

Information Spillovers and Firm Geographic Dispersion: Evidence from Local Stock Return Comovement

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Abstract

This paper investigates how geographic dispersion shapes information spillovers and local return comovement. Using state counts from 10-K filings as a measure of geographic dispersion, we show that geographically concentrated firms (operating in a few states) exhibit significantly stronger comovement with other firms headquartered in the same region than geographically dispersed firms. Consistent with the habitat and information diffusion views, local return comovement increases when nearby firms announce earnings or receive analyst revisions, indicating intra-regional information spillovers. We further show that social media coverage reduces the local return comovement of geographically concentrated firms by lowering information acquisition costs and expanding investor attention beyond the local habitat.

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1. Introduction

Investor attention and information access are unevenly distributed across firms, shaping how quickly and accurately shocks are incorporated into stock prices. When information is costly to acquire or process, investors rely on coarse signals, such as peer performance or local economic news, creating excess comovement among firms exposed to the same information set (see, e.g., Barberis, Shleifer, and Wurgler, 2005; Veldkamp, 2006; Mondria, 2010). We argue that a firm's geographic dispersion of operations is a fundamental determinant of these frictions. Firms whose activities are concentrated in a single region are effectively embedded in a local investor habitat, making their prices highly sensitive to local signals and news. In contrast, geographically dispersed firms attract broader investor audiences and draw information from more diverse sources, limiting the influence of local frictions. This observation yields a clear prediction: geographically concentrated firms should exhibit significantly stronger comovement with other local firms than geographically dispersed firms.

This prediction fits naturally within the friction-based comovement framework developed by Barberis et al. (2005). Their model shows that excess comovement can arise through three related channels: category trading, segmented investor habitats, and information diffusion. A firm with tightly concentrated geographic operations is a clear member of the "local" category and is disproportionately held and followed by local investors (e.g., Coval and Moskowitz, 1999, 2001; Grinblatt and Keloharju, 2001; Pirinsky and Wang, 2006), thereby forming a segmented habitat. When information is difficult to obtain or interpret, these investors reuse signals from nearby firms or local economic news, causing shocks to one local firm to spill over to others. In contrast, firms with broad geographic dispersion are less tied to any single region's investor base and are covered by more national attention sources, reducing the reliance on local heuristics. Geographic dispersion therefore predicts systematic variation in local return comovement: concentrated firms should load heavily on the local factor, while dispersed firms should be largely insulated from local trading waves.

To test these predictions, we construct firm-level measures of geographic dispersion from 10-K

filings by counting the number of distinct U.S. states in which each firm reports operating activities following Garcia and Norli (2012). Firms in the lowest decile of this measure, like those operating in only one or a few states, are classified as geographically concentrated, while firms in the highest decile, which spanning many states, are classified as geographically dispersed. We then estimate each firm's local beta following Pirinsky and Wang (2006), which is defined as the sensitivity of its returns to the equally weighted portfolio of other firms headquartered in the same metropolitan area. Our results strongly support these predictions. Geographically concentrated firms exhibit stronger excess comovement with local firms than geographically dispersed firms and a one-standard deviation increase in geographic dispersion corresponds to a 10.56-percent reduction in local-return comovement.

We then examine whether these patterns reflect intra-regional information spillovers. Mondria (2010) proposes that investors allocate attention across assets by reusing informational signals from one firm and extrapolating them to others within the same category. This form of inference generates cross-firm return responses and fits the definition of information transfer described by Schipper (1990)¹. In the context of local firm categorization, local investors could infer the payoffs of each firm in their local portfolio from a signal provided by one firm in that portfolio. This type of information spillover between firms would be particularly detectable during attention-grabbing information releases, such as earnings announcements (e.g., Pownall and Waymire, 1989; Ramnath, 2002; Thomas and Zhang, 2008; Drake et al., 2017). We show consistent evidence of intra-regional information spillovers. When neighboring firms in the same city release earnings, geographically concentrated firms display a pronounced increase in local beta, consistent with investors extrapolating or reusing other local signals in the same habitat. In contrast, geographically dispersed firms show little response

¹ The literature provides evidence of information spillovers in a wide variety of firm categorizations, largely by industry (e.g., Foster, 1981; Szewczyk, 1992; Firth, 1996; Jennings et al., 2017; Bhojraj et al., 2020; Liu et al., 2022; Desir et al., 2024), but also by others such as analyst coverage (e.g., Crawford et al., 2012; Muslu et al., 2014; Hameed et al., 2015), financial reporting frequency (e.g., Kajüter et al., 2019; Arif and De George, 2020; Breuer et al., 2022), and regulatory reporting standards (e.g., Yip and Young, 2012; Wang, 2014).

to other local firms' announcements. Symmetrically, when a concentrated firm announces its own earnings, its comovement with the local portfolio falls sharply, suggesting that the arrival of firm-specific information temporarily breaks the local linkage.

To illuminate the underlying mechanism, we also examine the role of geographic dispersion in explaining the price delay and return synchronicity. Following Hou and Moskowitz (2005) and Ahn and Patatoukas (2022), we find that geographically concentrated firms exhibit higher price delay and lower return synchronicity with market movements. This evidence links geographic concentration directly to the information diffusion channel emphasized in Barberis et al. (2005). These patterns, together with previous results, indicate slower incorporation of non-local information and greater dependence on local signals of geographically concentrated firms. We then examine StockTwits coverage as a plausibly exogenous reduction in the acquisition cost of information using the data from Cookson and Niessner (2023). Following a firm's first appearance on StockTwits, its excess local comovement declines materially, particularly among geographically concentrated firms previously invisible outside their home region. This attenuation is precisely what the habitat and information diffusion views would predict. New external information channel partially erodes geographic segmentation and extends investor base beyond the original habit for the geographically concentrated firms. Moreover, it lowers information acquisition costs that had previously hindered the speed of information diffusion. Taken together, the evidence shows that social media coverage reduces excess local return comovement for geographically concentrated firms.

Additional analyses reinforce the role of information frictions in shaping local return comovement. We show that firm scope, as measured by Hoberg and Phillips (2025), is closely associated with the processing costs investors face: high-scope firms span diverse product markets, making it harder for investors, especially local investors with limited attention, to interpret firm-specific signals. Consistent with this view, geographically concentrated firms with high scope exhibit the strongest local comovement, indicating that when operations are both locally anchored and complex, investors rely

most heavily on local heuristics and local signals. Finally, we conduct a comprehensive series of robustness tests. The main results hold (1) when dropping firms headquartered in the largest MSAs, (2) removing earnings announcements from months with heavy reporting activity, and (3) controlling for local economic conditions such as personal income, industry concentration, and state-level coincident indicators.

We make several contributions to the literature. First, we contribute to the research on stock return comovement and its underlying sources of information frictions. Our study introduces geographic dispersion as a central and previously underexplored determinant of these frictions. We show that the degree to which a firm's operations are geographically concentrated has a first-order effect on how strongly it comoves with local firms in the same region, which cannot be explained by market-wide factors, industry shocks, or regional economic conditions. This expands the empirical scope of Barberis et al. (2005) by demonstrating that geographic operational structure directly shapes the strength of friction-based comovement.

Second, we extend the literature on information transfer and spillovers in financial markets. Existing research focuses primarily on industry-based spillovers, analyst networks, or disclosure regimes (e.g., Muslu et al., 2014; Drake et al., 2017; Kajüter et al., 2019). We show that information transfer also occurs along geographic clusters that information of local earnings announcements and analyst revisions can propagate to nearby firms. This intra-regional information spillover is distinct from industry spillovers and reflects the local attention structure of investors. Our findings therefore reveal a new dimension of information transfer that is driven by geographic proximity rather than economic linkages. This advances the understanding of how investors use local signals to update valuations .

Third, we contribute to the growing research on social media in financial markets. We provide novel evidence that social media coverage mitigates the information frictions associated with geographic concentration. Following a firm's first appearance on StockTwits, its local comovement

declines, and the magnitude of intra-regional information spillovers weakens among geographically concentrated firms. Our results contribute to the study of social media in reducing the information process costs (Gomez et al., 2024) by illustrating how digital information platforms can improve information diffusion in capital markets.

The rest of this paper is organized as follows. In Section 2, we review relevant literature and develop the main hypotheses. In Section 3, we describe the data and research methodologies. In Section 4, we present and discuss the results. Lastly, Section 5 concludes the paper.

2. Relevant Literature and Hypotheses

Our study builds on several streams of literature. Firstly, it is related to the literature on return comovement. Barberis, Shleifer, and Wurgler (2005) argue that friction- and sentiment-based comovement arises for three (non-distinct) reasons. First, the category view suggests that some investors may categorize multiple assets into a single category, consistent with the model described by Peng and Xiong (2006). Therefore, this category-learning behavior, such as by considering ‘small cap’ or ‘oil’ stocks in the same category, would drive excess comovement through market frictions. Second, the habitat view supposes that some investors may limit their trading to a subset of available stocks, due to trading restrictions, costs, or a lack of available information (e.g., Veldkamp, 2006; Mondria, 2010). Third, the information diffusion view suggests that some stocks incorporate information into their prices faster than others (e.g., Hou and Moskowitz, 2005; Ahn and Patatoukas, 2022). Some stocks may be less costly to trade, and similarly, some stocks may have differences in information accessibility by select groups of investors.

A large empirical literature supports these channels. Several studies document excess comovement around corporate events such as index inclusion (Barberis, Shleifer, and Wurgler, 2005; Boyer, 2011) and stock splits (Green and Hwang, 2009; Kumar, Page and Spalt, 2013). Moreover, stock returns tend to covary when firms share the same lead underwriters in initial public offerings or seasoned equity offerings (Grullon, Underwood, and Weston, 2014), same active mutual fund owners (Antón and Polk,

2014), or the same analyst coverage (Israelsen, 2016). Hameed, Morck, Shen, and Yeung (2015) further support the predictions of Veldkamp (2006) and Mondria (2010) with empirical evidence that firms with high analyst coverage would become “bellwether firms” helping to predict the stock performance of their industry peers with lower coverage.

A sub-stream of literature focuses on the return covariance among geographically related firms. Pirinsky and Wang (2006) document strong return comovement of firms whose headquarters are in the same Metropolitan Statistical Area (MSA). Pirinsky and Wang (2006) also suggest that the comovement among local stocks cannot be explained by firm-level or regional economic fundamentals. Moreover, they show that the comovement effect is more pronounced for smaller firms, those with a greater share of individual investors, and for firms located in regions with lower levels of financial sophistication. Kumar et al. (2013) argue that retail investors are key participants in driving comovement, particularly during the period of high market-wide uncertainty (which creates more noisy signals for traders). Additionally, Kumar, Page, and Spalt (2016) document strong comovement among lottery-like stocks (which are typically favored by retail investors) and find this is more pronounced for the firm located in regions where local investors show a stronger propensity to gamble.

Our study also relates to the literature on local bias. Investors disproportionately invest in firms headquartered near them (e.g., Huberman, 2001; Grinblatt and Keloharju, 2001; Ivkovic and Weisbenner, 2005; Massa and Simonov, 2006). Although there is debate about whether the bias reflects information advantages or behavioral preferences (Seasholes and Zhu, 2010), quasi-natural experiments such as regional holidays and power outages show that local investors contribute directly to trading volume and price discovery of local stocks (e.g., Shive, 2012; Jacobs and Weber, 2012). Recently, Branikas, Hong and Xu (2020) use an instrumental variable approach to account for the potential endogeneity of the household’s location choice, and document similar patterns in local bias.

A related line of research examines the geographic dispersion of firms. Using state name counts from the 10-K filings as a proxy for geographic dispersion, Garcia and Norli (2012) document the

stock outperformance of geographically concentrated firms over geographically dispersed firms by 8.4% annually. They attribute the geographic concentration premium to Merton's (1987) investor recognition hypothesis; the premium is compensation to investors for insufficient diversification. Other studies find a similar negative relation between investor recognition and stock returns (e.g., Lehavy and Sloan, 2008; Bodnaruk and Ostberg, 2009). Subsequent research investigates the effect geographic dispersion has on firm monitoring and information quality. For example, Shi, Sun, and Luo (2015) find that firms' geographic dispersion is negative related to accruals-based earnings management. Additionally, Ma, Li, and Lobo (2020) demonstrate that geographically dispersed parent companies have fewer accounting misstatements in their financial reports than their concentrated counterparts. These studies support the investor recognition hypothesis and suggest that geographically dispersed firms garner more public attention, have more extensive monitoring, and exhibit a higher level of information transparency.

Bringing these strands together, we expect that investors hold a higher proportion of their investments in the firms located in the same region. Given the hypotheses of limited attention and costly information processing, investors may price local stocks using regional-specific information or using a common subset of information encompassing stocks in the same local habitat. In contrast, geographically dispersed firms attract more attention (Garcia and Norli, 2012) and a broader investor base than a geographically concentrated counterpart, reducing the headquarter-level effect of local bias. Consistent with the habitat view of Barberis et al. (2005), geographically concentrated firms should therefore exhibit stronger comovement with other local firms. This leads to our first hypothesis.

H1: Stock returns of geographically concentrated firms co-move more with the returns of other firms headquartered in the same region than with those of geographically dispersed firms.

The large literature on intra-industry information transfers (see, e.g., Foster, 1981; Firth, 1996; Ramnath, 2002; Thomas and Zhang, 2008; Chung et al., 2015; Brochet et al., 2018; Hann et al., 2019; Bergsma and Tayal, 2020; Bhojraj et al., 2020) documents that the earnings of a "first announcer" have

an impact on the non-announcing peer firms in the same industry. Drake et al. (2017) show that the earnings announcements of peer firms in the same industry affect market attention on the firm itself and that the information spillover is more pronounced in the firms exhibiting higher stock comovement. Corporate events other than earnings announcements also trigger intra-industry information spillovers. For example, Szewczyk (1992) finds that offerings of corporate securities generate information transfers to firms in the same industry. In addition, Desir et al. (2024) provide evidence that intra-industry information transfer accompanies CEO turnovers.

Information spillovers are not limited to industry categorization, however. Muslu et al. (2014) find that stocks covered by the same analyst have excess comovement when the analyst releases information about one of the firms, indicating information spillover between the firms that share analyst coverage. Kajüter et al. (2019) and Breuer et al. (2022) demonstrate information spillovers from firms with regulated disclosures to firms with unregulated disclosures. Similarly, Arif and De George (2020) show information transfer from firms that provide frequent disclosures to those with infrequent disclosures. Additionally, Wang (2014) finds evidence of stronger cross-border information spillover when countries use the same reporting standards.

