Social Connectedness and Local Stock Return Comovement

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Abstract

We explore the role of social connectedness in explaining the stock return comovement with the local portfolio. Using the Facebook Social Connectedness Index, we find the firms headquartered in the county with the higher average social connectedness with other counties exhibit lower local return comovement. Further, we explore the relationships between county-level social capital and social connectedness in affecting the local return comovement. Consistent with the information view of comovement (Veldkamp, 2006), we find the effects of social connectedness on local return comovement are more pronounced among the firms with higher pricing difficulties or during the periods with lower information production.

JEL Codes*:* G12, G14, G41
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1. Introduction

The emergence of social media reshapes how people behave and interact with each other. Using the real friendship data derived from the social media platform, Facebook, researchers show ample evidence that social interactions would affect information processing and economic decisions (see, e.g., Bailey, Cao, Kuchler, and Strobel, 2018; Kuchler et al., 2021) and even the pricing of the stocks (see., e.g., Bali et al., 2021; Hirshleifer et al., 2021). On the other hand, researchers show that stocks tend to comove with the market or certain groups of stocks sharing similar characteristics (e.g., Barberis, Shleifer, and Wurgler, 2005; Kumar, Page and Spalt, 2013; Grullon, Underwood, and Weston, 2014) and these comovements cannot be explained by fundamentals. Especially, Pirinsky and Wang (2006) show that firms comove within geographic clusters, based on corporate headquarters. Inspired by the recent development of social interaction data, this paper explores the role of social connectedness for corporate headquarters in explaining the patterns of local return comovement.

Based on the theoretical work of Veldkamp (2006) and Bikhchandani, Hirshleifer, and Welch (1992, 1998), we posit the primary hypothesis that the local return comovement is weaker for the firms headquartered in the regions of high social connectedness. Firms located in the regions with higher social connectedness with other regions are more visible to the entire population of investors through the higher volume of social interactions. Therefore, they are more likely to be held by a wide variety of people. However, the firms headquartered in the low social connectedness regions are less visible and those regions experience a lower level of information diffusion with outside regions. Consequently, they are more likely to be held by the local investors and investors tend to aggregate the local information to price those stocks, which eventually leads to a higher level of local stock comovement.

Using the Facebook Social Connectedness Index (SCI) dataset, we provide empirical evidence suggesting the negative effect of social connectedness in the corporate headquarters on the local return comovement, which is consistent with the main hypothesis. This result is also economically meaningful that a one-standard-deviation increase of average social connectedness in the county of the firm headquarters would lead to a 78.61% decrease in the level of local return comovement. Meanwhile, the social interactions might lead to the shift for the stocks from local comovement to market comovement. Specifically, a one-standard-deviation increase of *LOG(SCI)* contributes to a 22.2% increase in the market beta and these results are robust across different specifications or alternative return synchronicity metrics.

Next, we investigate the relationship between social capital and social connectedness. Social capital is the resource that emerged from trust and social ties to encourage cooperation within society (Coleman, 1990; Putnam, 1993, 2000; Servaes and Tamayo, 2017). We find the firms headquartered in the low social capital regions exhibit higher local comovement, while external social interactions are able to mitigate the effects of within-county social capital on local return comovement.

Lastly, we find evidence supporting the information-driven view of comovement (Veldkamp, 2006). The effect of social connectedness is more pronounced among firms with higher pricing difficulties or during periods of lower economic growth or higher market uncertainty. Social interaction through the social media platform would act as the alternative mechanism to facilitate the information transmission, and hence it exhibits greater effects on the price patterns of those stocks when there isn't sufficient information to price the stocks with higher pricing difficulties or during the periods with lower information production due to the recessions or higher information uncertainty.

This paper contributes to the literature on both social interactions and stock comovement. Firstly, it joins the fast-growing empirical literature that investigates the role of social interactions on the investment decision and the pricing of stocks (e.g., Kuchler et al., 2021; Bali et al., 2021; Hirshleifer et al., 2021). We find the social interactions would affect the visibility of the stocks and the investor behavior of information aggregation, which consequently is reflected in the pattern of stock comovement. Secondly, we add to the literature on stock comovement and suggest that social interaction could act as another channel to influence the pattern of stock comovement. Our paper supports the view of Veldkamp (2006) in terms of information-driven comovement and provides an extra explanation on local return comovement discovered by Pirinksky and Wang (2006). We suggest the social connectedness of the corporate headquarters would affect the level of local return comovement and the effects are more pronounced among stocks with higher pricing difficulties or during the periods of low information production.

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. Literature Review and Hypothesis Development

Ample evidence suggests asset returns would comove beyond the threshold implied by their fundamentals. Veldkamp (2006) models a market with high information processing costs, with rational investors only willing to purchase a subset of information for certain assets. This model then forecasts the information-driven price comovement as investors use this common information subset to price assets. Empirically, return comovement has been found around events including 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 an initial public offering or seasoned equity offering (Grullon, Underwood, and Weston, 2014), the same active mutual fund owners (Antón and Polk, 2014), or same sell-side analyst coverage (Muslu, Rebello, and Xu, 2014). Brockman, Liebenberg, and Schutte (2010) confirm the information-driven view by examining return comovement across business cycles and they find the countercyclical patterns of comovement which suggests the comovement is weak during the expansion phase with a high level of information production. Hameed, Morck, Shen, and Yeung (2015) further support the prediction of Veldkamp (2006) 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 the 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. Eun, Wang, and Xiao (2014) in a global setting find that stocks exhibit stronger comovement in countries with a higher level of tightness or collectivism in their cultures, consistent with previous findings of information-induced comovement (Veldkamp, 2006; Barberis et al., 2005; Kumar et al, 2013). 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.

People are likely to be influenced by others within the social networks through the social learning mechanism, which thus affects their information aggregation and decision making. Bikhchandani, Hirshleifer, and Welch (1992, 1998) develop the theory of "information cascade" that an individual observes and follows the behavior of predecessors irrespective of the individual's private information which results in the localized conformity and fragility of mass behaviors. However, economists face the empirical challenge to measure social interactions.

Bailey, Cao, Kuchler, Stroebel, and Wong (2018) introduce the novel social connectedness measure, Social Connectedness Index (SCI), based on friendship links on Facebook and they show social connectedness is correlated with cross-state trading activities, patent citations and migration flows. Thus, researchers are able to examine the causal effect of social interactions on economic decisions, including housing (Bailey, Cao, Kuchler, and Strobel, 2018), mortgage choices (Bailey, Dávila, Kuchler, and Stroebel, 2019), urban commuting flows (Bailey, Farrell, Kuchler, and Stroebel, 2020), international trade (Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel, 2021), and flood insurance decisions (Hu, 2022), due to the expansion of data availability.

