The Review of Financial Studies

News Diffusion in Social Networks and Stock Market Reactions

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We study how the social transmission of public news influences investors' beliefs and the securities markets. Using data on social networks, we find that earnings announcements from firms in higher-centrality counties generate a stronger immediate price, volatility, and trading volume reactions. Post-announcement, such firms experience weaker price drift and faster volatility decay but higher and more persistent volume. These findings suggest greater social connectedness facilitates the timely incorporation of news into prices, as well as opinion divergence and excessive trading. We propose the *social churning hypothesis*, which is confirmed using granular data from StockTwits messages and household trading records. (*JEL* G1, G4)

Received: March 31, 2023; Editorial decision: March 31, 2023
Editor: Laura Cohen
Authors have furnished an Internet Appendix, which is available on the Oxford University Press Web site next to the link to the final published paper online.

We appreciate helpful comments and discussions from Linda Allen, Kenneth Ahern, Brad Barber, Tony Cookson, Ming Dong, Anastassia Fedyk (discussant), William Goetzmann, Jeremiah Green (discussant), Harrison Hong (discussant), Chong Huang, Paul Irvine, Mark Kamstra, Matthew Jackson, Danling Jiang, Christian Leuz, Dongmei Li (discussant), Roger Loh, Yueran Ma, Suraj Malladi, Asaf Manela (discussant), William Mullins (discussant), Lilian Ng, Joshua Pollet (discussant), Asani Sarkar, Zheng Sun, Jun Tu, Wei Wu (discussant), Wei Xiong, Lu Zheng, Dexin Zhou, Qifei Zhu and participants at BESC University of Queensland, Nanyang Technological University, the University of California, Irvine, Peking University, Texas A&M University, the University of Miami, the University of South Carolina, York University, the European Securities and Markets Authority, ESCP Business School, the Bank of England, the Financial Intermediation Research Society Meetings, the International Virtual Research Seminars on Finance, the NBER conference on Big Data and Securities Markets, the American Economic Association Annual Meetings, the American Finance Association Annual Meetings, the China International Conference in Finance, the Midwest Finance Association Meetings, the USC/Marshall Conference on Social and Behavioral Finance, the Conference on Network Science and Economics, the Future of Financial Information Conference, the Western Finance Association Conference, and the Hawaii Accounting Research Conference. We appreciate the Driehaus Center for Behavioral Finance for recognizing us with a Research Prize. Peng thanks the Krell Research Fund and the Keynes Fund for generous support. This paper was previously circulated under the title "Social Networks and Market Reactions to Earnings News." Supplementary data can be found on *The Review of Financial Studies* web site. Send correspondence to Qiguang Wang, qiguangw@hkbu.edu.hk.

The Review of Financial Studies 38 (2025) 883–937

https://doi.org/10.1093/rfs/hhae025 Advance Access publication June 24, 2024

In classic models of information in asset markets, people learn from others only indirectly through observation of market prices or quantities. Growing evidence indicates that more direct forms of social interaction, such as conversation, also affect investment decisions (see the review of Kuchler and Stroebel 2021). Past models of social interactions in financial markets have identified both beneficial and deleterious effects on investor behavior. On the one hand, they can disseminate valuable information and lead to superior decisions and efficient prices. On the other hand, social interactions can also propagate incorrect beliefs and naïve investor attention, thereby reducing information efficiency.[1]

Here, we study the social dissemination of attention to a crucial type of public news: corporate earnings announcements. Past research has shown that stock prices do not incorporate this news promptly, leading to predictable abnormal returns over several months after the event date (e.g., Ball and Brown 1968; Bernard and Thomas 1989). The leading explanation for this delay is that not all investors are immediately attentive to earnings news (see, e.g., Bernard and Thomas 1989; Hirshleifer and Teoh 2003). When there are inattentive investors, attention to earnings news may spread through social networks. Accordingly, this paper explores how investor social transmission networks influence the speed of news diffusion, beliefs, trading behavior, and asset prices.

Our approach is motivated by the findings of Banerjee et al. (2013, 2019) that information about microfinance or immunization spreads faster when signals are seeded at central nodes in a network. In the stock market context, extensive evidence reveals that investors invest in local firms and are more attentive to news about local firms.[2] This suggests that earnings news may first capture the attention of local investors and that this attention is then disseminated through the network of investors via word of mouth.

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

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[1] Models in which social interactions potentially improve decision-making and efficiency include Ellison and Fudenberg (1995), Colla and Mele (2010), and Özsöylev and Walden (2011). However, other studies have shown that social interactions can lead to the spread of rumors, amplify behavior biases (DeMarzo, Vayanos, and Zwiebel 2003; Hirshleifer 2020; Han, Hirshleifer, and Walden 2021), trigger information cascades (Bikhchandani, Hirshleifer, and Welch 1992; Banerjee 1992), and create free-riding incentives (Han and Yang 2013).

[2] On local bias in investing, trading, and information search, see Coval and Moskowitz (1999); Ivković and Weisbenner (2005, 2007); Massa and Simonov (2006); Seasholes and Zhu (2010); Hong et al. (2014); Chi and Shanthikumar (2017).

To test for such effects, we define a firm's local investor base as the set of investors located in its headquarters county, and the firm's centrality (CEN) as the centrality of its local investor base in the social network of its potential U.S. investors. We find that earnings announcements by firms based in high-centrality locations tend to generate stronger immediate stock price, volatility, and trading volume responses for the 2-day window around the announcement, [0, 1]. Also consistent with earlier resolution of uncertainty, during the post-announcement period ([2, 61*]), returns exhibit weaker drift and faster decay of volatility.[3] Notably, however, for such firms, volume remains high and persistent in the post-announcement period.

More specifically, our proxy for network centrality is based up the newly available Social Connectedness Index (SCI), which measures the connectedness between U.S. counties (Bailey et al. 2018b) using data from Facebook, a social network with about a quarter of a billion users in the United States and Canada.[4] The centrality of a firm is measured as the centrality of its headquarters county in the matrix of SCIs between county pairs.

Figure 1 presents a heat map showing one of the centrality measures - eigenvector centrality, across U.S. counties that serve as headquarters for publicly listed firms. The darker colors correspond to higher centrality deciles. The image illustrates marked geographical variations, demonstrating that the centrality can vary significantly between two adjacent counties. For instance, Cook County, Illinois, which encompasses the city of Chicago, ranks among the counties with the highest centrality. In stark contrast, some counties neighboring Cook County, such as McHenry County in Illinois, Berrien County in Michigan, and Porter County in Indiana, have significantly lower centrality, falling into the bottom 30th percentile. This variation implies that social network centrality encompasses more than just state-level effects or factors related to geographic closeness. We provide further discussions of the centrality measures and their distinctions from other variables that might also influence information flow in Section 1.

The first set of empirical results concerns the relationship of centrality to price reactions to earnings news. Compared to announcements made by firms in the lowest decile of degree centrality, announcements by firms in the highest decile are associated with 29% stronger immediate price reactions during the [0, 1] window and 20% weaker post-announcement drift (PEAD), relative to their respective sample means, and faster decay in volatility. These results indicate that earnings news from more centrally located firms is more rapidly

[3] The post-announcement window ([2, 61*]) refers to the period from 2 days after an announcement to 5 days before the next announcement.

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

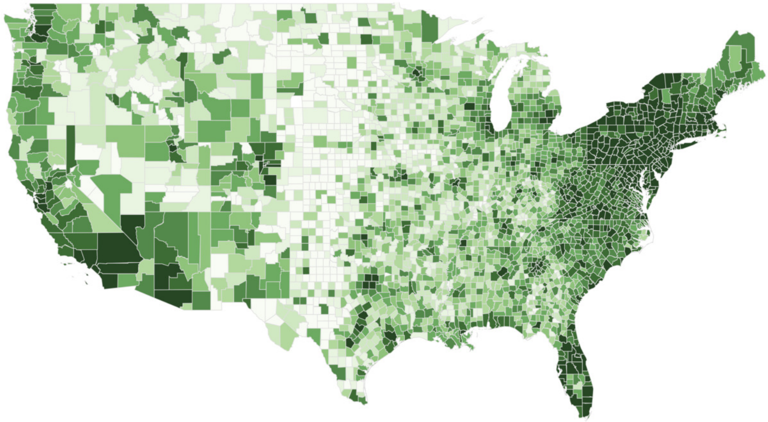

Figure 1
Heat map of eigenvector centrality
This heat map shows eigenvector centrality across U.S. counties that serve as headquarters for publicly listed firms as of June 2016. Darker colors represent higher centrality value deciles. The 10 counties with the highest eigenvector centrality are Los Angeles (CA), Cook (IL), Orange (CA), San Bernardino (CA), San Diego (CA), Riverside (CA), Maricopa (AZ), New York (NY), Clark (NV), and Harris (TX). The 10 counties with the lowest eigenvector centrality are King (TX), McPherson (NE), Wheeler (NB), Slope (ND), Sioux (NE), Blaine (NE), Arthur (NE), Petroleum (MT), Thomas (NE), and Banner (NE).

incorporated into stock prices. Therefore, network centrality is associated with greater diffusion of investor attention to earnings news and greater price efficiency.

Such an increase in centrality, from the lowest decile to the highest decile, also increases the immediate volume reaction to earnings news by 12% relative to its mean. Surprisingly, for the [2, 61*] window, we also find a positive relation between centrality and the level and persistence of trading volume—the same increase in centrality is associated with a 15% increase in average daily abnormal volume and a 10% increase in volume persistence. The pattern contrasts sharply with the negative relation between centrality and both returns and volatility persistence over this same post-announcement window. More intense social transmission of earnings news is associated with greater and *more* persistent stock trading.

The striking contrast in these findings poses a challenge to traditional frameworks that typically imply a faster decay in both volatility and trading volume with faster information diffusion.[5]

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

A starting point for resolving this puzzle is the strong evidence of extensive and persistent disagreement among retail investors (see the large panel survey of Giglio et al. 2021). We propose the *social churning hypothesis* of investor trading to explain the observed persistence in disagreement and the contrasting dynamics of return, volatility, and trading volume. As investors converse with different sets of acquaintances, some have attention triggered to a given stock and some do not. This triggered attention can promote naive bullishness or bearishness, causing the distribution of beliefs across investors, and investor disagreement, to shift.[6] Idiosyncratic fluctuations in disagreement need not impede the incorporation of news into stock prices, but they do imply persistent volume of trade. Thus, greater network centrality reduces post-earnings announcement drift and is followed by fast-decaying volatility, but can make volume more persistent.[7]

We evaluate the social churning hypothesis using granular data based on StockTwits messages and household trading records together with information about Google Search activities. Our evidence is consistent with the predictions of the social churning hypothesis about the effects of social interactions on investor attention, belief formation, and trading.

Our first set of tests of the social churning hypothesis is based on a sample of more than 10 million messages on StockTwits, a popular social media platform for investors to share their investment opinions. We classify StockTwits messages into two categories: New Messages, which corresponds to the number of initial mentions of a stock in a message thread, and Reply Messages, which refers to the number of replies to the initial messages. We use New Messages as a proxy for the number of newly informed investors, and Reply Messages for the intensity of subsequent discussions.

We find that announcements by firms in more central counties experience a larger initial increase in abnormal New Messages than less central counties during the [0, 1] window, relative to its preannouncement mean. Furthermore, the news of high-centrality firms is associated with a larger drop in abnormal New Messages for the [2, 61*] window. In contrast, greater centrality substantially increases abnormal Reply Messages for both the [0, 1] and [2, 61*] windows. These results are consistent with the prediction of the social churning hypothesis that investor attention to news quickly disseminates across different investors, but that the news also continues to attract investor attention and generate persistent intense discussions among investors for a substantial period post-announcement.