Applying the literature of information spillover to the regional context, we hypothesize that intra-regional information spillover is heightened when local firms located in the same region experience corporate events, since investors in the same habitat update beliefs about the focal firm using other local signals. This leads to stronger local return comovement, which can be summarized in Hypothesis 2.

H2: A firm's return comovement with their local portfolio increases when local firms in the same region experience information events.

Because geographically concentrated firms rely more heavily on local investors and face higher information frictions due to lower investor attention (Garcia and Norli, 2012), the local information events should have an even stronger impact on their comovement patterns. This follows naturally from

both the habitat view and the information diffusion view in Barberis et al. (2005). We therefore propose Hypothesis 3.

H3: Geographically concentrated firms exhibit greater comovement with their local portfolio when local firms in the same region experience information events than their geographically dispersed counterparts.

Finally, in an era of social media, opinions and discussions on social media platforms contain price-relevant signals and predict future stock returns and trading activities (Chen et al., 2014; Cookson and Niessner, 2020; Cookson et al., 2024). Recent work also shows that social media reduces disclosure-processing costs (Gomez et al., 2024) and improves analyst forecast quality (Jame et al., 2022). Consistent with habitat and information diffusion view, the coverage of social media might expand the investor base beyond the habitat and accelerate the diffusion of firm-specific information, which consequently reduces the local return comovement. This yields our last hypothesis.

H4: The coverage of social media reduces the local return comovement and local informational spillovers of the geographically concentrated firms.

3. Data and Methodology

We estimate stock return comovement with a local portfolio approach, following Pirinsky and Wang (2006). Our study focuses on U.S. domestic common stocks over the period from 1995 to 2023, excluding REITs, closed-end funds, and ADRs (firms with CRSP share codes other than 10 or 11). Following previous studies (e.g., Ivkovic and Weisbenner, 2005; Pirinsky and Wang, 2006), we define the firm's location as the headquarter location. However, researchers (see, e.g., Pirinsky and Wang, 2006; Bai et al., 2020) point out the issue of backfilling in headquarter location by COMPUSTAT. Thus, we obtain the historical headquarters data from the column of business address in the header of 10K/Q filings⁴ and define the firm's region by the Metropolitan Statistical Area (MSA) of its

⁴ We obtain the augmented 10-X header data from the Notre Dame Software Repository for Accounting and Finance, <https://sraf.nd.edu/data/augmented-10-x-header-data/>.

headquarters. Then, following Pirinsky and Wang (2006), we construct the local portfolio for each MSA, and we require each MSA to have at least 5 firms and 2 industries (by Fama-French (1997) 48 industries). The local portfolio return, $R_{i,t}^{LOC}$, for firm i in month t is the equally weighted return of the MSA portfolio based on corporate headquarters, after excluding the return of the firm i . We also calculate the equally weighted industry portfolio return, $R_{i,t}^{IND}$, for each firm i , similar to the process of estimating local portfolio return. Lastly, R_t^{MKT} is the excess return of the value-weighted market portfolio in month t .

We regress Model (1) for each firm and the coefficient, β^{LOC} , is expected to capture the degree of comovement of return on the firm with other local firms' returns in the same MSA. Hypothesis 1 predicts the higher β^{LOC} for the geographically local firms.

$$R_t = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t} \quad (1)$$

We estimate geographic dispersion by counting the number of states mentioned from the 10-K filings via the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR), consistent with previous literature (Garcia and Norli, 2012; Platikanova and Mattei, 2016). Then, we use the natural logarithms of one plus the number of different states mentioned and the corresponding decile ranks as the measures of geographic dispersion used in the later regressions. Figure 1 illustrates two examples. Kroger Co., headquartered in Ohio, operates supermarkets and department stores nationwide and mentioned 25 states in its FY2019 10-K report, reflecting high geographic dispersion. By contrast, AtriCure Inc., headquartered in the same MSA in Ohio, develops and sells medical devices and mentioned only 5 states in its FY2019 filing, indicating low geographic dispersion.

[Insert Figure 1 About Here]

To test Hypothesis 1 in a cross-sectional setting, we first use the firm-level local comovement measure, $\beta_{i,t}^{LOC}$ for each month using as a dependent variable and estimate regression Model (2). $GD_{i,t-1}$ are the lagged geographic dispersion measures including $NSTATES$, $LOG(1+NSTATES)$, and $LOCAL RANK$. $NSTATES$ is the number of different states mentioned in the firm's 10-K filings.

$\text{LOG}(1 + \text{NSTATES})$ is the natural logarithm of one plus NSTATES . LOCAL RANK is the decile rank of NSTATES times minus one for each year-month, ranging from 0 to 1. Industry fixed effects (determined by Fama-French (1997) 48 industries) are expected to capture the unobservable time-invariant patterns in each industry and year-month fixed effects are included to capture the time trends. Standard errors are clustered by the firm in the regression.

$$\begin{aligned} \beta_{i,t}^{\text{LOC}} = & b_0 + b_1 \text{GD}_{i,t-1} + \Gamma * \text{Firm} - \text{Level Controls}_{i,t-1} + \text{Industry FEs} \\ & + \text{Yearmonth FEs} + u_{i,t} \end{aligned} \quad (2)$$

A set of lagged control variables are included in Model (2), consistent with Pirinsky and Wang (2006). We include a set of firm-specific variables, AT (natural log of Total Assets), MB , ROA , DEBT , $\text{STD}(\text{EARN})$, TOBINQ , ADVERTISEMENT , DIV YIELD . Then, we include variables related to stock ownership including $\text{NUMBER OF SHAREHOLDERS}$ and IO . Additionally, ANALYSTS and ANALYST DISP are included to account for the level of information asymmetry. Table A1 provides the details of all variables used in this paper.

In order to test the intra-regional information spillover suggested in Hypothesis 2 and 3, we regress the monthly local comovement using Models (3) and (4), similar to the setting used in Drake et al. (2017). In the main regressions, we treat other firms headquartered in the same MSA as the local firms for each observation. We use annual earnings announcements as main corporate events. Then, LOCAL EA is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in each month. EA is a dummy variable equal to one if the firm announces its annual earnings in the same month and zero otherwise. The same set of control variables used in Model (2), industry, and year-month fixed effects are included in Model (3). The hypothesis of information spillover would predict the positive sign of c_2 , suggesting the earnings announcements of other local firms would distract attention away from the firm and lead to the increase of comovement with local stocks. Meanwhile, we predict the sign of c_1 would be negative, which implies that the corporate events of the firm itself would attract the attention of investors who invest in the local

portfolio back. Consequently, the degree of local return comovement is lower during the months of corporate events

$$\beta_{i,t}^{LOC} = c_0 + c_1 EA_{i,t} + c_2 LOCAL EA_{i,t} + \Gamma * Firm - Level Controls_{i,t-1} + Industry FEs + Yearmonth FEs + u_{i,t} \quad (3)$$

Panel A of Table 1 shows the descriptive statistics of the main variables used in the following sections⁶. After dropping observations with missing control variables, the sample contains 422,993 firm-month observations. The estimated local betas exhibit large variation, with a mean of 0.170 and a standard deviation of 1.238. The distribution is slightly right-skewed, as the median local beta is 0.079. The mean and median number of states mentioned in the firm's 10-K filing are 11.76 and 9, respectively. All continuous variables are winsorized at 1% and 99%.

[Insert Table 1 About Here]

Panel B displays the correlation coefficient matrix. The degree of local return comovement, $\beta(R_LOC_EW)$, is positively correlated with the geographic dispersion measure, *LOCAL RANK*, which supports the first hypothesis that geographically concentrated firms exhibit higher return comovement with the local portfolio. Furthermore, the correlation coefficient between $\beta(R_LOC_EW)$ and *EA* is -0.006, which suggests that firms exhibit less comovement with the local portfolio in months with earnings. In contrast, the correlation coefficient between $\beta(R_LOC_EW)$ and *LOCAL EA* is 0.020, which is in alignment with our second hypothesis. Return comovement with the local portfolio increases when other local firms in the same region experience corporate events since other local firms' activities may distract the attention away from the firm's investors.

4. Empirical Results

4.1. Time-Series Regressions

Table 2 reports the regressions of firms' daily excess returns using different models, and it reports the mean statistics in year t for each group sorted by tercile of the number of different states mentioned

⁶ We report the descriptive statistics by the terciles of geographical dispersion in Table A2.

in the 10-K filings in year $t - 1$. Overall, consistent with previous literature on return comovement (Pirinsky and Wang, 2006), firms exhibit significant return comovement with the return of the local portfolio.

[Insert Table 2 About Here]

Consistent with the first hypothesis, geographically local firms have higher loadings on the return of the local portfolio from Models 1 to 3⁷. Specifically, the slope of local portfolio return for a geographically local firm is higher than geographically dispersed firms by 0.123 ($p\text{-value} < 0.01$) in Model 2 after controlling the market and industry returns. This result is robust after accounting for the non-local portfolio returns suggested by Li and Zhao (2016) in Models 3 and 4, where $R_NLOC(EW)$ is the daily return on the equally-weighted non-local portfolio of firms headquartered in the different MSAs. Moreover, Table 1 documents the shifting patterns of the comovement with the market to the comovement with local returns after sorting by firms according to their geographic dispersion. The coefficient on market return is higher for dispersed firms by 0.170 units ($p\text{-value} < 0.01$) in Model 2. Similarly, Models 3 and 4 suggest that the geographically dispersed firms exhibit greater return comovement with non-local firms and less return comovement with local returns.

4.2. Firm-Month Cross-Sectional Regressions

To further test our first hypothesis, we estimate Equation (2) and present the results in Table 3⁸, where we use alternative specifications for geographic dispersion ($NSTATES$, $LOG(1 + NSTATES)$ and $LOCAL\ RANK$) as independent variables, both with and without controls. The results presented in Table 3 support the first hypothesis that geographically concentrated firms exhibit greater local return comovement. The results remain robust to the alternative forms of geographic dispersion measure. Specifically, the natural logarithm of the number of states mentioned in 10-Ks, $LOG(1 + NSTATES)$, is

⁷ Consistent with Pirinsky and Wang (2006), we use equally-weighted local and industry portfolios. We find our results still hold using value-weighted portfolios, which are available upon request.

⁸ We further report the cross-sectional regression of firm's market and industry beta on geographic dispersion in Table A3 in the Appendix. As with the pattern shown in Table 1, geographically dispersed firms have higher general return comovement ($b_{LOCAL\ RANK} = -0.162$, $p\text{-value} < 0.01$) with the market. Furthermore, Table A4 suggests our results remain robust after controlling market and industry betas.

negatively related to local return comovement with the coefficient of 0.027 ($p\text{-value} < 0.01$) in Column (4) of Table 3. Economically speaking, the one-standard-deviation increase in $LOG(1+NSTATES)$ would lead to about 10.56 ($= -0.027 \times 0.665/0.17$) percentage decrease in local return comovement, $\beta(R_LOC_EW)$. Table 3, Column (6) shows a positive relationship between $LOCAL\ RANK$ and local return comovement ($b_{LOCAL\ RANK} = 0.056, p\text{-value} < 0.01$) after controlling for firm-specific variables, industry fixed effects, and year-month fixed effects. The bottom decile (most concentrated group) of firms ranked by $NSTATES$ exhibits 32.75 percent ($= 0.056/0.17 \times 100$) higher local return comovement than firms ranked in the top decile (most dispersed group) of $NSTATES$.

[Insert Table 3 About Here]

Additionally, the signs of slope estimates of firm-specific variables on local beta are consistent with Pirinsky and Wang (2006). Local return comovement is more pronounced among small ($b_{AT} = -0.056, p\text{-value} < 0.01$) and less profitable ($b_{ROA} = -0.294, p\text{-value} < 0.01$) firms, from the estimation in Table 3, Column (6). Moreover, firms with a smaller number of shareholders and greater informational asymmetry (e.g., $b_{NUMBER\ OF\ SHAREHOLDERS} = -0.010$, $b_{ANALYSTS} = -0.036$ and $b_{ANALYST\ DISP} = 0.040$) comove more with stocks headquartered in the same MSA. These findings align with Veldkamp (2006): smaller, less profitable firms and those with fewer shareholders are less visible, and thus attract less attention from non-local investors. In turn, these stocks exhibit greater comovement with the local portfolio. Similarly, firms with higher information asymmetry (with fewer analysts or higher dispersion of opinion among analysts) exhibit higher information processing costs. As such, investors tend to utilize the common set of local information to price those stocks, which explains the greater local return comovement of stocks with higher informational asymmetry.

4.3. Relation Between Investor Attention and Geographic Dispersion

Merton (1987) suggests that greater attention on a stock creates a broader investor base. Therefore, in the context of this study, it is of interest to examine how geographic dispersion and investor attention are related. In the spirit of Chi and Shantikumar (2017), Cziraki et al. (2021), and Dyer et al. (2025),

for each stock ticker, we use the ratio of the home-state Google search volume index (SVI) to the total Google SVI as a proxy of how “local” searches on the tickers are (see equation 4). A value of 0 indicates no local searches on the ticker, while a value of 1 indicates that all searches were performed locally.

$$REL_ATTENTION = \frac{GOOGLE_ATTENTION(HEADQUARTER\ STATE)}{\Sigma\ GOOGLE\ ATTENTION} \quad (4)$$

We regress *REL_ATTENTION* on *LOCAL_RANK* and present the results in Table 4. The positive and significant relation between *LOCAL_RANK* and *REL_ATTENTION* in Column (2) ($b_{LOCAL_RANK} = 0.036, p < 0.01$) highlights that geographically concentrated firms disproportionately capture attention within their local hubs. This finding underscores how geographic concentration intensifies localized investor focus and suggests that these firms rely heavily on local information channels. Importantly, and consistent with the investor recognition hypothesis, the negative and significant coefficient for firm size ($b_{AT} = -0.012, p < 0.01$) indicates that larger firms experience non-local investor attention.

[Insert Table 4 About Here]

These results provide key insights into the dynamics of localized investor behavior and their implications for return comovement. Firms with highly concentrated local attention (high *REL_ATTENTION*) are likely to have higher information acquisition and processing costs for non-local investors, who must expend greater effort to access firm-specific signals dominated by local information channels. This aligns with the "habitat view" proposed by Barberis et al. (2005), where geographic segmentation creates localized investor bases and amplifies local return comovement. Furthermore, the heightened concentration of attention in the headquarter state slows the diffusion of information to broader markets, reinforcing the geographic frictions that drive localized trading behaviors. Larger firms, with lower *REL_ATTENTION*, are less reliant on local habitats, benefiting from broader investor visibility and reduced barriers to information flow.