Social connectedness also plays a role in the investment decision and the pricing of stocks. Kuchler et al. (2021) find that institutional investors tend to invest in the firms in the more socially connected regions, measured by the SCI between the headquarter county of the institution and the headquarter county of the firm. Moreover, firms headquartered in the counties with greater social proximity to capital exhibit higher valuation and liquidity. Bali et al. (2021) investigate the effect of social interactions on the lottery anomaly. They find that retail net purchases of lottery stocks are higher for firms located in high average SCI regions and the lottery anomaly returns are higher for the stocks with headquarters in higher average SCI regions. The possible explanation is that the social transmission of the information that lottery stocks would earn extremely high returns leads to greater retail demand and overvaluation for lottery stocks, which is consistent with Han et al. (2022). Hirshleifer et al. (2021) examine the relationship between social connectedness and earnings announcement

returns. Firms located in the areas with higher degrees of social network centrality, derived from SCI, exhibit greater investor attention, stronger immediate price and trading volume reactions to earnings announcements, and weaker post-earnings announcement drifts. They argue that this suggests that the higher centrality of social networks contributes to a faster speed of information diffusion across different investors.

This paper investigates the role of social connectedness on stock local return comovement. Building on the view of information-driven comovement (Veldkamp, 2006) and the social learning mechanism of the social interaction (Bikhchandani et al., 1992), we posit that the firm-specific information is aggregated and diffused more rapidly if the firm is located in the area with higher social connectedness, which contributes the lower degree of return comovement with the local portfolio. This leads to the first hypothesis

H1: The local return comovement is weaker for the firms headquartered in the regions of high social connectedness.

To further examine and confirm the informational role of social interaction, we further hypothesize that the negative effect of social connectedness on local return comovement is more pronounced among the firms which exhibit higher pricing difficulties or during the period of a higher level of market uncertainty or a lower level of information production. Therefore, we form the following two hypotheses.

H2: The effect of social connectedness on local return comovement is more pronounced among the firms with higher pricing difficulties.

H3: The effect of social connectedness on local return comovement is more pronounced during periods of higher market uncertainty or economic recessions.

3. Data and Methodology

First, following Pirinsky and Wang (2006), we estimate the local stock return comovement. Our study focuses on U.S. domestic common stocks over the period from 2001 to 2021, 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, Fairhurst, and Serfling, 2020) point out the issue of backfilling in headquarter location from COMPUSTAT. Thus, we obtain the historical headquarters data from the column of business address in the header of 10K/Q filings[1].

To have the consistent scope of local comovement and SCI metrics, we define the firm's region by the county of its headquarter. Then, we construct the local portfolio for each county, and we require each county to have at least 5 firms and 2 industries (by 2-digit SIC codes). The local portfolio return, $\boldsymbol{R_{i,t}^{LOC}}$, for firm $\boldsymbol{i}$ in month $\boldsymbol{t}$ is the equally weighted return of the county portfolio based on corporate headquarters, after excluding the return of the firm $\boldsymbol{i}$. We also calculate the equally weighted industry portfolio return, $\boldsymbol{R_{i,t}^{IND}}$, for each firm $\boldsymbol{i}$, similar to the process of estimating local portfolio return. Lastly, $\boldsymbol{R_{t}^{MKT}}$ is the excess return of the value-weighted market portfolio in month $\boldsymbol{t}$. We regress Model (1) for each firm and the coefficient, $\boldsymbol{\beta^{LOC}}$, is expected to capture the degree of comovement of return on the firm with other local firms' returns in the same county.

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

We collect the county-pair Facebook SCI data as of August 2020 from Bailey, Cao, Kuchler, Stroebel, and Wong (2018) and the Facebook Data for Good Program[2]. As is described by Kuchler and Stroebel (2021), the SCI measure captures the relative number of friendship links between each county pair. As in Equation (2), the SCI between county *i* and *j* ($\boldsymbol{SCI_{i,j}}$) equals the number of Facebook friendship links between users living in county *i* and *j* ($\boldsymbol{FB\ Friendship_{i,j}}$) divided by the product of the number of Facebook users in county *i* and

[1] 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/.

[2] Detailed data could be download via the following link, https://dataforgood.facebook.com/dfg/tools/social-connectedness-index#accessdata

j ($\boldsymbol{FB\ Users_i \times FB\ Users_j}$), then the value is scaled between 1 and one billion. Then, the social connectedness for the firm's headquarter i is estimated as the natural logarithm of average SCI between county i and every other county k. We assume the SCI metrics are relatively stable over time and the county-level social connectedness $\boldsymbol{LOG(SCI)_i}$, is able to capture the speed of diffusion of firm-specific information from the firm's headquarters.

$$\boldsymbol{SCI_{i,j} = \frac{FB\ Friendship_{i,j}}{FB\ Users_i \times FB\ Users_j}} \qquad \textbf{(2)}$$

In order to investigate the role of social interaction on local return comovement, we run the following annual cross-sectional Model (3).

$$\boldsymbol{\beta_{i,t}^{LOC} = b_0 + b_1 LOG(SCI)_i + \Gamma * Controls_{i,t-1} + Industry\ FEs + State\ FEs + Year\ FEs + u_{i,t}} \qquad \textbf{(3)}$$

A set of lagged control variables are included in Model (3) to account for firm-level characteristics including *SIZE*, *MARKET-TO-BOOK*, *ROA*, *LEVERAGE*, *ADVERTISEMENT*, *DIVIDEND YIELD*, *NO OF SHAREHOLDERS*, *INSTITUTIONAL OWNERSHIP*, *NO OF ANALYSTS*, and *ANALYST DISPERSION*, and county-level characteristics including *POPULATION*, *PERSONAL INCOME*, and *INVESTMENT INCOME*. Bailey, Cao, Kuchler, Stroebel, and Wong (2018) argue that over 60% of FB friends would reside within 100 miles. To isolate the effect of geographic concentration, we add one additional control variable, $\boldsymbol{LOCAL\_100_i}$, which is the number of counties, within a radius of 100 miles from county i, scaled by 100. Table A1 provides a detailed description of the variables used in this paper. Industry fixed effects (determined by 2-digit SIC codes) are expected to capture the unobservable time-invariant patterns in each industry, and state fixed-effects are expected to capture the unobservable time-invariant pattern in each state, and year fixed effects are included to capture the time trends. Standard errors are clustered by firms in the regression.