We then test whether stronger social interactions induce more persistent disagreement. We apply textual analysis to StockTwits messages to construct

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

7 The appendix provides a model to illustrate this mechanism.

a daily measure of disagreement in message sentiments. We find that earnings announcements of high-centrality stocks are associated with greater divergence of beliefs across investors for both the [0, 1] and [2, 61*] windows. This finding is consistent with the social churning hypothesis, which asserts that greater social news transmission contributes to more persistent belief heterogeneity.

We also use an alternative centrality measure constructed directly from StockTwits data, defining "influencers" as users with high centrality in the social network of StockTwits users. We find that earnings announcements that are more central in the investor social network—in the sense that they receive more initial mentions by influencers—generate more replies and greater disagreement among investors for the [2, 61*] window. Although influencers mentions are likely endogenous, these findings are consistent with the social churning hypothesis, in that messages originating from central nodes within social networks are associated with subsequent attention and disagreement. These findings also provide an out-of-sample validity check for the Facebook-based centrality measures.

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

We then use individual account-level data from a large U.S. discount brokerage (Barber and Odean 2000) to test whether investors who reside in counties with stronger social connections to a firm's county are more likely to trade on the firm's earnings announcements. We find that an increase in social connectedness substantially increases the likelihood of a household trading. Furthermore, an increase in social connectedness, from the lowest to the highest decile, is associated with greater household trading losses, by 17% relative to the sample mean. The evidence suggests that the greater trading of connected investors is excessive, presumably owing to erroneous beliefs.

Overall, an array of tests provides support for the social churning hypothesis across various types of behaviors (trading, text generation, and Google searches) and outcomes (volume, mean returns, volatility of returns, the persistence of these variables, and trading profitability). These finding are consistent with social interactions diffusing attention to relevant news announcements across investors, but also generating persistent disagreement and excessive trading.

The Facebook centrality measure, being a snapshot from 2016, does not capture time variation, and captures geographic rather than firm-level variations. This raises the questions of whether results are influenced by unobserved county characteristics associated with centrality, and whether the 2016 social network data are applicable for our sample period beginning in 1996. We address this concern in several ways.

First, we apply the omitted variable test of Oster (2019) to show that our results are unlikely to be driven by omitted variables. Second, our StockTwits-based analysis controls for firm fixed effects and has accounted for factors related to firm or county characteristics. Third, the household-firm pair level analysis controls for both firm and household fixed effects. Fourth, we obtain very similar results by using the 2020 Facebook data, consistent with recent studies suggesting that the Facebook-based social connectedness captures persistent real-world social ties (see, for instance, Bailey et al. 2018b, 2020; Chetty et al. 2022). Finally, we exploit an exogenous shock to social interactions triggered by Hurricane Sandy to provide further support for the role of social interactions in explaining price reaction to earnings news.

We also test the extent to which the effects of centrality (CEN) might be driven by social proximity to institutional capital (SPC, Kuchler et al. 2022). We find that CEN's influence remains robust and is not subsumed by SPC. This means that our results can be largely attributed to the social network of retail investors rather than firms' social proximity to institutional investors.

We therefore expect that the effects of CEN would be greater for smaller, locally focused, or lesser-known firms. These are the types of companies that retail investors might not pay much attention to unless they hear about them through their social network. Our empirical findings support this. To get at this pathway more directly, we examine retail trades, following Boehmer et al. (2021). We find a positive association between CEN and abnormal retail trading volume following earnings announcements. These results suggest that CEN influences the behavior of retail investors, and that retail investors affect market price reactions to news.

An interesting issue is whether different social media platforms, which potentially captures different kinds of investor social interactions, are associated with different market outcomes (Cookson et al. 2022). To explore this, we construct a StockTwits-based centrality measure (SCEN) by considering the number of messages mentioning a stock over a 3-month period leading up to a given announcement. We compare the influence of the Facebook-based social network and the StockTwits network on returns and trading volume. We find that SCEN is not significantly associated with price responses to earnings announcements, unlike the Facebook-based centrality. This suggests that the expansive nature of the Facebook social network may help it better capture aggregate equilibrium outcomes, such as prices. Regarding trading volume, both types of centrality are associated with a greater increase in trading volume immediately after earnings are announced; however, the influence of

StockTwits centrality diminishes quickly, while that of Facebook centrality is more sustained.

Our results are robust to controlling for physical proximity, state fixed effects, and to excluding firms located in the U.S. tri-state area of New York, New Jersey, and Connecticut, where many financial firms are headquartered. The results are also robust to controlling for whether the firm has geographically dispersed operations, which could contribute to firm visibility. We also confirm the robustness of our results using residual centrality measures that purge the effect of county characteristics, as well as alternative measures of persistence. Our findings are also consistent across various sample periods. In addition, we find similar effects of centrality on market reactions to an alternative form of news release—analyst forecast revisions.

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

We are not the first to apply social networks data to study how social interactions affect investment decisions. Our tests benefit from the relatively comprehensive nature of the Facebook social network data and the investing focus of StockTwits data. Many valuable previous studies of social networks have focused on more specialized sets of participants and their individual decisions.[8] Recent studies have used Facebook data to explore how social networks affect firm-level outcomes, such as valuation and liquidity (Kuchler et al. 2022), and aggregate outcomes, such as international trade (Bailey et al. 2021). Our paper differs from these studies in that we examine the effects of social connectedness on information transmission and return and volume dynamics.

A growing literature explores the role of beliefs and disagreement in explaining economic outcomes (see DellaVigna 2009; Carlin, Longstaff, and Matoba 2014; Bailey et al. 2018a; Benjamin 2019; Giannini, Irvine, and Shu 2019; Bailey et al. 2019; Giglio et al. 2021; Cookson and Niessner 2020; Fedyk 2024; Cookson, Engelberg, and Mullins 2023). Our paper contributes to this literature by demonstrating that social diffusion of investor attention to public news is associated with persistent post-event disagreement and by providing a unified explanation for the sharply contrasting dynamics of return and volume responses to news.

[8] 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), Hong et al. (2014), Pool, Stoffman, and Yonker (2015), Heimer (2016), Ahern (2017), Crawford, Gray, and Kern (2017), Maturana and Nickerson (2018), Mitton, Vorkink, and Wright (2018), Hong and Xu (2019), Ouimet and Tate (2020), Huang, Hwang, and Lou (2021), and Choi et al. (2022). Also, research has investigated social interactions and entrepreneurial and managerial decision-making (Lerner and Malmendier 2013; Shue 2013) and the performance of sell-side financial analysts (Cohen, Frazzini, and Malloy 2010).

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

1. Data and Variables

Our sample consists of all common stocks (SHRCD = 10 or 11) traded on the NYSE, AMEX, NASDAQ, and NYSE Arca. We obtain historical firm headquarters location data from the SEC EDGAR 10-K header file, available in electronic form since May 1996. 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.

1.1 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) (Bailey et al. 2018b). This measure is based on the number of Facebook friendship links between a pair of counties and was created using anonymized information on the universe of friendship links between U.S.-based Facebook users as of April 2016.

Facebook's scale and the relative representativeness of its user body make the SCI a useful proxy for real-world social connections. Strong evidence suggests that friendships observed on Facebook reflect long-run historic connections between people (Bailey et al. 2018b, 2020; Chetty et al. 2022). As noted by Chetty et al. (2022, p. 108), "The Facebook friendship network can therefore be interpreted as providing data on people's real-world friends and acquaintances rather than purely online connections."

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

As discussed in the introduction, the heat map in Figure 1 reveals substantial cross-sectional variation in centrality. The counties exhibiting the highest centrality include several in California, such as Los Angeles, Orange, San Bernardino, San Diego, and Riverside. Other notable examples include Cook County in Illinois, Maricopa County in Arizona, New York County in New York, Clark County in Nevada, and Harris County in Texas. Futhermore, even neighboring counties like Cook and McHenry in Illinois can exhibit starkly different centralities. Such variation helps us distinguish between the effects of physical proximity and social proximity.

1.2 Other variables

1.2.1 Earnings surprises. We define SUE as the decile rankings of standardized unexpected earnings, which is the split-adjusted actual earnings per share minus the same-quarter value from the year before, scaled by the standard deviation of this difference over the previous eight quarters (Foster 1977).[10]

1.2.2 Returns and trading volume. CAR[0, 1] and CAR[2, 61*] represent the cumulative buy-and-hold returns for the periods [0, 1] and [2, 61*], respectively, and are adjusted by size, B/M, and momentum following Daniel et al. (1997) (DGTW). We follow the convention used in the literature and denote the post-announcement window, [2, 61*], as the period from 2 days after an announcement to 5 days before the next announcement.[11] Daily log abnormal volume is the difference between the logarithm of the number of shares traded on a given day and its preannouncement average during the [–41, –11] window. LNVOL[0, 1] and LNVOL[2, 61*] correspond to the average log abnormal volume during the announcement and the post-announcement periods, respectively.[12]

1.2.3 Controls. We control for an extensive set of firm and county characteristics to account for factors that have been identified in the past

9 See Bonacich (1972), Stephenson and Zelen (1989), and Borgatti (2005) for more details.

10 We compare the announced earnings to the same-quarter earnings from the previous year, instead of to the analyst consensus forecast. We adopt this approach because we expect the social interaction effects to be stronger for small and retail stocks, which typically have low analyst following. Therefore, it is important to perform tests that account for such effects. Additionally, our centrality measure captures the social network of retail investors who respond more strongly to random-walk-based SUE (Ayers, Li, and Yeung 2011). Deflating unexpected earnings by quarter-end closing price yields similar results.

11 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).

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

literature as possible determinants of price and volume reactions to earnings news. We summarize these variables below and present the detailed definitions in Table A1 in the appendix.

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 return volatility (IVOL), reporting lag (RL), institutional owernship (IO), and industry fixed effects using Fama-French 10 industry classification. To further control for visibility and familiarity, 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 (SP500) that equals one if the firm belongs to the S&P 500 index and zero otherwise (Ivković and Weisbenner 2005), and advertising expenditure (ADX) (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, quarter, and day of the week to account for variations in investor attention (DellaVigna and Pollet 2009).

We incorporate county-level variables to control for factors that might affect the spread of information. To measure a county's social proximity to institution investor capital (SPC, Kuchler et al. 2022), we gather the historical headquarters locations of institutions from the headers of their 13F filings and construct the SPC as the SCI-weighted average of the total assets under management by fund families based in the county. The measure is compiled for the period of 1999–2016. We also introduce an urban indicator that equals one if the county contains one of the 10 largest U.S. cities and zero otherwise (Loughran 2007). To proxy for the amount of information that local investors have access to, we measure the percentage of the local workforce in the same industry of the firm (WSI). 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 length of household tenancy (Tenancy).[13]

1.3 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. EC is more positively skewed than DC because EC assigns extra weight to a node if it is connected to the nodes that are themselves important.

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

Table 1
Descriptive statistics

A. Descriptive statistics

					Percentile			
Variable	Mean	Median	Stdev	Skewness	10th	25th	75th	90th
DC	18.84	13.14	21.73	2.29	2.11	6.01	20.85	40.15
EC	4.76	0.47	17.91	5.02	0.04	0.17	1.78	5.14
IC	97.90	99.26	4.62	−5.42	95.34	98.42	99.61	99.90
SUE	0.29	0.19	1.36	0.46	−1.41	−0.49	1.02	1.97
CAR[0, 1] (%)	0.02	−0.11	8.91	1.78	−8.81	−3.64	3.49	8.69
CAR[2, 61*] (%)	−0.74	−1.73	26.98	12.23	−23.95	−11.69	7.88	20.24
LNVOL[0, 1]	0.64	0.61	0.99	−0.04	−0.38	0.13	1.14	1.75
LNVOL[2, 61*]	0.04	0.02	0.59	0.35	−0.61	−0.27	0.32	0.70
Size	3.58	0.34	17.60	0.00	0.03	0.09	1.42	5.61
B/M	0.65	0.53	0.47	1.19	0.16	0.30	0.87	1.34
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
IVOL	0.03	0.02	0.02	1.95	0.01	0.01	0.03	0.05
RL	33.65	30.00	16.99	4.59	18.00	23.00	40.00	50.00
IO	0.50	0.51	0.31	0.15	0.07	0.22	0.76	0.91
ADX	30.60	0.00	233.70	17.34	0.00	0.00	0.91	18.05
NA	219	204	136	0.61	46	111	304	420
WSI	0.09	0.08	0.06	1.37	0.03	0.04	0.12	0.17
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
Edu	13.32	13.34	0.68	−0.20	12.50	12.83	13.83	14.17
Income	54.50	51.88	19.07	0.00	32.24	42.24	65.89	80.94
PopDen	4647	1510	13356	4	237	676	2411	5452
Tenancy	7.17	7.00	2.49	0.34	4.00	5.39	9.00	10.00
SPC	13.61	13.41	1.04	0.71	12.43	12.94	14.15	14.96

(Continued)

To make results comparable across different centrality measures, we use the decile ranks of these measures.