Overall, the findings extend Barberis et al. (2005)’s theories by demonstrating how relative

attention serves as a robust proxy for localized information barriers, linking geographic concentration to segmented investor behavior. The results also emphasize the critical role of firm size in mitigating geographical effects. These insights contribute to a deeper understanding of the frictions underlying local return dynamics and highlight the interplay between geographic concentration, investor segmentation, and the broader market integration of firm-specific information.

4.4. Tests for Intra-Regional Information Spillover and Geographic Dispersion

4.4.1. Firm-Specific Information Events and Local Comovement

In this sub-section, we test the second and third hypotheses on intra-regional attention-transfer and information spillover using Equations (3). The theories of Barberis et al. (2005) propose that comovement arises from mechanisms such as category-based trading, investor habitat segmentation, and information diffusion. Our results on intra-regional information spillover directly support the **information diffusion** and **habitat view** hypotheses. Information diffusion posits that news propagates unevenly, generating localized reactions and comovement among investors with shared access to information. The habitat view highlights geographic segmentation, where local investors dominate trading activity, amplifying regional return dynamics. By analyzing the sensitivity of geographically concentrated firms to local events, we provide evidence for these mechanisms and demonstrate how localized information flows shape return comovement.

Table 5 presents the regression result of monthly local beta on *LOCAL EA* (Panel A) and *LOCAL REVISION* (Panel B). Column (2) in Panel A shows that firms exhibit higher local return comovement ($b_{LOCAL\ EA} = 0.046$, $p\text{-value} < 0.01$), when there is an increase in the number of earnings announcements of local firms in the same month. Economically speaking, a one-standard-deviation increase in *LOCAL EA* results in a 0.06-unit ($= 0.046 \times 1.223$) increase in local return comovement, which is equivalent to 33.1-percent ($= (0.046 \times 1.223) / 0.17 \times 100$) increase in local return comovement. Moreover, Column (2) of Panel A shows that firms comove less ($b_{EA} = -0.023$, $p\text{-value} < 0.01$) with the local portfolio in the month of their own earnings announcement, controlling for

firm-specific control variables, and with inclusions for industry and year-month fixed effects. As another information event, we also examine the effect of analysts' earnings forecast revisions on local comovement. The results, presented in Panel B, are qualitatively similar to those in Panel A; firms exhibit more local comovement when other local firms have analyst revisions and less comovement when there is a revision issued on their own stock.

[Insert Table 5 About Here]

Overall, the results in Table 4 are consistent with the second hypothesis. During the months with local firms' information events, the firm itself exhibits greater comovement with the local portfolio. This finding is consistent with local firms' information events distracting the attention of investors away in the setting of limited attention and high information processing costs, or investors using the information from earnings announcements of other regional firms to adjust price expectations. On the other hand, the firm exhibits less local comovement during the month of its own annual earnings announcement, as investors allocate more attention to the firm to process the firm-specific information acquired from the earnings.

This effect is notably weaker for geographically dispersed firms. Columns (3) and (4) of Table 5 report the regression results of monthly local return comovement on local firms' activities in the same month, separately for geographically concentrated and dispersed firms. The variable *CONC* is the bottom tercile group of firms ranked by *NSTATES* for each year-month and *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. Supporting the third hypothesis, intra-regional information spillover is prominent among geographically concentrated firms ($b_{LOCAL\ EA} = 0.074$, $p\text{-value} < 0.01$) from Column (3) of Panel A. The relationship between *LOCAL EA* and local beta is not statistically significant for geographically dispersed firms in Column (4) of Panel A ($b_{LOCAL\ EA} = 0.002$, $p\text{-value} > 0.1$, with a difference-in-coefficients of 0.072, $p\text{-value} < 0.01$). The results from using analysts' revisions as the information event proxy, displayed in Columns (3) and (4) of Panel B, again yield very similar results. Consistent with Panel A, geographically concentrated firms

exhibit stronger sensitivity to local revisions ($b_{LOCAL\ REVISION} = 0.082$, $p\text{-value} < 0.01$) compared to dispersed firms ($b_{LOCAL\ REVISION} = 0.008$, $p\text{-value} > 0.1$), with a difference-in-coefficients of 0.074 ($p\text{-value} < 0.01$). Moreover, firm-specific information announcements reduce local beta, indicating that such events temporarily shift investor focus from regional dynamics to firm-specific fundamentals. This reflects a short-term reduction in information acquisition and processing costs, where firm-level news provides clear and accessible signals for investors.

These findings align with Barberis et al. (2005)'s habitat view, as local events trigger correlated trading behavior among segmented local investors. The evidence also connects to the work of Veldkamp (2006) and Mondria (2010), who emphasize the importance of information processing costs in shaping investor behavior. In their framework, investors allocate limited attention across assets based on the costs and benefits of processing information. Our results suggest that geographically concentrated firms, with higher localized investor attention, face greater information frictions due to the difficulty of disseminating regional signals to non-local investors. Information events such as earnings announcements or recommendation revisions temporarily lower these processing costs by offering clear and broadly accessible signals, reducing reliance on localized information channels and moderating comovement. By integrating these perspectives, our study highlights the dynamic interplay between geographic frictions, information costs, and the diffusion of firm-specific signals in shaping return dynamics.

4.4.2. Information Content and Local Comovement

We propose the measures, *LOCAL SUE*, to examine how the magnitude of local firms' earnings surprises affect information spillovers. We first calculate the size-weighted average of absolute values of other local firms' standardized unexpected earnings (SUE^{10}) in the same month as $ABS(LOCAL\ SUE)$. Then, *LOCAL SUE* is the decile score¹¹ of $ABS(LOCAL\ SUE)$ by each year-month. Then, we

¹⁰ We calculate the *SUE* as the difference between actual EPS from IBES and the median of most recent analysts' forecasts, divided by the stock price at the fiscal year end.

¹¹ We compute the decile score by subtracting 1 from the decile rank (from 1 to 10) of $ABS(SUE)$ and then dividing the

replace the variables *LOCAL EA* in Table 5 with *LOCAL SUE* and report the results in Table 6. Our results support the view of friction-driven comovement. Columns (1) and (2) of Table 6 suggest that the firm would experience a higher degree of local return comovement when their local firms report greater magnitude of earnings surprises ($b_{LOCAL\ SUE} = 0.052$ in Column(2), $p\text{-value} < 0.01$). Columns (3) and (4) of Table 6 are also consistent with our results in Table 5. Geographically dispersed firms' comovement is 94% ($=0.076/0.081$, $p\text{-value} < 0.01$) less sensitive to *LOCAL SUE* than their geographically concentrated counterparts. The evidence as a whole supports our hypothesis that the friction-driven local return comovement is more pronounced in geographically concentrated firms. The results suggest that the larger the magnitude of local firms' earnings surprises (either positive or negative), the more information spillover there is to non-announcing local firms that are geographically concentrated. However, there is little evidence of information spillover to geographically dispersed local firms.

[Insert Table 6 About Here]

Intuitively, this reveals the distinctive patterns of attention allocation and information production between geographically local and dispersed firms. Geographically concentrated firms are more likely to be held by a smaller set of investors, based on the limited locations of their business operations. Therefore, the corporate events of the other firms headquartered in the same MSA are more likely to attract the attention of investors in the same habitat. Investors subsequently value those stocks using the regional level information (i.e., information spillover) due to informational frictions, which leads to comovement within the local firm portfolio.

4.5. Information Diffusion and Geographic Dispersion

Barberis et al.'s (2005) information diffusion view of comovement indicates that excess comovement can be generated by stocks incorporating information into their prices at different speeds. Stocks with similar diffusion speeds then exhibit excess comovement with one another. Our hypothesis

value by 9, which makes *LOCAL SUE* ranging from 0 to 1.

is that geographic concentration impedes information diffusion, which is one reason for excess comovement among local stocks. Thus, to test this hypothesis, we examine the relation between the geographic dispersion of firms and their price delay (Hou and Moskowitz, 2005). Since firm size is expected to serve as a mitigator to geographic concentration (e.g., concentrated firms that are large in size could receive more investor attention, benefit from lower transaction costs, etc., than their smaller counterparts), we interact *AT* with *LOCAL_RANK* to capture that effect. Columns (1) and (2) in Table 7 presents the results from the regression analyses. There is a positive correlation between price delay and *LOCAL_RANK* (i.e., in Column (2), $b_{LOCAL_RANK} = 0.044$, $p\text{-value} < 0.05$), indicating that geographically concentrated firms have higher price delay than dispersed firms.

[Insert Table 7 About Here]

Another measure of information diffusion is price synchronicity with market returns. According to studies such as Ali et al. (2003), Zhang (2006), and Ahn and Patatoukas (2022), higher price synchronicity is indicative of faster incorporation of market news and lower levels of unresolved uncertainty. Columns (3) and (4) show the results of regressing price synchronicity on geographic concentration. We find a negative relation between price synchronicity and *LOCAL_RANK* (i.e., in Column (4), $b_{LOCAL_RANK} = -0.535$, $p\text{-value} < 0.01$), suggesting a deteriorating information environment as geographic dispersion decreases. Taken altogether, the evidence supports information diffusion as a mechanism for excess comovement in geographically concentrated firms.¹²

4.6. Investor Attention and Geographic Dispersion

4.6.1. Geographic Concentration and Social Media Visibility

¹² We follow Ahn and Patatoukas (2022) to estimate alternative price delay measures including *Market Delay*, *Firm Delay*, *Industry Delay* and *Earnings Delay*. We further define *Local Delay* as 1 minus the ratio of the R2 from the regression of weekly firm returns on contemporaneous market, industry, and local portfolio returns over the R2 from the regression of weekly firm returns on contemporaneous market, industry and local portfolio returns and 4 lags of local portfolio returns. We find consistent results of greater price delays for geographically concentrated firms in Table A5.

Table 8 explores the relationship between geographic concentration and social media attention, with attention proxied by the average daily number of StockTwits posts per firm-month¹³. The primary explanatory variable, *LOCAL RANK*, measures geographic concentration, with higher values indicating firms operating in fewer states. The results in Column (4) demonstrate a significant negative relationship between *LOCAL RANK* and StockTwits attention, indicating that geographically concentrated firms attract less social media attention compared to geographically dispersed firms. This finding supports the notion that firms with more localized operations have narrower investor bases, resulting in lower visibility on platforms like StockTwits. By contrast, larger firms exhibit significantly higher levels of attention ($b_{AT} = 0.523$, $p\text{-value} < 0.01$), consistent with their broader appeal and ability to engage a wider audience. The interaction between geographic dispersion proxy and firm size ($LOCAL\ RANK \times AT$) is positive and significant, suggesting that even geographically concentrated firms benefit from greater attention when they are large enough to overcome the natural constraints of their localized operations.

[Insert Table 8 About Here]

The findings from Column (4) provide important insights into the role of geographic concentration in shaping social media visibility. The negative relationship between *LOCAL RANK* and social media attention suggests that geographic concentration imposes a visibility penalty on firms, likely due to the narrower scope of their investor base and reduced appeal to broader audiences. However, firm size serves as a mitigating factor, as larger firms are able to generate higher levels of attention regardless of their geographic concentration.

These results highlight the frictional nature of geographic concentration in the context of information diffusion and investor recognition, as described by Barberis et al. (2005). Social media platforms like StockTwits appear to amplify the visibility of larger firms, but geographically

¹³ We obtain the firm-day level StockTwits activity data developed by Cookson and Niessner (2020, 2023) for US stocks from 2009 to 2021 from Tony Cookson's website. <https://www.tonycookson.com/data-and-programs>

concentrated firms remain less represented unless they possess significant size to counteract this effect. This reinforces the idea that geographic concentration limits the dissemination of firm-specific information, but external platforms and firm-level characteristics like size can partially alleviate this barrier.

4.6.2. *Geographic Dispersion, StockTwits, and the Habitat and Information Views of Comovement*

To investigate the habitat and information views proposed by Barberis et al. (2005), we analyze the impact of StockTwits coverage on the relationship between geographic concentration and local return comovement using a subset of sample spanning from 2004 to 2021¹⁴. In this context, StockTwits coverage is defined as a binary variable (*ST COVERAGE*) that takes the value of one after a stock first appears on the platform. By providing a low-cost, easily accessible source of firm-specific information, StockTwits reduces the reliance of investors on localized information signals.

[Insert Table 9 About Here]

In the Column (2) of Table 9, the coefficient on the interaction term (*LOCAL RANK*×*ST COVERAGE*) is negative and statistically significant, which indicates that StockTwits coverage weakens the relationship between geographic concentration and local comovement. These results suggest that the availability of external information reduces the categorization of geographically concentrated firms into localized investor portfolios. This supports the "information diffusion" view, as StockTwits effectively lowers the costs associated with information acquisition, enabling investors to incorporate broader, firm-specific signals into their decision-making.

These results extend the "habitat view" of Barberis et al. by demonstrating how external information sources, like StockTwits, expand investor attention beyond localized "habitats," effectively reducing the segmentation that drives geographic comovement. The lack of a direct effect

¹⁴ We also drop the firms which were delisted before the first stock was covered on StockTwits.

of StockTwits coverage ($b_{ST\ COVERAGE} = 0.015$, $p\text{-value} > 0.1$) on local comovement further emphasizes that its impact is conditional on the geographic concentration of firms. Together, these findings highlight how geographic concentration remains the primary driver of local comovement, while external information availability, such as that provided by StockTwits, serves as a critical mechanism to alleviate this effect, fostering more efficient information diffusion and market integration.

4.6.3. Geographic Dispersion, StockTwits, and Information Spillover

Finally, we examine how social media coverage influences information diffusion around earnings announcements. We add *ST COVERAGE* and interaction terms ($EA * ST\ COVERAGE$ and $LOCAL\ EA * ST\ COVERAGE$) to Equation (3) and estimate the model separately for the geographically concentrated firms and geographically dispersed firms. Table 10 shows that the availability of social media coverage significantly reduce the information spillover among the geographically concentrated firms (e.g., in Column (1), $b_{LOCAL\ EA * ST\ COVERAGE} = -0.024$, $p\text{-value} < 0.1$). In contrast, the moderating effect on information spillover is not significant among dispersed firms, and the difference in coefficients on $LOCAL\ EA * ST\ COVERAGE$ between concentrated and dispersed firms is statistically significant ($p\text{-value} < 0.05$).

