Abstract

Prior research documents that firms in close geographic proximity tend to share commonalities in various outcomes and practices. Because local newspapers are important channels for discovering and sharing information about local conditions that is likely to be relevant for various firm decisions, we examine whether local newspapers contribute to geographic commonalities. We find that firms in metropolitan statistical areas (MSAs) with more local newspapers have more similar (i.e. less disperse) stock returns and stock market betas, indicating that local newspapers contribute to commonalities in overall fundamentals among co-located firms. We also find that the level of investment – a key driver of firm fundamentals - is more similar among firms in MSAs with more local newspapers, suggesting that local newspapers contribute to a shared understanding of investment opportunities available to co-located firms. The effect of local newspapers on geographic commonalities is more pronounced for newspapers with smaller circulations, which have been shown to be more dedicated to covering local news than larger newspapers. The effect is also more pronounced in communities that have adopted the inevitable disclosure doctrine, which limits labor market mobility – an alternative channel for information sharing. In addition, we find that the impact of local newspapers is most significant in promoting commonalities among local industry clusters. Using a difference-in-difference design to bolster causal inferences, we find that same-industry firms exhibit *less* similarities after local newspaper closures, which are exogenous shocks to local news coverage. Collectively, the results show that local media is an important driver of previously documented geographic commonalities.

1. Introduction

A growing literature documents that firms in close geographic proximity (hereafter, co-located firms) tend to share commonalities in various outcomes and practices such as stock returns, investment, and earnings management (Pirinsky and Wang, 2006; Kedia and Rajgopal, 2009; Dougal, Parsons, and Titman, 2015; Kedia, Koh, and Rajgopal, 2015; Core, Abramova, and Verdi, 2016; Bhabra and Hossain, 2018; Parsons, Sulaeman and Titman, 2018; Zhang and Chung, 2018; Franco, Hou, and Ma, 2019; Matsumoto, Serfling, and Shaikh, 2020). Such commonalities reflect either imitation among co-located firms or shared responses by co-located firms to operating in the same business environment. Both sources of commonalities depend on firms having access to information about the practices of neighboring firms or about local conditions generally. This paper focuses on the role of local newspapers in promoting local commonalities because local newspapers are potentially important channels for the exchange of such information (Bushee, Core, Guay, and Hamm, 2010; Engelberg and Parsons, 2011; Samuels, Taylor, and Verrecchia, 2020). Specifically, we examine whether commonalities are greater among firms in metropolitan statistical areas (MSAs) with more local newspapers.

While prior research documents the existence of geographic commonalities, our study examines *how* they form. Understanding how geographic commonalities form is important because such commonalities can have measurable impacts on local economies. For instance, the available jobs and the tax base in local communities will be more affected when local firms invest in unison. In addition, such commonalities have implications for portfolio management as they affect the degree of diversification investors can achieve, particularly investors who are subject to the well-documented home bias (Huberman, 2001).

We identify the geographic coordinates for all local U.S. newspapers that were in existence at some point from 2004 through 2017. We then compare those coordinates to the geographic coordinates of all cities of company headquarters listed in Compustat. We associate a local newspaper with an MSA if it is within 50 miles of at least 1 firm in the MSA. For each MSA-year, we then determine the number of active local newspapers. We examine the association between the number of local newspapers and the degree of similarity in returns, which have been shown in prior research to have a strong geographic component (Pirinsky and Wang 2006). We focus on returns because they reflect overall fundamentals. We measure stock returns alternatively as: equal-weighted market-adjusted annual buy and hold returns, value-weighted market-adjusted annual buy and hold returns, and market model beta estimated during the year. For each measure, we first compute the firm-specific component as the residual from stage-one annual regressions of the measure on known determinants as well as industry fixed effects. We then compute our commonality proxy for each measure as the standard deviation of the stage-one residuals for each MSA-year. Lower standard deviations correspond to higher commonality (i.e. greater similarity). We regress each standard deviation on local newspaper coverage, controlling for other determinants of commonalities within an MSA, such as average physical distance between firms in an MSA, the number of firms in the MSA, and the level of industry clustering in the MSA.

We find that firms in MSAs with more local newspapers have more similar (i.e. less disperse) stock returns and stock market betas, indicating that local newspapers contribute to commonalities in overall fundamentals among co-located firms. The effect of local newspapers on geographic commonalities is more pronounced for newspapers with smaller circulations, which have been shown in prior research to be more dedicated to covering local news than larger newspapers. Consistent with prior findings that local labor market serves an alternative channel for information sharing (Kim et al. 2021), the effect is also more pronounced in communities that have adopted the inevitable disclosure doctrine, a court ruling that limits labor market mobility.

To provide insight on specific actions firms take that contribute to commonalities in fundamentals as reflected in stock returns, we extend our examination to commonalities in co-located firms' investment decisions. We focus on investment because it is an economically important decision that drives firm fundamentals. We measure total investment as the sum of capital and R&D expenditures. We also separately examine both components of total investment. Using analogous procedures to those used to measure commonality in returns, we find that the level of investment – a key driver of firm fundamentals - is more similar among firms in MSAs with more local newspapers, suggesting that local newspapers contribute to a shared understanding among co-located firms of available investment opportunities. When we separately examine capital and R&D expenditures, we find that the level of capital expenditures is more similar among firms in MSAs with more local newspapers but not the level of R&D expenditures. A possible explanation is that the local media is better able to discover information about capital investment, which tends to be more observable than R&D efforts, which firms tend to keep private due to its proprietary nature.

Our results are robust to the use of alternative distances when linking newspapers to MSAs and to the use of alternative methods for measuring the strength of local newspaper coverage in an MSA. In additional analysis, we find that local newspapers are associated with commonalities among firms in the same industry but not among firms in different industries. Using a difference-in-difference design to bolster causal inferences, we find that same-industry firms exhibit *less* similarities in both stock returns and investment after local newspaper closures, which are exogenous shocks to local news coverage. Collectively, the results show that local media is an important driver of previously documented geographic commonalities.

This paper contributes to research on geographic commonalities by providing empirical evidence on how they arise. Prior research documents the existence of such commonalities and how analysts and investors exploit them (Bae, Tan, and Welker, 2008; Jensen, Kim, and Yi, 2015; Jennings, Lee, and Matsumoto, 2017; Engelberg, Ozoguz, and Wang 2018) but does not provide empirical evidence on the underlying mechanism. By contrast, this paper highlights local media as an important information sharing channel that leads to the creation of geographic commonalities. This paper fits within the broader inquiry of how economic shocks propagate. Acemoglu, Akcigit, and Kerr (2015) argue that networks formed through economic linkages can amplify firm-level shocks. They demonstrate the propagation of economic shocks among co-located firms, which they attribute to the greater volume of economic trade among firms that are closer in proximity. We show that shared information can also be the basis for networks among co-located firms and that local news coverage is an important source of such information.

This paper also contributes to the literature on the economic effects of media coverage, especially local newspapers. Relative to other types of media outlets, local newspapers play a critical role in producing and disseminating original news (Pew Research Center, 2010; Kim, Stice, Stice, and White 2021) due to their advantage in discovering information from local sources such as employees and local suppliers (Gurun and Butler, 2012). Prior studies document that the local newspaper coverage facilitates monitoring of local firms (Gao, Lee, and Murphy, 2020; Heese, Pérez-Cavazos, and Peter, 2021) and influences firms' stock market valuations and the decisions of local investors (Engelberg and Parsons, 2011). This study adds to our understanding of the role of the media by showing that the media also contributes to the convergence in business practices among neighboring firms, which can have measurable impacts on the local economy. Evidence on the multiple functions served by local newspapers contributes to a fuller understanding of their importance. Such understanding is relevant to ongoing policy discussions about the implications of the dramatic decline in local newspapers in recent years (Gao, Lee and Murphy, 2020) and whether measures should be taken to preserve these institutions, such as the Local Journalism Sustainability Act, a bill introduced in July 2020 by Representative Kirkpatrick of Arizona that proposes tax incentives to support local newspapers.

2. Literature Review

2.1 Geographic Commonalities

A growing literature documents that firms in close geographic proximity display commonalities on many dimensions. Pirinsky and Wang (2006) document that the stocks returns of firms in the same geographic area tend to co-move. Core, Abramova, and Verdi (2016) find that firms in close geographic proximity tend to make similar corporate investment and accrual quality decisions. Franco, Hou, and Ma, (2019) document higher financial statement comparability in location peers. Studies document strong geographical fixed effects in explaining option grants and financial misconduct (Kedia and Rajgopal 2009; Parsons, Sulaeman and Titman 2018). Prior research also documents that individual firms' financial reporting practices are partially influenced by the practices of co-located firms (Kedia, Koh, and Rajgopal, 2015; Matsumoto, Serfling, and Shaikh, 2020).

One theoretical explanation for such commonalities is imitation among co-located firms. Firms likely consider other firms that operate in the same environment to be a natural peer comparison group for inferring appropriate behaviors. For instance, Matsumoto, Serfling, and Shaikh (2020) theorize that firms infer the cost and benefit of issuing earnings forecasts after observing their neighbors' actions. Similarly, Kedia, Koh, and Rajgopal (2015) theorize that firms infer the cost of misreporting by observing the financial reporting practices of their neighbors.

Another theoretical explanation for such commonalities is that firms in the same geographic region are exposed to the same economic, political, or cultural conditions to which there is an appropriate shared response. Consistent with this possibility, Dougal, Parsons, and Titman (2015) find that Tobin's q and firm values tend to be higher in more vibrant regions, as measured by education rates and temperate weather. In addition, prior research shows that the design of CEO compensation packages differs systematically between urban and rural regions (Zhang and Chung, 2018; Bhabra and Hossain, 2018).

Both explanations depend on firms having access to the appropriate information. In the case of the first explanation, firms require information that allows them to infer the actions of their neighbors. In the case of the second explanation, firms require information about local conditions to which all affected firms must respond similarly. Co-located firms share information channels that facilitate the exchange of both types of information (Pirinsky and Wang, 2006; Kedia and Rajgopal, 2009; Dougal, Parsons, and Titman, 2015; Franco, Hou, and Ma, 2019). Examples of such information channels include local investors, local networks, and local media coverage.

Consistent with the existence of local information channels, prior studies show that geographic proximity facilitates information spillovers. Prior studies also indicate that many economic agents benefit from information spillovers by organizing their activities geographically. Specifically, firms in the same industry, especially innovative firms, tend to cluster geographically (Audretsch and Feldman, 1996; Alcácer, 2006; Engelberg, Ozoguz, and Wang 2018). In addition, analysts and auditors perform better when more of the firms in their portfolios are co-located and better performance for firms to which they are physically closer (Bae, Tan, and Welker, 2008; Jensen, Kim, and Yi, 2015; Jennings, Lee, and Matsumoto, 2017; Engelberg, Ozoguz, and Wang 2018).

While prior studies attribute geographic commonalities to various mechanisms that permit information sharing and spillovers among co-located firms, they have not documented the specific mechanisms. This paper focuses on the role of local newspapers because local newspapers are important channels for information sharing (Bushee, Core, Guay, and Hamm, 2010; Engelberg and Parsons, 2011; Samuels, Taylor, and Verrecchia, 2020).

2.2 Media Coverage

Newspapers produce and disseminate information. The information they produce about corporate activities aids monitoring and valuation of firms. Regarding monitoring, Miller (2006) documents that newspapers undertake original investigations of and rebroadcast information from other sources about accounting fraud. These activities lower the cost of monitoring by regulators and increase managers' perceived likelihood of detection (e.g., Qi, Yang, and Tian, 2014; Chahine, Mansi,and Mazboudi, 2015; Chen, Huynh, and Tao, 2018). Regarding valuation, Bushee, Core, Guay, and Hamm (2010) show that information asymmetry, captured by bid-ask spreads and market depth, decreases with media coverage. This association is more pronounced when there is broader information dissemination. Samuels, Taylor, and Verrecchia (2020) argue that greater media coverage increases the market response to earnings announcements. Similarly, Blankespoor, Miller & White (2014) emphasize the importance of information transmission by examining the impact of Twitter as an additional information channel to deliver messages from traditional media. The result indicates that supplemental dissemination significantly reduces information asymmetry, especially for less visible firms. Kim, Stice, Stice, and White (2021) use newspaper closure as a shock to information dissemination and find that firms respond to it by increasing their voluntary disclosure and dividend payouts to improve the information environment.