Panel B reports the correlation coefficients. The centrality rank measures are highly correlated amongst each other, with correlations ranging from 0.875 to 0.969. The correlations between CEN, the centrality measures, and firm characteristics are relatively small, with an absolute magnitude of no more than 0.093. For instance, the correlation between CEN and firm size—an often-used proxy for a firm's visibility—is only between 0.03 and 0.06. Consider Cook County, Illinois, as a case in point: it hosts a diverse array of firms, from industry giants like Boeing, Allstate Insurance, and Sears, to mid-scale enterprises, such as Groupon and GrubHub, down to smaller outfits like Lifeway Foods. Despite the considerable variation in their sizes, these firms are all associated with the same centrality measure. This example underscores that centrality is different from conventional firm visibility attributes like size.

When it comes to county-level characteristics, centrality measures show only modest correlations. For instance, CEN is positively correlated with population density and negatively with average age, the proportion of retired individuals, and average tenancy duration. This suggests that counties with higher centrality are likely to have a younger, more transient

Table 1
(Continued)

B. Correlation structure

	DC	EC	IC
DC	1.000		
EC	0.875	1.000	
IC	0.969	0.902	1.000
SUE	−0.035	−0.046	−0.036
CAR[0, 1] (%)	−0.005	−0.004	−0.005
CAR[2, 61*] (%)	−0.006	−0.005	−0.006
LNVOL[0, 1]	0.005	0.023	0.008
LNVOL[2, 61*]	0.004	0.005	0.005
Size	0.062	0.033	0.057
B/M	−0.036	−0.093	−0.056
EP	−0.019	0.012	−0.013
EVOL	−0.017	−0.021	−0.013
IVOL	0.022	0.073	0.034
RL	0.037	0.039	0.049
IO	0.014	−0.007	0.009
ADX	0.052	0.039	0.064
NA	0.024	0.034	0.029
WSI	−0.169	−0.100	−0.194
AvgAge	−0.245	−0.211	−0.225
Retire	−0.257	−0.317	−0.281
Edu	−0.165	−0.028	−0.109
Income	−0.063	−0.059	−0.050
PopDen	0.309	0.313	0.353
Tenancy	−0.248	−0.210	−0.270
SPC	0.360	0.349	0.426

This table reports the summary statistics and correlation matrix for the main variables used in the paper. Panel A reports the mean, median, standard deviation, skewness, and the 10th, 25th, 75th, and 90th percentiles 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 the time-series averages for the cross-sectional correlations of the decile ranks of the centrality measures against other variables. Variable descriptions are in Table A1 in the appendix.

population. However, these correlations do not exceed an absolute value of 0.353.

Centrality is non-negligibly correlated with another county-level variable, social proximity to institutional equity capital (SPC). The correlation between SPC and CEN ranges from 0.35 to 0.43. This further indicates a substantial cross-sectional variation in CEN that SPC does not account for. This is also evident in Figure S1. Harris County, TX, which encompasses Houston, ranks among the top 10 in CEN and is home to a variety of firms, from large ones like Phillips 66, Sysco, and Shell Oil to smaller companies like American Electric Technologies. However, when evaluated by SPC, these firms fall into the third decile of our firm sample.

These initial comparisons suggest that network centrality (CEN) captures information distinct from firm-level and county-level indicators related to visibility and accessibility of institutional capital. In our further analysis, we control for firm-level and county-level characteristics extensively. Additionally, we apply a residual centrality measure to focus on variation in centrality unrelated to the firm and county characteristics. Our main findings remain robust under this residual centrality measure.

2. Centrality and Price Dynamics

We start by investigating the relationship between investor social network centrality and stock market reactions to earnings news. As mentioned earlier, previous research documents short-run price underreaction to earnings announcements, followed by post-announcement return drift that is most pronounced for about 3 months after the announcement date. We therefore examine whether the social network centrality is associated with greater diffusion of earnings news.

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

2.1 Announcement returns and post-announcement drift

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

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

The dependent variable, CAR, is either the abnormal 2-day earnings announcement return, CAR[0, 1], or the post-announcement cumulative abnormal return, CAR[2, 61*]. SUE is the earnings surprise decile rank; CEN is the decile rank of one of the county-level centrality measures. X consists of the lagged firm- and county-level control variables and industry and time fixed effects, as outlined in Section 1.2, as well as their interactions with SUE. The coefficient of interest is β_2, which captures the relationship between a firm's headquarters centrality and return responsiveness to its earnings announcements.

Table 2 presents the key results, with panels A–C corresponding to CAR[0, 1], CAR[2, 40], and CAR[2, 61*], respectively. The complete list of coefficient estimates are reported in Internet Appendix Table S1. Table 2, panel A, column 1, presents the baseline specification for DC, the degree centrality. The coefficient for SUE is positive and significant, consistent with the previous literature that stock prices tend to react positively to positive earnings surprises and negatively to negative surprises.

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

Table 2
Centrality and returns following earnings announcements

A. CAR[0, 1]

	Degree centrality			Eigenvector centrality			Information centrality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN·SUE	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)
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)
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

B. CAR[2, 40]

	Degree centrality			Eigenvector centrality			Information centrality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN·SUE	−0.0180***	−0.0206***	−0.0123**	−0.0218***	−0.0238***	−0.0142**	−0.0166***	−0.0187***	−0.00997
	(−3.70)	(−4.10)	(−2.03)	(−4.48)	(−4.73)	(−2.29)	(−3.44)	(−3.74)	(−1.60)
SUE	0.390***	0.400***	0.201	0.412***	0.419***	0.201	0.382***	0.390***	0.118
	(12.73)	(12.55)	(0.36)	(13.91)	(13.58)	(0.37)	(12.81)	(12.56)	(0.21)
CEN	0.159***	0.163***	0.116***	0.215***	0.207***	0.151***	0.153***	0.154***	0.104**
	(4.75)	(4.61)	(2.88)	(6.15)	(5.70)	(3.59)	(4.53)	(4.32)	(2.49)
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	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6

(Continued)

Table 2
(Continued)

	C. CAR[2, 61*]								
	Degree centrality			Eigenvector centrality			Information centrality		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CEN·SUE	−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)
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)
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

This table reports the regression results of cumulative abnormal returns (CAR) on the centrality of the firm's headquarters location. Panels A, B, and C correspond to the CARs for the announcement period (CAR[0, 1]) and the post-announcement periods (CAR[2, 40] and CAR[2, 61*]), respectively. CEN is the decile rank of the centrality of a firm's headquarters county, measured by degree centrality, eigenvector centrality, or information centrality. SUE is the decile rank of standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 and their interactions with SUE are included. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

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. An increase of degree centrality from the lowest to the highest decile is associated with a sensitivity increase of 0.137 (=0.0152 × 9), or 28.6% of the sample average marginal effect of 0.479.[14]

The results are similar for the other two centrality measures, presented in columns 4–9: the coefficients of CEN·SUE 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 than those in decile 1, relative to the sample average.

Turning to post-earnings announcement drift over the window of [2, 40], Table 2, panel B, shows that the β_2 coefficients are negative for all three centrality measures and statistically significant for DC and EC. The results suggest that announcements by firms headquartered in high-centrality counties experience substantially less post-announcement drift. Based on the full model (columns 3, 6, and 9), 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 29.2% to 41.6% relative to the sample mean.

Panel C reports the results for CAR[2, 61*] and shows that the β_2 coefficients remain negative but with somewhat weaker magnitude and statistical significance. Additionally, we examine return responses for different windows post-announcement: [2, 3], [2, 5], [2, 10], [2, 20], and [2, 30]. Table S4, panel A, and Figure A1 presents the findings using EC as the centrality measure and shows that the coefficient for EC·SUE is consistently negative across all periods and is also significant for the [2, 3] and [2, 40] window.[15]

Notably, as shown in Table 2, the inclusion of standalone control variables does not substantially affect the coefficient of our variable of interest, CEN·SUE. However, the inclusion of interactive controls noticeably influence the coefficient of interest. One reason for this is that the effect of adding

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

[15] One possible reason for the weaker result for CAR[2, 61*] compared to CAR[2, 40] is that a longer window introduces additional noise deriving from news unrelated to the earnings announcements on day 0, or because of activities incurred in anticipation of the next earnings announcement (see, e.g., Chi and Shanthikumar 2017). We have also replicated Table 2 for subsamples of positive and negative SUE, respectively, and find that the estimated coefficients of interest are not significantly different between the two subsamples. Hence, we will focus on the full sample analysis for the remainder of the paper.

interactive control variables depends on the correlations among CEN·SUE, the control·SUE, and CAR (see Internet Appendix for details).[16]

In sum, we find that earnings announcements from more centrally located firms are associated with stronger immediate price reactions and weaker post-announcement drifts. This evidence suggests that social network centrality facilitates the dissemination of relevant informatio, leads to a faster resolution of uncertainty, and enhances the informational efficiency of asset prices. Consequently, we expect to observe a faster decay in volatility reactions to earnings surprises during the post-announcement period. Next, we explore the relationship between the centrality of a firm's headquarters county and the persistence of return volatility following the firm's earnings announcements.

2.2 Volatility persistence

To estimate volatility persistence, we follow Bollerslev and Jubinski (1999) and apply the autoregressive fractionally integrated moving average (ARFIMA) model to $|R|$, the daily absolute returns, for the [0, 61*] window. The estimated fractional integration parameter, d, 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 then regress $d_{|R|}$ on the centrality measure and other variables:

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

where |SUE| is the decile rank of absolute SUE to control for the magnitude of earnings surprises, and X is the list of lagged control variables and industry and time fixed effects described in Section 1.2. Since $d_{|R|}$ is scale-free, there is no compelling reason to believe that the size of |SUE| affects the CEN-persistence relation. Hence, we do not include |SUE|· CEN in the regression.

Table 3 presents the key results, with the complete list of coefficient estimates presented in Internet Appendix Table S2. 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

[16] We can also assess the robustness of our findings to omitted variable bias by comparing the coefficient estimates with and without controls following the approach suggested by Altonji, Elder, and Taber (2005) and Oster (2019). With R_{max} set to 1.3R as recommended, the estimates for the parameter of proportional selection for the full regression models (3), (6), and (9) range from −0.59 to −0.42 for the CAR[0, 1] results, −0.54 to −0.36 for the CAR[2, 40] results, and −0.36 to −0.23 for the CAR[2, 61*]. As suggested by Satyanath, Voigtländer, and Voth (2017), a negative parameter value suggests that the presence of omitted variables likely results in an attenuation bias. Including more controls can help mitigate this bias.