For geographically concentrated firms, this broader dissemination of firm-specific news on social media platforms dilutes the necessity of inferring stock value from local firms' earnings announcements, reducing the extent of local comovement. Geographically dispersed firms, on the other hand, already tend to attract investors from diverse locations and may benefit from broader analyst coverage, multiple communication platforms, and a wider network of stakeholders. As a result, incremental information from social media might not substantially alter the information environment for these firms.

[Insert Table 10 About Here]

4.7. Robustness Tests

4.7.1. Firm Scope and Geographic Dispersion

In the previous section, we present consistent evidence supporting the habitat and information diffusion view of return comovement. A firm's geographical footprint shapes its investor base and influences the speed at which information spreads across markets. In this section, we extend the analysis by considering an additional dimension of information frictions: firm scope. Building on Hoberg and Phillips (2025), who apply natural language processing to firms' 10-K filings to construct firm-year measures of product market scope, we argue that the breadth of a firm's product market activities introduces an extra layer of informational complexity. Operating in a larger set of product markets increases the difficulty investors face when processing firm-specific fundamentals. As firms become more complex, investors may rely more heavily on signals from geographically proximate firms. This increased dependence on local information would, in turn, amplify local return comovement for firms with broader product market scope.

Table 11 reports the results from sub-sample regressions. We categorize firms into low and high scope groups based on the bottom and top terciles of the firm scope in each year-month. Panel A presents results for the return comovement tests. Column (4) shows that the coefficient on *LOCAL RANK* is significantly larger for the high scope group, suggesting that local return comovement is stronger for geographically concentrated firms that operate in multiple product markets. This pattern is consistent with the habitat view introduced earlier. When firms operate across multiple product markets, investors face greater difficulty in processing firm-specific information. As these frictions rise, investors increasingly rely on signals from nearby firms held by investors in the same habitat, which consequently increases the local return comovement. Panel B reports the information spillover tests and shows that spillovers are more pronounced in the High Scope–CONC group. These findings support our conjecture that the pricing difficulties and information frictions associated with broader firm scope increase investors' reliance on information from geographically proximate firms.

[Insert Table 11 About Here]

4.7.2. Decomposition of Local and Industry Effects

Geographically dispersed firms are more likely to be held by investors located in regions beyond the firm's headquarters. Therefore, local firms in the same MSAs are less likely to be held by investors holding geographically dispersed firms. In turn, the corporate events of local firms are less influential in terms of attention allocation and information production for geographically dispersed firms. As a result, the intra-regional information spillover effect driven by other local firms' earnings announcements is less influential among the sub-sample of geographically dispersed firms.

Thus, we explore the differences between the roles of local and industry information in explaining the intra-regional information spillover. In previous results, we define the local firms as the other firms headquartered in the same MSA. To distinguish the geographical and industry effects, we create a set of new variables, *LOCAL_IND_EA*, *LOCAL_NIND_EA*, *NLOCAL_IND_EA*, and *NLOCAL_NIND_EA*. *LOCAL_IND_EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in the same Fama-French (1997)-48 industry in each month. *LOCAL_NIND_EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in the different Fama-French (1997)-48 industry in the same month. *NLOCAL_IND_EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the different MSAs in the same Fama-French (1997)-48 industry in the same month. *NLOCAL_NIND_EA* is the natural logarithm of one plus the number of annual earnings announcements for firms headquartered in the different MSAs in the different Fama-French (1997)-48 industry in the same month. Then, we add these new variables into Equation (3). Column (4) of Table A6 suggests that the finding of intra-regional information spillover, captured by *LOCAL_IND_EA* and *LOCAL_NIND_EA*, would still hold after adding this set of variables and the industry-related information from other MSAs may distract the investor attention and lead to lower local return comovement ($b_{NLOCAL_IND_EA} = -0.017, p\text{-value} < 0.01$).

Then, we re-estimate the regressions for geographically concentrated and dispersed firms separately in Columns (3) to (6). Among the geographically local firms, the local return comovement is driven by both the local information in the same industry ($b_{LOCAL_IND\ EA} = 0.077, p\text{-value} < 0.01$) as well as those from other different industries ($b_{LOCAL_NIND\ EA} = 0.057, p\text{-value} < 0.01$), which is shown in Column (5) of Table A5. Interestingly, the magnitude of this less relevant geographical effect is lower than the effect of local firms in the same industry for the geographically-local firms.

4.7.3. *Asymmetric Responses to Information Spillovers*

Investors may exhibit asymmetric reactions to positive and negative firm-specific information. To explore this possibility, we examine the heterogeneity of information spillovers and report the results in Table A7. In Panel A, we define *POSITIVE EA* (*NEGATIVE EA*) as an indicator variable equal to one if the firm announces annual earnings with a positive (negative) SUE in the month and zero otherwise. *LOCAL POSITIVE EA* (*LOCAL NEGATIVE EA*) is the natural logarithm of one plus the number of annual earnings announcements with positive (negative) SUEs by other firms headquartered in the same MSA in each month. In Panel B, we define *UPGRADE* (*DOWNGRADE*) as an indicator variable equal to one if the firm receives an upgrade in analysts' recommendations in the month. *LOCAL UPGRADE* (*LOCAL DOWNGRADE*) is the natural logarithm of one plus the number of upgrades (downgrades) for other firms headquartered in the same MSA.

Within the sub-sample of geographically concentrated firms, we find that information spillovers are stronger for negative local news. Local return comovement increases more significantly when nearby firms announce lower-than-expected earnings or receive analyst downgrades. This pattern is consistent with the view that investors respond more strongly to negative firm-specific news than to positive news (e.g., Conrad et al., 2002; Josefy et al., 2023). It also aligns with evidence that analysts are generally reluctant to issue sell recommendations or downgrades, and that the associated market impacts are more pronounced when they do (e.g., Womack, 1996; Conrad et al., 2006). Taken together, these findings suggest that negative news generated by geographically proximate firms produces more

substantial information spillovers and leads to a higher degree of local return comovement for the focal firm.

4.7.4. *Dropping Specific Observations*

We test the robustness of our results by examining the sample dropping the firms headquartered in the Top 3 MSAs, New York-Newark-Jersey City, NY-NJ-PA, Boston-Cambridge-Newton, MA-NH, and Chicago-Naperville-Elgin, in terms of the number of firm-month observations in Table A8.¹⁵ Firms located in the Top 3 MSAs comprise more than 20% of the sample. Panel A of Table A8 suggests that the negative relationship between geographic dispersion and local return comovement remains robust. Columns (1) and (3) of Panel B show that geographically concentrated firms continue to exhibit greater intra-regional information spillover after dropping the firms located in the three largest clusters. In further the robustness, reported in Table A9, we examine earnings announcements excluding those occurring in January, February, and March. Results remain materially unaltered, suggesting that the intra-regional information spillover is not simply a clustering effect on earnings announcements.

4.7.5. *Adding Local Regional Economic Control Variables*

As a further robustness check, we examine whether local economic conditions drive return comovement. Brockman, Liebenberg, and Schutte (2010) document a countercyclical pattern of stock comovement and argue that the return comovement is low during the economic expansion of increasing information production. Pirinsky and Wang (2006) document that the local comovement is more pronounced for the areas with the higher number of firms, higher industry concentration, and greater regional economic development. We add *NO OF FIRMS*, *INDUSTRY CONCENTRATION*, *PERSONAL INCOME*, *INVESTMENT INCOME*, and *COINCIDENT INDEX*¹⁶ as additional control

¹⁵ We find qualitatively similar results after dropping the firms headquartered in New York-Newark-Jersey City, NY-NJ-PA and results are available upon request.

¹⁶ *COINCIDENT INDEX* data is obtained from the website of the Federal Reserve Bank of Philadelphia, <http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident>. *PERSONAL INCOME* and *INVESTMENT INCOME* are obtained from the Regional Economic Accounts by U.S. Bureau of Economic Analysis, <https://www.bea.gov/data/economic-accounts/regional>.

variables in Table 10. The former four variables are estimated in the same approach described in Pirinsky and Wang (2006). We employ State Coincident Indexes (SCI) developed by Crone and Clayton-Matthews (2005) (utilized in many studies, e.g., Pirinsky and Wang, 2006; Amore, Schneider, and Žaldokas, 2013; Smajlbegovic, 2019; Wei and Zhang, 2020) to capture current state-level economic conditions including nonfarm payroll employment, average hours worked, the unemployment rate, and real wages. Both Panels A and B of Table A10 show that our results remain statistically significant after controlling for regional economic activities. We obtain results consistent with Pirinsky and Wang (2006) that local return comovement is more pronounced for the firms headquartered in the areas with the higher industry concentration, and higher personal income. Additionally, Column (3) of Panel A in Table A10 suggests the firms headquartered in regions with lower levels of financial sophistication exhibit higher local comovement ($b_{INVESTMENT\ INCOME} = -0.014, p - value < 0.01$), consistent with Brown et al. (2008).

5. Conclusion

This paper investigates the relation between geographic dispersion and information spillover by examining stock return comovement with local stocks headquartered in the same region. Using the number of different states mentioned in the 10-K filings as the proxy of geographic dispersion, we find evidence that geographically concentrated firms exhibit greater return comovement with the local stocks whose headquarters are located in the same region. Economically speaking, the geographically concentrated firm ranking in the bottom decile of geographic dispersion exhibits 32.75 percent higher local return comovement than the geographically dispersed firm ranking in the top decile does, after controlling firm-level control variables, industry, and year-month fixed effects.

We further examine information spillover within the geographic cluster by using informational corporate events. Specifically, we find evidence consistent with previous literature (e.g., Ramnath, 2002; Thomas and Zhang, 2008; Drake et al., 2017), that return comovement with the local portfolio of the firm increases when other local firms in the same region experience earnings announcements or

analysts' recommendation revisions. Notably, this result is more pronounced for geographically concentrated firms and consistent with a habitat-view of Barberis et al. (2005), in which local investors process information jointly across firms in the same habitat (geographic region) and rely on other news in the same habitat to update valuations when direct information is costly or limited. Our analysis of the magnitude and content of local information further reinforces this interpretation. Local comovement intensifies when nearby firms experience larger earnings surprises and when news is negative rather than positive, highlighting the role of salient information shocks and asymmetric investor reactions in driving local information spillovers.

We also document that geographically concentrated firms have higher price delays and lower price synchronicity with market returns, which points to a slower information diffusion. These patterns align closely with the information diffusion view in Barberis et al. (2005). Then, we explore how social media platforms affect local return comovement and show that the social media coverage weakens the link between geographic concentration and local comovement and attenuates intra-regional information spillovers around earnings announcements for concentrated firms. These results indicate that external information channels partially erode geographic segmentation by broadening investor reach, lowering information acquisition costs, and reducing the reliance on other regional signals.

Importantly, our results are qualitatively and quantitatively similar after a battery of robustness checks such as dropping sample firms headquartered in specific regions, removing observations in certain months, adding additional control variables for regional economic activities. Overall, our evidence supports Barberis et al.'s (2005) framework of friction-based comovement. Our study advances the understanding of how geographic presence and information technology interact to generate, and sometimes mitigate, excess comovement in the market.

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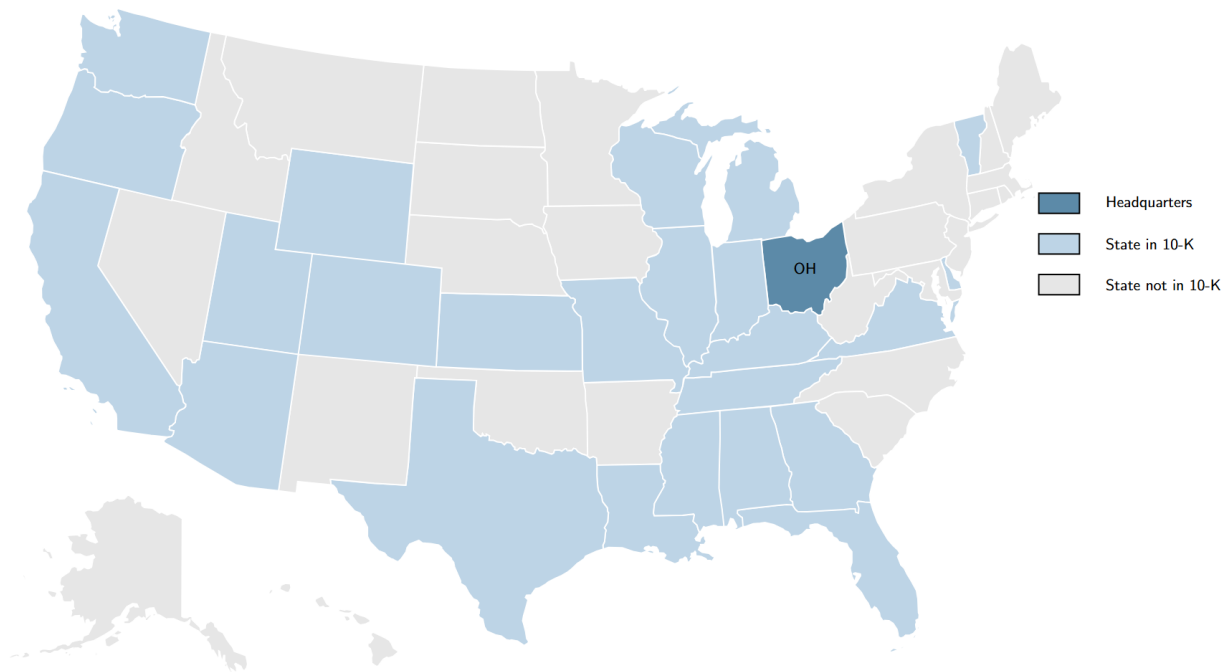
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Figure 1: Examples of Dispersed and Concentrated Firms

This figure shows the examples of dispersed and concentrated firms. Two firms (Kroger Co and AtriCure Inc) are headquartered in the same state (Ohio) and same MSA (Cincinnati, OH-KY-IN) and we highlight the states mentioned in their 10-K reports filed in 2020 in light blue and the headquarter states in dark blue.