Table 1 shows the summary statistics for the main variables used in the baseline cross-sectional regressions. All continuous variables are winsorized at 1% and 99%, the stock returns exhibit a positive relationship with the local portfolio with the average *Local Beta* equal to 0.147, which is consistent with Pirinsky and Wang (2006). Table 2 presents the correlation matrix and the correlation coefficient between *Local Beta* and *LOG(SCI)* equals -0.136, which supports the first hypothesis that local return comovement is negatively related to the average level of social connectedness in the region where the firm locates.

[Insert Table 1 About Here]

[Insert Table 2 About Here]

4. Main Results

4.1. Baseline Regressions

To examine the first hypothesis, we run the baseline cross-sectional regressions of local return on social connectedness measures as described in Model (3). Table 3 suggests that the coefficients on *LOG(SCI)* are negative across all specifications. Column 5 of Table 3 shows that the coefficient on *LOG(SCI)* is -0.216 and negatively significant at the 1% level after controlling the firm characteristics, county-specific variables, and fixed effects. The effect of regional social connectedness on the return comovement with the local portfolio is also economically substantial. A one-standard-deviation increase of *LOG(SCI)* in the county of the firm headquarter would lead to a 78.61% (= -0.216*0.535/0.147) decrease in local return comovement.

Interestingly, the coefficients of *LOCAL_100* are positively significant in Columns 3 to 5 of Table 5. *LOCAL_100* measures the geographic concentration for the county where the firm is headquartered, which is the number of other counties, within a radius of 100 miles from the headquarter county, scaled by 100. The positive coefficients on *LOCAL_100* suggest that the firms located in the highly geographically concentrated areas exhibit a higher degree of local return comovement as the firm-specific information is slowly diffused outside the scope of its headquarter. This further supports the view of Veldkamp (2006) in terms of the information-driven comovement.

Moreover, the signs of the coefficients on control variables are consistent with Pirinsky and Wang (2006). Column 5 of Table 3 shows the local return comovement is more pronounced among small and less profitable firms or firms with lower analyst coverage or higher analyst dispersion. Since it is hard to value the firms with a higher level of information asymmetry, investors tend to use common regional-specific information to price these stocks which leads to the higher local return comovement. Furthermore, the coefficient on *INVESTMENT INCOME* is negatively significant at 1% ($\boldsymbol{b_{INVESTMENT} = -0.004}$) , which suggests the firms located in the regions with higher investor sophistication exhibit lower local return comovement, which is consistent with previous studies (Pirinsky and Wang, 2006; Brown et al., 2008).

Overall, our finding supports the first hypothesis that the firms headquartered in the regions of high social connectedness exhibit a lower degree of local return comovement. This result supports the information-driven view of comovement (Veldkamp, 2006) that the transmission speed of firm-specific information is slower in the area of low social connectedness, therefore the stocks in the region of low social connectedness are more likely to be priced by the common set of regional information.

[Insert Table 3 About Here]

4.2. Market Beta and Return Synchronicity

Building on the findings of Table 3, we further explore the relationship between social connectedness and market return comovement by replacing the local beta with the market beta in Model (3). Table 4 suggests the shift from local return comovement to market return comovement for the firms located in the high social connectedness region. The coefficients on *LOG(SCI)* are positively significant across all specifications and the Column (5) suggests that a one-standard-deviation increase of *LOG(SCI)* would lead to 0.07 (=0.136*0.535) unit or 22.2% (=0.136*0.535/0.328) increase in the market beta. Combining the results in Tables 3 and 4, we find that the information is diffused faster for the firms in high social connectedness areas, and they are more visible across all states. Consequently, those stocks are more likely to comove with the market portfolio.

[Insert Table 4 About Here]

To supplement the analysis of social connectedness, we follow previous papers (e.g., Chan et al., 2014; Chan and Chan, 2014) and estimate annual stock return synchronicity using the market model or the market model with industry returns. Stock return synchronicity is the alternative market comovement metric that measures the level of systematic volatility relative to idiosyncratic volatility (detailed descriptions of the metrics, *SYNCH_1* and *SYNCH_2*, are provided in Table A1). Consistent with the results in Table 4, Column (6) of Table 5 shows that the firms headquartered in the high social connectedness regions exhibit greater stock return synchronicity ($\boldsymbol{b_{LOCAL(SCI)} = 0.137, p < 0.05}$), and their stocks are more likely to comove with the market portfolio, after controlling the firm and regional characteristics and fixed effects.

This sub-section supplements the results of baseline regressions. The stocks of the firms located in the counties with higher social interactions are more visible, and they exhibit greater market comovement and less local comovement. On the other hand, the stock of the firm headquartered in the low social connectedness regions is less visible for the investors who reside far from the corporate headquarter. Moreover, the group of those remote investors is unable to acquire information through social interaction. As a consequence, those stocks exhibit greater local comovements.

[Insert Table 5 About Here]

4.3. Social Capital and Social Connectedness

In this section, we examine the relationship between social capital and social connectedness. Social capital is viewed as the resource that emerged from trust and social ties to encourage cooperation in society, which consequently facilitates the production of socially efficient outcomes (Coleman, 1990; Putnam, 1993, 2000; Servaes and Tamayo, 2017). There is a growing literature showing the economic impacts of social capital (e.g., Guiso, Sapienza and Zingales, 2004; Jha and Cox, 2015; Hasan, Hoi, Wu and Zhang, 2017a, 2017b; Gupta, Raman, and Shang, 2018; Hoi, Wu and Zhang, 2019; Huang and Shang, 2019) and firms located in the regions with high social capital exhibit lower cost of equity, lower leverage, and lower loan spreads. Overall, the social capital measures internal social ties within the counties, which might affect the regional level of information production and discovery, while social connectedness measures the overall level of external social interactions with other areas.

We obtain the county-level social capital data developed by Rupasingha, Goetz, and Freshwater (2006) from the Northeast Regional Center for Rural Development (NRCRD) of Pennsylvania State University[3]. Then, we backfill the social capital measures for the missing year using the values in the preceding year with available data following Hasan et al. (2017a, 2017b)[4]. Then, we present the spatial distribution of county-level social connectedness and average social capital om Figure 1 and 2. Even though the plains areas exhibit both high social capital and social connectedness, we observe the differences in spatial distributions in the areas including east and west coasts. Table A2 provides an example of the counties that exhibits

[3] Social capital data is available via the following website, https://aese.psu.edu/nercrd/community/social-capital-resources.

[4] Following Jha and Cox (2015), we also perform tests using the linear interpolated social capital metrics and obtain the similar results.

different levels of social capital and social connectedness.