Table 3
Centrality and volatility persistence

	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)
Ctrls		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%

This table reports the regression of volatility persistence on the centrality of the 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 rank 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 standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. $^*p$ <.1; $^{**}p$ <.05; $^{***}p$ <.01.

effect of an earnings news shock on volatility is shorter-lived for firms in more central locations.[17]

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

3. Centrality and Volume Dynamics

Next, we examine the trading behavior of investors following firms' earnings announcements. Theoretical models predict that the arrival of news triggers trading (see, e.g., Kim and Verrecchia 1991; Harris and Raviv 1993; Kandel and Pearson 1995). To the extent that attention to news from more centrally located firms diffuses across investors more rapidly, we expect such firms to have stronger immediate volume responses.

If the diffusion of attention to such news also helps investors more rapidly resolve their opinion differences, we also expect volume dynamics to be less persistent and the level of volume for the [2, 61*] window to be lower for such firms. On the other hand, if social interactions generate persistent opinion differences regarding the news, it could instead result in persistent excess trading. To investigate the relationship between centrality and the sensitivity of trading volume at different dates to earnings news, we analyze three characteristics of volume dynamics: immediate volume responses, post-announcement volume responses, and the persistence of volume responses.

[17] Similar to our analysis on return reactions, we conduct the omitted variable tests following Oster (2019). The estimates of the parameter of proportional selection for the full regression models in Table 3 ranges from 1.34 to 1.53, all exceeding the threshold of 1. Hence, the test suggests that the omitted variable bias is unlikely to explain our results.

Table 4
Centrality and trading volume

	LNVOL[0, 1]			LNVOL[2, 61*]			d_{VOL}		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)	DC (7)	EC (8)	IC (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)
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

This table reports the regression of trading volume on the centrality of the firm's headquarters location. In columns 1–3 and 4–6 the dependent variables are LNVOL[0, 1] and LNVOL[2, 61*], the average daily abnormal 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 volume over the [0, 61*] window. CEN is the decile rank 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 standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

3.1 Immediate and Post-Announcement Volume Responses

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

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

where the dependent variables, LNVOL[0, 1] and LNVOL[2, 61*], are the average daily abnormal log volume during the [0, 1] and the [2, 61*] period, respectively. |SUE| is the absolute earnings surprise decile rank, CEN is the county-level centrality measure, and X consists of the lagged control variables and industry and time fixed effects mentioned in Section 1.2. Given the log-linear specification, the variable of interest here is β_1, the coefficient for CEN.

Table 4, columns 1–3, presents the [0, 1] volume reactions immediately after the earnings announcement. These indicate that earnings news from more centrally located firms triggers stronger immediate volume increases than news from 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 centrality from the lowest to the highest decile increases the LNVOL[0, 1] by 0.076 to 0.092, an increase of 11.90% to 14.32% relative to its sample mean. Evidence about the [2, 61*] volume dynamics is presented in Table 4, columns 4–6. The coefficients of CEN are positive and significant across all three centrality measures. Economically, an increase in centrality from the lowest to the highest decile increases LNVOL[2, 61*] by 14.68% to 30.79% relative to the sample average.[18]

This finding is in sharp contrast to the *negative* relationship between centrality and post-announcement returns that we document earlier. This contrast suggests that the effect of discussions of news on investor belief heterogeneity differs from their effects on prices. Next, we directly analyze the relationship between news centrality and the post-announcement volume persistence.

3.2 Volume persistence

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

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

The results provide a sharp contrast to the negative association between centrality and volatility persistence. This suggests that the social diffusion of investor attention to news can contribute to excessive and persistent trading. Social networks influence investor beliefs and trading in a more subtle way than is implied by the aforementioned models.

4. A Framework for Information Diffusion via Social Interactions

The striking contrast between the dynamics of the reactions of prices versus trading volumes to earnings news presents a puzzle. In this section, we offer a possible explanation and propose the social churning hypothesis, as defined in the introduction. We present the intuition here, and a formal model can be

18 Internet Appendix C Table S3 provides a complete list of coefficient estimates for all the controls. As in our earlier tests and as suggested by Oster (2019), our analysis indicates that omitted variables are unlikely to drive our findings. Specifically, in the LNVOL[0, 1] regression, the estimate of the parameter of proportional selection from the Oster (2019) test ranges from 6.7 to 13.3, far exceeding the recommended threshold of 1. Similarly, in the LNVOL[2, 61*] regression, the estimated parameter ranges from −1.35 to −0.33, indicating that the omitted variables actually act as a bias against observing the relationship that we find. Furthermore, Internet Appendix Table S4 and Figure A1 present results for various PEAD windows showing that the results are robust.

found in the appendix. The appendix also present stylized models that indicate that our findings pose challenges for several traditional frameworks. We then test further implications of the hypothesis.

4.1 The social churning hypothesis

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

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

When investors talk, they do not just convey the earnings surprise; they convey their opinions and interpretations. Such a discussion after the arrival of earnings news further triggers changes in investor beliefs and disagreement about asset valuation, and hence trading. Investor beliefs continually fluctuate as a result of social interactions. As investor discussions continue, their beliefs and disagreements fluctuate over a substantial period of time too.[19] These belief fluctuations produce trading volume. However, the fluctuations are mostly idiosyncratic, limiting their contribution to price movements, and, therefore, to the persistence of return volatility.

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

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

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

4.2 Evidence from StockTwits

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

We test these implications with a data set of 10.9 million messages on StockTwits, a popular social media platform for investors to share opinions and ideas. This social networking platform is specifically designed for the financial community, enabling us to directly capture interactions among investors. The dynamic nature of this data allows us to incorporate firm fixed effects in our analysis, which helps control for latent, confounding factors tied to firm or county characteristics that might be associated with our Facebook-based measures.

Our StockTwits tests complement the Facebook CEN analysis. Facebook's extensive reach and the relative representativeness of its user base make CEN a highly informative proxy for enduring real-world social connections at the county level. However, the StockTwits analysis enables us to use high-frequency fluctuations in social interactions among the StockTwits users during a specific period.

On the platform, users can directly mention a security in the message through "cashtags" by placing a dollar sign before its ticker (e.g., $APPL for Apple). As shown by Cookson, Engelberg, and Mullins (2023), StockTwits users include a wide range of market participants, ranging in experience from novice, intermediate, to professional, with nearly 20% self-identified as professionals working in finance or holding financial certifications, such as a CFA. The dispersion of opinions expressed on StockTwits has been shown to be positively associated with market-level trading volume (Cookson and Niessner 2020).

Our sample consists of messages posted by 79,176 unique users from 2009 to 2013, covering 9,131 distinct symbols.[20] In the subsequent tests, we analyze the messaging activities and the divergence of beliefs as reflected in the messages following an earnings announcement. We also construct an alternative, time-varying measure of social network centrality based on StockTwits influencers, and examine the roles of influencers on message activities and disagreement. Our findings provide support to the social churning hypothesis and serve as validation checks that complement our earlier analysis using Facebook's SCI measures.

[20] We are grateful to Yakun Wang for sharing this data.

4.2.1 Messaging activities. For each stock on a given day, we define New Messages as the number of initial messages that mention a stock, and we define Reply Messages as the number of replies to the initial messages.[21] We use New Messages to proxy for the number of newly informed investors, and Reply Messages for the intensity of subsequent discussions.

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

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

We then test whether the centrality of the announcing firm is associated with StockTwits messaging activities. We estimate Equation (3), 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 (multiplied by 100) is positive and significant, indicating that high-centrality announcements trigger a more pronounced increase in Abnormal New Messages immediately following the announcement. For abnormal replies, panel B indicates that higher centrality is also associated with a greater increase in the number of replies on StockTwits, suggesting more discussions of the stock upon announcement.

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

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

Table 5
Centrality and StockTwits mentions

A. New messages

	ANM[0, 1]			ANM[2, 61*]		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
CEN	0.34**	0.42**	0.40**	−0.07***	−0.09***	−0.07**
	(2.07)	(2.56)	(2.37)	(−2.82)	(−3.00)	(−2.51)
|SUE|	2.69***	2.70***	2.70***	0.44**	0.43**	0.44**
	(5.37)	(5.40)	(5.39)	(2.40)	(2.39)	(2.40)
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

B. Reply messages

	ARM[0, 1]			ARM[2, 61*]		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
CEN	0.83***	1.16***	0.86***	1.08***	1.51***	1.18***
	(3.42)	(4.68)	(3.39)	(4.03)	(5.51)	(4.22)
|SUE|	1.97**	2.00**	1.97**	3.01***	3.06***	3.02***
	(2.27)	(2.31)	(2.28)	(3.35)	(3.40)	(3.36)
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

This table reports the regression of abnormal StockTwits message activities on the centrality of the firm's headquarters location. Panels A and B present the results for abnormal new messages and abnormal replies, respectively. Abnormal New Messages, ANM[0, 1] and ANM[2, 61*], are the abnormal average daily number of new messages for the [0, 1] and [2, 61*] windows, respectively, relative to its preannouncement average. Similarly, ARM[0, 1] and ARM[2, 61*] are the abnormal average daily reply messages for the corresponding windows. CEN is the decile rank 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 standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Standard errors are two-way clustered by firm and announcement date and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

For the [2, 61*] window, panel A of Table 5, columns 4–6, shows a negative and significant association between centrality and Abnormal New Messages, indicating a more rapid reduction in new message activities for high-centrality announcements than low-centrality ones. This is consistent with our conceptual framework, which posits that the number of individuals unaware of the news quickly diminishes following high-centrality announcements compared to the low-centrality announcements.

In sharp contrast, the CEN coefficient of 1.51 for panel B, column 2, indicates that the same increase in CEN increases ARM by 34.85% ($=0.0151 \times 9/0.39$). Additionally, Internet Appendix Table S4 and Figure A1 present the results for various PEAD windows, showing a robust and consistent effect of CEN on the post-announcement dynamics of ANM and ARM. These findings suggest that high-centrality announcements attract more discussion of the news and that these discussions are, on average, substantially more persistent than the new mentions. The evidence is consistent with the first key implication of the social churning hypothesis.

4.2.2 Disagreement. The next key implication of the hypothesis is that social interactions drive persistent disagreement. To test this, we first measure the probability (in %) that a given message conveys positive sentiment using a convolutional neural network (CNN).[22] We then measure disagreement as the standard deviation of that probability across messages related to a stock for a given day.

The average daily message disagreement over the announcement and post-announcement windows, respectively, have sample averages of 20% and 19%, suggesting that disagreements do not dissipate over these windows. The average daily disagreement measures for the two windows are 9% and 5%, respectively. We then define abnormal disagreement, DIS[0, 1] and DIS[2, 61*], as the logarithmic difference between the average disagreement during the corresponding window and the $[-41, -11]$ preannouncement average.

We then run regression tests as in Equation (3), replacing the dependent variable with either DIS[0, 1] or DIS[2, 61*]. Table 6, panel A, presents the results. Columns 1–3 show that the coefficients of CEN are positive and significant for EC. This indicates that earnings announcements by high-centrality stocks are associated with greater disagreements among investors. More importantly, these greater disagreements do not dissipate over time in the post-announcement window, as shown by the positive and significant coefficient for CEN in columns 4–6. Moreover, columns 7–10 show that d_{DIS}, the persistence of disagreement estimated with the ARFIMA model discussed earlier, also increases significantly with centrality.

As before, we illustrate the economic magnitude of our findings using the EC measure. Columns 2 and 5 show that announcements from stocks in the highest centrality decile elicit significantly higher levels of investor disagreement compared to those from stocks in the lowest centrality decile. Specifically, the difference amounts to $10.35(=1.150 \times 9)$ for the announcement window and $19.76(=2.196 \times 9)$ for the post-announcement period. These magnitudes correspond to 9.7% and 22.5% of the sample standard deviations, respectively.