Relative to other types of media outlets, local newspaper plays a critical role in producing and disseminating *original* news (Pew Research Center, 2010; Kim, Stice, Stice, and White, 2021) due to their advantage in discovering information from local sources such as employees and local suppliers (Gurun and Butler, 2012). Prior research provides evidence that the loss of local newspapers results in a substantial loss of information about local firms. For example, firms increase dividends after the closure of local newspapers to alleviate investor concerns about the loss of information (Kim, Stice, Stice, and White, 2021). In addition, prior research documents that the loss of local newspapers undermines monitoring and that firms respond to the decreased media exposure by engaging in subsequent earnings management and other forms of misconduct (Qi, Yang, and Tian, 2014; Samuels, Taylor, and Verrecchia, 2020; (Heese, Pérez-Cavazos, and Peter, 2021). Engelberg and Parsons (2011) examine how geographic variation in media coverage affects investors' reactions to the same event. They find a significant relationship between local trading and local media coverage, which indicates that local investors rely heavily on local news sources.

Just as local news sources aid the activities of monitors and local investors, they can also aid the activities of other participants in the local economy, such as firms. Specifically, the information that newspapers produce that aids monitoring and valuation can also allow local firms to infer neighboring firms' activities and to identify local conditions to which all firms in the local economy must respond similarly. For example, newspapers can transmit useful information to firms about investment opportunities, which may lead local firms to make similar investment decisions. Thus, local newspapers represent a potential information sharing channel that promotes commonalities among co-located firms. If the information generated by local newspapers influences local firms' collective decisions (especially, their investment decisions), then the loss of such information can have a significant impact on the allocation of resources within local economies. Evidence on this possibility is relevant to ongoing policy discussions about the implications of the dramatic decline in local newspapers in recent years (Gao, Lee and Murphy 2020) and whether measures should be taken to reverse this trend.

3. Hypotheses Development

As discussed earlier, existing explanations for commonalities among co-located firms rely on information sharing. Local newspapers represent a potential information sharing channel because they produce information about the local economy that they then disseminate to its inhabitants, including local firms. This information can help local firms to infer neighboring firms' activities, which then facilitates imitation. This information can also help local firms to identify local conditions (e.g. economic, political, and cultural) that require a shared response. Both possibilities lead to the expectation that greater coverage by local newspapers leads to greater commonality in business practices and outcomes. Accordingly, I test the following hypothesis:

H1: There is a positive association between geographic commonality and the number of local newspapers.

The effect of local newspapers on commonalities among co-located firms depends on their content. Local newspapers that provide little insight into the activities of local firms or local conditions are unlikely to provide a sufficient basis for firms to infer the actions of their neighbors or to formulate a shared response to local conditions. Prior economics research shows that newspapers with smaller circulations tend to be more dedicated to covering local news than newspapers with larger circulations, which are attempting to appeal to wider audiences (George and Waldfogel, 2006). Thus, we expect any relationship between the number of newspapers and geographic commonalities to vary based on the circulation of newspapers. Accordingly, we test the following hypothesis.

H2: The association between geographic commonality and the number of local newspapers with low circulation is more positive than the association between geographic commonality and the number of local newspapers with high circulation.

Local newspapers operate in the context of other information sharing channels that also potentially affect geographic commonalities. The most obvious information sharing channel made possible by geographic proximity is human interaction (Gertler 2003), such as occurs when employees change jobs (Almeida and Kogut 1999; Song, Almeida and Wu 2003; Chen, Gao and Ma 2021). The Inevitable Disclosure Doctrine (IDD) argues that employees are likely to reveal knowledge gained at one employer to their next employer.

States that recognize IDD limit employee mobility to allow firms to maintain their trade secrets, thus curtailing an important information sharing channel (Klasa, Ortiz-Molina, Serfling and Srinivasan 2018; Kim, Su, Wang and Wu 2021; Dey and White 2021). The importance of local newspapers as an information sharing channel is likely to be heightened when this alternative information channel is not available to firms. Accordingly, we test the following hypothesis.

H3: The positive association between geographic commonality and the number of local newspapers is more pronounced in states that adopt IDD.

4. Research Design and Sample

4.1 Test of H1

To test H1, we use the following regression framework on samples of MSA-years associated with corporate headquarters in Compustat.

$$\sigma_{i,t} = \beta_0 + \beta_1 NO\_NEWS_{i,t} + \beta_2 \sigma'(Controls)_{i.t} + \beta_3 Density_{i,t} + \beta_4 No\_Firms_{i,t} + \beta_5 Industry\ Cluster_{i,t} + \varepsilon_{i,t} \quad (1)$$

where:

$\sigma_{i,t}$: the standard deviation of firm-year realizations of the firm-specific components of each measure, calculated at the MSA-year level.

$NO\_NEWS_{i,t}$: an MSA-year level measure of the number of local newspapers in year t, using the residual from the regression model:

$$NEWS_{i,t} = \beta_0 + \beta_1 LABOR_{i,t} + \beta_2 UR_{i,t} + \beta_3 PERCAPITA_{i,t} + \varepsilon_{i,t}$$

where $NEWS_{i,t}$ is the logarithm of (1+ the number of active local newspapers within 50 miles[1] of the city for the year according to Editor and Publisher Yearbook) based on the geographic coordinates of the newspaper and that of the cities within the MSA where firms'

[1] There is no consensus about the distance in related studies. Potential choices are 50 miles, 100 miles, and 200 miles from prior literature. Some measures are sensitive to the distance, but most of the results exhibit similar patterns with different choices of distance.

headquarters are located. $LABOR_{i,t}$ is the logarithm of labor force. $UR_{i,t}$ is the logarithm of unemployment rate. $PERCAPITA_{i,t}$ is the logarithm of per capita income.

$\sigma'(Controls)_{i.t}$: a vector that consists of the standard deviations of previously documented determinants of the measure under examination.

$Density_{i,t}$: a measure that captures the closeness of firms locations within the MSA, following Core et al. (2016).

$No\_Firms_{i,t}$: the logged number of firms listed in Compustat for the MSA-year.

$Industry\ Clustering_{i,t}$: the percentage of the dominant industry for the MSA-year.

Since $\sigma_{i,t}$ captures the standard deviations of the firm-specific component for each measure, a smaller value of $\sigma_{i,t}$ corresponds to a higher level of commonality (i.e. similarity) on the measured dimension. If local newspapers contribute to geographic commonalities, as predicted by H1, then we expect the coefficient on $NO\_NEWS_{i,t}$ to be significantly negative.

We include $\sigma'(Controls)_{i.t}$ to control for variability in the determinants of the measure, which contributes to variability in the measure itself. We also include $Density_{i,t}$ and $No\_Firms_{i,t}$ to control for local conditions that might be associated with both the extent of coverage by local newspapers and with variation in local practices and outcomes. *Industry Clustering* is used to control for alternative explanations of geographical commonalities, as prior literature suggests that high industry concentration leads to information and knowledge spillovers (Audretsch and Feldman, 1996; Alcácer, 2006; Engelberg et al., 2018).

We include year fixed effects in order to control for systematic differences in commonality across years. We exclude MSA-level fixed effects because they absorb common factors within an MSA, whereas our aim is to explain differences in commonality across MSAs. The inclusion of MSA-level fixed effects would demean all variables measures at the MSA-year level with the average value of these variables for the MSA throughout all years, which hinders the direct comparison of each measure between different MSAs.

We apply the above regression framework to stock returns because prior research shows that stock returns of co-located firms tend to co-move (Pirinsky and Wang, 2006) and because stock returns comprehensively reflect firm fundamentals. The stock return measures we examine are equal- and value-weighted market-adjusted buy and hold returns. We also examine market model beta to shed light on whether local newspapers affect the degree of commonality in co-located firms' sensitivity to market returns. In additional analysis, we also examine the impact of local media on commonalities in firms' total investment, capital and research and development expenditures.

Appendix A illustrates the application of the above framework to each of the individual measures and the variables that comprise $\sigma(Controls)_{i.t}$ for each measure. Appendix B shows how we generate the MSA-year standard deviation measure from firm-specific components.

4.2 Test of H2

To test H2, we estimate the following variant of H1 that decomposes the total number of newspapers into the total number of newspapers with low circulation and the total number of newspapers with high circulation.

$$\sigma_{i,t} = \beta_0 + \beta_1 NO\_LOWCIR_{i,t} + \beta_2 NO\_HIGHCIR_{i,t} + \beta_3 \sigma'(Controls)_{i.t} + \beta_4 Density_{i,t} + \beta_5 No\_Firms_{i,t} + \beta_6 Industry\ Cluster_{i,t} + \varepsilon_{i,t} \quad (2)$$

where:

$NO\_HIGHCIR_{i,t}$: the number of local newspapers that are associated with a top quintile circulation for all newspapers of the year.

$NO\_LOWCIR_{i,t}$: the number of local newspapers that are not within the top quintile circulation.

We classify newspapers with high circulation as those with circulations that are in the top circulation quintile for all newspapers of that year. To test H2, we compare the coefficient on $NO\_LOWCIR_{i,t}$ and $NO\_HIGHCIR_{i,t}$. If the greater focus on local news by newspapers with lower circulations contributes to greater geographic commonalities, then we expect the coefficient on $NO\_LOWCIR_{i,t}$ to be significantly more negative than the corresponding coefficient on $NO\_HIGHCIR_{i,t}$.

4.3 Test of H3

To test H3, we test the following variant of equation (1) that allows the coefficient on $NO\_NEWS_{i,t}$ to vary based on whether an MSA is located in a state that has adopted employment laws inhibiting employee mobility based on IDD.

$$\sigma_{i,t} = \beta_0 + \beta_1 NO\_NEWS_{i,t} + \beta_2 NO\_NEWS_{i,t} * IDD_{i,t} + \beta_3 \sigma'(Controls)_{i.t} + \beta_4 Density_{i,t} + \beta_5 No\_Firms_{i,t} + \beta_6 Industry\ Cluster_{i,t} + \varepsilon_{i,t} \quad (3)$$

where:

$IDD_{i,t}$: an indicator that equals 1 if the MSA has passed the Inevitable Disclosure Doctrine, 0 otherwise.

The coefficient on the interaction of $NO\_NEWS_{i,t}$ and $IDD_{i,t}$ provides a test of H2. If local newspapers become more an important information channel when the employee mobility channel is curtailed then we expect the coefficient on the interaction term to be significantly negative.

5. Sample

The sample consists of MSA-years associated with firms listed in Compustat between 2004 and 2017. We classify industries based on Fama-French 48 industrial classifications. The identity and locations of active local newspapers each year are based on Editor and Publisher Yearbook, which maintains an annual directory of US newspapers. Graph A depicts the distribution of local newspapers as of 2021. The economic factors of MSAs (i.e., labor population, per capital income, and unemployment rate) are obtained from U.S.

Bureau of Economic Analysis (BEA). In order to calculate the standard deviations of each measure, we require an MSA to have at least 5 firms with non-missing values on the measured dimension to be included in the analysis. After dropping observations without required variables, the sample for Beta, Equal Return, and Value Return analysis consists of 1,059, 1,045, 1,048 MSA-year observations, respectively.