[Insert Figure 1 About Here]

[Insert Figure 2 About Here]

Panel A of Table 6 suggests that the social capital of the corporate headquarter is negatively correlated with the local return comovement. One plausible explanation would be the local bias as investors in low-trust regions exhibit higher local bias in investing in local firms (see, Wei and Zhang, 2020; Shao and Wang, 2021). Therefore, the firms headquartered in the low social capital regions are more likely to be held by the group of local investors and thus comove with the local portfolio. However, both Panel A and B show external social interactions can mitigate these effects of social capital. The negatively significant coefficient on the interaction term ($\boldsymbol{b_{LOCAL(SCI)*Low\ Social\ Capital} = -0.065, p < 0.01}$) in Column (2) of Table 6 Panel B implies that the effect of social connectedness on local comovement is 37.8%(=-0.065/-0.172) higher for the low social capital group than the high social capital group. For the firms located in the regions with low internal social ties, the degree of local return comovement is more likely to be affected by the external social interactions with other regions.

[Insert Table 6 About Here]

4.4. Firm Heterogeneity

Then, we examine the role of social connectedness conditional on firm heterogeneity. We hypothesize that the effects of social connectedness are more pronounced for the firms which are hard to value. In Table 7, we use the specifications similar to Bernile et al. (2015) and interact the social connectedness measure with a set of indicator variables for firm characteristics including *Young* (below-median firm age), *Small* (below-median *Size*), *Low Coverage* (below-median *NO OF ANALYSTS*), *Low Priced* (below median stock price in the fiscal year-end), *Skewed* (above-median idiosyncratic stock return skewness estimated over the last year using the market model), *Volatile* (above-median idiosyncratic stock return volatility estimated over the last year using the market model), *Illiquid* (above-median average Amihud (2002) illiquidity ratio over the last year), *R&D intensive* (above-median R&D expenses scaled by total assets), and *High AnalystDisp* (above median *ANALYST DISPERSION*).

Table 7 suggests that the effects of social interaction on local comovement are more pronounced among young or low-priced stocks with skew returns, or among the firms which have higher R&D expenses or higher analyst dispersion. Furthermore, we estimate the proxy for pricing difficulty, *PDScore* as the sum of indicator variables described above. *High_PDScore* is the indicator variable that equals one if the *PDScore* is above the median in each year and zero otherwise. Column (10) of Table 7 shows that the coefficient on the interaction term is -0.041 ($\boldsymbol{p < 0.05}$) and implies that the effect of *LOG(SCI)* on *Local Beta* is 21.2% (=-0.041/-0.193) higher for the stocks which are hard to value. This is consistent with our second hypothesis. Intuitively, the information for the stocks with higher *PD_Score* would be harder to process for the investors. The consequent information processing and diffusion are more likely to be influenced by social interactions.

[Insert Table 7 About Here]

Additionally, we consider the geographic dispersion of the firms as the additional metric since firms might be more difficult to value if they operate across the states. Consistent with García and Norli (2012), we estimate the geographic dispersion variable, *NSTATE*, which is the number of different states mentioned in the firm's 10-K filings and we also find the external social interactions are able to mitigate the negative effects of geographic dispersion on local comovement. Detailed regressions are presented in Table A3.

4.5. The role of Social Connectedness across Time Periods

Lastly, we assess the third hypothesis by investigating the effects of social connectedness conditional on the overall economic growth and market uncertainty. Brockman et al (2010) find the countercyclical patterns of comovement, which suggests the comovement is weak during the expansion phase with a high level of information production. We employ State Coincident Indexes 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 economic conditions including nonfarm payroll employment, average hours worked, the unemployment rate, and real wages. Then, we create the indicator variable, *Low EconGrowth*, which *is* equal to one if the average monthly growth in U.S. Coincident Index (Crone and Clayton-Matthews, 2005) in the year is below the median over the sample period and zero otherwise. Column (1) of Table 8 shows the greater effect of social interactions on comovement during the periods with slow economic growth ($\boldsymbol{b_{LOCAL(SCI)*Low\ Econ\ Growth} = -0.065, p < 0.01}$). Similarly, we construct the dummy variable, *High VIX*, which equals one is the average daily VIX in the year is above the median over the sample period and zero otherwise, and we find the results consistent with the third hypothesis that the effect of social connectedness on local return comovement is more pronounced during the periods of higher market uncertainty. The results are both statistically and economically significant. The effect of *LOG(SCI)* on *Local Beta* is 19% (=-0.037/-0.195) higher during the period of higher market uncertainty. To sum up, social interactions play a more pronounced role in influencing stocks' local return comovement when the overall level of information production is low.

[Insert Table 8 About Here]

5. Conclusion

This paper examines the role of social connectedness in explaining the stock's comovement with the local portfolio. By aggregating the county-pair Facebook social connectedness index data, we find the firms located in the county with high average social connectedness exhibit a lower degree of local return comovement. Economically speaking, A one-standard-deviation increase of *LOG(SCI)* in the county of the firm's headquarter would lead to a 78.61% decrease in local return comovement. To supplement the analysis, we estimate the market beta and stock return synchronicity and show the shift from local comovement to market comovement for the firms located in the higher social interaction regions.

Furthermore, this paper explores the relationship between external social interactions and social capital which captures the county-level internal social ties. We find the firms headquartered in the low social capital regions are more likely to comove with the local portfolio while external social interactions can mitigate these effects of social capital. Specifically, the results suggest the effect of social connectedness on local comovement is 37.8% higher for the low social capital group than the high social capital group.

Lastly, this study investigates the effect of social interactions on stock local return comovement conditional on firm characteristics and time periods. We find the evidence consistent with the view of information-driven comovement (Veldkamp, 2006) that the effect of *LOG(SCI)* is more pronounced among the firms with higher pricing difficulties or during the period of lower economic growth or higher market uncertainty.

Overall, this paper highlights the importance of social connectedness in explaining and understanding the patterns of stock comovement. The emergence of social media facilitates social interactions and information transmissions across the states, which affects the visibility of the firms, the speeds of information diffusion, and hence the behavior of stock prices.