Based on our conceptual framework, social transmission of news is particularly important in explaining the dynamics of disagreements during the post-announcement period. To gain further empirical insight into the influence of social networks, we shift our focus to examining disagreement among reply messages over the [2, 61*] window. Panel B describes regression of disagreement or the persistence of disagreement on CEN, while controlling for the same set of variables as in the corresponding analysis in panel A. We find that the coefficients of CEN remain positive and statistically significant,

[22] We do not use the self-reported sentiment by StockTwits users for this test because this variable is only available for 10% of the messages in our sample. CNN is a widely used model for sentiment analysis in artificial neural networks. It has been shown to outperform 14 alternative models in sentiment classification (Kim 2014). Our training sample is based on StockTwits messages with self-labeled bullish/bearish indicators.

Table 6
Centrality and StockTwits disagreement

A. Message disagreement

	DIS[0, 1]			DIS[2, 61*]			d_{DIS}		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)	DC (7)	EC (8)	IC (9)
CEN	0.521	1.150***	0.516	1.448***	2.196***	1.528***	0.388***	0.490***	0.423***
	(1.28)	(2.61)	(1.19)	(3.66)	(5.40)	(3.71)	(3.67)	(4.51)	(3.87)
|SUE|	−0.101	−0.090	−0.101	−0.021	−0.008	−0.019	0.058	0.060	0.059
	(−0.41)	(−0.37)	(−0.42)	(−0.09)	(−0.03)	(−0.08)	(0.82)	(0.85)	(0.82)
Obs.	21,460	21,460	21,460	30,105	30,105	30,105	26,562	26,562	26,562
Adj. R^2 (%)	10.4	10.4	10.4	18.8	18.9	18.8	8.3	8.4	8.3

B. Reply disagreement

	DIS[2, 61*]			d_{DIS}		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)
CEN	1.336***	2.080***	1.520***	0.374***	0.479***	0.384***
	(3.41)	(5.21)	(3.79)	(3.56)	(4.45)	(3.54)
|SUE|	0.138	0.153	0.141	0.004	0.006	0.004
	(0.59)	(0.65)	(0.60)	(0.05)	(0.07)	(0.05)
Obs.	28,895	28,895	28,895	25,591	25,591	25,591
Adj. R^2 (%)	19.6	19.7	19.7	7.4	7.5	7.4

This table reports the regression of disagreement of StockTwits messages on the centrality of the firm's headquarters location. Panel A corresponds to disagreement across all messages, and panel B corresponds to disagreement across relies. DIS[0, 1] and DIS[2, 61*] refer to the average abnormal daily disagreement over the [0, 1] and [2, 61*] windows, respectively, compare to the preannouncement mean. d_{DIS} is the persistence parameter of disagreement, measured over the [0, 61*] window. CEN is the decile rank of the centrality of a firm's headquarters county based on the degree centrality (DC), eigenvector centrality (EC), or information centrality (IC). |SUE| is the decile rank of absolute standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

with a similar magnitude as those presented in panel A. This provides further support for the proposed mechanism.

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

We run regression tests as in Equation (3), replacing the dependent variable with the decomposed DIS measures and report the results in the Internet Appendix Table S5, panels A and B, respectively. The coefficients of CEN are positive and significant for both the level (DIS[2, 61*]) and the persistence of the disagreement (d_{DIS}) for both panels and across all centrality measures. The results indicate that high-centrality news triggers greater disagreement and more persistent disagreement both within threads and across threads. The findings suggest that both the diffusion of attention to news and the discussions of news contribute to disagreement about stock valuations. Together, the positive effects of centrality on the level and persistence of investor disagreement support the second key implication of the social churning hypothesis.

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

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

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

$$\text{ARM}[2, 61^*]_{it} = \beta_1 \text{INFL}[0, 1]_{it} + \beta_2 \text{ANM}[0, 1]_{it} + \beta_3 |\text{SUE}|_{it} + \gamma X_{it} + \epsilon_{it}, \quad (4)$$

where ANM[0, 1] is the average daily abnormal new messages for the [0, 1] window as defined before, |SUE| is the decile rank of the absolute SUE, and X consists of laggged firm- and county-level control variables and industry and time fixed effects, as listed in Section 1.2. We also include firm fixed effects and hence are able to control for any omitted variables that are associated with the firm or the firm's location that can potentially contribute to the different messaging activities.

Table 7, column 1, presents the result. The coefficient of INFL[0, 1] is 0.019 and highly significant, indicating that a one-standard-deviation increase in INFL increases ARM by 4.4% relative to the preannouncement level.

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

Table 7
Influencer posts, replies, and the persistence of volatility and volume

	(1) ARM[2, 61*]	(2) DIS[2, 61*]	(3) $d_{\|R\|}$	(4) d_{VOL}
INFL[0, 1]	0.019***	0.015***	−0.114*	0.662***
	(4.19)	(3.16)	(−1.86)	(9.45)
ANM[0, 1]	0.398***	−0.074****	0.498**	0.900***
	(12.59)	(−5.18)	(2.17)	(3.48)
|SUE|	0.005***	−0.002	0.035	0.006
	(2.89)	(−0.60)	(1.30)	(0.23)
Obs.	34,232	20,917	35,940	35,940
Adj. R^2 (%)	46.7	42.8	7.4	13.2

This table reports the results of the regression analysis of StockTwits influencer posts and the subsequent messaging activities as well as the volatility and volume persistence. The dependent variables for columns 1 and 2 are ARM[2, 61*] and DIS[2, 61*], the abnormal number of replies and the abnormal daily message disagreement for the post-announcement window of [2, 61*], respectively. For columns 3 and 4, the dependent variables are volatility persistence ($d_{|R|}$) and volume persistence (d_{VOL}), respectively. The independent variables are INFL[0, 1] and ANM[0, 1], the average sender centrality of new messages and abnormal new messages for the [0, 1] window, respectively, and |SUE|, the decile rank of absolute standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

The finding suggests that, all else being equal, earnings announcements that are discussed by high-centrality users on StockTwits generate more subsequent discussions on the platform.

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

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

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

Table 8
Centrality and Google searches

	ASV[0, 1]			ASV[2, 61*]			d_{ASV}		
	DC (1)	EC (2)	IC (3)	DC (4)	EC (5)	IC (6)	DC (7)	EC (8)	IC (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)
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

This table reports the regression of investor attention on the centrality of the firm's headquarters location. The dependent variable for columns 1–3 is ASV[0, 1], the abnormal Google searches for the announcing stock in the announcement window. The dependent variable for columns 4–6 is ASV[2, 61*], the abnormal Google searches in the post-announcement window. For columns 7–9, the dependent variable is d_{ASV}, the persistence of Google searches over the [0, 61*] window. CEN is the decile rank 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 standardized unexpected earnings. All county- and firm-level control variables (lagged) and industry and time fixed effects listed in Section 1.2 are included. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and announcement date, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

driven by endogeneity, the relation with discussion and disagreement still points to a dynamic social churning effect.

4.3 Evidence from Google Search

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

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

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

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

4.4 Evidence from individual investor trading data

Having established that the earnings announcements of firms located in high-centrality areas generate more sustained attention and investor disagreement as measured with StockTwits messages and Google searches, we now examine the relations between centrality and investors' trading decisions and performance.

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

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

As discussed earlier, earnings news is likely to reach local investors first and then disseminates across the network of investors via discussions. Hence,

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

[25] We take the logarithm transformation because the total number of friendship ties has a large skewness.

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

To investigate households' trading behavior following earnings announcements, we modify Equation (3) by replacing the centrality measure with RSCI and the dependent variable with measures of household trading activities. We estimate the following regression model at the announcement-household level:

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

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

As in our previous analysis, we consider the windows [0, 1] and [2, 61*]. The vector X_{it} consists of firm-level controls, including firm fixed effects and indicator variables for year, quarter, and day of the week. The vector Z_{jt} contains household fixed effects and other household characteristics.[26] The inclusion of these controls and fixed effects enables us to explore variations within firms and households, which helps address the possibility that unaccounted-for firm-level or household-level variables are responsible for the observed associations between Facebook-based connectedness and household trading behaviors and outcomes.

Table 9, panel A, presents the results, with two-way clustered standard errors by firm and household. The coefficients for RSCI are positive and significant for all three measures of trading. Columns 1 and 2 indicate that households residing in locations that share strong social ties with the headquarters location of the announcing firm are more likely to trade both during the announcement period and during the 3-month post-announcement period.[27] Economically, an increase in RSCI from the 10^{th} percentile to the 90th percentile increases a household's trading likelihood by 8.4% relative to the corresponding sample mean of 0.78 percentage points. Similarly, for the window [2, 61*], the increase in RSCI results in a 9.4% increase in trading likelihood relative to the sample mean.

Columns 3 and 4 focus on the number of trades by households and reveal that the high-RSCI households not only make more trades immediately after the

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[26] These characteristics include income, sex 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.

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

Table 9
Social ties and household trading

A. Trading activities

	Trading Indicator		Number of Trades		Relative Trade Size	
	[0, 1]	[2, 61*]	[0, 1]	[2, 61*]	[0, 1]	[2, 61*]
	(1)	(2)	(3)	(4)	(5)	(6)
RSCI	0.015***	0.162***	0.018***	0.321***	0.005***	0.143***
	(3.08)	(9.61)	(3.43)	(8.45)	(4.56)	(8.88)
|SUE|	0.056***	0.379***	0.063***	0.740***	0.011***	0.184***
	(4.19)	(6.13)	(4.18)	(5.17)	(4.55)	(5.42)
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

B. Trading profits

	[0, 1]			[2, 61*]		
	Profit^{net}	Profit^{gross}	Cost	Profit^{net}	Profit^{gross}	Cost
	(1)	(2)	(3)	(4)	(5)	(6)
RSCI	−0.007	−0.002	0.005***	−0.151**	0.009	0.178***
	(−1.48)	(−0.45)	(2.79)	(−2.31)	(0.15)	(6.76)
|SUE|	−0.032**	−0.017	0.014***	−0.687***	−0.404***	0.254***
	(−2.42)	(−1.56)	(3.67)	(−3.71)	(−2.67)	(5.17)
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

This table analyzes households' trading activities and profits following earnings announcements. In panel A, the dependent variable is the trading activity of a household on the announcing stock for a given window, measured three ways: (1) a trading indicator, (2) the number of trades, or (3) relative trade size. For panel B, the dependent variable is the profit of a household from trading the announcing stock for a given window, with a negative value corresponding to a loss. Profit^{net} and Profit^{gross} are the net and gross profit for a household, respectively. Cost is the trading costs. All Profit and Cost measures are scaled by the household's beginning-of-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 standardized unexpected earnings. We include time indicator variables, lagged firm and household control variables, and firm and household fixed effects. Coefficients are multiplied by 100. Standard errors are two-way clustered by firm and household, and the resultant t-statistics are shown in parentheses. *p <.1; **p <.05; ***p <.01.

announcement but also trade more post-announcement.[28] In economic terms, an increase in RSCI from the 10th percentile to the 90th percentile increases the number of trades by 9.4% and 14.5% for the [0, 1] and [2, 61*], respectively, relative to the corresponding sample means of 0.0083 and 0.096. With regard to relative trade size, columns 5–6 indicate that a similar change in RSCI increases the relative trade size by 18.1% and 27.6% for the two windows.

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

4.4.2 Household performance. Next, we investigate how the greater trading of high-RSCI households affects trading profits. Following Barber and Odean (2000), we compute Profit^{gross}, which is the gross profit of each trade

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

following earnings announcements, before considering any transaction costs. Specifically, we define Profit^{gross} as $n_t P_t^{cl}$CAR$[t, 61^*]$, where n_t is the number of shares traded (positive for purchase and negative for sale), P_t^{cl} is the closing price on the day of the trade, and CAR$[t, 61^*]$ is the DGTW-adjusted cumulative abnormal return between days t and 61, based on the closing prices.[29] A positive Profit^{gross} refers to gains from the trade and a negative value implies losses.