Table 1 summarizes the descriptive statistics. The mean (median) of our measure of the number of local newspapers (*NO_NEWS*) for Beta, Equal Return, and Value Return analysis has similar magnitudes of 0.103 (0.124), 0.105 (0.124), and 0.103 (0.120), respectively. The mean (median) of Beta commonality measure is 1.024 (0.992). The mean (median) of Equal Return commonality measure is 0.335 (0.325). The mean (median) of Value Return commonality measure is 0.336 (0.324). The relatively smaller standard deviations of return measures indicate greater commonalities in returns on average. The standard deviations of market-to-book ratio (σ'*_MTB*) are significantly larger than other operation measures, reflecting a greater divergence of investors' perceptions of the market value for the firms in one MSA.

Panel A, Panel B, and Panel C of Table 2 report correlation matrices for Beta, Equal Return, and Value Return sample, respectively. The number of local newspapers (*NO_NEWS*) is negatively correlated with all standard deviation measures, consistent with local newspapers decreasing deviations in co-located firms' fundamentals. The associations between *IND_CLUSTER* and other standard deviation measures are also significantly negative, which could be driven by the contagion effects of industry concentrations.

6. Results of Hypotheses Tests

Table 3 reports the result from estimating equation (1), which tests H1. Column (1) - (3) presents the results using beta, equal weighted returns, and value weighted returns as dependent variables, respectively. We find significant negative coefficients on

$NO\_NEWS_{i,t}$ ($p < 0.05$) across all three dependent measures. The result is consistent with H1 indicates that a greater number of local newspapers is associated with greater local commonalities in fundamental as reflected in systematic risk and returns for co-located firms.

Table 4 reports the result of estimating equation (2), which tests H2. The coefficient on $NO\_LOWCIR_{i,t}$ is significantly negative ($p < 0.01$) while the coefficient on $NO\_HIGHCIR_{i,t}$ insignificant. Consistent with H2, these results indicate that newspapers with a lower circulation and, therefore, a more local focus produce information that leads to local commonalities while newspapers with less of a local focus do not.

Table 5 reports result for estimating equation (3), which tests H3. The coefficient on the interaction between $NO\_NEWS_{i,t}$ and $IDD_{i,t}$ is significantly negative coefficient ($p <$ 0.05). Consistent with H3, this result indicates that importance of local newspapers in producing information that contributes to local commonalities is heightened in MSAs where the alternative labor market channel for information exchange is curtailed due to the adoption of IDD.

7. Additional Analysis

7.1 Within and Across Industry Commonalities

In this section, we analyze whether local news coverage leads to different levels of commonalities among co-located firms in the same industries versus co-located firms in different industries. Firms in the same industry are often interdependent (Devenow and Welch 1996; Lieberman and Asaba 2006; Leary and Roberts 2014). Those firms are more likely to be affected by similar economic forces (e.g. industry wide supply and demand shocks), which makes one firm's information particularly relevant for its industry peers. Prior literature demonstrates a significant information spillover effect recognized by the capital market participants by showing that one firm's information environment can generate information externalities on its peers in the capital market (Shroff, Verdi and Yost

2017). In addition, studies also show that firms can also be aware of (and exploit) such spillover effect, which can lead to important real economic consequences. For example, evidence shows that companies often make their disclosure or real decisions following their peers' information or actions, resulting in commonalities in investment decisions and accounting outcomes among industry peers (Badertscher, Shroff and White 2013; Beatty, Liao and Yu 2013; Durnev and Mangen 2020; Seo 2021).

Research on co-located firms also focuses on industry clusters (i.e. firms in both the same industry and geographic area). These studies argue that firms in the same industry cluster often have common information channels. For example, important information producers and users such as analysts, fund managers, and local labor forces usually develop their specializations by industry (Clement 1999; Kadan, Madureira, Wang and Zach 2012; Jennings, Lee and Matsumoto 2017). As a result, those participants tend to enjoy decreased marginal costs of information by following the firms within the same industry. The reduced information cost thus makes information transfer more likely among industry peers (Engelberg, Ozoguz and Wang 2018; Parsons, Sabbatucci and Titman 2020).

To examine the differential impacts of local newspapers on commonalities among firms in the same industry and commonalities among firms in different industries, we partition the dependent variables (i.e. the variance measures) into an average within-industry component and an average across-industry component. Specifically, for an MSA i that has n firms ($f_1 \ldots f_n$) and m industries ($d_1 \ldots d_m$, each with n_k firms), the main dependent variable (constructed in a form of population adjusted variance) can be expressed as:[2]

$$\sigma_{i,t}^2 = \frac{1}{n}\sum_{k=1}^{n}(f_{k,i,t} - \overline{f_{i,t}})^2$$

[2] For specific math illustrations and proofs, please refer to Appendix B

The average within industry component[3], which captures the average commonality for co-located firms that operate in the same industries, can be expressed as:

$$\overline{\sigma^2_{\iota,t}} = \frac{n_1}{n}\sigma^2_{d1,i,t} + \frac{n_2}{n}\sigma^2_{d2,i,t} + \cdots \frac{n_m}{n}\sigma^2_{dm,i,t} = \frac{1}{n}\sum_{k=1}^{m}(n_k * \sigma^2_{dk,i,t})$$

The across-industry component, which captures the average commonality of different industry clusters, can be expressed as:

$$\overline{\gamma^2_{\iota,t}} = \tfrac{n_1 n_2}{n^2}\left(\overline{\beta_{1,\iota,t}} - \overline{\beta_{2,\iota,t}}\right)^2 + \tfrac{n_1 n_3}{n^2}\left(\overline{\beta_{1,\iota,t}} - \overline{d\beta_{3,\iota,t}}\right)^2 + \cdots \tfrac{n_{m-1} n_m}{n^2}\left(\overline{\beta_{m-1,\iota,t}} - \overline{\beta_{m,\iota,t}}\right)^2 =$$

$$\tfrac{1}{n^2}\sum_{k=1}^{m}\sum_{j<k}\left(\overline{\beta_{k,\iota,t}} - \overline{\beta_{J,\iota,t}}\right)^2$$

We replace the dependent variable of the MSA-year level variances with the average within- and across-industry components for each MSA-year and test the following equation. We also replace the independent variables of the variances to be the corresponding within- and across-industry components. Based on the above discussion, we expect a greater commonality for the within industry component (i.e. $\overline{\sigma^2_{\iota,t}}$).

$$\overline{\sigma^2_{\iota,t}} = \beta_0 + \beta_1 NO\_NEWS_{i,t} + \beta_2 \overline{\sigma'^2(Control)_{\iota.t}} + \beta_3 Density_{i,t} + \beta_4 No\_Firms_{i,t} +$$
$$\beta_5 Industry\ Cluster_{i,t} + \varepsilon_{i,t} \tag{4a}$$

$$\overline{\gamma^2_{\iota,t}} = \beta_0 + \beta_1 NO\_NEWS_{i,t} + \beta_2 \overline{\gamma'^2(Control)_{\iota.t}} + \beta_3 Density_{i,t} + \beta_4 No\_Firms_{i,t} +$$
$$\beta_5 Industry\ Cluster_{i,t} + \varepsilon_{i,t} \tag{4b}$$

where:

$\overline{\sigma^2_{\iota,t}}$: the average variance of betas and returns (i.e. equal weighted and value weighted) for firms that operate in the same industries within the MSA.

[3] Since different industry groups may have different number of observations, we calculate the average within-industry commonality using weighted average of the commonality speed of each industry, the weight being the number of firms within each industry cluster.

$\overline{\gamma_{i,t}^2}$: the mean squares of the average level of betas and returns for different industry groups within the MSA.

Table 6 presents the result of the within and across industry analysis. The coefficients on *$NO\_NEWS_{i,t}$* are significantly negative ($p < 0.05$) across all three panels when the average within industry commonality is the dependent variable. By contrast, the coefficients on *$NO\_NEWS_{i,t}$* is insignificant across all three panels when the average across industry commonality speed is the dependent variable. These results indicate that the effect of local newspapers in promoting commonalities is most significant among firms in the same industry.

7.2 Alternative Outcomes for Local Commonalities

Our main analysis indicate that local newspapers promote commonalities in overall fundamentals as reflected in stock returns. To provide insight on specific actions firms take that contribute to commonalities in overall fundamentals, we extend our examination to commonalities in co-located firms' investment decisions. We focus on firms' investment behavior for a few reasons. Investment strategies reflect a critical dimension of firms' decisions. Firms create values through profitable investment projects (Nickell 1978). Therefore, a firm's investment plan usually has a significant impact on its stock price (Woolridge and Snow 1990; Bizjak, Brickley and Coles 1993). Prior studies show that a firm often makes similar investment decisions under the influence of its peers or neighbors (Beatty et al. 2013; Core et al. 2016; Shroff et al. 2017). Thus, we examine the role of newspaper in promoting similar investment decisions among local peers.

We measure total investment as the sum of capital and R&D expenditures. We also separately examine both components of total investment. We use analogous procedures to those used to measure commonality in returns to measure commonalities in these investment measures.

Table 7 reports the results using the alternative outcome measures of investment. The coefficients on $NO\_NEWS_{i,t}$ are significantly negative ($p < 0.01$) for both total investment and capital expenditures. This finding, taken together with the result of our main analysis, indicates that the effect of local newspapers on promoting stock market commonalities among co-located firms is at least partially attributable to their effect in promoting commonality in investment. The coefficient on $NO\_NEWS_{i,t}$, however, is insignificant for R&D expenditures. A possible explanation is that firms tend to keep their R&D plans private due to its proprietary nature. Therefore, the R&D information is much less observable and thus much harder for the local media to discover.

We also extend the across- and within-industry analysis to investment. Panel A-C of Table 8 presents the results. Consistent with the main analysis, we find a more significant impact of local newspapers on promoting commonality in total investment ($p < 0.01$) and R&D ($p < 0.1$) among local industry peers. The only exception is the capital expenditure, which shows significant results for both within- and across-industry commonality. One possible explanation is that capital expenditures are likely to be deployable across different industries whereas R&D expenditures are more likely to be industry-specific.

7.3 Difference-in-difference analysis

To maximize causal inferences, we adopt a difference-in-difference design that exploits newspaper closures, mergers and de-frequencies as exogenous shocks to the coverage power of local daily newspapers. We first identify 394 disappeared newspapers as the ones that exited the market, merged out, or decreased frequencies to weekly issuance. For each MSA in each year, we create a potential pool of treated industries as those containing affected firms that are located within 50 miles of these disappeared newspapers. In order to identify economically significant shocks to local newspapers, we also require treated industries to have more than 10% of total firms to be affected by disappeared newspapers in the shock year and no affected firms in the preceding two years (year t-1 and t-2) and in the subsequent two years (year t+1 and t+2). We also identify a potential control industry-MSA-year group as those without affected firms within a 50-miles radius of these disappeared newspapers in the five consecutive years from year t-2 to year t+2 relative to the treated industry's shock year. In terms of the matching procedure, we first require that the matched treatment and control must be in the same industry and in the same corresponding year. We then employ propensity score matching with replacement based on three MSA-level covariates and one industry-MSA-level covariate. The MSA-level covariates needed to be balanced are labor population, per capita income, and unemployment rate. The industry-MSA-level covariate needed to be balanced is the total number of firms. As a consequence, each matched-pair has the same industry in the same year but in two different MSAs. This design allows us to better capture the impact of local newspaper coverage on within-industry commonalities.

To sharpen the comparison of pre- and post-periods, we exclude the industry-MSA-year observations of the shock year (year t) for both groups and only the observations in the pre-periods (year t-1 and t-2) and in the post-periods (year t+1 and t+2) are left. We perform the following difference-in-difference regression for the resulting sample. A positive coefficient on $TREAT_{k,i,t} \times POST_{k,i,t}$ would be consistent with our argument and indicate that the reduction of newspapers leads to a reduction in commonalities among co-located firms in affected industries.

$$\sigma_{k,i,t} = \beta_0 + \beta_1\, TREAT_{k,i,t} + \beta_2 TREAT_{k,i,t} \times POST_{k,i,t} + \beta_3\, POST_{k,i,t} + \beta_4 \sigma'(Controls)_{k,i,t} + \beta_5 Density_{i,t} + \varepsilon_{k,i,t} \quad (5)$$

where:

$\sigma_{k,i,t}$: the standard deviation of firm-year realizations of the firm-specific components of each measure, calculated at the MSA-industry-year level.