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Appendix

Table A1 Variable Descriptions

Variables	Definition
A. FB Connectedness Variables	
LOG(SCI)	Natural logarithm of average Facebook Social Connectedness Index (SCI) for the county where the firm is headquartered
LOCAL_100	The number of counties, which are within a radius of 100 miles from the county where the firm is headquartered, scaled by 100
B. Main Dependent Variables	
Local Beta	Estimated coefficient on local portfolio returns at firm-year level, estimated from Equation (1) using daily returns.
Market Beta	Estimated coefficient on market returns at firm-year level, estimated from Equation (1) using daily returns.
SYNCH_1	$Log(R^2/1\text{-}R^2)$ and R^2 is the coefficient of determination from the following model $\boldsymbol{R_t = \alpha_i + \beta^{MKT} R_t^{MKT} + \varepsilon_{i,t}}$
SYNCH_2	$Log(R^2/1\text{-}R^2)$ and R^2 is the coefficient of determination from the following model $\boldsymbol{R_t = \alpha_i + \beta^{MKT} R_t^{MKT} + \beta^{IND} R_t^{IND} + \varepsilon_{i,t}}$
C. Control Variables	
SIZE	Natural logarithm of total asset (AT).
MARKET-TO-BOOK	Market-to-book equity ratio (PRCC_F*CSHO/CEQ).
ROA	Earnings before interest, taxes, depreciation, and amortization (EBITDA) over total assets (AT).
LEVERAGE	Total outstanding debt (DLC+DLTT) over total assets (AT).
ADVERTISEMENT	Advertising expenditure (XAD) over total assets (AT) and we set missing value to zero.
DIVIDEND YIELD	Annual cash dividend payout (DV) over the market capitalization (PRCC_F*CSHO)
NO OF SHAREHOLDERS	Natural logarithm of the number of shareholders (CSHR).
INSTITUTIONAL OWNERSHIP	The percentage of outstanding shares owned by institutional investors.
NO OF ANALYSTS	Natural logarithm of one plus the number of analysts following.
ANALYST DISPERSION	Standard deviation of earnings forecasts (STDEV) scaled by the absolute value of the mean earnings forecast (MEANEST).
POPULATION	Population of the county where the firm is headquartered.
PERSONAL INCOME	Per capita personal income for the firm headquarter's MSA, scaled by 1,000.
INVESTMENT INCOME	Per capita personal income derived from dividends, interest, and rent for the firm headquarter's MSA, scaled by 1,000.
SOC_CAP	Proxy of the level of social capital for the county where the firm is headquartered
NSTATE	Number of different states mentioned in firm's 10-K filings

Table A2 Examples of High/Low Social Capital and SCI Counties

	FB Connectedness	
Social Capital	Low	High
Low	Los Angeles County, CA	Dallas County, TX
High	New York County, NY	Denver County, CO

Table A3 Geographical Dispersion and Social Connectedness

This table reports the regressions of local return comovement on social connectedness measures and geographical dispersion measures. The dependent variable, *Local Beta*, is the estimated coefficient of local portfolio returns at the firm-year level, from Equation (1) using daily returns. Panel A reports the regressions after adding the geographic dispersion variable, *NSTATE*, which is the number of different states mentioned in the firm's 10-K filings. Panel B reports the regression of local return comovement on social connectedness, conditional on the firm's geographical dispersion. *Low GeoDisp* is the indicator variable that equals one if *NSTATE* is below the median in each year and zero otherwise. The same set of control variables in Column (5) of Table 4 are 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<0.01, ** p<0.05, * p<0.1.

Panel A Adding NSTATE as Additional Control Variable

	(1)	(2)	(3)	(4)
VARIABLES		Local Beta		
LOG(SCI)	**-0.196***** **(-5.44)**	**-0.241***** **(-5.86)**	**-0.180***** **(-4.97)**	**-0.211***** **(-5.17)**
NSTATE	**-0.005***** **(-5.96)**	**-0.036***** **(-3.17)**	**-0.002**** **(-2.32)**	**-0.024**** **(-2.43)**
LOG(SCI)*NSTATE		**0.004***** **(2.78)**		**0.003**** **(2.26)**
CONTROLS	NO	NO	YES	YES
CONSTANT	YES	YES	YES	YES
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES
OBSERVATIONS	12,744	12,744	12,744	12,744
ADJ R-SQUARED	0.204	0.204	0.202	0.203

Panel B Role of SCI on Local Beta, Conditional on Geographical Dispersion

	(1)	(2)
VARIABLES	Local Beta	
LOG(SCI)	**-0.220***** **(-7.81)**	**-0.210***** **(-7.63)**
Low GeoDisp	**0.137** **(0.87)**	**0.131** **(0.87)**
LOG(SCI)*Low GeoDisp	**-0.017** **(-0.87)**	**-0.017** **(-0.92)**
CONTROLS	NO	YES
CONSTANT	YES	YES
IND FE	YES	YES
YEAR FE	YES	YES
STATE FE	YES	YES
Observations	24,897	24,897
Adjusted R-squared	0.099	0.136

Table 1 Summary Statistics

This table reports the descriptive statistics 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.

VARIABLES	(1) N	(2) MEAN	(3) SD	(4) P5	(5) P50	(6) P95
LOG(SCI)	24,916	7.699	0.535	6.884	7.611	8.626
LOCAL_100	24,916	0.372	0.226	0.030	0.380	0.880
Local Beta	24,916	0.147	0.418	-0.390	0.060	0.985
Market Beta	24,916	0.328	0.565	-0.683	0.365	1.178
SYNCH_1	24,916	-1.504	1.387	-4.164	-1.270	0.287
SYNCH_2	24,916	-1.061	1.212	-3.380	-0.915	0.665
SIZE	24,916	7.269	1.991	4.195	7.138	10.790
MARKET-TO-BOOK	24,916	3.173	5.062	0.498	2.245	10.360
ROA	24,916	-0.008	0.218	-0.447	0.039	0.187
LEVERAGE	24,916	0.253	0.245	0.000	0.212	0.729
ADVERTISEMENT	24,916	0.013	0.033	0.000	0.000	0.078
DIVIDEND YIELD	24,916	0.011	0.017	0.000	0.000	0.045
NO OF SHAREHOLDERS	24,916	0.465	2.335	-3.270	0.436	4.424
INSTITUTIONAL OWNERSHIP	24,916	0.705	0.249	0.209	0.755	1.028
NO OF ANALYSTS	24,916	2.120	0.668	1.099	2.079	3.219
ANALYST DISPERSION	24,916	0.081	0.205	0.000	0.021	0.333
POPULATION	24,916	1673000.000	1807000.000	348755.000	1090000.000	5208000.000
PERSONAL INCOME	24,916	93919.000	89809.000	15454.000	61587.000	286912.000
INVESTMENT INCOME	24,916	12.260	8.040	5.264	9.902	29.620

Table 2 Correlation Matrix

This table reports the correlation matrix for the variables used in the cross-sectional regressions.