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

We estimate the same regression as in Equation (5) with the scaled ($\times 10^4$) Profit and Cost measures for each household-announcement observation as the dependent variables. The results are reported in Table 9, panel B. Columns 1 and 2 analyze the net and gross Profits for trades placed during the [0, 1] window. The coefficients of RSCI are negative but insignificant, suggesting that the trading by the high-RSCI households immediately after the announcement does not result in significant Profit or loss. Additionally, column 3 corresponds to Cost, and the positive coefficient of RSCI indicates that the high-RSCI households are subject to significantly higher transaction costs.

For trades placed during the [2, 61*] window, column 4 presents the results for Profit^{net} and shows that high-RSCI households incur significantly more losses relative to other households. The coefficient of -0.151 indicates that an increase in RSCI from the 10th percentile to the 90th increases the trading loss by 16.6% relative to the sample average.[31]

The remaining columns identify the sources of trading losses for the high-RSCI households. In column 5, for Profit^{gross}, the coefficient of RSCI is insignificant, indicating that the high-RSCI households do not underperform

[29] We use the closing price on day 61 as the liquidation price to focus on the profitability of trading in the 61-day period following an earnings announcement. Most households hold a stock for a considerable period. According to Barber and Odean (2000), the mean household portfolio turnover is 6.49%, which implies an average holding period of 15.4 months. As such, including the full holding period beyond the 61-day period likely introduces noise unrelated to the given earnings announcement. We obtain similar results with raw cumulative returns.

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

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

before transaction costs. In contrast, in column 6, for the total transaction costs these household pay, the coefficient is positive and highly significant. This result indicates that the trading costs are the primary contributor to the household's losses during this sample period.

The evidence is consistent with the social churning hypothesis, which maintains that more intense trading by more connected households derives in part from incorrect beliefs that are triggered by social interactions.[32] Together, our empirical analyses of StockTwits messages, Google searches, and household trading activities provide support from several angles for the social churning hypothesis. That is, social interactions direct investor attention to relevant news, but also promote churning of beliefs, persistent disagreement, and excessive trading.

Finally, the inclusion of firm fixed effects in our analysis, both for the StockTwits and Google Search tests, as well as using both firm and household fixed effects for the household-level tests, suggest that our findings do not derive from county, firm, or investor characteristics.

5. Additional Analysis and Robustness Checks

In this section, we provide results of additional analysis and further robustness checks. First, we consider the extent to which a county's social proximity to institutional capital (SPC) can explain our results associated with centrality. We then explore heterogeneity along the dimension of small and local firms versus large and visible firms and analyze how centrality influences retail trading activities. We also compare the influence of the Facebook network with that of the StockTwits network on market reactions to earnings announcements. Finally, we perform various robustness checks.

5.1 Institutional capital, local versus large and visible firms, and retail trading

In this subsection, we consider the extent to which a county's social proximity to institutional capital (SPC) can explain our results about the effects of centrality on return dynamics. Next, we explore whether the effects of CEN would be greater for small, locally focused, or lesser-known firms. Additionally, we analyze how CEN influences retail trading activities.

5.1.1 Institutional capital. As shown in Kuchler et al. (2022), firms headquartered in high-SPC counties have greater institutional ownership,

[32] These belief errors at the individual investor level do not appear to generate systematic mispricing in our context, as evidenced by the faster price adjustment following earnings releases by high-centrality firms. The result aligns with a conclusion of Barber and Odean (2000), who attribute the poor performance of households to costs associated with excessive trading. However, in other settings, social interactions can contribute to systematic mispricing. For example, Bali et al. (2021) demonstrate that social interactions amplify investors' attraction to "lottery-like" stocks, leading to a greater overvaluation of such stocks.

higher valuation, and greater stock liquidity. These points suggest that high-centrality firms may also have better access to institutional investors. If so, they may receive more investor attention and have faster information dissemination as a result of this access.

To evaluate how SPC affects our results, we replicate our tests in Tables 2–4 by adding the SPC variable and report the findings in Internet Appendix Table S6. Panel A presents results for return regressions. Column 1 shows a positive and significant coefficient for SPC·SUE, indicating that announcements by firms in places more connected to institutional capital do experience stronger immediate price reactions. However, the coefficient is no longer significant once we include CEN·SUE in columns 2–12, whereas the latter remains positive and significant. Similarly, panels B and C show that the effects of CEN for volume, as well as the persistence of volatility and volume, remain largely robust. In comparison, SPC is not significant in the presence of CEN.

One possible reason for the different effects of SPC and CEN in our setting lies in the different types of social connections that these two measures capture. While SPC corresponds to the county's connectedness to institutional capital, CEN is more likely to correspond to the word-of-mouth communication among individual investors.

Evidence indicates that both institutional investors (Ben-Rephael, Da, and Israelsen 2017; Ben-Rephael et al. 2021) and retail investors (Kelley and Tetlock 2013, 2017; Boehmer et al. 2021) contribute to price discovery, and that retail investors are more attentionally constrained. In particular, as shown in Liu, Peng, and Tang (2023), stocks that are favored by retail investors tend to exhibit less immediate return responses and more post-announcement drifts during periods of investor distraction. Our results, which indicate that high-CEN announcements attract more retail attention, as indicated by more Google searches, and are associated with faster price discovery, suggest that social interactions accelerate the contribution of retail investors to price discovery.

Social networks can also transmit bias and irrational sentiments, and retail individuals are likely to be especially susceptible to such effects. This can explain why CEN is strongly associated with investor disagreement and unprofitable trading following earnings announcements, whereas SPC is not. As discussed in the introduction (see also scenario 3 of the model in Internet Appendix A), idiosyncratic fluctuations in disagreement do not impede the incorporation of news into stock prices, but such fluctuations do imply higher and more persistent trading volume.

Overall, these results suggest that the effects of CEN reflect the social network of retail investors rather than connection to institutional investors as captured by SPC.

5.1.2 Small, local firms versus large and visible firms. The conclusion that the effects of CEN likely derive form retail investors further suggests that these effects will be stronger for small and local firms and less important for large and visible firms.

We test for this by modifying the tests of Tables 2–4 by adding interaction terms of the SUE variables and the controls with an indicator variable $\mathbf{I}_{\text{Low}}$ that is defined in three alternative ways, by size, S&P 500 index membership, or localness. Under the size-based definition, $\mathbf{I}_{\text{Low}}$ takes a value of one if firm size is below the NYSE median and zero otherwise. Under the S&P 500 index membership definition, $\mathbf{I}_{\text{Low}}$ equals one if the stock belongs to the index, and zero vice versa. For localness, the indicator equals one if a firm has subsidiary operations in less than three states and zero otherwise.[33]

The findings, presented in Internet Appendix Table S7, panels A–C, indicate that the effects of CEN on price discovery during the [0, 1] window and volume persistence are more pronounced for smaller, less visible, and more local firms.

The results are consistent with our interpretation that the person-to-person social network's role in facilitating the transmission of earnings news and in generating more persistent trading is more pronounced in the small, less visible, or local firms. These findings suggest that centrality is especially important for the dissemination of information (or bias) for less visible companies and captures effects that go beyond traditional visibility measures.

5.1.3 Retail trading. Next, we turn our focus directly to retail trading. Following Boehmer et al. (2021) (hereinafter BJZZ), we define retail trades as those that occur off-exchange (i.e., with an exchange code equal to "D") for the period of January 2010 through December 2022 using the TAQ data.

We then define retail LNVOL[0, 1] and LNVOL[2, 61*] as the log average daily abnormal retail trading volume (in number of shares) over the [0, 1] and [2, 61*] windows, respectively, relative to the preannouncement period average. We estimate Equation (3) with retail trading volume measures as the dependent variables and present the results in Table S7, panel D. The positive and significant coefficient for CEN indicates that high-centrality announcements trigger greater abnormal retail trading volume for both the [0, 1] and [2, 61*] windows.

Overall, these findings indicate that social network centrality remains significant in explaining the return and volume responses even after accounting for proximity to institutional capital and is particularly informative in explaining retail trading activities.

33 We obtain the data on a firm's subsidiary locations from Dyreng, Lindsey, and Thornock (2013). The number of states where a firm has subsidiary operations has a median value of 1 and a standard deviation of 5.14. In our sample, 36% of firms do not have subsidiaries, and 75% of firms have subsidiaries in fewer than three states. See García and Norli (2012) for a similar application using the number of states where a firm operates (identified by counting distinct state names mentioned in a firm's annual reports) to identify local firms.

5.2 Comparing Facebook-based and StockTwits-based firm centrality measures

As highlighted by Bailey et al. (2018b, 2020) and Chetty et al. (2022), the Facebook's social network is a valuable proxy for real-world friendships, suggesting that the Facebook-based centrality measure encapsulates both online and offline social interactions. This observation raises an interesting question on how real-world social networks correlate with purely online-based social networks. In this subsection, we explore the comparative effect of the Facebook network and the StockTwits network on market responses to earnings announcements.

We examined the role of StockTwits user centrality in Subsection 4.2 (Table 7), defining user influence based on log degree centrality—the logarithm of a user's number of followers. The findings align with our hypothesis: announcements mentioned by users with higher centrality lead to increased discussion, disagreement, and sustained trading volume.

We now compute a StockTwits-based centrality measure at the firm-announcement level, SCEN, as the decile rank of the number of posts mentioning a particular stock in the 3-month window ending 11 days before an announcement. The correlation between eigenvector centrality (EC) and SCEN is 0.15, indicating that these measures may reflect distinct aspects of social interaction.[34]

We include SCEN in Tables 2 and 3 and perform horse race tests to compare their effects on market reactions to earnings announcements. We focus here on the overlapping sample period of 2009 to 2013. The results in Table 10, panel A, reveal that the coefficient for SCEN·SUE is insignificant, indicating that StockTwits activities are not significantly associated with price reactions. On the other hand, the coefficient for CEN·SUE remains positive and marginally significant for CAR[0, 1]. Also consistent with our earlier results, the coefficient of CEN·SUE is negative over the [2, 61*] window, although insignificant.

Panel B of Table 10 examines abnormal log trading volumes. Columns 1–4 show that both SCEN and CEN are associated with increased immediate trading volume in the [0, 1] window, with SCEN's effect being notably stronger. The larger magnitude of the SCEN coefficient compared to the three CEN coefficients indicates that the social interactions on the online investment platform have a greater effect in generating trading in the short term than the general types of interactions among friends as captured by the Facebook data.

[34] For instance, firms in Los Angeles County have the highest CEN, but some of them have low SCEN. 1st Century Bancshares Inc., a small bank, and Abraxis Bioscience Inc., a biopharmaceutical company, are associated with an average SCEN that falls into the 1st and 2nd SCEN deciles for our sample period of 2010–2013, respectively. In contrast, large and well-known firms located in low-CEN counties attract more intense discussions on StockTwits. For example, Walmart Inc., an American multinational retail corporation headquartered in Benton County, Arkansas (AR), ranks in the 2nd CEN decile but the 10th average SCEN decile.