$TREAT_{k,i,t}$: an indicator variable that equals 1 for treatment observations and 0 for control observations.

$POST_{k,i,t}$: an indicator that equals 1 for observations after the treatment firm's shock year and 0 for observations prior to the treatment firm's shock year.

$\sigma'(Controls)_{k,i.t}$: a vector that consists of the standard deviations of previously documented determinants of the measure under examination.

$Density_{i,t}$: a measure that captures the closeness of firms locations within the MSA, following Core et al. (2016).

Panel A and Panel B in Table 9 exhibit the results of estimating equation (5) for the Beta (Return) and investment commonality measures, respectively. In Panel A, the coefficients on $TREAT_{k,i,t} \times POST_{k,i,t}$ are positive and significant ($p < 0.10$) for two out of the three measures, suggesting that losing newspapers leads to loss of commonality in returns. Panel B shows that the coefficients on $TREAT_{k,i,t} \times POST_{k,i,t}$ are positive and significant ($p < 0.05$) for investment divergence and CAPEX divergence but insignificant for R&D divergence, consistent with the findings in cross-sectional tests that local newspapers have differential impact on investment components.

8. Robustness

8.1 Measurement of the number of local newspapers

In the previous analysis, we measure the impact of local newspapers using the number of unique newspapers that are within 50 miles of any firm whose headquarter is located in the MSA. In this section, we adopt an alternative approach to measure the impact of local newspaper. Specifically, we use the percentage of local firms in the MSA that are 'covered' by (within the radius of 50 miles of) a local newspaper. To construct this measure, for each MSA, the denominator would be the total number of firms whose headquarter reside in the

MSA. We take into the consideration that one firm might be covered by multiple local newspapers and calculate the numerator as the total number of newspapers covering each local firm, summed across all the firms within the MSA (If a firm is not covered by any local newspapers, we assign it 0).

Graph B demonstrates the two methods respectively. Table 10 presents the result under this alternative approach of measuring the impact of local newspapers. Consistent with our main approach, we find a negative coefficient on the number of local newspapers across different dependent variables for both the capital market and investment matrixes. The result provides robust evidence that local newspapers promote commonalities of the fundamentals among co-located firms.

8.2 Controlling for Local Geographic Factors

The U.S. Office of Management and Budget (OMB) defines the metropolitan statistical area (MSA) as ***"The formal definition of a region that consists of a city and surrounding communities that are linked by social and economic factors".*** The number of local newspapers in an MSA is not exogenously determined. Like any local business, the number of local newspapers is determined by local social and economic factors, such as local GDP and employment (Shaver and Shaver 2005; Bakker and Picard 2008). These factors are also likely to affect decisions and performance of the local firms. To address this omitted variable problem, we construct our main measure (i.e. the number of local newspapers) using the residual from a regression that regresses the total number of local newspapers on geographic factors including per capital GDP, local labor forces, and local unemployment rate. In the robustness test, we use the original number (logged) of local newspapers directly as the independent variables, and add the geographic factors as additional control variables. Our results are robust to this alternative specification.

8.3 Definition of 'Local'

We conducted our analysis on the MSA-year level and consider a newspaper to be a local newspaper associated with the MSA if the newspaper is located within 50 miles of any firms whose headquarter is located within the MSA. Our result is robust if we define local newspaper following prior studies' criteria of 100 miles radius.

9. Conclusion

The existence of geographic commonalities is well documented but there is limited empirical evidence on the drivers of such commonalities. Theoretically, such commonalities depend on firms having information that allows them to infer and imitate the actions of their neighbors or to develop shared responses to the same economic environment. Local newspapers are important channels for discovering and sharing information about local conditions that is likely to be relevant for various firm decisions. Therefore, we examine whether local newspapers contribute to geographic commonalities.

We find that firms in MSAs with more local newspapers have more similar (i.e. less disperse) stock returns and stock market betas, indicating that local newspapers contribute to commonalities in overall fundamentals among co-located firms. We also find that the level of investment – a key driver of firm fundamentals - is more similar among firms in MSAs with more local newspapers, suggesting that local newspapers contribute to a shared understanding of investment opportunities available to co-located firms. The effect of local newspapers on geographic commonalities is more pronounced for newspapers with smaller circulations, which have been shown to be more dedicated to covering local news than larger newspapers. The effect is also more pronounced in communities that have adopted the inevitable disclosure doctrine, which limits labor market mobility – an alternative channel for information sharing. In additional analysis, we find that local newspapers are associated with commonalities among firms in the same industry but not among firms in different industries. Using a difference-in-difference design to bolster causal inferences, we find that same-industry firms exhibit less similarities after local newspaper closures, which are exogenous shocks to local news coverage. Collectively, the results show that local media is an important driver of previously documented geographic commonalities.

This paper extends prior research that documents the existence of geographic commonalities by providing empirical evidence on how such commonalties arise. Specifically, this paper highlights the local media as an important information sharing that leads to the creation of geographic commonalities. Understanding how geographic commonalities form is important because such commonalities can have measurable impacts on local economies and also affect the degree of diversification investors can achieve, particularly investors who are subject to the well-documented home bias.

This study also adds to the literature on the impact of media coverage on corporate activities. Prior studies on media coverage have documented its monitoring role or its role in aiding investment decisions. Our evidence that local newspapers enable information sharing that leads to the creation of geographic commonalities highlights another previously undocumented role of the local media. This evidence is relevant to ongoing policy discussions about the implications of the dramatic decline in the number of local newspapers in recent years and whether measures should be taken to reverse this trend. The introduction by Representative Kirkpatrick of Arizona of the Local Journalism Sustainability Act, a bill that proposes tax incentives to support local newspapers, reflects widespread concerns about this trend. Our findings that the information generated by local newspapers influences firms' collective investment decisions indicate that the loss of local newspapers can have a significant impact on the allocation of resources within local economies, lending further validity to these concerns.

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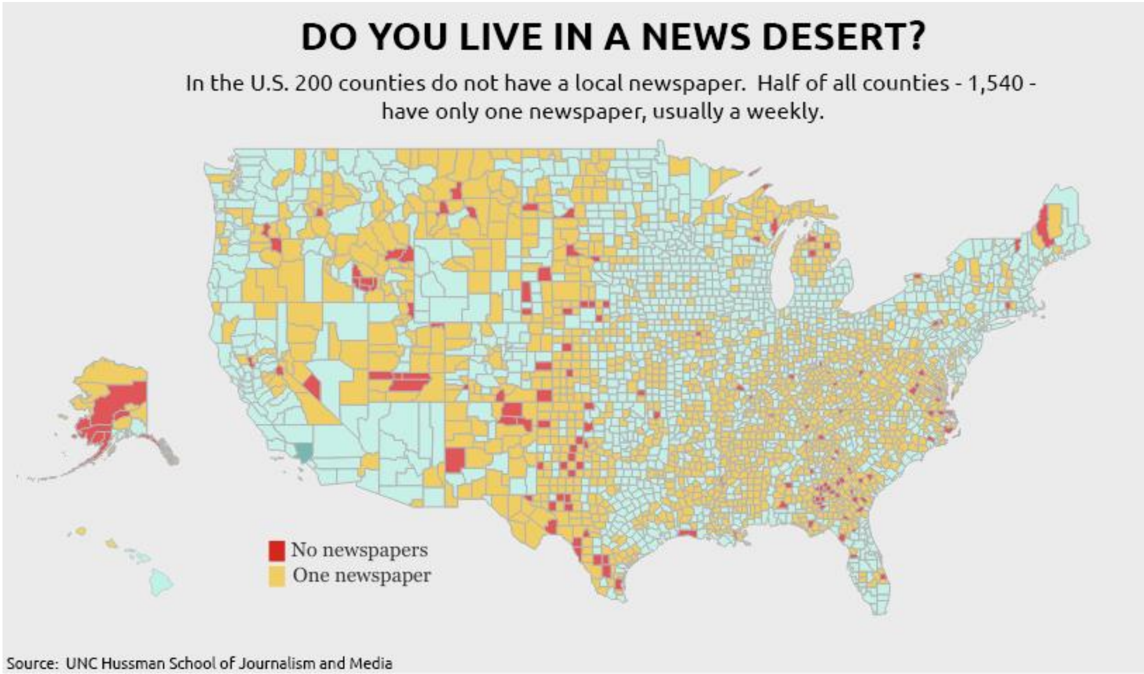
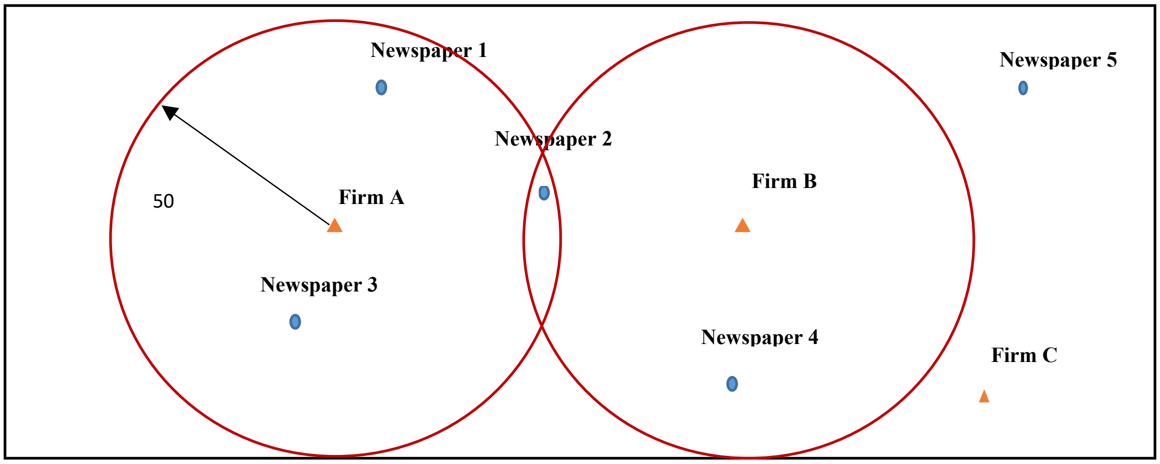
Graph A: Distribution of Local newspapers Across the United States



Graph B: Alternative Approaches of Measuring Local Newspapers



<u>Approach 1:</u>

Under the first approach, the total number of newspapers associated with MSA K would be 4. We calculate the number as the total numbers of nonduplicated newspapers that are within a 50-mile radius of any firm whose headquarter is located in the MSA. Therefore, newspaper 1, 2, 3 are considered local newspapers for firm A, and newspaper 2 and 3 for firm B. The total newspapers that are local to MSA K are therefore newspaper 1-4.

<u>Approach 2:</u>

We consider an alternative approach of measuring local newspapers. Under this approach, we capture the impact of local newspapers as the percentage of local firms in the MSA that are 'covered' by (within the radius of 50 miles of) a local newspaper. We take into the consideration that one firm might be covered by multiple local newspapers. Under this approach, firm A is covered by 3 local newspapers, firm B by 2, and firm C by 0. Therefore, the total percentage of firms covered by local newspapers would be (3+2+0)/3=5/3.