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Local Beta	(1)	1.000															
LOG(SCI)	(2)	-0.136	1.000														
LOCAL_100	(3)	-0.132	0.532	1.000													
SIZE	(4)	-0.225	0.146	0.189	1.000												
MARKET-TO-BOOK	(5)	0.000	-0.073	-0.037	-0.047	1.000											
ROA	(6)	-0.117	0.135	0.107	0.345	-0.007	1.000										
LEVERAGE	(7)	-0.021	0.117	0.090	0.241	-0.046	0.000	1.000									
ADVERTISEMENT	(8)	0.009	-0.012	0.000	-0.083	0.074	0.046	-0.018	1.000								
DIVIDEND YIELD	(9)	-0.107	0.146	0.165	0.400	-0.068	0.147	0.131	-0.003	1.000							
NO OF SHAREHOLDERS	(10)	-0.176	0.161	0.209	0.546	-0.032	0.211	0.047	-0.006	0.336	1.000						
INSTITUTIONAL OWNERSHIP	(11)	-0.044	0.039	0.028	0.304	0.031	0.321	0.071	-0.003	-0.021	0.004	1.000					
NO OF ANALYSTS	(12)	-0.165	-0.001	0.031	0.629	0.111	0.221	0.078	0.047	0.130	0.326	0.332	1.000				
ANALYST DISPERSION	(13)	0.084	-0.014	-0.039	-0.128	-0.028	-0.127	0.032	0.002	-0.024	-0.084	-0.121	-0.151	1.000			
POPULATION	(14)	0.099	-0.333	-0.426	-0.022	-0.005	-0.006	-0.011	0.006	-0.020	-0.087	0.007	-0.021	0.053	1.000		
PERSONAL INCOME	(15)	0.127	-0.429	-0.377	0.028	0.027	-0.035	0.002	0.028	-0.007	-0.134	0.042	0.024	0.050	0.886	1.000	
INVESTMENT INCOME	(16)	0.040	-0.273	0.041	0.095	0.067	-0.077	0.022	0.067	0.036	-0.107	0.071	0.081	-0.005	-0.073	0.332	1.000

Table 3 Baseline Regressions

This table reports the regressions of local return comovement on social connectedness measures. The dependent variable, *Local Beta*, is the estimated coefficient of local portfolio returns at the firm-year level, from Equation (1) using daily returns. 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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES			Local Beta		
LOG(SCI)	**-0.225*** **	**-0.230*** **	**-0.245*** **	**-0.249*** **	**-0.216*** **
	(-8.11)	**(-8.26)**	**(-9.02)**	**(-9.25)**	**(-7.88)**
LOCAL_100		**0.132**	**0.190** **	**0.195** **	**0.141* **
		(1.61)	**(2.43)**	**(2.51)**	**(1.82)**
SIZE			-0.036***	-0.024***	-0.025***
			(-9.42)	(-5.35)	(-5.67)
MARKET-TO-BOOK			-0.001*	-0.001	-0.001
			(-1.68)	(-0.93)	(-1.07)
ROA			-0.099***	-0.098***	-0.099***
			(-3.92)	(-3.90)	(-3.97)
LEVERAGE			0.056***	0.047**	0.049**
			(2.83)	(2.39)	(2.50)
ADVERTISEMENT			-0.075	-0.035	-0.063
			(-0.53)	(-0.25)	(-0.45)
DIVIDEND YIELD			0.547**	0.419*	0.416*
			(2.32)	(1.78)	(1.75)
NO OF SHAREHOLDERS			-0.005	-0.005*	-0.005
			(-1.61)	(-1.67)	(-1.53)
INSTITUTIONAL OWNERSHIP				0.011	0.015
				(0.51)	(0.72)
NO OF ANALYSTS				-0.041***	-0.040***
				(-4.18)	(-4.16)
ANALYST DISPERSION				0.074***	0.072***
				(4.34)	(4.22)
POPULATION					-0.000***
					(-5.29)
PERSONAL INCOME					0.000***
					(6.09)
INVESTMENT INCOME					-0.004***
					(-3.09)
CONSTANT	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES
OBSERVATIONS	24,913	24,913	24,913	24,913	24,913
ADJ R-SQUARED	0.099	0.100	0.128	0.131	0.136

Table 4 Market Beta

This table reports the regressions of market beta on social connectedness measures. The dependent variable, Market *Beta*, is the estimated coefficient of market returns at the firm-year level, from Equation (1) using daily returns. 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.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Market Beta in Local Model				
LOG(SCI)	**0.094****	**0.100****	**0.140*****	**0.134*****	**0.136*****
	(2.39)	**(2.50)**	**(4.41)**	**(4.23)**	**(4.14)**
LOCAL_100		**-0.145**	**-0.264*****	**-0.250*****	**-0.284*****
		(-1.25)	**(-2.83)**	**(-2.67)**	**(-2.75)**
SIZE			0.094***	0.099***	0.099***
			(20.50)	(17.72)	(17.61)
MARKET-TO-BOOK			0.006***	0.006***	0.006***
			(6.36)	(6.75)	(6.77)
ROA			0.426***	0.391***	0.394***
			(14.67)	(13.31)	(13.37)
LEVERAGE			-0.008	-0.014	-0.014
			(-0.35)	(-0.60)	(-0.58)
ADVERTISEMENT			0.390**	0.463***	0.454***
			(2.31)	(2.76)	(2.69)
DIVIDEND YIELD			-0.822**	-0.736**	-0.742**
			(-2.57)	(-2.28)	(-2.31)
NO OF SHAREHOLDERS			-0.000	0.002	0.002
			(-0.02)	(0.47)	(0.50)
INSTITUTIONAL OWNERSHIP				0.114***	0.114***
				(4.64)	(4.61)
NO OF ANALYSTS				-0.044***	-0.044***
				(-4.11)	(-4.15)
ANALYST DISPERSION				-0.067***	-0.066***
				(-3.01)	(-2.96)
POPULATION					0.000
					(1.45)
PERSONAL INCOME					-0.000
					(-1.58)
INVESTMENT INCOME					0.003**
					(2.12)
CONSTANT	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES
OBSERVATIONS	24,913	24,913	24,913	24,913	24,913
ADJ R-SQUARED	0.096	0.096	0.217	0.220	0.221

Table 5 Stock Return Synchronicity

This table reports the regressions of stock return synchronicity on social connectedness measures. The dependent variables are stock return synchronicity measures, SYNCH_1 and SYNCH_2 estimated from Equations (2) and (3) using daily returns. 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.