Table 10
Facebook versus StockTwits centrality

A. Return reactions

	CAR[0, 1]				CAR[2, 61*]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCEN·SUE	0.00870	0.00833	0.00784	0.00822	0.00872	0.00941	0.00929	0.00940
	(1.36)	(1.31)	(1.23)	(1.29)	(0.53)	(0.57)	(0.56)	(0.57)
DC·SUE		0.0111*				−0.0203		
		(1.72)				(−1.28)		
EC·SUE			0.0126*				−0.0134	
			(1.85)				(−0.82)	
IC·SUE				0.0126*				−0.0208
				(1.86)				(−1.28)
SCEN	−0.157***	−0.154***	−0.151***	−0.153***	−0.147	−0.153	−0.158	−0.154
	(−3.85)	(−3.77)	(−3.69)	(−3.75)	(−1.24)	(−1.29)	(−1.34)	(−1.30)
SUE	2.648***	2.461***	2.605***	2.506***	1.928	2.269	1.976	2.161
	(4.36)	(4.00)	(4.28)	(4.10)	(1.13)	(1.38)	(1.17)	(1.29)
Ctrls(· SUE)	X	X	X	X	X	X	X	X
Obs.	47,335	47,335	47,335	47,335	47,191	47,191	47,191	47,191
Adj. R^2 (%)	3.9	3.9	3.9	3.9	1.6	1.6	1.6	1.6

B. Volume reactions

	LNVOL[0, 1]				LNVOL[2, 61*]			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
SCEN	1.470***	1.430***	1.405***	1.423***	−1.091***	−1.099***	−1.115***	−1.101***
	(6.78)	(6.60)	(6.48)	(6.57)	(−8.61)	(−8.65)	(−8.76)	(−8.67)
DC		0.694**				0.145*		
		(2.56)				(1.85)		
EC			0.772***				0.298***	
			(2.82)				(3.84)	
IC				0.791***				0.182**
				(2.76)				(2.18)
|SUE|	1.114***	1.128***	1.131***	1.131***	0.719***	0.722***	0.725***	0.723***
	(7.78)	(7.90)	(7.93)	(7.93)	(8.94)	(8.97)	(9.02)	(8.99)
Ctrls	X	X	X	X	X	X	X	X
Obs.	48,714	48,714	48,714	48,714	48,651	48,651	48,651	48,651
Adj. R^2 (%)	5.1	5.1	5.1	5.1	3.0	3.0	3.0	3.0

This table reports the regression results of return and volume reactions on StockTwits centrality and Facebook centrality, presented in panels A and B, respectively. SCEN is the decile rank of the StockTwits centrality of a firm, measured by the total number of messages mentioning the firm's stock ticker on the social media platform in the past 3 months. CEN is the decile rank 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 industry and time fixed effects listed in Section 1.2 are included. For panel A, the control variables are also interacted with SUE. Standard errors are two-way clustered by firm and announcement date, and the resultant *t*-statistics are shown in parentheses. $^{*}p<.1$; $^{**}p<.05$; $^{***}p<.01$.

However, in the [2, 61*] window, the coefficient for SCEN in column 5 becomes negative, indicating that the trading volume associated with high levels of SCEN reverts faster to preannouncement levels compared to those associated with low SCEN. This suggests that the influence of online social interactions, as measured by StockTwits activities, on trading volume is transient. In contrast, the consistently positive significance of CEN in columns 6–8 suggests that real-world social networks have a more enduring effect on trading volume.[35]

These results suggest that while both social networks lead to more pronounced immediate trading volume reactions, the specific online investment platforms exemplified by StockTwits have a greater short-term effect on trading activity compared to the broader patterns of interaction among individuals on Facebook. The Facebook-based social network is more influential in the process of price discovery and sustaining trading volume over the long term.

The divergent effects of CEN and SCEN may derive from distinct information captured by these social platforms. These platforms differ in several ways. First, the Facebook network represents enduring characteristics of real-world social structures, as influenced by historical events and linked to economic outcomes, such as upward mobility, as we mentioned earlier. Hence, because of its long-standing and diverse connections, Facebook-based centrality is more apt to reflect the slow and sometimes indirect diffusion of information across a wide range of investors. In contrast, StockTwits specifically caters to investors with a focus on financial markets. In consequence, StockTwits-based centrality tends to reflect the immediate effects of news in capturing the attention of investors who are active on the StockTwits platform.

Second, the expansive nature of the Facebook social network suggests that it may be more closely aligned with aggregate equilibrium outcomes, such as prices better than StockTwits data. In contrast, the StockTwits platform offers more detailed data about users' postings, enhancing our understanding of the underlying mechanisms. However, a limitation of the StockTwits data is that the observations patterns is confined to the much smaller set of individuals who use StockTwits. Further research on how different types of social media platforms affect communication and decisions would be valuable (see Cookson et al. 2022).

5.3 Extensions and further robustness checks

5.3.1 An exogenous shock to social interaction. We use an exogenous shock, Hurricane Sandy, to the intensity of social interactions to further assess whether the observed associations between centrality and price and volume reactions are driven by omitted firm or county characteristics. 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). As suggested by Kuchler et al. (2022),

[35] In unreported tables, we have also examined the extent to which CEN and SCEN contribute to activities on StockTwits, respectively. Both CEN and SCEN are positive and significant in explaining the number of StockTwits replies and message disagreement, with the coefficient of SCEN larger as expected.

given the very large number of investors in the heavily affected areas, Hurricane Sandy presents a unique means of testing the causal effects of social network.

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

We hypothesize a more disruptive effect of Sandy on information dissemination from people in the high HSS counties to those in the affected areas than on the dissemination from people in the low HSS counties. We test the hypothesis empirically and find that, during the Sandy period, the association between network centrality and the responsiveness of returns and trading volume to earnings announcements weakened more for firms in the high-HSS counties, relative to the less connected firms. The analysis is described in detail in the Internet Appendix, and the results are reported in Internet Appendix Tables S8–S10. These results provide additional confirmation that our earlier results on the association between centrality and earnings responsiveness are likely causal and are not a manifestation of omitted firm or county characteristics.

5.3.2 Analyst forecast revisions. We have found that greater social connectivity is associated with less underreaction to earnings announcements and triggers verbally expressed disagreement and trading that is excessive in the sense of losing money. Next, we provide insight into the generalizability of this findings by considering an alternative type of news, in the form of analyst forecast revisions.

We define the event date as the day on which analyst forecast revision is released. We calculate the standardized analyst revision (SAR) as the daily change in the consensus forecast, adjusted by the closing stock price of the market on the day before the revision.[36] As before, we perform price and volume reaction tests, as well as volatility and volume persistence tests. The results are presented in Table S11. The market's responses to analyst forecasts are qualitatively similar to its reactions to earnings announcements. The consistent effects of centrality on market reactions to both earnings surprises and analyst forecast revisions reinforce our conclusions and are supportive of the proposed social churning hypothesis.

5.3.3 Robustness. In Internet Appendix Section D, we describe the list of the additional robustness checks that we have conducted. We have considered

[36] Following the literature, we focus on analyst forecasts for the upcoming fiscal year-end earnings (FPI = 1). The consensus forecast is determined using the median of the latest forecasts from the analysts.

other factors that could contribute to firm visibility, such as the geographical dispersion of firm subsidiaries, state fixed effects, whether a firm is located in the U.S. tristate area of New York, New Jersey, and Connecticut, and the physical proximity between households and firms. We also consider alternative measures of CEN, constructed with the 2020 Facebook SCI data or with county characteristics purged, as well as alternative measures of persistence. Our findings are also consistent across two subperiods. Finally, we demonstrate that the centrality–persistence relationship that we document persists even after controlling for endogenous responses from analyst or media coverage to earnings announcements. The results are reported in the Internet Appendix Tables S12–S20.

6. Conclusion

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

Using a newly available firm-level investor social network centrality measure, we find that earnings announcements made by firms that are more centrally located generate stronger immediate reactions in stock prices, volatility, and volume, which are followed by weaker price drift. Moreover, these stocks also exhibit less persistent volatility but substantially more persistent trading volume that lasts up to 3 months after the announcement.

These findings pose challenges to the traditional theories of information diffusion. Instead, they suggest that the arrival of earnings news triggers a process of discussion (which we measure using social network data) and belief updating via the social network, and that this communication process takes time. For a substantial period after earnings announcements, social media activity is elevated, different investors update their beliefs differently, and this updating triggers trading. We call our predictions about these dynamics the social churning hypothesis. Granular data based on StockTwits messages by individual users, household account-level trading records, and Google Search activities at the stock level provide support for this hypothesis. In addition, the inclusion of firm and household fixed effects addresses important forms of the concern that omitted factors may drive our findings.

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

Our findings raise several important issues that suggest future avenues of research.

First, our paper has focused on testing the transmission of a useful source of information, earnings news, to investors through social interaction. Recent social finance modeling has proposed that the distribution of biased beliefs in the investor population is influenced by social interaction, and that social transmission biases can amplify investor biases (Shiller 1989; Hirshleifer 2020; Han, Hirshleifer, and Walden 2021). This raises the question of how social transmission biases influences the dynamics of market reactions to earnings news. This is an interesting topic for future theoretical modeling and empirical research.

More broadly, survey evidence suggests that investors' beliefs have substantial and persistent heterogeneity (Giglio et al. 2021). As the authors suggest (p. 1484), "models that explicitly feature heterogeneous agents with different beliefs are likely to offer a fruitful starting point for future work." Therefore, it would be valuable to test for the effects of social interactions in response to the arrival of other types of public information (anticipated or unanticipated), private information, or even fake news. This would then help us understand how social networks contribute to the polarization of people's opinions on economic, social, and political issues.

Second, it would be interesting to examine how the social transmission of information in financial markets can influence real corporate decision-making through feedback effects from stock prices to operations (for a review of feedback effects, see Goldstein 2023).

Third, and lastly, these studies, as outlined above, have the potential to offer insights into how policies and the design choices of social media platforms can harness the power of social networks while mitigating the potential risks of undue speculative trading.

Code Availability: The replication code is available in the Harvard Dataverse at https://doi.org/10.7910/DVN/GJDLSC.

Appendix

A. Figure and Variable List

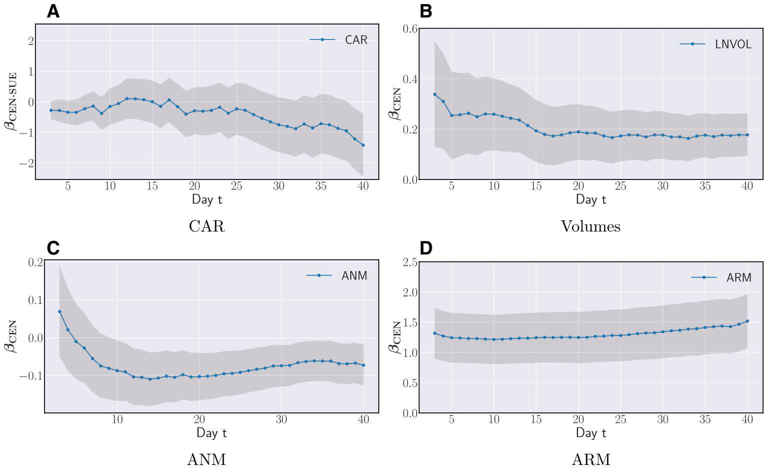

Figure A1
Centrality and post-announcement dynamics
This figure summarizes the regression coefficients of eigenvector centrality in explaining returns, trading volume, and message activities over the post-announcement windows [2, 3], [2, 4], ..., [2, 40]. Panels A through D correspond to regressions in which the dependent variables are cumulative abnormal returns (CAR), average daily volume (LNVOL), and StockTwits new messages (ANM) and replies (ARM) for the corresponding windows. The solid lines represent the coefficients of eigenvector centrality (EC), and the shaded areas represent the region between the 90% confidence intervals.