Appendix A: Variable Definitions

Variable Name	Description
Hypothesis Test Variables	
$NO\_NEWS_{i,t}$	MSA-year level measure of the number of local newspapers in year t, using the residual from the following model: $NEWS_{i,t} = \beta_0 + \beta_1 LABOR_{i,t} + \beta_2 PERCAPITA_{i,t} + \beta_3 UR_{i,t} + \varepsilon_{i,t}$ where $NEWS_{i,t}$ is the logarithm of one plus the number of local newspapers within 50 miles of each firm's headquarter city in the MSA. $LABOR_{i,t}$ is the logarithm of labor force. $PERCAPITA_{i,t}$ is the logarithm of per capita income. $UR_{i,t}$ is the logarithm of unemployment rate.
$\sigma\_BETA_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from annual regressions of market model beta in year t (for the 12 months spanning month -4 to month +3 relative to year-end) on industry fixed effects.
$\sigma\_ERETURN_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from annual regressions of equal-weighted market-adjusted buy and hold returns in year t (for the 12 months spanning from month -4 to month +3 relative to year-end) on industry fixed effects.
$\sigma\_VRETURN_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from annual regressions of value-weighted market-adjusted buy and hold returns in year t (for the 12 months spanning from month -4 to month +3 relative to year-end) on industry fixed effects.
$\sigma'\_BETA_{i,t}$	The standard deviation of betas in year t at MSA-year level.
$\sigma'\_MTB_{i,t-1}$	The standard deviation of market-to-book ratio in year t-1 (measured as the market value scaled by the book value of equity) at MSA-year level.
$\sigma'\_MV_{i,t-1}$	The standard deviation of the logarithm of one plus market value in year t-1 (measured as the number of shares outstanding multiplied by stock price) at MSA-year level.
$\sigma'\_LEV_{i,t-1}$	The standard deviation of leverage in year t-1 (measured as total liabilities scaled by total assets) at MSA-year level.

Appendix A: Continued

DENSITY$_{i,t}$	Firm density for the MSA in year t, measured as the weighted average of the distance of firm-pairs, following Core et al. (2016).
NO_FIRMS$_{i,t}$	Number of total firms in the MSA in year t.
IND_CLUSTER$_{i,t}$	Percentage of the dominant industry in the MSA in year t.
IDD$_{i,t}$	Indicator that captures the adoption of Inevitable Disclosure Doctrine. It is equal to one for states that have adopted the Doctrine by year t, zero otherwise.
NO_HIGHCIR$_{i,t}$	MSA-year measure of the number of local newspapers with highest circulations in year t, using the residual from the following model: $HIGHCIR_{i,t} = \beta_0 + \beta_1 LABOR_{i,t} + \beta_2 PERCAPITA_{i,t} + \beta_3 UR_{i,t} + \varepsilon_{i,t}$ where *HIGHCIR*$_{i,t}$ is the logarithm of one plus the number of local newspapers with top quintile circulations within 50 miles of each firm in the MSA. *LABOR*$_{i,t}$ is the logarithm of labor force. *PERCAPITA*$_{i,t}$ is the logarithm of per capita income. *UR*$_{i,t}$ is the logarithm of unemployment rate.
NO_LOWCIR$_{i,t}$	MSA-year measure of the number of local newspapers with low circulations in year t, using the residual from the following model: $LOWCIR_{i,t} = \beta_0 + \beta_1 LABOR_{i,t} + \beta_2 PERCAPITA_{i,t} + \beta_3 UR_{i,t} + \varepsilon_{i,t}$ where *LOWCIR*$_{i,t}$ is the logarithm of one plus the number of local newspapers with lowest four quintile circulations within 50 miles of each firm in the MSA. *LABOR*$_{i,t}$ is the logarithm of labor force. *PERCAPITA*$_{i,t}$ is the logarithm of per capita income. *UR*$_{i,t}$ is the logarithm of unemployment rate.

Appendix A: Continued

Variables for Additional Analysis and Robustness Tests

$\sigma\_INVEST_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from the following model: $$INVEST_{i,t} = \beta_0 + \beta_1 OPCASH_{i,t} + \beta_2 MV_{i,t-1} + \beta_3\, MTB_{i,t-1} + \beta_4 LEV_{i,t-1} + \varepsilon_{it}$$ where $INVEST_{i,t}$ is the sum of capital expenditures and research and development expenditures scaled by lagged total assets. $OPCASH_{i,t}$ is cash flows from operations scaled by lagged total assets. $MV_{i,t-1}$ is the number of shares outstanding multiplied by stock price. $MTB_{i,t-1}$ is the market value of equity scaled by the book value of equity. $LEV_{i,t-1}$ is total liabilities scaled by lagged total assets.
$\sigma\_R\&D_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from the following model: $$R\&D_{i,t} = \beta_0 + \beta_1 OPCASH_{i,t} + \beta_2 MV_{i,t-1} + \beta_3\, MTB_{i,t-1} + \beta_4 LEV_{i,t-1} + \varepsilon_{it}$$ where $R\&D_{i,t}$ is research and development expenditures scaled by lagged total assets. $OPCASH_{i,t}$ is cash flows from operations scaled by lagged total assets. $MV_{i,t-1}$ is the number of shares outstanding multiplied by stock price. $MTB_{i,t-1}$ is the market value of equity scaled by the book value of equity. $LEV_{i,t-1}$ is total liabilities scaled by lagged total assets.
$\sigma\_CAPEX_{i,t}$	The standard deviation, measured at MSA-year level, of the residual from the following model: $$CAPEX_{i,t} = \beta_0 + \beta_1 OPCASH_{i,t} + \beta_2 MV_{i,t-1} + \beta_3\, MTB_{i,t-1} + \beta_4 LEV_{i,t-1} + \varepsilon_{it}$$ where $CAPEX_{i,t}$ is capital expenditures scaled by lagged total assets. $OPCASH_{i,t}$ is cash flows from operations scaled by lagged total assets. $MV_{i,t-1}$ is the number of shares outstanding multiplied by stock price. $MTB_{i,t-1}$ is the market value of equity scaled by the book value of equity. $LEV_{i,t-1}$ is total liabilities scaled by lagged total assets.
$\overline{\sigma^2_{i,t}}$	The average variance of each measure for firms that operate in the same industries within the MSA in year t. The measures are betas, equal (value) -weighted market-adjusted buy and hold returns, total investment, R&D expenditure, and capital expenditure.

Appendix A: Continued

$\overline{\gamma_{i,t}^2}$	The mean squares of the average level of each measure for different industry groups within the MSA in year t. The measures are betas, equal (value) -weighted market-adjusted buy and hold returns, total investment, R&D expenditure, and capital expenditure.
$\overline{\sigma'^2\_BETA_{i,t}}$	The weighted average of the standard deviation of beta within each industry located in the same MSA in year t.
$\overline{\sigma'^2\_MV_{i,t-1}}$	The weighted average of the standard deviation of market value within each industry located in the same MSA in year t-1.
$\overline{\sigma'^2\_MTB_{i,t-1}}$	The weighted average of the standard deviation of market-to-book ratio within each industry located in the same MSA in year t-1.
$\overline{\sigma'^2\_LEV_{i,t-1}}$	The weighted average of the standard deviation of leverage within each industry located in the same MSA in year t-1.
$\overline{\sigma'^2\_OPCASH_{i,t}}$	The weighted average of the standard deviation of cash flows from operations scaled by lagged total assets within each industry located in the same MSA in year t.
$\overline{\gamma'^2\_BETA_{i,t}}$	The weighted sum of squares of the means of beta of different industries in the same MSA in year t.
$\overline{\gamma'^2\_MV_{i,t-1}}$	The weighted sum of squares of the means of market value of different industries in the same MSA in year t-1.
$\overline{\gamma'^2\_MTB_{i,t-1}}$	The weighted sum of squares of the means of market-to-book ratio of different industries in the same MSA in year t-1.
$\overline{\gamma'^2\_LEV_{i,t-1}}$	The weighted sum of squares of the means of leverage of different industries in the same MSA in year t-1.
$\overline{\gamma'^2\_OPCASH_{i,t}}$	The weighted sum of squares of the means of cash flows from operations scaled by lagged total assets of different industries in the same MSA in year t.
$\sigma'\_OPCASH_{i,t}$	The standard deviation of cash flows from operations scaled by lagged total assets in year t at MSA-year level.
$MEAN\_RETURN_{i,t}$	The average market model return in year t at MSA-year level.

Appendix A: Continued

NO_NEWS2$_{i,t}$	Alternative MSA-year measure of the number of local newspapers in year t, using the residual from the following model: $NEWS2_{i,t} = \beta_0 + \beta_1 LABOR_{i,t} + \beta_2 PERCAPITA_{i,t} + \beta_3 UR_{i,t} + \varepsilon_{i,t}$ where *NEWS2*$_{i,t}$ is the logarithm of one plus the sum of local newspaper coverage (the ratio of firms covered by newspapers within 50 miles to total firms in the industry) for the MSA. *LABOR*$_{i,t}$ is the logarithm of labor force. *PERCAPITA*$_{i,t}$ is the logarithm of per capita income. *UR*$_{i,t}$ is the logarithm of unemployment rate.
TREAT$_{k,i,t}$	MSA-industry-year level indicator that captures the impact of newspaper closures. It is equal to 1 if firms of the MSA-industry-year level are located within 50 miles of a local newspaper with closures, mergers or de-frequencies. Treatment industries are also required to have more than 10% of total firms to be affected by disappeared newspaper in the shock year and no affected firms in the preceding two years (year t-1 and t-2) and in the subsequent two years (year t+1 and t+2).
POST$_{k,i,t}$	Indicator that is equal to 1 for observations after the treatment industry's shock year and 0 for observations prior to the treatment industry's shock year.

Appendix B:

Consider the following scenario: MSA i has n firms, $f_1 \ldots f_n$. The n firms belong to m industries ($d_1 \ldots d_m$) ($m \geq 2$). Each industry d_k has n_k firms. We consider a firm year specific measure β (i.e. β refers to the measures in the return, investment or the real earnings management matrix. Firm f_k is associated with $\beta_{k,t}$ for year t). We know the mean of β for MSA i is $\overline{\beta_{\iota,t}}$. The population variance of β for MSA k is $\sigma^2_{i,t}$. We also denote the mean of β for each industry group d_i within the MSA as $\overline{\beta_{d_k,\iota,t}}$, and the variance as $\sigma^2_{d_k,i,t}$.

$$\underbrace{\boxed{\sigma^2_{i,t}}}_{\text{Total Variance}} = \underbrace{\boxed{\frac{1}{n}\sum_{k=1}^{m}\left(n_k * \sigma^2_{d_k,i,t}\right)}}_{\text{Average Within-Industry Variances}} + \underbrace{\boxed{\frac{1}{n^2}\left\{\sum_{k=1}^{m}\sum_{j<i}\left[n_k n_j \left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{d_j,\iota,t}}\right)^2\right]\right\}}}_{\text{Average Across-Industry Variances}}$$

Where:

$\sigma^2_{i,t}$ is the total variance of β for all the firm-year observations in MSA i.

$\frac{1}{n}\sum_{k=1}^{m}\left(n_k * \sigma^2_{d_k,i,t}\right)$ is the weighted average of the within-industry variances of β for all the industry clusters within MSA k.

$\frac{1}{n^2}\left\{\sum_{k=1}^{m}\sum_{j<k}\left[n_k n_j \left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{d_j,\iota,t}}\right)^2\right]\right\}$ is the weighted average of the across-industry variances of β for all pairs of industry groups within MSA k.

