-of-the-month stock portfolio balance. 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, household-level controls, and the 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.

	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%

Table 9: Social Ties and Trading Profits

This table reports the regression of households' trading profit following earnings announcements. 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^{net} equals to Profit^{gross}, the profit before any transaction cost, minus Cost, 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, household-level controls, and the firm and household fixed effects. 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.

	[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 VOL[0, 1] and VOL[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 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·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)
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)
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						
	VOL[0,1]			VOL[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·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)
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)
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 A: 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 derive the relationship between centrality and the dynamics of price, volatility, and trading volume considering three cases: 1) investors have identical priors and interpretation of the earnings news, 2) investors have heterogeneous priors and static disagreement, and 3) investors have heterogeneous priors and stochastic disagreement.

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 $T+1$ can be viewed as the date of the next earnings announcements and therefore the model describes the dynamics of prices and trading volume for the three months between the announcements. There is also a riskless 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:

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

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 $\mathcal{E} \subseteq \mathcal{N} \times \mathcal{N}$ defines which investors are connected in the network. Specifically, two investors $i, i' \in \mathcal{N}$ are directly connected via an edge if and only if $(i, i') \in \mathcal{E}$. 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* $A \in \{0, 1\}^{N \times N}$, whose $(i, i')^t$ element $(A)_{ii'} = 1$ if $(i, i') \in \mathcal{E}$, and $(A)_{ii'} = 0$ otherwise.

Denote $p(i,i')$ 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.

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*

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

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*

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

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 $I_0 \subset \mathcal{N}^m$.[48] At date 1, the public news arrives at

[48] 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 $\mathcal{G}^m$.

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 $t-1$ 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, $\{F_t\}_{t=0,1,\dots,T}$ 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:

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

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. We will use this property for the analysis of trading volume.

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 cases of investor belief formation.

Case 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:

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

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

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

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

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

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:

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

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

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

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

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

For simplicity, we assume that $\sigma_\epsilon^2 \ll \sigma_R^2$ for all three cases, 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:

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

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 (A.11), the immediate price reaction is

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

which is increasing in $F_{\hat{t}}$ and, based on Equation (A.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:

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

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

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

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

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

It follows from Equation (A.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:

$$V_t = \frac{1}{2}\left(F_{t-1}|x_t^I - x_{t-1}^I| + (F_t - F_{t-1})|x_t^I - x_{t-1}^U| + (1-F_t)|x_t^U - x_{t-1}^U|\right)$$
$$= (F_t - F_{t-1})\frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1-F_t)\,\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)}|Y - \bar{R}|. \tag{A.17}$$

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

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

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:

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

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 $s = 1, \ldots, \hat{t}$.[49] Then the cumulative trading volume within $[0, \hat{t}]$ becomes

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

[49] 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 (A.20) as $\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{\sigma_R^2}log(F_{\hat{t}})|Y - \bar{R}|$.

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

Similarly, applying Taylor's expansion to Equation (A.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:

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

Equation (A.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.

Based on the set of assumptions mentioned above, we summarize the implications of Case 1 below:

Prediction 1 *When investors have common priors and identical interpretation of news, then public news that diffuses from a more central subgraph generates:*
i) stronger immediate price reactions and weaker post-announcement price drifts;
ii) less-persistent return volatility; and
iii) stronger immediate volume reactions, followed by lower post-announcement volume that is also less persistent.

Case 2: Heterogenous Prior and Static Disagreement

Next, we consider a case in which investors' interpretations of news are heterogeneous and remain fixed once the interpretation is formed. We show that this setting, the relationship between centrality and price, volatility, and volume dynamics are very similar to those of Case 1.

Investors have heterogeneous priors of the asset payoff as well as differential interpretations of the public news.[50] 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 interpretation of the signal noise. For simplicity, we assume that $e^{(i)}$ follows the binary distribution of $(-\bar{e}, +\bar{e})$ with equal probabilities.

[50] We allow for both types of heterogeneity for generality. However, heterogeneous priors are not crucial to our results, as they do not affect price dynamics or volume dynamics.

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

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

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

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

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

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

Imposing the market-clearing condition,

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

the price can be solved by

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

Note that the equilibrium price is identical to Equation (A.10) in case 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, which is a property that is also shared by other models in which investors agree to disagree (see, for example, Banerjee and Kremer 2010). 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:

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

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

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

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

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

where V_t^B is the same as Equation (A.17) of Case 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 (A.28) is always positive for all t. Then the volume becomes

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

and the volume–price relation is

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

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 news from the more central subgraph generates stronger immediate volume reaction, weaker post-announcement volume drift, and lower volume persistence. That is, although investors' heterogeneous priors contribute to an additional trading volume component, the empirical predictions on subgraph centrality and trading volume remain the same as in Case 1. Based on the set of aforementioned assumptions, we summarize the implications of Case 2 below:

Prediction 2 *When investors have heterogeneous priors and if their disagreement is static, then public news that diffuses from a more central subgraph generates:*
i) stronger immediate price reactions and weaker post-announcement price drifts;
ii) less-persistent return volatility; and
iii) stronger immediate volume reactions, followed by lower and less-persistent post-announcement volume.