Table A1
Description of variables

Variable	Definition
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
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.
CAR	Daily abnormal returns adjusted by size, B/M, and momentum following Daniel et al. (1997) (DGTW). CAR[0, 1] is the cumulative buy-and-hold abnormal announcement returns of the announcement window. CAR[2, 61*] is the post-announcement cumulative buy-and-hold abnormal returns
LNVOL	Daily abnormal log volume. Defined as the difference between the log volume for a given day and the average daily log volume over days $[-41,-11]$. LNVOL[0, 1] is the daily average abnormal log volume over the announcement window and LNVOL[2, 61*] is the daily 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 LNVOL in the window of [0, 61*]
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
EP	Earnings persistence, calculated as the first-order autocorrelation coefficient of quarterly earnings per share during the past 4 years
EVOL	Earnings volatility, calculated as the standard deviation in the previous 4 years of the difference between quarterly earnings and the same-quarter value one year before
IVOL	Idiosyncratic volatility, calculated as the standard deviation of the residuals from the Fama-French three-factor model with daily returns in the preannouncement window
RL	Reporting lag, the difference in days between the fiscal quarter end and the earnings announcement day
IO	Institutional ownership, measured as the percentage of shares owned by institutions in the most recent quarter
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
SP500	An indicator variable for S&P 500 constituent stocks
ADX	Advertising expenses in millions of dollars. Logged in the regression tests
NA	The number of the same-day earnings announcements. Decile rank is used in regression test following Hirshleifer, Lim, and Teoh (2009)
Urban	An indicator variable for firms headquartered in the 10 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
WSI	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
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
PopDen	Population density at the county level, measured as the number of residents per square mile
Tenancy	The median number of years since a household has moved into the county
SPC	The social proximity to capital, calculated as $\sum_j \text{AUM}_{jt} \cdot \text{RFP}_{ij}$, where AUM_{jt} is the total assets under management of all fund families headquartered in county j, and RFP_{ij} equals the total Facebook friendship ties between county i and county j divided by the product of the populations of i and j

B. 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; Fedyk 2024). We investigate the relationship between centrality and the dynamics of price, volatility, and trading volume under three scenarios: (1) investors have identical priors and interpretation of the earnings news, (2) investors have heterogeneous priors and a static disagreement, and (3) social interactions trigger sustained fluctuations in disagreements. The third scenario corresponds to what we refer to as the "social churning hypothesis." We show that the first two scenarios imply that news seeded from high-centrality nodes leads faster decays in returns, volatility, and trading volume and are at odds with our empirical findings. We then demonstrate that the third scenario provides a unified explanation for the observed empirical findings. We present the model setup and the results here and delegate the technical details and derivations to the Internet Appendix.

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

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

$$\max_{x_t^i} \mathbb{E}_{it}[W_T^i] - \frac{\gamma_i}{2}\mathrm{Var}_{it}[W_T^i] \tag{B.1}$$

$$s.t. \quad W_T^i = W_t^i + x_t^i (R - P_t).$$

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

B.1 Centrality and Information Diffusion. We now describe the network structure of investors, the information diffusion process, and how centrality is related to the speed of diffusion. We delegate the technical details to the Internet Appendix and hereby only describe the general settings.

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 $|\mathcal{N}|=N$ and $\mathcal{E}$ the set of edges. Investors are connected to each other in a social network and can be categorized into county-level subnetworks that correspond to their geographic locations. We partition graph $\mathcal{G}$ into M subgraphs, $\mathcal{G}^m=(\mathcal{N}^m,\mathcal{E})$, for $m=1,\ldots,M$, where the subsets of investors $\mathcal{N}^m$ for $m=1,\ldots,M$ are mutually disjoint subsets within $\mathcal{N}$. 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 as the total number of investors that the investors $\mathcal{N}^m$ can reach within no more than k steps.

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 $I_0 \subset \mathcal{N}^m$. At date 1, the public news arrives at subgraph $\mathcal{G}^m$, which is informative of R and takes the form of $Y=R+\epsilon$, where $\epsilon \sim \mathcal{N}(0,\sigma_\epsilon^2)$. Each investor $i \in \mathcal{N}^m$ becomes informed, and the investor starts to broadcast the news to each of his direct neighbors. At each subsequent time t, the newly informed investors from the previous period $t-1$

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

In our setting, the sequence of the total fraction of attentive investors at each date t, $\{F_t\}_{t=0,1,\ldots,T}$ characterizes the information diffusion process and determines the corresponding price and volume dynamics. Therefore, the percentage of the population that becomes informed (F_t) follows a deterministic process and is directly mapped to D_t^m, the centrality of the subgraph where the news originated $F_t = D_t^m/N, t=1,2,\ldots,T$.

Scenario 1: Identical Interpretations of News

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

Proposition 1 (Equilibrium with identical interpretation). When investors have identical interpretations of news, the equilibrium price and total trading volume at time t are:

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

$$V_t = (F_t - F_{t-1}) \frac{F_{t-1}\left(\sigma_R^2 + \sigma_\epsilon^2\right) + (1-F_t)\sigma_\epsilon^2}{\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t \sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|. \tag{B.3}$$

For simplicity, and for ease of driving empirical implications, we assume that $\sigma_\epsilon^2 \ll \sigma_R^2$ for all three scenarios, that is, earnings news is informative such that the noise in the earnings signal is small relative to the variance of investors' prior beliefs about the asset payoff. 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. The following lemma express the price and volume dynamics as functions of F_t

Lemma 1. When investors interpret the news identically, the immediate price reaction and the delayed price reaction are

$$\Delta P_{0,\hat{t}} = P_{\hat{t}} - P_0 = \frac{F_{\hat{t}}\sigma_R^2}{\sigma_\epsilon^2 + F_{\hat{t}}\sigma_R^2}(Y - \bar{R}), \quad \Delta P_{0,\hat{t}} = P_{\hat{t}} - P_0 = \frac{F_{\hat{t}}\sigma_R^2}{\sigma_\epsilon^2 + F_{\hat{t}}\sigma_R^2}(Y - \bar{R}); \tag{B.4}$$

the cumulative volatility of price changes from date 0 to date $\hat{t}$ and the amount of volatility yet to be incorporated at date $\hat{t}$ are

$$\sum_{s=1}^{t} \sigma_{\Delta P_s} = \frac{F_t \sigma_R^2}{\sigma_\epsilon^2 + F_t \sigma_R^2}\sqrt{\sigma_\epsilon^2 + \sigma_R^2}, \quad \sum_{s=t+1}^{T} \sigma_{\Delta P_s} = \frac{\sigma_\epsilon^2 \sigma_R^2}{\sqrt{\sigma_\epsilon^2 + \sigma_R^2}} \frac{1 - F_{\hat{t}}}{\sigma_\epsilon^2 + F_{\hat{t}}\sigma_R^2}; \tag{B.5}$$

Moreover, when $\sigma_\epsilon^2 \ll \sigma_R^2$, the immediate trading volume and the post-announcement volume are

$$\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{\sigma_R^2} \log\left(\frac{F_{\hat{t}}}{F_0}\right) |Y - \bar{R}|, \quad \sum_{s=\hat{t}+1}^{T} V_s \approx \frac{1}{\sigma_R^2} \log\left(\frac{1}{F_{\hat{t}}}\right) |Y - \bar{R}|. \tag{B.6}$$

Lemma 1 implies that the more central the subgraph of the stock, the higher the value of $F_{\hat{t}}$, and hence, a stronger immediate price reaction, a weaker drift, less persistent volatility, but more persistent volume. We summarize these implications below:

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

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

Scenario 2: Heterogenous Prior and Static Disagreement
In the second scenario, we assume that earnings news triggers investor disagreement over asset valuation. Disagreement could stem from investors either having different priors about the valuation or having different interpretations of the information (see, e.g., Kim and Verrecchia 1991; Harris and Raviv 1993; Kandel and Pearson 1995; Scheinkman and Xiong 2003). Disagreement is static in the sense that investors perform a one-time belief update upon observing the news. Investors' beliefs, once updated, remain unchanged until the arrival of the next round of information. We show that this setting, the relationship between centrality and price, volatility, and volume dynamics are very similar to those of scenario 1.

Specifically, investor i believes that $R \sim \mathcal{N}(\bar{R}^{(i)}, \sigma_R^2)$. And $\bar{R}^{(i)}$ follows normal distribution $\mathcal{N}(\bar{R}, \eta)$. In addition, investors also interpret the public signal differently. Following Banerjee and Kremer (2010), we assume that investor i's belief of the public signal is given by $Y = R + \epsilon$, with $\epsilon \sim \mathcal{N}(e^{(i)}\sigma_\epsilon^2)$, where $e^{(i)}$ denotes investor i's idiosyncratic interpretation of the signal noise. For simplicity, we assume that $e^{(i)}$ follows the binary distribution of $(-\bar{e}, +\bar{e})$ with equal probabilities. We summarize the equilibrium below.

Proposition 2 (Equilibrium with static disagreement). When investors have heterogenous priors and static disagreement about the earnings news, the equilibrium price is identical to (B.2) and total trading volume at time t is:

$$V_t = V_t^B + \max\left((F_t - F_{t-1}) \frac{\bar{e}}{2\sigma_\epsilon^2} - \frac{1}{2} V_t^B, 0 \right), \tag{B.7}$$

where V_t^B is the same as Equation (B.3) of scenario 1, which corresponds to the component driven by information diffusion.

Similarly, we derive the results on price and volume dynamics below.

Lemma 2. When investors have heterogeneous priors and static disagreement about earnings news, the price dynamics and volatility dynamics are the same as scenario 1. However, the immediate trading volume and the post-announcement volume are

$$\sum_{s=1}^{\hat{t}} V_s \approx \frac{1}{2\sigma_R^2} \log\left(\frac{F_{\hat{t}}}{F_0}\right) |Y - \bar{R}| + F_{\hat{t}} \frac{\bar{e}}{2\sigma_\epsilon^2}, \quad \sum_{s=\hat{t}+1}^{T} V_s \approx \frac{1}{2\sigma_R^2} \log\left(\frac{1}{F_{\hat{t}}}\right) |Y - \bar{R}| + (1 - F_{\hat{t}}) \frac{\bar{e}}{2\sigma_\epsilon^2}. \tag{B.8}$$

From Lemma 2, the two components in the trading volume are evident: the first component is the baseline volume as in scenario 1, and the second component is due to disagreement. However, both components grow rapidly for high-centrality stocks and quickly dissipate afterward. So the volume dynamics also resemble those in scenario 1. We summarize the implications of scenario 2 below.

Scenario 2 Predictions When investors have heterogeneous priors and if their disagreement is static, the effect of centrality on price, volatility, and volume dynamics is identical to those in scenario 1.

Scenario 3: Social Churning and Fluctuating Disagreement

In the third scenario, we extend the second scenario and consider a setting in which social interactions generate stochastic disagreement among investors. We show that this setting provides an unified explanation of the dynamics of price 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.[37] That is, for $i \in I_t$, his belief of the public signal at t is given by $Y = R + \epsilon_t$, with $\epsilon_t \sim \mathcal{N}(e_t^{(i)}, \sigma_\epsilon^2)$, where $e_t^{(i)}$ denotes investor i's interpretation of the signal noise at time t. $e_t^{(i)}$ follows a random walk

$$e_t^{(i)} = e_{t-1}^{(i)} + \xi_t^{(i)}, \tag{B.9}$$

where $\xi_t^{(i)}$ is independent over time and across investors and follows a binary distribution $(-\bar{\xi}, +\bar{\xi})$ with equal probabilities. Essentially, $\xi_t^{(i)}$ corresponds to additional disagreement generated by social interactions.

Proposition 3 (Equilibrium with stochastic disagreement). When investors have stochastic disagreement about the earnings news, the equilibrium price is identical to (B.2) and total trading volume at time t is:

$$V_t = V_t^B + F_{t-1} \max\left(\frac{\bar{\xi}}{2\sigma_\epsilon^2} - \frac{(F_t - F_{t-1})\left(\sigma_R^2 + \sigma_\epsilon^2\right)}{2\left(F_{t-1}\sigma_R^2 + \sigma_\epsilon^2\right)\left(F_t\sigma_R^2 + \sigma_\epsilon^2\right)} |Y - \bar{R}|, 0 \right). \tag{B.10}$$

where V_t^B is the same as Equation (B.3) of scenario 1.

Similarly, we derive the results on price and volume dynamics below.

Lemma 3. When investors have heterogeneous priors and static disagreement about earnings news, the price dynmaics and volatility dynamics are the same as scenario 1. However, the immediate trading volume and the post-announcement volume are

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

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

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

We summarize the implications of the social churning hypothesis below:

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

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

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

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