To prove (1), We have:

$\overline{\beta_{\iota,t}} = \frac{n_k * \overline{\beta_{d_k,\iota,t}}}{n}$

$$\sigma_{i,t}^2 = \frac{1}{n}\left(\sum_{k=1}^{n}(\beta_{k,i,t} - \overline{\beta_{\iota,t}})^2\right)$$

$$= \frac{1}{n}\sum_{d_1}^{d_m}\left(\sum_{k\in d_k}\left(\beta_{k,i,t} - \overline{\beta_{\iota,t}}\right)^2\right)$$

$$= \frac{1}{n}\sum_{d_1}^{d_m}\left(\sum_{k\in d_k}\left(\beta_{k,i,t} - \overline{\beta_{d_k,\iota,t}} + \overline{\beta_{d_k,\iota,t}} - \overline{\beta_{\iota,t}}\right)^2\right)$$

$$= \frac{1}{n}\sum_{d_1}^{d_m}\sum_{k\in d_k}\left\{\left(\beta_{k,i,t} - \overline{\beta_{d_k,\iota,t}}\right)^2 + \left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{\iota,t}}\right)^2 + 2\left(\beta_{k,i,t} - \overline{\beta_{d_k,\iota,t}}\right) * \left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{\iota,t}}\right)\right\}$$

Since we have the following:

$$\sum_{k\in d_k}\left(\beta_{k,i,t} - \overline{\beta_{d_k,\iota,t}}\right)^2 = n_k * \sigma_{d_k,i,t}^2$$

$$\sum_{d_1}^{d_m}\sum_{k\in d_k}\left(\beta_{k,i,t} - \overline{\beta_{d_k,\iota,t}}\right) * \left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{\iota,t}}\right)=0$$

$$\sum_{d_1}^{d_m}\sum_{k\in d_k}\left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{\iota,t}}\right)^2 = \sum_{d_1}^{d_m}\left(n_k * \overline{\beta_{d_k,\iota,t}}^2\right) - n * \overline{\beta_{\iota,t}}^2$$

$$= \sum_{d_1}^{d_m}\left(n_k * \overline{\beta_{d_k,\iota,t}}^2\right) - \left(\sum_{d_1}^{d_m} n_k\right) * \left(\frac{n_k * \overline{\beta_{d_k,\iota,t}}}{n}\right)^2$$

$$= \frac{1}{n}\left\{\sum_{k=1}^{m}\sum_{j<k}\left[n_k n_j\left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{d_j,\iota,t}}\right)^2\right]\right\}$$

Therefore, we can decompose the total variance for MSA k as:

$$\sigma_{i,t}^2 = \frac{1}{n}\sum_{k=1}^{m}\left(n_k * \sigma_{d_k,i,t}^2\right) + \frac{1}{n^2}\left\{\sum_{k=1}^{m}\sum_{j<k}\left[n_k n_j\left(\overline{\beta_{d_k,\iota,t}} - \overline{\beta_{d_j,\iota,t}}\right)^2\right]\right\}$$

Proved.

Table 1 Descriptive Statistics

Table 1 reports descriptive statistics for the main variables used in the sample. All variables are defined in Appendix A.

VARIABLES	N	Mean	Std	P25	P50	P75
Panel A: Beta Sample						
NO_NEWS	1,059	0.103	0.638	-0.372	0.124	0.574
σ_BETA	1,059	1.024	0.348	0.771	0.992	1.251
σ'_MV	1,059	1.723	0.375	1.502	1.770	1.969
σ'_MTB	1,059	16.45	48.74	1.447	2.976	7.243
σ'_LEV	1,059	0.280	0.175	0.209	0.247	0.283
DENSITY	1,059	41.22	61.84	8.879	17.22	41.17
IND_CLUSTER	1,059	0.254	0.120	0.167	0.222	0.318
NO_FIRMS	1,059	32.98	50.38	7	13	32
Panel B: Equal Return Sample						
NO_NEWS	1,045	0.105	0.634	-0.371	0.124	0.574
σ_ERETURN	1,045	0.335	0.120	0.252	0.325	0.398
σ'_BETA	1,045	1.307	0.710	0.831	1.137	1.587
σ'_MV	1,045	1.722	0.371	1.494	1.764	1.968
σ'_MTB	1,045	16.21	50.40	1.468	2.935	6.863
σ'_LEV	1,045	0.261	0.115	0.206	0.245	0.279
DENSITY	1,045	41.59	61.84	9.204	17.35	42.00
IND_CLUSTER	1,045	0.252	0.117	0.167	0.220	0.313
NO_FIRMS	1,045	32.95	50.00	7	14	32
Panel C: Value Return Sample						
NO_NEWS	1,048	0.103	0.635	-0.372	0.120	0.571
σ_VRETURN	1,048	0.336	0.120	0.250	0.324	0.401
σ'_BETA	1,048	1.296	0.704	0.828	1.122	1.583
σ'_MV	1,048	1.719	0.373	1.492	1.757	1.969
σ'_MTB	1,048	16.14	50.40	1.440	2.932	6.834
σ'_LEV	1,048	0.264	0.129	0.207	0.245	0.279
DENSITY	1,048	41.48	61.68	9.061	17.35	41.80
IND_CLUSTER	1,048	0.253	0.118	0.167	0.220	0.313
NO_FIRMS	1,048	32.89	49.82	7	13	31

Table 2 Correlations

Table 2 presents the correlation metrics for the main variables used in the sample. Spearman (Pearson) correlation coefficients for main variables used in the analysis are reported above (below) the diagonal. Correlations that are significant at the 10% level or better are presented in bold. All variables defined in Appendix A.

Panel A: Beta Sample

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
(1) σ_BETA		**-0.051**	**0.088**	**0.201**	**0.174**	**0.288**	**0.255**	**-0.123**
(2) NO_NEWS	**-0.063**		**-0.073**	**-0.068**	-0.034	**-0.115**	**-0.092**	**0.129**
(3) σ'_MV	**0.086**	**-0.095**		**0.241**	**0.137**	**0.414**	**0.483**	**-0.257**
(4) σ'_MTB	**0.066**	0.011	**0.106**		**0.300**	**0.522**	**0.544**	**-0.242**
(5) σ'_LEV	**0.129**	-0.037	**0.092**	**0.135**		**0.314**	**0.277**	**-0.134**
(6) DENSITY	**0.193**	**0.074**	**0.314**	**0.456**	**0.161**		**0.948**	**-0.455**
(7) NO_FIRMS	**0.165**	**0.120**	**0.319**	**0.448**	**0.145**	**0.983**		**-0.461**
(8) IND_CLUSTER	**-0.095**	**0.090**	**-0.251**	**-0.105**	**-0.083**	**-0.230**	**-0.226**	

Table 2 Continued

Panel B: Equal Return Sample

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(1) σ_ERETURN		**-0.106**	**0.129**	**0.225**	**0.167**	**0.206**	**0.360**	**0.302**	**-0.151**
(2) NO_NEWS	**-0.111**		-0.031	**-0.083**	**-0.055**	-0.030	**-0.115**	**-0.090**	**0.131**
(3) σ'_BETA	**0.085**	-0.047		**0.122**	**0.238**	**0.194**	**0.303**	**0.292**	**-0.164**
(4) σ'_MV	**0.202**	**-0.111**	**0.126**		**0.228**	**0.092**	**0.394**	**0.452**	**-0.264**
(5) σ'_MTB	**0.079**	0.027	**0.063**	**0.096**		**0.307**	**0.519**	**0.545**	**-0.252**
(6) σ'_LEV	**0.159**	-0.010	**0.123**	0.038	**0.176**		**0.303**	**0.264**	**-0.145**
(7) DENSITY	**0.218**	**0.074**	**0.169**	**0.307**	**0.450**	**0.113**		**0.945**	**-0.457**
(8) NO_FIRMS	**0.179**	**0.120**	**0.163**	**0.312**	**0.443**	**0.094**	**0.981**		**-0.467**
(9) IND_CLUSTER	**-0.102**	**0.103**	**-0.093**	**-0.264**	**-0.109**	**-0.090**	**-0.230**	**-0.226**	

Table 2 Continued

Panel C: Value Return Sample

VARIABLES	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(1) σ_VRETURN		**-0.100**	**0.150**	**0.213**	**0.179**	**0.209**	**0.369**	**0.309**	**-0.160**
(2) NO_NEWS	**-0.117**		-0.030	**-0.081**	**-0.058**	-0.032	**-0.110**	**-0.084**	**0.127**
(3) σ'_BETA	**0.112**	-0.046		**0.132**	**0.244**	**0.197**	**0.315**	**0.302**	**-0.173**
(4) σ'_MV	**0.182**	**-0.106**	**0.136**		**0.231**	**0.088**	**0.403**	**0.463**	**-0.270**
(5) σ'_MTB	**0.074**	0.027	**0.066**	**0.096**		**0.306**	**0.525**	**0.554**	**-0.254**
(6) σ'_LEV	**0.163**	-0.019	**0.119**	0.041	**0.162**		**0.310**	**0.273**	**-0.149**
(7) DENSITY	**0.217**	**0.075**	**0.173**	**0.312**	**0.449**	**0.130**		**0.946**	**-0.456**
(8) NO_FIRMS	**0.179**	**0.122**	**0.166**	**0.318**	**0.442**	**0.113**	**0.982**		**-0.468**
(9) IND_CLUSTER	**-0.095**	**0.095**	**-0.101**	**-0.268**	**-0.109**	**-0.089**	**-0.230**	**-0.227**	

Table 3 Local Newspaper Numbers and Beta (Return) Commonalities

Table 3 reports results of estimating equation (1), which captures the impact of the number of local newspapers on Beta (Return) commonalities for co-located firms. The dependent variable of column (1), (2), and (3) is $\sigma\_BETA_{i,t}$, $\sigma\_ERETURN_{i,t}$, and $\sigma\_VRETURN_{i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	Dependent Variable		
	(1)	(2)	(3)
	$\sigma\_BETA_{i,t}$	$\sigma\_ERETURN_{i,t}$	$\sigma\_VRETURN_{i,t}$
$NO\_NEWS_{i,t}$	-0.041***	-0.017***	-0.017***
	(-4.035)	(-4.696)	(-5.286)
$\sigma'\_BETA_{i,t}$		0.027***	0.032***
		(4.061)	(5.640)
$\sigma'\_MV_{i,t-1}$	0.033	0.030**	0.026**
	(1.201)	(2.961)	(2.485)
$\sigma'\_MTB_{i,t-1}$	-0.000*	-0.000	-0.000
	(-2.086)	(-0.987)	(-1.148)
$\sigma'\_LEV_{i,t-1}$	0.186***	0.114***	0.105***
	(4.636)	(3.176)	(3.115)
$DISTANCE_{i,t}$	0.003***	0.001***	0.001***
	(4.819)	(3.424)	(3.203)
$NO\_FIRMS_{i,t}$	-0.003***	-0.001**	-0.001**
	(-3.184)	(-2.309)	(-2.250)
$IND\_CLUSTER_{i,t}$	-0.034	-0.014	-0.011
	(-0.394)	(-0.396)	(-0.257)
Constant	0.892***	0.212***	0.216***
	(17.994)	(7.558)	(7.071)
Observations	1,059	1,045	1,048
R-squared	0.353	0.289	0.272
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.340	0.274	0.257

Table 4 Cross Sectional Analysis on the Effect of Local Newspapers – Circulation

Table 4 reports results of the association between the number of high- versus low-circulated local newspapers and local Beta (Return) commonalities. The dependent variable of column (1), (2), and (3) is $\sigma\_BETA_{i,t}$, $\sigma\_ERETURN_{i,t}$, and $\sigma\_VRETURN_{i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	Dependent Variable		
	(1) $\sigma\_BETA_{i,t}$	(2) $\sigma\_ERETURN_{i,t}$	(3) $\sigma\_VRETURN_{i,t}$
$NO\_LOWCIR_{i,t}$	-0.045***	-0.015***	-0.014***
	(-4.097)	(-3.771)	(-3.833)
$NO\_HIGHCIR_{i,t}$	0.018	-0.010	-0.013
	(0.978)	(-1.417)	(-1.546)
$\sigma'\_BETA_{i,t}$		0.026***	0.031***
		(3.995)	(5.544)
$\sigma'\_MV_{i,t-1}$	0.030	0.030**	0.026**
	(1.085)	(2.876)	(2.452)
$\sigma'\_MTB_{i,t-1}$	-0.000**	-0.000	-0.000
	(-2.231)	(-0.894)	(-1.072)
$\sigma'\_LEV_{i,t-1}$	0.170***	0.110**	0.103**
	(4.236)	(2.989)	(2.973)
$DISTANCE_{i,t}$	0.003***	0.001***	0.001***
	(4.487)	(3.299)	(3.253)
$NO\_FIRMS_{i,t}$	-0.003**	-0.001*	-0.001*
	(-2.877)	(-1.973)	(-2.094)
$IND\_CLUSTER_{i,t}$	-0.027	-0.011	-0.009
	(-0.300)	(-0.319)	(-0.202)
Constant	0.899***	0.212***	0.214***
	(17.863)	(7.185)	(6.644)
Observations	1,059	1,045	1,048
R-squared	0.355	0.291	0.274
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.342	0.276	0.258