	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES		SYCH_1			SYCH_2	
LOG(SCI)	**0.139***	**0.133***	**0.133***	**0.152****	**0.156****	**0.137****
	(1.90)	**(1.89)**	**(1.86)**	**(2.34)**	**(2.55)**	**(2.20)**
LOCAL_100	**-0.339**	**-0.258**	**-0.424***	**-0.090**	**-0.025**	**-0.127**
	(-1.54)	**(-1.22)**	**(-1.83)**	**(-0.45)**	**(-0.13)**	**(-0.61)**
SIZE	0.329***	0.277***	0.277***	0.298***	0.228***	0.230***
	(31.65)	(24.33)	(24.31)	(32.53)	(21.94)	(21.99)
MARKET-TO-BOOK	0.018***	0.017***	0.016***	0.012***	0.010***	0.010***
	(8.31)	(7.99)	(7.97)	(6.18)	(5.41)	(5.42)
ROA	0.874***	0.625***	0.629***	0.495***	0.273***	0.277***
	(14.66)	(10.78)	(10.84)	(10.14)	(5.82)	(5.89)
LEVERAGE	-0.246***	-0.243***	-0.243***	-0.306***	-0.290***	-0.291***
	(-4.98)	(-5.02)	(-5.00)	(-6.86)	(-6.68)	(-6.71)
ADVERTISEMENT	-0.827*	-0.589	-0.609	-0.938**	-0.802**	-0.800**
	(-1.90)	(-1.37)	(-1.42)	(-2.38)	(-2.08)	(-2.08)
DIVIDEND YIELD	-1.470**	0.089	0.124	-1.283**	0.344	0.378
	(-2.09)	(0.13)	(0.18)	(-2.17)	(0.60)	(0.66)
NO OF SHAREHOLDERS	-0.009	0.006	0.006	-0.001	0.013**	0.013**
	(-1.47)	(0.96)	(1.00)	(-0.15)	(2.44)	(2.42)
INSTITUTIONAL OWNERSHIP		0.924***	0.925***		0.834***	0.833***
		(17.06)	(17.04)		(17.47)	(17.42)
NO OF ANALYSTS		-0.010	-0.014		0.069***	0.066***
		(-0.46)	(-0.63)		(3.42)	(3.25)
ANALYST DISPERSION		-0.330***	-0.326***		-0.296***	-0.292***
		(-7.62)	(-7.53)		(-8.22)	(-8.10)
POPULATION			-0.000			0.000
			(-0.69)			(0.82)
PERSONAL INCOME			0.000			-0.000
			(0.20)			(-1.54)
INVESTMENT INCOME			0.002			0.004
			(0.76)			(1.45)
CONSTANT	YES	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES	YES
OBSERVATIONS	24,913	24,913	24,913	24,913	24,913	24,913
ADJ R-SQUARED	0.432	0.454	0.454	0.479	0.505	0.505

Table 6 Social Capital and Social Connectedness

This table reports the regressions of local return comovement on social connectedness measures and social capital measures. The dependent variable, *Local Beta*, is the estimated coefficient of local portfolio returns at the firm-year level, from Equation (1) using daily returns. Panel A reports the regressions after adding the social capital variable, *SOC_CAP*, which is the proxy of the level of social capital for the county where the firm is headquartered. Panel B reports the regression of local return comovement on social connectedness, conditional on county-level social capital. *Low Social Capital* is the indicator variable which equals one if the social capital of the county where the firm is headquartered is below the median in each year and zero otherwise. The same set of control variables in Column (5) of Table 4 are 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<0.01, ** p<0.05, * p<0.1.

Panel A Adding Social Capital as Additional Control Variable

	(1)	(2)	(3)	(4)
VARIABLES		Local Beta		
LOG(SCI)	**-0.221*****	**-0.182*****	**-0.183*****	**-0.113*****
	(-7.87)	**(-6.33)**	**(-6.64)**	**(-4.05)**
SOC_CAP	**-0.006**	**-0.498*****	**-0.039*****	**-0.761*****
	(-0.54)	**(-3.34)**	**(-3.48)**	**(-5.09)**
LOG(SCI)*SOC_CAP		**0.065*****		**0.094*****
		(3.35)		**(4.88)**
CONTROLS	NO	NO	YES	YES
CONSTANT	YES	YES	YES	YES
IND FE	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES
OBSERVATIONS	24,913	24,913	24,913	24,913
ADJ R-SQUARED	0.099	0.100	0.137	0.139

Panel B Role of SCI on Local Beta, Conditional on Social Capital

	(1)	(2)
VARIABLES	Local Beta	
LOG(SCI)	**-0.193*****	**-0.172*****
	(-6.65)	**(-5.94)**
Low Social Capital	**0.425****	**0.495*****
	(2.40)	**(3.01)**
LOG(SCI)*Low Social Capital	**-0.057****	**-0.065*****
	(-2.52)	**(-3.06)**
CONTROLS	NO	YES
CONSTANT	YES	YES
IND FE	YES	YES
YEAR FE	YES	YES
STATE FE	YES	YES
Observations	24,897	24,897
Adjusted R-squared	0.100	0.137

Table 7 The Effect of Social Connectedness on Local Comovement, Conditional on Firm Heterogeneity

This table reports the regressions of local return comovement on social connectedness measures, conditional on firm characteristics. The dependent variable, *Local Beta,* is the estimated coefficient of local portfolio returns at the firm-year level, from Equation (1) using daily returns. Social connectedness measure is interacted with a set of indicator variables for firm characteristics including *Young* (below-median firm age), *Small* (below-median *Size*), *Low Coverage* (below-median *NO OF ANALYSTS*), *Low Priced* (below median stock price in the fiscal year-end), *Skewed* (above-median idiosyncratic stock return skewness estimated over the last year using the market model), *Volatile* (above-median idiosyncratic stock return volatility estimated over the last year using the market model), *Illiquid* (above-median average Amihud (2002) illiquidity ratio over the last year), *R&D intensive* (above-median R&D expenses scaled by total assets), *High AnalystDisp* (above median *ANALYST DISPERSION*). We estimate the proxy for pricing difficulty, *PDScore* as the sum of indicator variables described above. *High_PDScore* is the indicator variable that equals one if the *PDScore* is above the median in each year and zero otherwise. The same set of control variables in Column (5) of Table 4 are 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<0.01, ** p<0.05, * p<0.1.