Case 3: Heterogeneous Priors with Stochastic Disagreement

In the third case, we extend the second case and consider a setting in which social interactions that 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. That is, for $i \in I_t$, his belief of the public signal at t is given by

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

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

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

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 belief divergence generated by social interactions. We postulate that the sustained discussions last for the post-announcement window and generate continuing shifts in investor disagreement.[51]

[51]The assumption of sustained discussion for the post-announcement window is made to match the horizon of our empirical analysis. In reality, one would expect investors' attention to an announcement to decay over time due to reasons such as other extraneous events. This could be modeled by introducing the assumption of exponential decay of attention. In such a model, we would still expect to see a similar relationship between news centrality and the persistence of trading volume.

It can be easily shown that the stochastic disagreements cancel out in the market clearing process and leave the price identical to that of Cases 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

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

If social interactions generate substantially greater opinion divergence than the initial belief divergence 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 (A.32) is positive for all t. Given the earlier assumption that $\sigma_\epsilon^2 \ll \sigma_R^2$, volume can be approximated as

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

and the volume-price relation is

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

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

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

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.

To summarize, in the stochastic disagreement setting, centrality increases the immediate price and volume reactions to news, decreases the post-announcement return drift and volatility persistence, but increases both the post-announcement period volume level and volume persistence. We summarize the implications of Case 3 in the following prediction (subject to the set of assumptions mentioned above):

Prediction 3 *When investors have heterogeneous priors and stochastic disagreement, then public news that diffuses from a more central subgraph generates:*
i) stronger immediate price reactions and weaker post-announcement price drifts;
ii) less-persistent return volatility; and
iii) stronger immediate volume reactions, followed by higher and more persistent post-announcement volume.

Appendix B: Variables List and Additional Tests

Table B1: 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.
DMR	Bloomberg's daily maximum readership. DMR[0,1] is the two-day average DMR 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 cumulative buy-and-hold abnormal returns.
VOL	Daily abnormal log dollar volume. Defined as the difference between the log dollar volume for a given day and the average daily log volume over days [–41, -11]. VOL[0, 1] is the average abnormal log dollar volume over the announcement window and VOL[2, 61] is the average for the post-announcement window.
$d_{\|R\|}$	Volatility persistence parameter, estimated with an ARFIMA$(0, d, 0)$ model for daily absolute returns in the window of [0, 61].
d_{VOL}	Volume persistence parameter, estimated with an ARFIMA$(0, d, 0)$ model for VOL in the window of [0, 61].
d_{ASV}	ASV persistence parameter, estimated with an 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 1 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	Advertisement 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 B2: Sandy and Firm Fundamentals

This table reports the regression results of the impact of Hurricane Sandy on a firm's fundamentals. Firm performance is measured by ROA and ROE. ΔROA and ΔROE are the changes in ROA and ROE compared to the values in the same quarter in the previous year. 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 for fiscal quarters after October 22, 2012. Models (1) and (2) regress HSS on ΔROA and ΔROE using the four quarters after Hurricane Sandy, respectively. Coefficients are multiplied by 100. 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.

	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 B3: 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 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 B4: Robustness Checks for Persistence: Controlling for Media Coverage

This table reports robustness tests for the relationship between centrality and post-announcement persistence while controlling for the media coverage of the announcement firm. Media is the log number of news articles about the firm for the post-announcement window. $d_{|R|}$ 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 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 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}		
	DC	EC	IC	DC	EC	IC
CEN	-0.084***	-0.114***	-0.094***	0.315***	0.354***	0.346***
	(-4.70)	(-6.32)	(-5.02)	(10.05)	(11.19)	(10.59)
|SUE|	0.006	0.005	0.006	0.036**	0.040**	0.037**
	(0.50)	(0.39)	(0.47)	(2.22)	(2.43)	(2.30)
Media	0.452***	0.472***	0.459***	2.499***	2.450***	2.471***
	(4.27)	(4.45)	(4.34)	(10.79)	(10.53)	(10.67)
Ctrls	X	X	X	X	X	X
Obs.	156,068	156,068	156,068	146,377	146,377	146,377
Adj. R^2	7.0%	7.0%	7.0%	15.2%	15.2%	15.2%