Panel A: Example of A Dispersed Firm (Kroger Co)



Panel B: Example of A Concentrated Firm (AtriCure Inc)

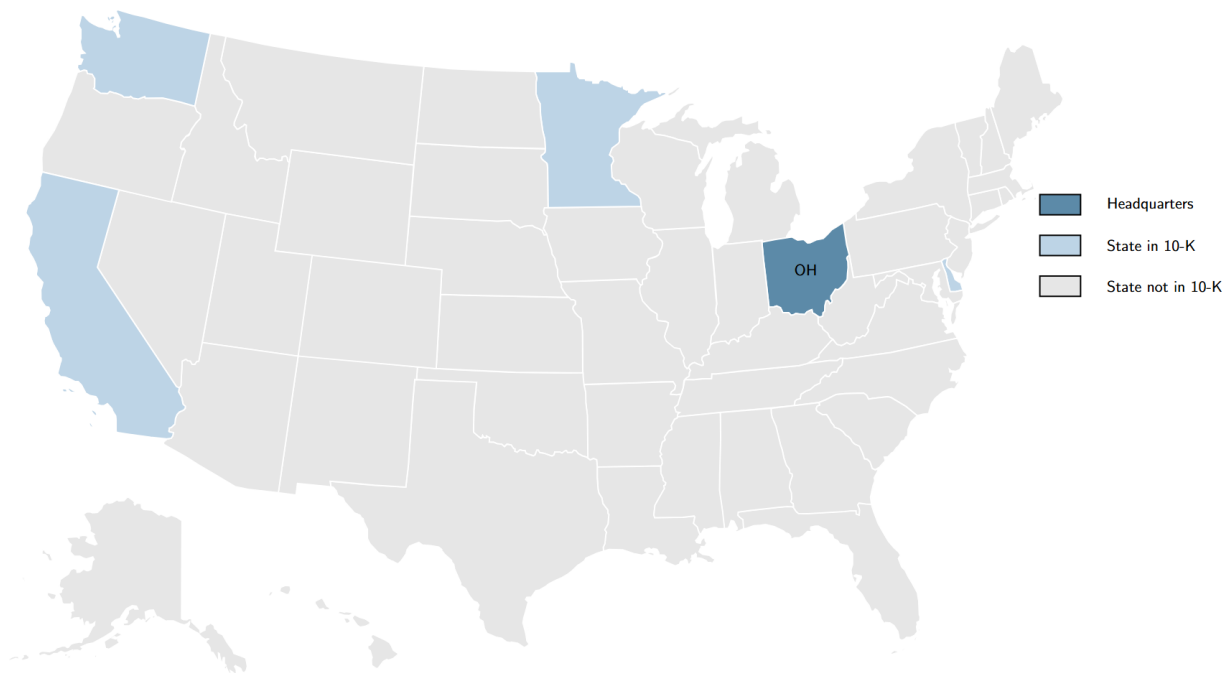


Table 1 Variable Summary Statistics

This table reports the descriptive statistics and correlations for the variables used in the cross-sectional regressions. All continuous variables are winsorized at 1% and 99%. Detailed descriptions of variables are provided in Table A1.

Panel A: Descriptive Statistics

VARIABLES	N	MEAN	SD	P5	P25	P50	P75	P95
$\beta(R_LOC_EW)$	422,993	0.170	1.238	-1.716	-0.408	0.079	0.688	2.345
NSTATES	422,993	11.760	8.622	3.000	6.000	9.000	15.000	31.000
LOG(1+NSTATES)	422,993	2.240	0.665	1.099	1.792	2.197	2.708	3.434
LOCAL RANK	422,993	0.525	0.327	0.000	0.222	0.556	0.778	1.000
AT	422,993	7.239	1.871	4.334	5.897	7.124	8.448	10.590
MB	422,993	3.452	5.752	0.549	1.454	2.346	4.054	11.410
ROA	422,993	0.109	0.174	-0.216	0.068	0.126	0.190	0.331
DEBT	422,993	0.270	0.253	0.000	0.061	0.231	0.396	0.747
STD(EARN)	422,993	1.241	1.622	0.150	0.372	0.701	1.386	4.275
TOBINQ	422,993	2.169	1.577	0.905	1.186	1.627	2.509	5.447
ADVERTISEMENT	422,993	0.013	0.032	0.000	0.000	0.000	0.007	0.073
DIV YIELD	422,993	0.010	0.016	0.000	0.000	0.000	0.016	0.043
NUMBER OF SHAREHOLDERS	422,993	0.344	2.310	-3.411	-1.366	0.370	2.001	4.149
IO	422,993	0.719	0.227	0.265	0.579	0.770	0.902	1.000
ANALYSTS	422,993	2.139	0.675	1.099	1.609	2.079	2.708	3.258
ANALYST DISP	422,993	0.083	0.211	0.000	0.009	0.022	0.059	0.333
EA	422,993	0.085	0.278	0.000	0.000	0.000	0.000	1.000
LOCAL EA	422,993	1.430	1.223	0.000	0.693	1.099	2.079	3.970

Panel B: Correlation Coefficient Matrix

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\beta(R_LOC_EW)$	(1)	1.000								
NSTATES	(2)	-0.053	1.000							
LOCAL RANK	(3)	0.056	-0.869	1.000						
AT	(4)	-0.108	0.331	-0.382	1.000					
MB	(5)	-0.013	-0.055	0.070	0.001	1.000				
ROA	(6)	-0.066	0.156	-0.172	0.245	0.028	1.000			
DEBT	(7)	0.000	0.127	-0.175	0.236	-0.025	0.038	1.000		
STD(EARN)	(8)	-0.009	0.095	-0.123	0.288	-0.046	0.008	0.129	1.000	
TOBINQ	(9)	-0.008	-0.184	0.238	-0.189	0.439	-0.018	-0.073	-0.116	1.000
ADVERTISEMENT	(10)	-0.010	0.053	-0.013	-0.036	0.064	0.110	-0.007	-0.042	0.118
DIV YIELD	(11)	-0.050	0.142	-0.169	0.350	-0.057	0.118	0.096	0.036	-0.174
NUMBER OF SHAREHOLDERS	(12)	-0.084	0.181	-0.200	0.460	-0.015	0.211	0.005	0.032	-0.097
IO	(13)	-0.018	0.130	-0.132	0.330	0.039	0.170	0.058	0.150	0.014
ANALYSTS	(14)	-0.092	0.210	-0.203	0.650	0.134	0.187	0.079	0.106	0.152
ANALYST DISP	(15)	0.031	-0.036	0.031	-0.126	-0.030	-0.146	0.046	0.075	-0.056
EA	(16)	-0.006	0.000	0.000	-0.001	0.000	-0.001	0.000	0.000	0.000
LOCAL EA	(17)	0.020	-0.089	0.100	-0.039	0.031	-0.039	-0.049	-0.025	0.070

Panel B Correlation Coefficient Matrix (Continued)

		(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
$\beta(R_LOC_EW)$	(1)								
NSTATES	(2)								
LOCAL RANK	(3)								
AT	(4)								
MB	(5)								
ROA	(6)								
DEBT	(7)								
STD(EARN)	(8)								
TOBINQ	(9)								
ADVERTISEMENT	(10)	1.000							
DIV YIELD	(11)	-0.002	1.000						
NUMBER OF SHAREHOLDERS	(12)	0.020	0.316	1.000					
IO	(13)	0.016	-0.059	-0.088	1.000				
ANALYSTS	(14)	0.061	0.105	0.304	0.324	1.000			
ANALYST DISP	(15)	-0.004	-0.045	-0.084	-0.119	-0.138	1.000		
EA	(16)	0.000	-0.001	-0.001	0.000	-0.001	0.001	1.000	
LOCAL EA	(17)	0.023	-0.052	-0.020	-0.019	0.022	0.005	0.282	1.000

Table 2 Regression of Return Comovement with Local Stocks, by Geographical Dispersion Tercile

This table reports the mean statistics for the time-series regressions of daily excess returns by the tercile of firms' geographical dispersion. Models are estimated for each firm annually. *CONC* is the bottom tercile group of firms ranked by NSTATES for each year. *DISP* is the top tercile group of firms ranked by NSTATES by each year. *MKTRF* is the daily excess return of the value-weighted market portfolio. *R_LOC(EW)* is the daily return on the equally-weighted local portfolio of firms headquartered in the same MSA, excluding the firm itself. *R_NLOC(EW)* is the daily return on the equally-weighted non-local portfolio of firms headquartered in the different MSAs. *R_IND(EW)* is the daily returns on equally-weighted portfolio of firms in the same industry (by Fama-French (1997) 48 industries), excluding the firm itself. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

$$R_{i,t} = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{MKT} R_t^{MKT} + \varepsilon_{i,t}$$

$$R_t = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t}$$

$$R_t = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{NLOC} R_t^{NLOC} + \varepsilon_{i,t}$$

$$R_t = \alpha_i + \beta^{LOC} R_t^{LOC} + \beta^{NLOC} R_t^{NLOC} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t}$$

MODEL	GD TERCILE	ALPHA	T	MKTRF	T	R_LOC(EW)	T	R_NLOC(EW)	T	R_IND(EW)	T	ADJ-R2	OBS
1	CONC	0.008%	4.55	0.387	85.17	0.624	144.42	.	.	.	.	0.179	26041
1	MID	0.000%	0.25	0.493	97.88	0.561	120.34	.	.	.	.	0.211	22627
1	DISP	-0.001%	-0.76	0.606	144.80	0.423	103.10	.	.	.	.	0.241	22235
	C - D			-0.219***		0.201***							
	T-Stats			(-35.43)		(33.79)							
2	CONC	0.000%	-0.28	0.108	24.50	0.256	57.14	.	.	0.655	138.99	0.205	26041
2	MID	-0.007%	-3.76	0.202	40.85	0.226	38.52	.	.	0.628	101.50	0.243	22627
2	DISP	-0.007%	-5.41	0.278	68.13	0.133	36.14	.	.	0.631	151.32	0.286	22235
	C - D			-0.170***		0.123***				0.024***			
	T-Stats			(-28.25)		(21.24)				(3.96)			
3	CONC	-0.003%	-1.67	.	.	0.296	55.71	0.737	121.02	.	.	0.181	26041
3	MID	-0.012%	-6.78	.	.	0.271	48.82	0.786	124.06	.	.	0.209	22627
3	DISP	-0.014%	-10.01	.	.	0.228	50.40	0.779	146.03	.	.	0.232	22235
	C - D					0.068***		-0.042***					
	T-Stats					(9.71)		(-5.21)					
4	CONC	-0.004%	-2.18	.	.	0.164	33.27	0.265	35.66	0.596	100.64	0.204	26041
4	MID	-0.012%	-6.44	.	.	0.149	26.46	0.345	46.58	0.557	77.43	0.239	22627
4	DISP	-0.014%	-9.86	.	.	0.115	29.65	0.336	53.59	0.579	114.24	0.279	22235
	C - D					0.049***		-0.071***		0.017**			
	T-Stats					(7.82)		(-7.33)		(2.19)			

Table 3 Cross-Sectional Regression of Local Return Comovement on Geographic Dispersion

This table reports the regressions of monthly local return comovement on geographic dispersion measures. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. *NSTATES* is the number of different states mentioned in the firm's 10-K filings. $LOG(1+NSTATES)$ is the natural logarithm of one plus *NSTATES*. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year-month, ranging from 0 to 1. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	$\beta(R_LOC_EW)$					
NSTATES	-0.006***	-0.002***				
	(-8.40)	(-3.00)				
LOG(1+NSTATES)			-0.087***	-0.027***		
			(-9.36)	(-3.46)		
LOCAL RANK					0.173***	0.056***
					(9.46)	(3.58)
AT		-0.057***		-0.056***		-0.056***
		(-12.16)		(-11.94)		(-11.92)
MB		-0.000		0.000		0.000
		(-0.00)		(0.01)		(0.02)
ROA		-0.295***		-0.294***		-0.294***
		(-8.87)		(-8.85)		(-8.83)
DEBT		0.099***		0.100***		0.101***
		(5.09)		(5.19)		(5.21)
STD(EARN)		0.007**		0.007**		0.007**
		(2.17)		(2.15)		(2.14)
TOBINQ		-0.017***		-0.018***		-0.018***
		(-4.56)		(-4.69)		(-4.71)
ADVERTISEMENT		0.020		0.024		0.024
		(0.12)		(0.15)		(0.15)
DIV YIELD		-0.462		-0.467*		-0.466*
		(-1.64)		(-1.66)		(-1.65)
NUMBER OF SHAREHOLDERS		-0.010***		-0.010***		-0.010***
		(-3.42)		(-3.44)		(-3.43)
IO		0.059**		0.060**		0.060**
		(2.34)		(2.39)		(2.39)
ANALYSTS		-0.035***		-0.035***		-0.036***
		(-3.28)		(-3.32)		(-3.34)
ANALYST DISP		0.040**		0.040**		0.040**
		(2.47)		(2.47)		(2.49)
CONSTANT	YES	YES	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES	YES	YES
YEAR-MONTH FE	YES	YES	YES	YES	YES	YES
OBSERVATIONS	422,993	422,993	422,993	422,993	422,993	422,993
ADJ-R2	0.009	0.021	0.009	0.021	0.009	0.021

Table 4: Relationships between Relative Google Attention and Local Rank – Annual Level

This table reports the regression of annual relative google attention on geographic dispersion. *REL_ATTENTION* is the measure of relative google attention, which is the ratio of the annual Google Search Index (GSI) in the headquarter state to the sum of annual GSIs across all states. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year, ranging from 0 to 1. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

$$REL_ATTENTION = \frac{GOOGLE_ATTENTION(HEADQUARTER\ STATE)}{\sum GOOGLE_ATTENTION}$$

Q VARIABLES	(1) REL_ATTENTION	(2)
LOCAL RANK	0.057*** (5.92)	0.036*** (3.60)
AT		-0.012*** (-4.63)
MB		-0.000 (-1.41)
ROA		0.035** (2.24)
DEBT		-0.033*** (-3.56)
STD(EARN)		-0.001 (-0.92)
TOBINQ		0.000 (0.16)
ADVERTISEMENT		-0.068 (-0.71)
DIV YIELD		-0.162 (-1.16)
NUMBER OF SHAREHOLDERS		-0.002 (-1.39)
IO		0.017 (1.32)
ANALYSTS		0.013** (2.33)
ANALYST DISP		0.009 (1.30)
CONSTANT	YES	YES
INDUSTRY FE	YES	YES
YEAR-MONTH FE	YES	YES
Observations	24,517	24,517
Adjusted R-squared	0.055	0.066