			FirmChar_Dummy		
	Young	Small	Low Coverage	Low Priced	Skewed
	(1)	(2)	(3)	(4)	(5)
VARIABLES			Local Beta		
Log(SCI)	-0.194***	-0.205***	-0.230***	-0.184***	-0.169***
	(-6.48)	(-6.83)	(-7.66)	(-6.33)	(-5.96)
FirmChar_Dummy	0.351**	0.169	-0.134	0.427***	0.658***
	(2.14)	(1.06)	(-0.99)	(3.45)	(5.32)
Log(SCI)*FirmChar_Dummy	**-0.042****	**-0.020**	**0.022**	**-0.045*****	**-0.074*****
	(-2.01)	**(-1.00)**	**(1.29)**	**(-2.83)**	**(-4.71)**
CONTROLS	YES	YES	YES	YES	YES
CONSTANT	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES
Observations	24,897	24,897	24,897	24,897	24,422
Adjusted R-squared	0.138	0.137	0.137	0.143	0.147
			FirmChar_Dummy		
	Volatile	Illiquid	R&D Intensive	High AnalystDisp	High_PDScore
	(6)	(7)	(8)	(9)	(10)
VARIABLES			Local Beta		
Log(SCI)	-0.224***	-0.220***	-0.166***	-0.201***	-0.193***
	(-7.92)	(-7.30)	(-6.10)	(-7.24)	(-6.60)
FirmChar_Dummy	-0.117	0.032	0.729***	0.279**	0.395***
	(-1.39)	(0.22)	(4.80)	-2.52	(2.69)
Log(SCI)*FirmChar_Dummy	**0.015**	**0.007**	**-0.095*****	**-0.032****	**-0.041****
	(1.38)	**(0.35)**	**(-4.90)**	**(-2.25)**	**(-2.17)**
CONTROLS	YES	YES	YES	YES	YES
CONSTANT	YES	YES	YES	YES	YES
IND FE	YES	YES	YES	YES	YES
YEAR FE	YES	YES	YES	YES	YES
STATE FE	YES	YES	YES	YES	YES
Observations	24,422	24,451	24,897	24,897	24,422
Adjusted R-squared	0.138	0.142	0.139	0.138	0.143

Table 8 The Effect of Social Connectedness on Local Comovement, Conditional on Time

This table reports the regressions of local return comovement on social connectedness measures, conditional on time periods. The dependent variable, *Local Beta*, is the estimated coefficient of local portfolio returns at the firm-year level, from Equation (1) using daily returns. Social connectedness measure is interacted with a set of indicator variables for time period including *Low EconGrowth* and *High VIX*. *Low EconGrowth* is the indicator variable equal to one if the average monthly growth in U.S. Coincident Index (Crone and Clayton-Matthews, 2005) in the year is below the median over the sample period and zero otherwise. *High VIX* is the indicator variable equal to one is the average daily VIX in the year is above the median over the sample period and zero otherwise. The same set of control variables in Column (5) of Table 4 are 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<0.01, ** p<0.05, * p<0.1.

	(1)	(2)	(3)	(4)
VARIABLES	Local Beta			
Log(SCI)	-0.203***	-0.208***	-0.190***	-0.195***
	(-7.27)	(-7.45)	(-6.82)	(-7.02)
Low EconGrowth	0.131*			
	(1.83)			
Log(SCI)*Low EconGrowth	**-0.018***	**-0.018***		
	(-1.96)	**(-1.94)**		
High VIX			0.292***	
			(3.85)	
Log(SCI)*High VIX			**-0.037*****	**-0.037*****
			(-3.85)	**(-3.80)**
CONTROLS	YES	YES	YES	YES
CONSTANT	YES	YES	YES	YES
IND FE	YES	YES	YES	YES
YEAR FE	NO	YES	NO	YES
STATE FE	YES	YES	YES	YES
Observations	24,897	24,897	24,897	24,897
Adjusted R-squared	0.136	0.136	0.136	0.137

Figure 1 Distribution of FB Connectedness

This figure presents the spatial distribution of the Facebook Social Connectedness Index (SCI) for 10 decile groups. A darker area in the figure indicates a higher rank in SCI.

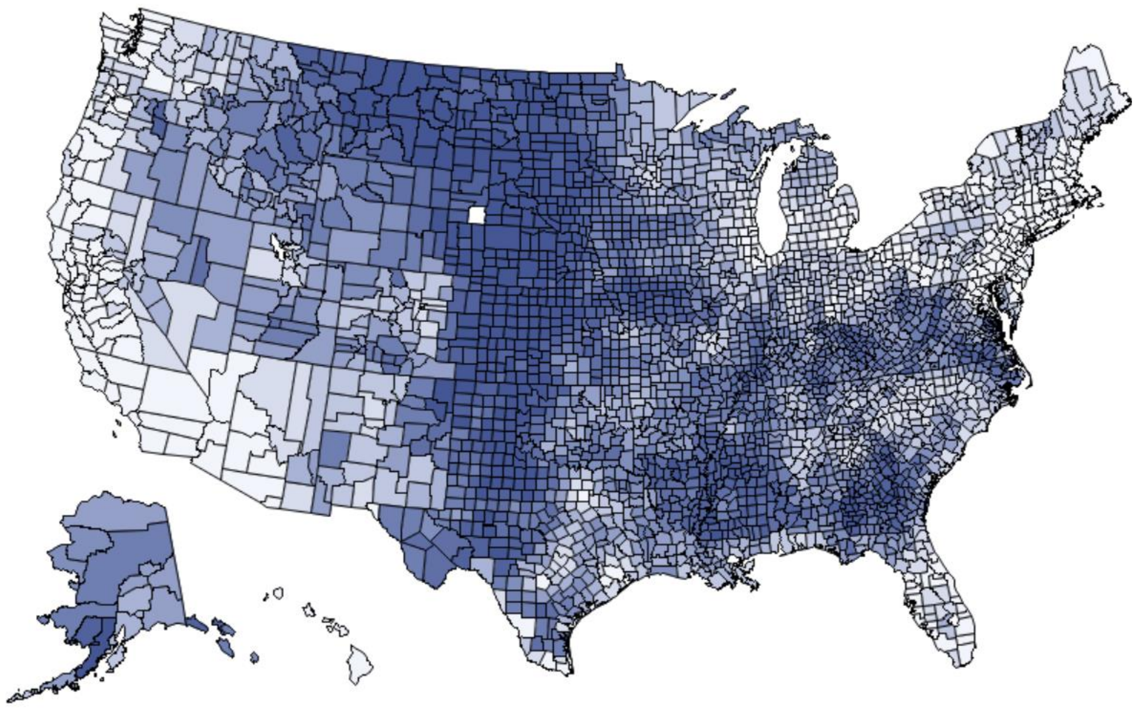

Figure 2 Distribution of Social Capital

This figure presents the spatial distribution of *SOC_CAP* for 10 decile groups. A darker area in the figure indicates a higher rank in *SOC_CAP*.