Table B5: 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 different states. Panels A–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. VOL[0,1] and VOL[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 VOL, 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 VOL 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)			
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)			
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|							0.0150	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 Dynamics									
	VOl[0,1]			VOL[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 B6: 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–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. VOL[0,1] and VOL[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 VOL, 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 VOL 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)			
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)			
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|							0.0148	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									
	VOL[0,1]			VOL[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 B7: Robustness Checks with Residual Centrality

This table reports robustness tests of our main results using residual centrality measures. Residual centrality measures (DC, EC, and IC) are decile ranks of residuals obtained from regressing the corresponding raw centrality measures on the following county-level variables: population density, mean age, educational attainment, ratio of retired population, and length of household tenancy. Panels A–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. VOL[0,1] and VOL[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 VOL, respectively. SUE (|SUE|) is the decile rank of (absolute) earnings surprises. The controls for the CAR and VOL 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 and Volatility Persistence

	CAR[0,1]			CAR[2,61]			$d_{\|R\|}$		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
SUE·CEN	0.0131***	0.0134***	0.0119***	-0.00627	-0.00961	0.000589			
	(4.60)	(4.61)	(3.91)	(-0.93)	(-1.42)	(0.09)			
SUE	1.757***	1.788***	1.626***	1.506**	1.513**	1.435*			
	(6.52)	(6.63)	(5.95)	(2.06)	(2.08)	(1.95)			
CEN	-0.0725***	-0.0793***	-0.0637***	0.0805*	0.136***	0.0360	-0.0496***	-0.0569***	-0.0083
	(-4.37)	(-4.72)	(-3.60)	(1.85)	(3.15)	(0.83)	(-3.51)	(-4.03)	(-0.60)
|SUE|							0.0158	0.0154	0.0164
							(1.47)	(1.43)	(1.53)
Ctrls	X	X	X	X	X	X	X	X	X
Obs.	226,986	226,986	226,986	226,106	226,106	226,106	223,698	223,698	223,698
Adj. R^2	3.2%	3.2%	3.2%	0.7%	0.7%	0.7%	6.8%	6.8%	6.8%

Panel B: Volume Dynamics									
	VOL[0,1]			VOL[2,61]			d_{VOL}		
	DC	EC	IC	DC	EC	IC	DC	EC	IC
CEN	0.729***	0.868***	0.457***	0.010	0.070**	-0.019	0.229***	0.247***	0.161***
	(5.17)	(6.18)	(3.28)	(0.30)	(2.07)	(-0.56)	(9.04)	(9.79)	(6.57)
|SUE|	1.598***	1.605***	1.588***	0.833***	0.834***	0.832***	0.042***	0.044***	0.039***
	(18.96)	(19.07)	(18.83)	(18.32)	(18.34)	(18.32)	(2.88)	(2.99)	(2.66)
Ctrls	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%	4.3%	2.8%	2.8%	2.8%	10.9%	10.9%	10.8%

Table B8: Local versus Distant Connections, Population, and Spatial Centrality

This table reports the regression of the two-day cumulative abnormal announcement returns on measures of the centrality of a firm's headquarters location. log(DC_{across}) is the logarithm of across-state degree centrality, constructed using the number of cross-state friendship links, respectively. log($DC_{>100m}$) is the logarithm of degree centrality constructed using the number of friendship ties to counties located more than 100 miles away from the home county. log(pop) is the logarithm of the population size of the county. log($DC_{spatial}$) is the county's spatial network centrality based on physical distance. log$(DC_{across})^{res}$, log$(DC_{>100m})^{res}$, and log($DC^{res}_{spatial}$) are the residuals from the regression of the corresponding raw variables on log(pop), respectively. SUE is the decile rank of earnings surprises. All control variables and fixed effects listed in Section 2.2 and their interactions with SUE, as well as the corresponding stand-alone alternative centrality measures, 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)	(7)	(8)	(9)
SUE· log(DC_{across})	0.0400***								
	(5.31)								
SUE· log($DC_{>100m}$)		0.0382***							
		(5.16)							
SUE· log(pop)			0.0358***	0.0391***	0.0400***		0.0359***	0.0389***	0.0406***
			(4.80)	(5.17)	(5.20)		(4.80)	(5.14)	(5.20)
SUE· log$(DC_{across})^{res}$				0.0611**				0.0630***	
				(2.53)				(2.58)	
SUE· log$(DC_{>100m})^{res}$					0.0601**				0.0631**
					(2.16)				(2.19)
SUE· log($DC_{spatial}$)						0.0257***			
						(4.23)			
SUE· log$(DC_{spatial})^{res}$							0.00205	-0.00398	0.00625
							(0.18)	(-0.35)	(0.54)
Ctrls (· SUE)	X	X	X	X	X	X	X	X	
Obs.	227,826	227,826	227,826	227,826	227,826	227,826	227,826	227,826	227,826
Adj. R^2	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%	3.2%