Table 5 Tests for Information Spillover

This table reports the regression for intra-regional information spillover. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. *LOCAL EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA each month. *EA* is a dummy variable equal to one if the firm announces its annual earnings in this month and zero otherwise. *LOCAL REVISION* is the natural logarithm of one plus the number of events when other firms headquartered in the same MSA in each month experience one analysts' recommendation revision. *REVISION* is a dummy variable equal to one if the firm receives the analysts' recommendation revisions in this month and zero otherwise. *CONC* is the bottom tercile group of firms ranked by *NSTATES* for each year-month. *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. Other control variables are lagged and described in Table A1. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Earnings Announcements					
VARIABLES	(1)	(2)	$\beta(R_LOC_EW)$		(3) - (4)
	Full Sample		CONC	DISP	
EA	-0.023*** (-2.80)	-0.023*** (-2.84)	-0.033** (-2.19)	0.002 (0.14)	-0.035 [0.07]
LOCAL EA	0.041*** (6.93)	0.046*** (9.42)	0.074*** (9.84)	0.002 (0.29)	0.072 [0.00]
AT		-0.060*** (-12.75)	-0.064*** (-8.61)	-0.058*** (-7.56)	
MB		-0.000 (-0.08)	0.000 (0.32)	-0.001 (-1.30)	
ROA		-0.286*** (-8.63)	-0.217*** (-5.29)	-0.488*** (-6.17)	
DEBT		0.102*** (5.33)	0.052* (1.81)	0.194*** (6.39)	
STD(EARN)		0.007** (2.12)	0.014** (2.28)	0.004 (0.92)	
TOBINQ		-0.017*** (-4.63)	-0.016*** (-3.25)	-0.032*** (-3.73)	
ADVERTISEMENT		-0.023 (-0.14)	-0.301 (-1.38)	0.325 (1.40)	
DIV YIELD		-0.444 (-1.58)	-0.914** (-2.06)	-0.034 (-0.09)	
NUMBER OF SHAREHOLDERS		-0.009*** (-3.18)	-0.010** (-2.44)	-0.005 (-1.22)	
IO		0.056** (2.22)	0.072** (1.97)	-0.019 (-0.47)	
ANALYSTS		-0.037*** (-3.53)	0.016 (0.96)	-0.073*** (-5.37)	
ANALYST DISP		0.037** (2.33)	-0.002 (-0.09)	0.045* (1.84)	
CONTROL	NO	YES	YES	YES	
CONSTANT	YES	YES	YES	YES	
INDUSTRY FE	YES	YES	YES	YES	
YEAR-MONTH FE	YES	YES	YES	YES	
Observations	422,993	422,993	159,373	131,276	
Adjusted R-squared	0.009	0.022	0.014	0.036	

Panel B: Recommendation Revisions

VARIABLES	(1)	(2)	(3)	(4)	(3) - (4)
			$\beta(R_LOC_EW)$		
		Full Sample	CONC	DISP	
REVISION	-0.095*** (-13.03)	-0.012* (-1.96)	-0.018 (-1.57)	-0.014* (-1.72)	-0.004 [0.78]
LOCAL REVISION	0.048*** (9.81)	0.052*** (11.97)	0.082*** (13.11)	0.008 (1.31)	0.074 [0.00]
AT		-0.061*** (-12.70)	-0.065*** (-8.78)	-0.058*** (-7.54)	
MB		-0.000 (-0.13)	0.000 (0.38)	-0.001 (-1.32)	
ROA		-0.278*** (-8.43)	-0.205*** (-5.03)	-0.486*** (-6.15)	
DEBT		0.105*** (5.46)	0.055* (1.93)	0.195*** (6.40)	
STD(EARN)		0.007** (2.04)	0.014** (2.18)	0.004 (0.94)	
TOBINQ		-0.018*** (-4.75)	-0.016*** (-3.26)	-0.032*** (-3.76)	
ADVERTISEMENT		-0.043 (-0.27)	-0.323 (-1.47)	0.326 (1.40)	
DIV YIELD		-0.405 (-1.44)	-0.738* (-1.66)	-0.037 (-0.10)	
NUMBER OF SHAREHOLDERS		-0.008*** (-2.94)	-0.009** (-2.13)	-0.005 (-1.19)	
IO		0.053** (2.09)	0.067* (1.84)	-0.020 (-0.49)	
ANALYSTS		-0.038*** (-3.61)	0.014 (0.88)	-0.070*** (-5.17)	
ANALYST DISP		0.035** (2.22)	-0.006 (-0.25)	0.045* (1.84)	
CONTROL	NO	YES	YES	YES	
CONSTANT	YES	YES	YES	YES	
INDUSTRY FE	YES	YES	YES	YES	
YEAR-MONTH FE	YES	YES	YES	YES	
Observations	422,993	422,993	159,373	131,276	
Adjusted R-squared	0.010	0.023	0.015	0.036	

Table 6 Tests for Magnitude of Information Spillover

This table reports the regression for intra-regional information spillover. We first calculate the size-weighted average of absolute values of standardized unexpected earnings of the firms located in the same MSA in each month as $ABS(LOCAL\ SUE)$. $LOCAL\ SUE$ is the decile score of $ABS(LOCAL\ SUE)$ by each year-month, ranging from 0 to 1. $CONC$ is the bottom tercile group of firms ranked by $NSTATES$ for each year-month. $DISP$ is the top tercile group of firms ranked by $NSTATES$ by each year-month. The same set of control variables in Table 5 is used in this table. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(3) - (4)
	Full Sample		CONC	DISP	
VARIABLES	$\beta(R_LOC_EW)$				
LOCAL SUE	0.048***	0.052***	0.081***	0.005	0.076
	(5.19)	(6.33)	(5.96)	(0.41)	[0.00]
EA	-0.022***	-0.022***	-0.031**	0.002	-0.033
	(-2.69)	(-2.71)	(-2.03)	(0.13)	[0.09]
CONTROL	NO	YES	YES	YES	
CONSTANT	YES	YES	YES	YES	
INDUSTRY FE	YES	YES	YES	YES	
YEAR-MONTH FE	YES	YES	YES	YES	
Observations	422,993	422,993	159,373	131,276	
Adjusted R-squared	0.008	0.021	0.012	0.036	

Table 7 Price Synchronicity and Price Delay - Annual Level

This table reports the regression of annual stock price synchronicity/price delay on geographic dispersion. For Columns (1) to (4), we follow Morck, Yeung and Yu (2000) to estimate the dependent variable, *Price Synchronicity*, as $\ln(R^2/1-R^2)$ using R^2 from the market model for each firm-year using daily returns. For Columns (5) to (8), we follow Hou and Moskowitz (2005) to estimate annual *Price Delay* using weekly returns. *LOCAL RANK* is the decile rank of NSTATES times minus one for each year, ranging from 0 to 1. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Price Synchronicity				Price Delay		
LOCAL RANK	0.135***	-0.799***	0.076**	-0.535***	-0.020***	0.063***	-0.013**	0.044**
	(4.03)	(-6.26)	(2.51)	(-4.54)	(-3.37)	(2.75)	(-2.18)	(1.99)
LOCAL RANK*AT		0.127***		0.083***		-0.011***		-0.008***
		(7.62)		(5.38)		(-3.77)		(-2.64)
AT	0.340***	0.272***	0.330***	0.287***	-0.043***	-0.037***	-0.042***	-0.038***
	(47.42)	(24.13)	(37.82)	(23.84)	(-35.00)	(-17.82)	(-25.75)	(-16.71)
MB			0.001	0.001			-0.000*	-0.000*
			(1.31)	(1.32)			(-1.79)	(-1.79)
ROA			0.295***	0.250***			-0.001	0.004
			(5.27)	(4.48)			(-0.05)	(0.31)
DEBT			-0.337***	-0.346***			0.038***	0.039***
			(-11.19)	(-11.50)			(6.15)	(6.28)
STD(EARN)			-0.037***	-0.037***			0.003***	0.003***
			(-7.87)	(-7.80)			(3.31)	(3.28)
TOBINQ			0.139***	0.140***			-0.018***	-0.018***
			(24.84)	(24.92)			(-15.26)	(-15.38)
ADVERTISEMENT			-1.078***	-1.137***			0.244***	0.249***
			(-3.51)	(-3.70)			(3.92)	(4.02)
DIV YIELD			-1.236**	-1.174**			0.220**	0.214**
			(-2.28)	(-2.18)			(2.05)	(2.01)
NUMBER OF SHAREHOLDERS			-0.001	0.001			0.000	-0.000
			(-0.25)	(0.28)			(0.25)	(-0.00)
IO			0.941***	0.914***			-0.105***	-0.103***
			(20.74)	(20.20)			(-12.17)	(-11.91)
ANALYSTS			-0.061***	-0.062***			0.008**	0.008**
			(-3.62)	(-3.74)			(2.38)	(2.43)
ANALYST DISP			-0.233***	-0.233***			0.031***	0.031***
			(-7.80)	(-7.79)			(4.80)	(4.80)
CONSTANT	YES	YES	YES	YES	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES	YES	YES
OBSERVATIONS	35,595	35,595	35,595	35,595	35,274	35,274	35,274	35,274
ADJ-R2	0.487	0.490	0.540	0.541	0.250	0.251	0.270	0.270

Table 8 Geographic Dispersion and Social Media Attention

This table reports regressions of monthly social media activities on geographic dispersion. We obtain the data of social media activities on StockTwits at the firm-day level from Cookson and Niessner (2023) via <https://www.tonycookson.com/data-and-programs>. *Attention* is proxied as the average daily number of posts for each firm-month. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year, ranging from 0 to 1. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)
			Attention	
LOCAL RANK	2.172***	0.838	1.408***	-4.506**
	(4.41)	(0.47)	(3.47)	(-2.56)
LOCAL RANK* AT		0.172		0.762***
		(0.65)		(2.97)
AT	0.756***	0.662***	0.925***	0.523***
	(6.22)	(5.75)	(6.53)	(4.05)
MB			0.007	0.008
			(0.43)	(0.50)
ROA			-5.961***	-6.432***
			(-7.53)	(-8.35)
DEBT			0.835*	0.763*
			(1.94)	(1.77)
STD(EARN)			0.320***	0.316***
			(3.42)	(3.48)
TOBINQ			0.596***	0.607***
			(5.93)	(6.01)
ADVERTISEMENT			17.462***	16.912***
			(3.74)	(3.64)
DIV YIELD			-13.443**	-12.855**
			(-2.26)	(-2.18)
NUMBER OF SHAREHOLDERS			-0.001	0.019
			(-0.02)	(0.46)
IO			-7.016***	-7.300***
			(-9.16)	(-9.02)
ANALYSTS			0.847***	0.827***
			(5.15)	(5.03)
ANALYST DISP			1.045***	1.048***
			(2.94)	(2.95)
CONSTANT	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES
YEAR-MONTH FE	YES	YES	YES	YES
Observations	187,146	187,146	187,146	187,146
Adjusted R-squared	0.129	0.129	0.212	0.216

Table 9 The Effects of StockTwits Coverage on Local Return Comovement

This table reports the effect of StockTwits coverage on local return comovement. *ST COVERAGE* is a dummy variable which equals to one if it has been covered by StockTwits and zero otherwise. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. *NSTATES* is the number of different states mentioned in the firm's 10-K filings. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year-month, ranging from 0 to 1. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)
	$\beta(R_LOC_EW)$	
LOCAL RANK	0.252*** (9.11)	0.098*** (3.88)
ST COVERAGE	-0.036 (-1.13)	0.015 (0.52)
LOCAL RANK*ST COVERAGE	-0.080*** (-3.03)	-0.054** (-2.14)
AT		-0.056*** (-9.91)
MB		0.000 (0.24)
ROA		-0.296*** (-7.02)
DEBT		0.109*** (4.63)
STD(EARN)		0.004 (1.16)
TOBINQ		-0.016*** (-3.54)
ADVERTISEMENT		0.116 (0.55)
DIV YIELD		-0.154 (-0.47)
NUMBER OF SHAREHOLDERS		-0.009*** (-2.73)
IO		0.061** (1.97)
ANALYSTS		-0.055*** (-4.47)
ANALYST DISP		0.053*** (2.66)
CONSTANT	YES	YES
INDUSTRY FE	YES	YES
YEAR-MONTH FE	YES	YES
Observations	278,461	278,461
Adjusted R-squared	0.012	0.025

Table 10 The Effects of StockTwits Coverage on Information Spillover

This table reports the effect of StockTwits coverage on information spillover. *ST COVERAGE* is a dummy variable which equals to one if it has been covered by StockTwits and zero otherwise. *CONC* is the bottom tercile group of firms ranked by *NSTATES* for each year-month. *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. *LOCAL EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in each month. *EA* is a dummy variable equal to one if the firm announces its annual earnings in this month and zero otherwise. Other control variables are lagged and described in Table A1. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-value for the test of difference in coefficients are reported in the bracket. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1) CONC	(2) DISP $\beta(R_LOC_EW)$	(1)-(2)
EA	-0.032 (-0.87)	-0.002 (-0.09)	
ST COVERAGE	-0.082 (-1.56)	0.010 (0.30)	
EA * ST COVERAGE	-0.007 (-0.17)	-0.003 (-0.09)	
LOCAL	0.092*** (7.36)	-0.012 (-1.07)	
LOCAL EA * ST COVERAGE	-0.024* (-1.72)	0.016 (1.35)	-0.040 [0.03]
CONTROLS	YES	YES	
CONSTANT	YES	YES	
INDUSTRY FE	YES	YES	
YEAR-MONTH FE	YES	YES	
Observations	103,948	86,892	
Adjusted R-squared	0.016	0.041	

Table 11 Firm Scope and Geographic Dispersion

This table reports the regressions for local return comovements and information spillover conditional on firm scope. We obtain the firm scope data from Hoberg and Phillips (2025). *Low Scope* (*High Scope*) represents the bottom (top) tercile of sample based on the firm scope in each year-month. *CONC* is the bottom tercile group of firms ranked by *NSTATES* for each year-month. *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. Panel A reports the sub-sampled regressions of local return comovement on geographic dispersion, consistent with Table 3. Panel B reports the sub-sampled regressions for information spillover, consistent with Table 5. Other control variables are consistent with Tables 3 and 5. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A: Local Return Comovement