Table 5 Cross Sectional Analysis on the Effect of Local Newspapers – Labor Market Channel

Table 5 reports results of the cross-sectional analysis. The result captures the differential impact of local newspapers on geographic commonality for MSAs that (have not) adopted the Inevitable Disclosure Doctrine. The dependent variable of column (1), (2), and (3) is $\sigma\_BETA_{i,t}$, $\sigma\_ERETURN_{i,t}$, and $\sigma\_VRETURN_{i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	Dependent Variable		
	(1)	(2)	(3)
	$\sigma\_BETA_{i,t}$	$\sigma\_ERETURN_{i,t}$	$\sigma\_VRETURN_{i,t}$
$NO\_NEWS_{i,t}$	0.007	0.003	0.001
	(0.377)	(0.462)	(0.078)
$NO\_NEWS_{i,t}*IDD_{i,t}$	-0.089**	-0.036**	-0.034**
	(-2.906)	(-2.770)	(-2.523)
$IDD_{i,t}$	0.004	-0.001	0.001
	(0.195)	(-0.093)	(0.211)
$\sigma'\_BETA_{i,t}$		0.026***	0.031***
		(3.878)	(5.499)
$\sigma'\_MV_{i,t-1}$	0.037	0.032***	0.027**
	(1.319)	(3.104)	(2.589)
$\sigma'\_MTB_{i,t-1}$	-0.000	-0.000	-0.000
	(-1.607)	(-0.051)	(-0.260)
$\sigma'\_LEV_{i,t-1}$	0.172***	0.104**	0.098**
	(4.500)	(2.791)	(2.774)
$DISTANCE_{i,t}$	0.004***	0.001***	0.001***
	(5.363)	(3.423)	(3.359)
$NO\_FIRMS_{i,t}$	-0.004***	-0.001**	-0.001**
	(-3.738)	(-2.495)	(-2.493)
$IND\_CLUSTER_{i,t}$	0.010	0.001	0.004
	(0.105)	(0.039)	(0.081)
Constant	0.884***	0.213***	0.215***
	(15.940)	(7.607)	(7.053)
Observations	1,059	1,045	1,048
R-squared	0.358	0.296	0.278
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.345	0.280	0.262

Table 6 Within versus Across Industry Commonalities Test

Table 6 reports results of the association between the number of local newspapers and within- versus across-industry Beta (Return) commonalities. Panel A reports the result for beta commonalities, and the dependent variable of column (1) and (2) is $\overline{\sigma^2\_BETA}_{i,t}$ and $\overline{\gamma^2\_BETA}_{i,t}$, respectively. Panel B (C) reports the result for commonalities of equal (value) weighted returns, and the dependent variable of column (1) and (2) is $\overline{\sigma^2\_ERETURN}_{i,t}$ ($\overline{\sigma^2\_VRETURN}_{i,t}$) and $\overline{\gamma^2\_ERETURN}_{i,t}$ ($\overline{\gamma^2\_VRETURN}_{i,t}$), respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Beta Commonalities

	Dependent Variable	
VARIABLES	(1) Within Industry Commonalities $\overline{\sigma^2\_BETA}_{i,t}$	(2) Across Industry Commonalities $\overline{\gamma^2\_BETA}_{i,t}$
$NO\_NEWS_{i,t}$	-0.078***	0.033
	(-3.281)	(1.559)
$\overline{\sigma'^2\_MV}_{i,t-1}$	0.146***	
	(6.034)	
$\overline{\sigma'^2\_MTB}_{i,t-1}$	-0.000***	
	(-4.048)	
$\overline{\sigma'^2\_LEV}_{i,t-1}$	0.726***	
	(4.496)	
$\overline{\gamma'^2\_MV}_{i,t-1}$		0.046*
		(1.965)
$\overline{\gamma'^2\_MTB}_{i,t-1}$		-0.000
		(-0.630)
$\overline{\gamma'^2\_LEV}_{i,t-1}$		0.258
		(1.618)
$DENSITY_{i,t}$	0.005	0.003
	(1.683)	(1.625)
$NO\_FIRMS_{i,t}$	-0.003	-0.007***
	(-0.780)	(-3.106)
$IND\_CLUSTER_{i,t}$	0.521***	-0.554***
	(3.651)	(-7.007)
Constant	0.073	0.787***
	(1.501)	(14.071)
Observations	1,059	1,059
R-squared	0.466	0.262
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.455	0.247

Table 6 Continued

Panel B: Equal Return Commonalities

VARIABLES	Dependent Variable (1) Within Industry Commonalities $\overline{\sigma^2\_ERETURN}_{i,t}$	 (2) Across Industry Commonalities $\overline{\gamma^2\_ERETURN}_{i,t}$
$NO\_NEWS_{i,t}$	-0.005***	-0.000
	(-3.059)	(-0.163)
$\overline{\sigma'^2\_BETA_{i,t}}$	0.006***	
	(3.161)	
$\overline{\sigma'^2\_MV_{i,t-1}}$	0.015***	
	(7.950)	
$\overline{\sigma'^2\_MTB_{i,t-1}}$	-0.000**	
	(-2.407)	
$\overline{\sigma'^2\_LEV_{i,t-1}}$	0.291***	
	(5.135)	
$\overline{\gamma'^2\_BETA_{i,t}}$		0.003**
		(2.791)
$\overline{\gamma'^2\_MV_{i,t-1}}$		0.005***
		(3.062)
$\overline{\gamma'^2\_MTB_{i,t-1}}$		0.000
		(0.301)
$\overline{\gamma'^2\_LEV_{i,t-1}}$		0.068**
		(2.424)
$DENSITY_{i,t}$	0.000*	0.000
	(2.149)	(1.195)
$NO\_FIRMS_{i,t}$	-0.000	-0.001**
	(-1.335)	(-2.732)
$IND\_CLUSTER_{i,t}$	0.053***	-0.065**
	(4.124)	(-2.522)
Constant	0.002	0.080***
	(0.401)	(8.943)
Observations	1,045	1,045
R-squared	0.452	0.246
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.441	0.231

Table 6 Continued

Panel C: Value Return Commonalities

VARIABLES	Dependent Variable (1) Within Industry Commonalities $\overline{\sigma^2\_VRETURN}_{i,t}$	Dependent Variable (2) Across Industry Commonalities $\overline{\gamma^2\_VRETURN}_{i,t}$
$NO\_NEWS_{i,t}$	-0.005**	-0.001
	(-2.941)	(-0.326)
$\overline{\sigma'^2\_BETA_{i,t}}$	0.006***	
	(4.416)	
$\overline{\sigma'^2\_MV_{i,t-1}}$	0.017***	
	(8.926)	
$\overline{\sigma'^2\_MTB_{i,t-1}}$	-0.000**	
	(-2.293)	
$\overline{\sigma'^2\_LEV_{i,t-1}}$	0.173***	
	(5.100)	
$\overline{\gamma'^2\_BETA_{i,t}}$		0.005***
		(4.449)
$\overline{\gamma'^2\_MV_{i,t-1}}$		0.003*
		(1.832)
$\overline{\gamma'^2\_MTB_{i,t-1}}$		0.000
		(0.066)
$\overline{\gamma'^2\_LEV_{i,t-1}}$		0.070**
		(2.438)
$DENSITY_{i,t}$	0.001**	0.000
	(2.199)	(1.619)
$NO\_FIRMS_{i,t}$	-0.000	-0.001***
	(-1.395)	(-3.252)
$IND\_CLUSTER_{i,t}$	0.043***	-0.062
	(4.178)	(-1.735)
Constant	0.004	0.081***
	(1.107)	(6.044)
Observations	1,048	1,048
R-squared	0.458	0.212
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.447	0.196

Table 7 Alternative Commonalities Outcomes - Investment Analysis

Table 7 reports results of estimating equation (1) using the investment matrix as alternative outcome measures for commonalities among local firms. The dependent variable of column (1), (2), and (3) is $\sigma\_INVEST_{i,t}$, $\sigma\_R\&D_{i,t}$, and $\sigma\_CAPEX_{i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

VARIABLES	Dependent Variable		
	(1) $\sigma\_INVEST_{i,t}$	(2) $\sigma\_R\&D_{i,t}$	(3) $\sigma\_CAPEX_{i,t}$
$NO\_NEWS_{i,t}$	-0.013***	0.000	-0.016***
	(-5.812)	(0.114)	(-11.067)
$\sigma'\_OPCASH_{i,t}$	0.218***	0.184***	0.015
	(10.529)	(8.380)	(1.252)
$\sigma'\_MV_{i,t-1}$	-0.005	0.005	-0.003
	(-1.453)	(0.826)	(-1.005)
$\sigma'\_MTB_{i,t-1}$	0.001*	0.001*	0.000
	(2.154)	(1.939)	(1.504)
$\sigma'\_LEV_{i,t-1}$	-0.010	0.003	-0.005
	(-0.594)	(0.195)	(-0.590)
$MEAN\_RETURN_{i,t}$	0.007	0.012	0.008
	(0.518)	(0.797)	(0.655)
$DENSITY_{i,t}$	-0.000	-0.000	0.000
	(-0.809)	(-1.296)	(0.952)
$NO\_FIRMS_{i,t}$	0.000*	0.000***	0.000
	(2.083)	(3.942)	(0.081)
$IND\_CLUSTER_{i,t}$	0.055***	0.041**	0.031***
	(3.822)	(2.197)	(3.021)
Constant	0.039***	0.024	0.038***
	(4.916)	(1.768)	(6.298)
Observations	1,049	521	1,048
R-squared	0.327	0.405	0.149
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.312	0.379	0.130

Table 8 Within versus Across Industry Commonalities Test – Investment Analysis

Table 8 reports results of the association between the number of local newspapers and within- versus across-industry investment commonalities. Panel A reports the result for total investment, and the dependent variable of column (1) and (2) is $\overline{\sigma^2\_INVEST_{i,t}}$ and $\overline{\gamma^2\_INVEST_{i,t}}$, respectively. Panel B (C) reports the result for commonalities of R&D (Capital) expenditures, and the dependent variable of column (1) and (2) is $\overline{\sigma^2\_R\&D_{i,t}}$ ($\overline{\sigma^2\_CAPEX_{i,t}}$) and $\overline{\gamma^2\_R\&D_{i,t}}$ ($\overline{\gamma^2\_CAPEX_{i,t}}$), respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Within versus Across Industry Commonalities Test – Total Investment

	Dependent Variable	
VARIABLES	(1) Within Industry Commonalities $\overline{\sigma^2\_INVEST_{i,t}}$	(2) Across Industry Commonalities $\overline{\gamma^2\_INVEST_{i,t}}$
$NO\_NEWS_{i,t}$	-0.001***	-0.000
	(-3.270)	(-1.102)
$\overline{\sigma'^2\_OPCASH_{i,t}}$	0.129***	
	(4.662)	
$\overline{\sigma'^2\_MV_{i,t-1}}$	0.003***	
	(6.751)	
$\overline{\sigma'^2\_MTB_{i,t-1}}$	0.000	
	(1.442)	
$\overline{\sigma'^2\_LEV_{i,t-1}}$	0.023	
	(1.324)	
$\overline{\gamma'^2\_OPCASH_{i,t}}$		0.068***
		(6.330)
$\overline{\gamma'^2\_MV_{i,t-1}}$		-0.000***
		(-3.076)
$\overline{\gamma'^2\_MTB_{i,t-1}}$		0.000
		(0.070)
$\overline{\gamma'^2\_LEV_{i,t-1}}$		-0.004
		(-1.354)
$MEAN\_RETURN_{i,t}$	-0.000	0.001
	(-0.006)	(0.634)
$DENSITY_{i,t}$	0.000	-0.000
	(0.009)	(-1.117)
$NO\_FIRMS_{i,t}$	-0.000	-0.000
	(-0.172)	(-0.588)
$IND\_CLUSTER_{i,t}$	0.019***	-0.006***
	(6.274)	(-5.500)
Constant	-0.005***	0.006***
	(-4.982)	(17.498)
Observations	1,049	1,049
R-squared	0.396	0.186
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.383	0.168