VARIABLES	(1)	(2)	(2) - (1)	(3)	(4)	(4) - (3)
	Low Scope	High Scope		Low Scope	High Scope	
	$\beta(R_LOC_EW)$					
LOCAL RANK	0.150*** (5.76)	0.259*** (8.38)	0.109 [0.01]	0.047** (2.17)	0.121*** (4.10)	0.074 [0.04]
CONTROLS	NO	NO		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
Observations	148,841	122,238		148,841	122,238	
Adjusted R-squared	0.009	0.013		0.022	0.023	

Panel B: Information Spillover

VARIABLES	(1)	(2)	(2) - (1)	(3)	(4)	(4) - (3)
	CONC			DISP		
	Low Scope	High Scope		Low Scope	High Scope	
	$\beta(R_LOC_EW)$					
EA	-0.025 (-1.05)	-0.023 (-0.75)	0.002 [0.96]	-0.008 (-0.34)	0.027 (1.18)	0.035 [0.29]
LOCAL EA	0.059*** (5.75)	0.088*** (6.26)	0.029 [0.08]	0.011 (1.08)	-0.008 (-0.72)	-0.019 [0.19]
CONTROLS	YES	YES		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
Observations	63,747	40,739		37,543	43,560	
Adjusted R-squared	0.016	0.011		0.036	0.035	

Appendix A

Table A1 List of Variables

Variables	Description	Source
$\beta(R_LOC_EW)$	Estimated coefficient on local portfolio return at firm-month level, estimated from Equation (1) using daily returns.	CRSP
AT	Natural logarithm of the total asset (AT).	COMPUSTAT
MB	Market-to-book equity ratio ($PRCC_F \times CSHO / CEQ$).	COMPUSTAT
ROA	Earnings before interest, taxes, depreciation, and amortization (EBITDA) over total assets (AT).	COMPUSTAT
DEBT	Total outstanding debt ($DLC + DLTT$) over total assets (AT).	COMPUSTAT
STD(EARN)	Standard deviation of income before extraordinary items (IB) per share (CSHO) using a five-year rolling window.	COMPUSTAT
TOBINQ	The market value of assets divided by the book value of Assets and is empirically estimated following Kaplan and Zingales (1997) and Gompers, Ishii, and Metrick (2003).	COMPUSTAT
ADVERTISEMENT	Advertising expenditure (XAD) over total assets (AT) and we set the missing value to zero.	COMPUSTAT
DIV YIELD	Annual cash dividend payout (DV) over the market capitalization ($PRCC_F \times CSHO$)	COMPUSTAT
NUMBER OF SHAREHOLDERS	Natural logarithm of the number of shareholders (CSHR).	COMPUSTAT
IO	The percentage of outstanding shares owned by institutional investors.	THOMSON REUTERS 13/F
ANALYSTS	Natural logarithm of one plus the number of analysts following.	I/B/E/S
ANALYST DISP	Standard deviation of earnings forecasts (STDEV) scaled by the absolute value of the mean earnings forecast (MEANEST).	I/B/E/S
NSTATES	Number of different states mentioned in firm's 10-K filings.	10-K FILINGS
LOG(1+NSTATES)	Natural logarithm of one plus the <i>NSTATES</i> .	10-K FILINGS
LOCAL RANK	Decile rank of <i>NSTATES</i> * (-1) by each year-month, ranging from 0 to 1.	10-K FILINGS
EA	Dummy variable equal to one if the firm announces its annual earnings in the same month and zero otherwise.	COMPUSTAT
LOCAL EA	Natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same in each month.	COMPUSTAT
LOCAL_IND EA	Natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in each month.	COMPUSTAT
LOCAL_NIND EA	Natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in the different Fama-French (1997)-48 industry in each month.	COMPUSTAT
NLOCAL_IND EA	Natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the different MSAs in the same Fama-French (1997)-48 industry in each month.	COMPUSTAT
NLOCAL_NIND EA	Natural logarithm of one plus the number of annual earnings announcements for firms headquartered in the different MSAs in the different Fama-French (1997)-48 industry in each month.	COMPUSTAT
SUE	The difference between actual EPS from IBES and the median of most recent analysts' forecasts, divided by the stock price at the fiscal year end ($PRCC_F$).	COMPUSTAT, I/B/E/S
ABS(LOCAL SUE)	The size-weighted average of absolute values of standardized unexpected earnings of the firms located in the same MSA in each month	COMPUSTAT, I/B/E/S
LOCAL SUE	Decile score of <i>ABS(LOCAL SUE)</i> by each year-month, ranging from 0 to 1.	COMPUSTAT, I/B/E/S
REL_ATTENTION	The ratio of the annual Google Search Index (GSI) in the headquarter state to the sum of annual GSIs across all states.	Google
Price Synchronicity	The ratio as $Ln(R^2/1-R^2)$ using R^2 from the market model for each firm-year using daily returns.	CRSP
Price Delay	One minus the ratio of the R^2 from the following equation restricting $\delta_j^{(-n)} = 0, \forall n \in [1,4]$ over the R^2 from the following regression with no restrictions for each firm-year, where $r_{j,t}$ is the weekly return on the stock j and $r_{m,t}$ is the weekly market return. $r_{j,t} = \alpha_j + \beta_j r_{m,t} + \sum_{n=1}^4 \delta_j^{(-n)} r_{m,t-n} + \varepsilon_{j,t}$	CRSP
Attention	Average daily number of posts for each firm-month on StockTwits.	Cookson and Niessner (2023)

ST COVERAGE	The dummy variable which equals to one if it has been covered by StockTwits and zero otherwise.	StockTwits
NO OF FIRMS	Number of firms headquartered in the MSA, scaled by 100.	CRSP
INDUSTRY CONCENTRATION	The Herfindahl index of industry concentration (by Fama-French (1997) 48 industries) in the MSA	CRSP
COINCIDENT INDEX	The State Coincident Indexes of the regional economic level for the state where the firm is headquartered, scaled by 100.	THE FEDERAL RESERVE BANK OF PHILADELPHIA The Regional Economic Accounts by U.S. Bureau of Economic Analysis
PERSONAL INCOME	Per capita personal income for the firm headquarter's MSA, scaled by 1,000.	The Regional Economic Accounts by U.S. Bureau of Economic Analysis
INVESTMENT INCOME	Per capita personal income derived from dividends, interest, and rent for the firm headquarter's MSA, scaled by 1,000.	Economic Accounts by U.S. Bureau of Economic Analysis

Table A2 Descriptive Statistics by GD Terciles

This table reports the descriptive statistics for the variables used in the cross-sectional regressions by the tercile of firms' geographical dispersion. All continuous variables are winsorized at 1% and 99%. Detailed descriptions of variables are provided in Table A1

VARIABLES	CONC				MID				DISP				(2) - (10)
	(1) N	(2) MEAN	(3) MEDIAN	(4) SD	(5) N	(6) MEAN	(7) MEDIAN	(8) SD	(9) N	(10) MEAN	(11) MEDIAN	(12) SD	
$\beta(R_LOC_EW)$	159,373	0.237	0.135	1.393	132,344	0.182	0.087	1.215	131,276	0.077	0.024	1.041	0.160
NSTATES	159,373	5.069	5.000	1.442	132,344	9.768	10.000	1.577	131,276	21.900	19.000	8.560	-16.831
LOG(1+NSTATES)	159,373	1.575	1.609	0.324	132,344	2.266	2.303	0.160	131,276	3.019	2.944	0.357	-1.444
LOCAL RANK	159,373	0.875	0.889	0.110	132,344	0.494	0.444	0.115	131,276	0.131	0.111	0.108	0.744
AT	159,373	6.491	6.304	1.771	132,344	7.242	7.159	1.707	131,276	8.143	8.022	1.743	-1.652
MB	159,373	3.923	2.661	6.492	132,344	3.357	2.306	5.502	131,276	2.977	2.117	4.942	0.946
ROA	159,373	0.076	0.115	0.221	132,344	0.120	0.128	0.158	131,276	0.140	0.133	0.104	-0.065
DEBT	159,373	0.220	0.146	0.257	132,344	0.280	0.247	0.248	131,276	0.322	0.292	0.239	-0.102
STD(EARN)	159,373	1.021	0.597	1.382	132,344	1.252	0.726	1.594	131,276	1.497	0.833	1.865	-0.476
TOBINQ	159,373	2.594	1.956	1.879	132,344	2.111	1.601	1.508	131,276	1.711	1.404	1.001	0.883
ADVERTISEMENT	159,373	0.012	0.000	0.033	132,344	0.013	0.000	0.034	131,276	0.012	0.000	0.028	0.000
DIV YIELD	159,373	0.007	0.000	0.015	132,344	0.010	0.000	0.015	131,276	0.014	0.008	0.017	-0.006
NUMBER OF SHAREHOLDERS	159,373	-0.143	-0.324	2.199	132,344	0.314	0.374	2.250	131,276	0.965	1.081	2.354	-1.108
IO	159,373	2.010	1.946	0.666	132,344	2.119	2.079	0.664	131,276	2.315	2.398	0.657	-0.305
ANALYSTS	159,373	0.089	0.025	0.216	132,344	0.083	0.021	0.213	131,276	0.075	0.019	0.202	0.014
ANALYST DISP	159,373	0.687	0.737	0.244	132,344	0.727	0.780	0.225	131,276	0.750	0.790	0.202	-0.063
EA	159,373	0.085	0.000	0.279	132,344	0.085	0.000	0.278	131,276	0.085	0.000	0.278	0.000
LOCAL EA	159,373	1.564	1.386	1.232	132,344	1.405	1.099	1.215	131,276	1.294	1.099	1.203	0.270

Table A3 Cross-Sectional Regression of Market and Industry Beta on Geographic Dispersion

This table reports the regressions of monthly market beta or industry beta on geographic dispersion measures. The dependent variable, $\beta(MKTRF)$, is the estimated coefficient of market excess returns at the firm-month level, from Equation (1) using daily returns. $\beta(R_IND_EW)$ is the estimated coefficient of industry returns (by Fama-French (1997) 48 industries) at the firm-month level, from Equation (1) using daily returns. *NSTATES* is the number of different states mentioned in the firm's 10-K filings. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year-month, ranging from 0 to 1. The same set of control variables in Table 3 is included. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

VARIABLES	(1)	(2)	(3)	(4)
	$\beta(MKTRF)$		$\beta(R_IND_EW)$	
LOCAL RANK	-0.162***	0.012	0.043**	-0.011
	(-8.42)	(0.80)	(2.13)	(-0.56)
FIRM CONTROLS	NO	YES	NO	YES
CONSTANT	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES
YEAR-MONTH FE	YES	YES	YES	YES
OBSERVATIONS	422,993	422,993	422,993	422,993
ADJ-R2	0.013	0.036	0.024	0.031

Table A4 Robustness Tests: Adding Market and Industry Betas as Controls

This table reports the robustness tests by adding additional control variables of market and industry betas. Panel A reports the regressions of local return comovement on geographic dispersion, consistent with Table 3. Panel B reports the regressions for information spillover, consistent with Table 5. $\beta(MKTRF)$, is the estimated coefficient of market excess returns at the firm-month level, from Equation (1) using daily returns. $\beta(R_IND_EW)$ is the estimated coefficient of industry returns (by Fama-French (1997) 48 industries) at the firm-month level, from Equation (1) using daily returns. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A						
VARIABLES	(1)	(2)	(3)	$\beta(R_LOC_EW)$		
NSTATES	-0.002*** (-3.23)					
LOG(1+NSTATES)		-0.026*** (-4.06)				
LOCAL RANK			0.055*** (4.53)			
$\beta(MKTRF)$	-0.618*** (-233.24)	-0.618*** (-233.25)	-0.618*** (-233.28)			
$\beta(R_IND_EW)$	-0.732*** (-201.91)	-0.732*** (-201.93)	-0.732*** (-201.93)			
FIRM CONTROLS	YES	YES	YES			
CONSTANT	YES	YES	YES			
INDUSTRY FE	YES	YES	YES			
YEAR-MONTH FE	YES	YES	YES			
OBSERVATIONS	422,993	422,993	422,993			
ADJ-R2	0.622	0.622	0.622			
Panel B						
VARIABLES	(1) CONC	(2) DISP	(1) - (2)	(3) CONC	(4) DISP	(3) - (4)
EA	-0.003 (-0.31)	0.004 (0.59)	-0.007 [0.54]	-0.003 (-0.39)	0.004 (0.52)	-0.004 [0.53]
LOCAL EA	0.034*** (5.87)	-0.002 (-0.25)	0.036 [0.00]	0.028*** (5.31)	0.002 (0.34)	0.026 [0.00]
$\beta(MKTRF)$	-0.611*** (-165.91)	-0.623*** (-117.97)		-0.611*** (-168.27)	-0.614*** (-119.48)	
$\beta(R_IND_EW)$	-0.753*** (-167.04)	-0.672*** (-91.81)		-0.756*** (-169.71)	-0.675*** (-93.07)	
FIRM CONTROLS	NO	NO		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
OBSERVATIONS	159,373	131,276		159,373	131,276	
ADJ-R2	0.640	0.572		0.644	0.581	

Table A5 Alternative Price Delay Measures

This table reports the regressions of alternative annual price delay measures on geographic dispersion. We follow Ahn and Patatoukas (2022) to estimate alternative price delay measures. *Market Delay* is measured as 1 minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and 4 lags of market returns. *Firm Delay* is measured as measured as 1 minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and 4 lags of firm returns. *Industry Delay* is measured as 1 minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns over the R^2 from the regression of weekly firm returns on contemporaneous market and industry returns and 4 lags of industry returns. To estimate *Earnings Delay*, we first measure the quarterly delay as 1 minus the ratio of the R^2 from the regression of daily firm returns on contemporaneous market and industry returns over the R^2 from the regression of the daily firm returns on contemporaneous market and industry returns and 4 lags of firm returns around the 20-day trading window commencing 2 days after the quarterly earnings announcement. *Earnings Delay* is the annual average of the quarterly earnings delay. Finally, *Local Delay* is measured as 1 minus the ratio of the R^2 from the regression of weekly firm returns on contemporaneous market, industry, and local portfolio returns over the R^2 from the regression of weekly firm returns on contemporaneous market, industry and local portfolio returns and 4 lags of local portfolio returns. Following Ahn and Patatoukas (2022), we use the logit transformations of the price-delay measures, that is $\log(\text{Delay}/1-\text{Delay})$. *LOCAL RANK* is the decile rank of *NSTATES* times minus one for each year, ranging from 0 to 1. We use the same set of control variables from Table 7. All independent variables are lagged and described in Table A1. Fixed effects are included in different models. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

VARIABLES	(1) Market Delay	(2) Firm Delay	(3) Industry Delay	(4) Earnings Delay	(5) Local Delay
LOCAL RANK	0.246** (2.06)	0.243** (2.13)	0.227* (1.93)	0.343*** (4.36)	0.180* (1.69)
LOCAL RANK*AT	-0.042*** (-2.61)	-0.036** (-2.31)	-0.039** (-2.44)	-0.053*** (-4.82)	-0.033** (-2.29)
AT	-0.141*** (-10.62)	-0.151*** (-11.79)	-0.149*** (-11.26)	-0.122*** (-13.94)	-0.143*** (-12.24)
CONTROLS	YES	YES	YES	YES	YES
CONSTANT	YES	YES	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
OBSERVATIONS	35,583	35,583	35,583	35,564	35,583
ADJ-R2	0.233	0.252	0.243	0.451	0.235

Table A6 Decomposition of Local and Industry Effects

This table reports the regressions for intra-regional information spillover with different local or industry effects for the full sample and sub-samples. *LOCAL* is the bottom tercile group of firms ranked by *NSTATES* for each year-month. *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. *EA* is a dummy variable equal to one if the firm announces its annual earnings in the same month and zero otherwise. *LOCAL_IND EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in the same Fama-French (1997)-48 industry in each month. *LOCAL_NIND EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the same MSA in the different Fama-French (1997)-48 industry in each month. *NLOCAL_IND EA* is the natural logarithm of one plus the number of annual earnings announcements for other firms headquartered in the different MSAs in the same Fama-French (1997)-48 industry in each month. *NLOCAL_NIND EA* is the natural logarithm of one plus the number of annual earnings announcements for firms headquartered in the different MSAs in the different Fama-French (1997)-48 industry in each month. Other control variables are lagged and described in Table A1. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)	(3) - (4)	(5)	(6)	(5) - (6)
	Ful Sample		CONC	DISP		CONC	DISP	
VARIABLES	$\beta(R_LOC_EW)$							
EA	-0.031***	-0.031***	-0.041***	-0.003	-0.038	-0.040***	-0.002	-0.038
	(-3.71)	(-3.67)	(-2.64)	(-0.26)	[0.06]	(-2.61)	(-0.20)	[0.06]
LOCAL_IND EA	0.062***	0.067***	0.071***	0.024	0.047	0.077***	0.027**	0.050
	(6.89)	(8.12)	(5.77)	(1.59)	[0.01]	(6.50)	(1.99)	[0.00]
LOCAL_NIND EA	0.022***	0.026***	0.054***	-0.013	0.067	0.057***	-0.003	0.060
	(3.82)	(5.18)	(6.46)	(-1.53)	[0.00]	(7.40)	(-0.45)	[0.00]
NLOCAL_IND EA	-0.010*	-0.017***	-0.002	0.003		-0.011	-0.002	
	(-1.71)	(-3.39)	(-0.25)	(0.38)		(-1.15)	(-0.22)	
NLOCAL_NIND EA	-0.110	-0.127*	0.057	-0.041		0.056	-0.040	
	(-1.45)	(-1.90)	(0.51)	(-0.34)		(0.54)	(-0.39)	
CONTROLS	NO	YES	NO	NO		YES	YES	
CONSTANT	YES	YES	YES	YES		YES	YES	
INDUSTRY FE	YES	YES	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES	YES	YES		YES	YES	
Observations	422,993	422,993	159,373	131,276		159,373	131,276	
Adjusted R-squared	0.009	0.022	0.008	0.014		0.014	0.036	

Table A7 Asymmetric Responses

This table reports the regressions for asymmetric responses of local beta to earnings announcements or analyst recommendation revisions. The dependent variable, $\beta(R_LOC_EW)$, is the estimated coefficient of local portfolio returns at the firm-month level, from Equation (1) using daily returns. In Panel A, *POSITIVE EA* is a dummy variable equal to one if the firm announces its annual earnings with a positive *SUE* in the month and zero otherwise. *NEGATIVE EA* is a dummy variable equal to one if the firm announces its annual earnings with a negative *SUE* in the month and zero otherwise. *LOCAL POSITIVE EA* is the natural logarithm of one plus the number of annual earnings announcements with positive *SUEs* for other firms headquartered in the same MSA in each month. *LOCAL NEGATIVE EA* is the natural logarithm of one plus the number of annual earnings announcements with negative *SUEs* for other firms headquartered in the same MSA in each month. In Panel B, *UPGRADE* is a dummy variable equal to one if the firm receives the upgrades of analysts' recommendations in this month and zero otherwise. *DOWNGRADE* is a dummy variable equal to one if the firm receives the downgrades of analysts' recommendations in this month and zero otherwise. *LOCAL UPGRADE* is the natural logarithm of one plus the number of events when other firms headquartered in the same MSA in each month experience the upgrade of analysts' recommendations. *LOCAL DOWNGRADE* is the natural logarithm of one plus the number of events when other firms headquartered in the same MSA in each month experience the downgrade of analysts' recommendations. *CONC* is the bottom tercile group of firms ranked by *NSTATES* for each year-month. *DISP* is the top tercile group of firms ranked by *NSTATES* by each year-month. Other control variables are consistent with Table 5. Industry and Year-month fixed effects are included. Standard errors are clustered at the firm level. T-stats are reported in the parentheses.

Panel A: Earnings Announcement

VARIABLES	(1)	(2)	(3)	(4)
	$\beta(R_LOC_EW)$			
	FULL	FULL	CONC	DISP
POSITIVE EA	-0.052***	-0.037***	-0.048***	0.002
	(-5.35)	(-3.83)	(-2.64)	(0.16)
NEGATIVE EA	0.010	-0.022	-0.042	-0.001
	(0.71)	(-1.58)	(-1.64)	(-0.03)
LOCAL POSITIVE EA	0.022***	0.025***	0.027**	0.002
	(2.93)	(3.49)	(2.06)	(0.16)
LOCAL NEGATIVE EA	0.023***	0.026***	0.052***	0.000
	(2.69)	(3.33)	(3.90)	(0.03)
CONSTANT	YES	YES	YES	YES
CONTROLS	NO	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES
YEAR-MONTH FE	YES	YES	YES	YES
Observations	422,993	422,993	159,373	131,276
Adjusted R-squared	0.009	0.022	0.014	0.036

Panel B: Analyst Recommendations

VARIABLES	(1)	(2)	(3)	(4)
	$\beta(R_LOC_EW)$			
	FULL	FULL	CONC	DISP
UPGRADE	-0.088***	-0.009	-0.018	-0.011
	(-10.60)	(-1.25)	(-1.25)	(-1.05)
DOWNGRADE	-0.113***	-0.027***	-0.033**	-0.019*
	(-13.46)	(-3.57)	(-2.44)	(-1.92)
LOCAL UPGRADE	0.024***	0.026***	0.037***	0.007
	(5.81)	(6.64)	(5.62)	(1.26)
LOCAL DOWNGRADE	0.032***	0.034***	0.057***	0.000
	(7.02)	(7.99)	(7.81)	(0.06)
CONSTANT	YES	YES	YES	YES
CONTROLS	NO	YES	YES	YES
INDUSTRY FE	YES	YES	YES	YES
YEAR-MONTH FE	YES	YES	YES	YES
Observations	422,993	422,993	159,373	131,276
Adjusted R-squared	0.011	0.023	0.016	0.036

Table A8 Robustness Tests: Dropping Top 3 MSAs

This table reports the robustness tests by dropping the observations of sample firms headquartered in NewYork-Newark-Jersey City, NY-NJ-PA, Boston-Cambridge-Newton, MA-NH, and San Jose-Sunnyvale-Santa Clara, CA. Panel A reports the regressions of local return comovement on geographic dispersion, consistent with Table 3. Panel B reports the regressions for information spillover, consistent with Table 5. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A						
VARIABLES	(1)	(2)	(3)	$\beta(R_LOC_EW)$		
NSTATES	-0.001*					
	(-1.92)					
LOG(1+NSTATES)		-0.020**				
		(-2.44)				
LOCAL RANK			0.045***			
			(2.85)			
FIRM CONTROLS	YES	YES	YES			
CONSTANT	YES	YES	YES			
INDUSTRY FE	YES	YES	YES			
YEAR-MONTH FE	YES	YES	YES			
OBSERVATIONS	330,554	330,554	330,554			
ADJ-R2	0.021	0.021	0.021			
Panel B						
VARIABLES	(1) CONC	(2) DISP	(1) - (2)	(3) CONC	(4) DISP	(3) - (4)
	$\beta(R_LOC_EW)$					
EA	-0.037**	0.007	-0.044	-0.037**	0.007	-0.044
	(-2.35)	(0.56)	[0.03]	(-2.36)	(0.55)	[0.03]
LOCAL EA	0.074***	0.001	0.073	0.074***	0.005	0.069
	(8.79)	(0.13)	[0.00]	(9.68)	(0.70)	[0.00]
FIRM CONTROLS	NO	NO		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
OBSERVATIONS	122,444	103,730		122,444	103,730	
ADJ-R2	0.009	0.014		0.015	0.034	

Table A9 Robustness Tests: Dropping Observations in January, February, and March

This table reports the robustness tests by dropping observations in January, February, and March. Panel A reports the regressions of local return comovement on geographic dispersion, consistent with Table 3. Panel B reports the regressions for information spillover, consistent with Table 5. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A						
VARIABLES	(1)	(2)	(3)	$\beta(R_LOC_EW)$		
NSTATES	-0.002***					
	(-3.06)					
LOG(1+NSTATES)		-0.029***				
		(-3.59)				
LOCAL RANK			0.061***			
			(3.76)			
FIRM CONTROLS	YES	YES	YES			
CONSTANT	YES	YES	YES			
INDUSTRY FE	YES	YES	YES			
YEAR-MONTH FE	YES	YES	YES			
OBSERVATIONS	316,335	316,335	316,335			
ADJ-R2	0.022	0.022	0.022			
Panel B						
VARIABLES	(1) CONC	(2) DISP	(1) - (2)	(3) CONC	(4) DISP	(3) - (4)
	$\beta(R_LOC_EW)$					
EA	-0.033	-0.019	-0.014	-0.029	-0.030	-0.001
	(-1.23)	(-0.68)	[0.72]	(-1.09)	(-1.14)	[0.97]
LOCAL EA	0.081***	-0.013	0.068	0.085***	-0.001	0.086
	(7.91)	(-1.26)	[0.00]	(9.06)	(-0.08)	[0.00]
FIRM CONTROLS	NO	NO		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
OBSERVATIONS	119,210	97,962		119,210	97,962	
ADJ-R2	0.007	0.015		0.014	0.038	

Table A10 Robustness Tests: Adding Regional Economic Control Variables

This table reports robustness tests by adding additional control variables for regional economic activities. Panel A reports the regressions of local return comovement on geographic dispersion, consistent with Table 3. Panel B reports the regressions for information spillover, consistent with Table 5. *NO OF FIRMS* is the number of firms headquartered in the same MSA, scaled by 100. *INDUSTRY CONCENTRATION* is the Herfindahl index of industry concentration (by Fama-French (1997) 48 industries) in the MSA where the firm is headquartered. *COINCIDENT INDEX* is the State Coincident Indexes of the regional economic level for the state where the firm is headquartered, scaled by 100. *PERSONAL INCOME* is the per capita personal income for the firm's headquarter's MSA, scaled by 1,000. *INVESTMENT INCOME* is the per capita personal income derived from dividends, interest, and rent for the firm's headquarter's MSA, scaled by 1,000. T-stats are reported in the parentheses. P-values for the tests of difference in coefficients are reported in the brackets. *** p<0.01, ** p<0.05, * p<0.1.

Panel A						
VARIABLES	(1)	(2)	(3) β(R LOC EW)			
NSTATES	-0.002** (-2.35)					
LOG(1+NSTATES)		-0.023*** (-2.82)				
LOCAL RANK			0.048*** (2.99)			
NO OF FIRMS	0.016*** (2.78)	0.015*** (2.72)	0.015*** (2.73)			
INDUSTRY CONCENTRATION	0.387*** (4.08)	0.385*** (4.06)	0.383*** (4.04)			
COINCIDENT INDEX	0.040 (0.58)	0.041 (0.58)	0.041 (0.58)			
PERSONAL INCOME	0.007*** (6.18)	0.007*** (6.19)	0.007*** (6.20)			
INVESTMENT INCOME	-0.014*** (-3.65)	-0.014*** (-3.66)	-0.014*** (-3.67)			
FIRM CONTROLS	YES	YES	YES			
CONSTANT	YES	YES	YES			
INDUSTRY FE	YES	YES	YES			
YEAR-MONTH FE	YES	YES	YES			
OBSERVATIONS	376,527	376,527	376,527			
ADJ-R2	0.023	0.023	0.023			
Panel B						
VARIABLES	(1) CONC	(2) DISP	(1) - (2)	(3) CONC	(4) DISP	(3) - (4)
EA	-0.039** (-2.38)	-0.002 (-0.18)	-0.037 [0.08]	-0.038** (-2.34)	-0.002 (-0.16)	-0.036 [0.08]
LOCAL EA	0.064*** (7.34)	0.018** (2.33)	0.046 [0.00]	0.060*** (7.30)	0.018** (2.39)	0.042 [0.00]
NO OF FIRMS	-0.005 (-0.40)	-0.027** (-2.33)		0.002 (0.23)	-0.021** (-2.30)	
INDUSTRY CONCENTRATION	0.779*** (5.49)	0.086 (0.61)		0.789*** (5.67)	-0.037 (-0.28)	
COINCIDENT INDEX	0.163 (1.33)	0.040 (0.37)		0.080 (0.68)	-0.071 (-0.75)	
PERSONAL INCOME	0.009*** (5.70)	0.001 (0.83)		0.010*** (6.71)	0.002 (1.11)	
INVESTMENT INCOME	-0.019*** (-3.17)	-0.005 (-1.00)		-0.021*** (-3.75)	-0.004 (-0.81)	
FIRM CONTROLS	NO	NO		YES	YES	
CONSTANT	YES	YES		YES	YES	
INDUSTRY FE	YES	YES		YES	YES	
YEAR-MONTH FE	YES	YES		YES	YES	
OBSERVATIONS	142,802	116,450		142,802	116,450	
ADJ-R2	0.010	0.014		0.017	0.034	