Table 8 Continued

Panel B: Within versus Across Industry Commonalities Test – R&D Expenditure

VARIABLES	Dependent Variable (1) Within Industry Commonalities $\overline{\sigma^2\_R\&D_{i,t}}$	Dependent Variable (2) Across Industry Commonalities $\overline{\gamma^2\_R\&D_{i,t}}$
$NO\_NEWS_{i,t}$	-0.001*	0.001
	(-2.100)	(1.507)
$\overline{\sigma'^2\_OPCASH_{i,t}}$	0.063***	
	(5.024)	
$\overline{\sigma'^2\_MV_{i,t-1}}$	0.000	
	(0.443)	
$\overline{\sigma'^2\_MTB_{i,t-1}}$	0.000**	
	(2.895)	
$\overline{\sigma'^2\_LEV_{i,t-1}}$	0.018	
	(1.260)	
$\overline{\gamma'^2\_OPCASH_{i,t}}$		0.062***
		(9.357)
$\overline{\gamma'^2\_MV_{i,t-1}}$		0.000
		(1.201)
$\overline{\gamma'^2\_MTB_{i,t-1}}$		0.000
		(0.238)
$\overline{\gamma'^2\_LEV_{i,t-1}}$		-0.005**
		(-3.005)
$MEAN\_RETURN_{i,t}$	0.002	0.000
	(0.851)	(0.260)
$DENSITY_{i,t}$	-0.000*	-0.000*
	(-1.794)	(-1.917)
$NO\_FIRMS_{i,t}$	0.000***	-0.000*
	(4.570)	(-2.112)
$IND\_CLUSTER_{i,t}$	0.016***	-0.006
	(5.123)	(-1.645)
Constant	-0.002**	0.004***
	(-2.882)	(4.463)
Observations	521	521
R-squared	0.458	0.287
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.434	0.256

Table 8 Continued

Panel C: Within versus Across Industry Commonalities Test – Capital Expenditure

VARIABLES	Dependent Variable (1) Within Industry Commonalities $\overline{\sigma^2\_CAPEX_{i,t}}$	Dependent Variable (2) Across Industry Commonalities $\overline{\gamma^2\_CAPEX_{i,t}}$
NO_NEWS$_{i,t}$	-0.001***	-0.001***
	(-6.338)	(-5.459)
$\overline{\sigma'^2\_OPCASH_{i,t}}$	-0.007***	
	(-4.295)	
$\overline{\sigma'^2\_MV_{i,t-1}}$	0.001***	
	(9.172)	
$\overline{\sigma'^2\_MTB_{i,t-1}}$	0.000	
	(0.082)	
$\overline{\sigma'^2\_LEV_{i,t-1}}$	0.010*	
	(2.160)	
$\overline{\gamma'^2\_OPCASH_{i,t}}$		0.006*
		(2.113)
$\overline{\gamma'^2\_MV_{i,t-1}}$		-0.000*
		(-2.124)
$\overline{\gamma'^2\_MTB_{i,t-1}}$		0.000
		(1.002)
$\overline{\gamma'^2\_LEV_{i,t-1}}$		-0.000
		(-0.070)
MEAN_RETURN$_{i,t}$	0.000	0.001
	(0.367)	(0.878)
DENSITY$_{i,t}$	0.000**	-0.000
	(2.207)	(-1.299)
NO_FIRMS$_{i,t}$	-0.000*	-0.000
	(-1.848)	(-0.477)
IND_CLUSTER$_{i,t}$	0.007***	-0.001
	(9.699)	(-1.391)
Constant	-0.002***	0.002***
	(-6.351)	(6.961)
Observations	1,048	1,048
R-squared	0.242	0.082
Year FE	YES	YES
Cluster by Year	YES	YES
Adjusted R-squared	0.225	0.0622

Table 9 Difference-in-Difference Analysis

Table 9 reports results of the difference-in-difference analysis. The dependent variable of column (1), (2), and (3) in Panel A is $\sigma\_BETA_{k,i,t}$, $\sigma\_ERETURN_{k,i,t}$, and $\sigma\_VRETURN_{k,i,t}$, respectively. The dependent variable of column (1), (2), and (3) in Panel B is $\sigma\_INVEST_{k,i,t}$, $\sigma\_R\&D_{k,i,t}$, and $\sigma\_CAPEX_{k,i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Beta (Return) Commonalities

VARIABLES	Dependent Variable		
	(1) $\sigma\_BETA_{k,i,t}$	(2) $\sigma\_ERETURN_{k,i,t}$	(3) $\sigma\_VRETURN_{k,i,t}$
$TREAT_{k,i,t}$	0.011	-0.051**	-0.047**
	(0.225)	(-2.484)	(-2.256)
$TREAT_{k,i,t}*POST_{k,i,t}$	-0.020	0.048*	0.052*
	(-0.310)	(1.669)	(1.778)
$POST_{k,i,t}$	0.038	-0.044**	-0.046**
	(0.829)	(-2.188)	(-2.221)
$\sigma'\_BETA_{k,i,t}$		0.044***	0.039***
		(4.553)	(4.124)
$\sigma'\_MV_{k,i,t-1}$	0.013	0.020**	0.021**
	(0.650)	(2.189)	(2.304)
$\sigma'\_MTB_{k,i,t-1}$	0.005***	0.001*	0.001*
	(2.864)	(1.719)	(1.880)
$\sigma'\_LEV_{k,i,t-1}$	0.389***	0.173***	0.193***
	(2.963)	(2.987)	(3.242)
$DENSITY_{i,t}$	0.001***	0.000***	0.000***
	(4.511)	(4.652)	(4.564)
Constant	0.650***	0.229***	0.231***
	(13.583)	(10.241)	(10.126)
Observations	1,112	1,040	1,056
R-squared	0.048	0.082	0.079
Adjusted R-squared	0.0417	0.0746	0.0723

Table 9 Continued

Panel B: Investment Commonalities

VARIABLES	Dependent Variable		
	(1) $\sigma\_INVEST_{k,i,t}$	(2) $\sigma\_R\&D_{k,i,t}$	(3) $\sigma\_CAPEX_{k,i,t}$
$TREAT_{k,i,t}$	-0.004	0.007	-0.006*
	(-0.942)	(0.626)	(-1.953)
$TREAT_{k,i,t}*POST_{k,i,t}$	0.013**	-0.003	0.009**
	(2.077)	(-0.212)	(2.151)
$POST_{k,i,t}$	-0.010**	0.007	-0.009***
	(-2.235)	(0.677)	(-3.035)
$\sigma'\_BETA_{k,i,t}$	0.199***	0.168***	0.019*
	(12.035)	(5.884)	(1.707)
$\sigma'\_MV_{k,i,t-1}$	-0.004**	0.001	-0.002*
	(-2.030)	(0.139)	(-1.750)
$\sigma'\_MTB_{k,i,t-1}$	0.001**	0.001	0.001**
	(2.410)	(1.026)	(2.264)
$\sigma'\_LEV_{k,i,t-1}$	0.040***	0.030	0.037***
	(3.067)	(1.067)	(4.052)
$MEAN\_RETURN_{k,i,t}$	-0.009*	0.015	-0.012***
	(-1.664)	(1.276)	(-2.940)
$DENSITY_{i,t}$	0.000***	0.000**	0.000**
	(3.419)	(2.242)	(2.340)
Constant	0.028***	0.015	0.029***
	(5.984)	(1.309)	(8.614)
Observations	960	200	952
R-squared	0.219	0.289	0.065
Adjusted R-squared	0.212	0.255	0.0562

Table 10 Alternative Approach of Calculating Local Newspaper Numbers

Table 10 reports results using an alternative approach of calculating local newspaper numbers, as described in Graph B. The dependent variable of column (1), (2), and (3) in Panel A is $\sigma\_BETA_{i,t}$, $\sigma\_ERETURN_{i,t}$, and $\sigma\_VRETURN_{i,t}$, respectively. The dependent variable of column (1), (2), and (3) in Panel B is $\sigma\_INVEST_{i,t}$, $\sigma\_R\&D_{i,t}$, and $\sigma\_CAPEX_{i,t}$, respectively. All variables are defined in Appendix A. The corresponding t-statistics are reported in the parentheses below each coefficient. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Beta (Return) Commonalities

VARIABLES	Dependent Variable		
	(1)	(2)	(3)
	$\sigma\_BETA_{i,t}$	$\sigma\_ERETURN_{i,t}$	$\sigma\_VRETURN_{i,t}$
$NO\_NEWS2_{i,t}$	-0.054***	-0.020***	-0.021***
	(-4.870)	(-5.035)	(-4.978)
$\sigma'\_BETA_{i,t}$		0.027***	0.032***
		(4.041)	(5.575)
$\sigma'\_MV_{i,t-1}$	0.026	0.028**	0.023**
	(0.918)	(2.674)	(2.191)
$\sigma'\_MTB_{i,t-1}$	-0.000**	-0.000	-0.000
	(-2.226)	(-1.200)	(-1.371)
$\sigma'\_LEV_{i,t-1}$	0.188***	0.114***	0.105***
	(4.734)	(3.177)	(3.121)
$DISTANCE_{i,t}$	0.003***	0.001***	0.001***
	(4.942)	(3.789)	(3.514)
$NO\_FIRMS_{i,t}$	-0.003***	-0.001**	-0.001**
	(-3.255)	(-2.592)	(-2.495)
$IND\_CLUSTER_{i,t}$	-0.028	-0.012	-0.010
	(-0.326)	(-0.340)	(-0.223)
Constant	0.900***	0.215***	0.219***
	(17.932)	(7.571)	(7.057)
Observations	1,059	1,045	1,048
R-squared	0.354	0.288	0.271
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.341	0.274	0.256

Table 10 Continued

Panel B: Investment Commonalities

VARIABLES	Dependent Variable		
	(1) $\sigma\_INVEST_{i,t}$	(2) $\sigma\_R\&D_{i,t}$	(3) $\sigma\_CAPEX_{i,t}$
$NO\_NEWS2_{i,t}$	-0.016***	0.001	-0.019***
	(-5.818)	(0.215)	(-10.671)
$\sigma'\_OPCASH_{i,t}$	0.216***	0.184***	0.015
	(10.658)	(8.574)	(1.196)
$\sigma'\_MV_{i,t-1}$	-0.006*	0.005	-0.005
	(-1.965)	(0.877)	(-1.584)
$\sigma'\_MTB_{i,t-1}$	0.001**	0.001*	0.000
	(2.201)	(1.904)	(1.618)
$\sigma'\_LEV_{i,t-1}$	-0.008	0.003	-0.003
	(-0.460)	(0.200)	(-0.365)
$MEAN\_RETURN_{i,t}$	0.007	0.012	0.008
	(0.467)	(0.800)	(0.625)
$DENSITY_{i,t}$	-0.000	-0.000	0.000
	(-0.622)	(-1.295)	(1.440)
$NO\_FIRMS_{i,t}$	0.000*	0.000***	-0.000
	(2.082)	(3.817)	(-0.180)
$IND\_CLUSTER_{i,t}$	0.057***	0.041*	0.032***
	(3.835)	(2.119)	(3.088)
Constant	0.041***	0.024*	0.040***
	(5.124)	(1.807)	(6.403)
Observations	1,049	521	1,048
R-squared	0.327	0.405	0.138
Year FE	YES	YES	YES
Cluster by Year	YES	YES	YES
Adjusted R-squared	0.312	0.379	0.120