Social connectedness and mergers and acquisitions*

Giang Nguyen
Department of Accounting and Corporate Finance, emlyon business school
23 Av. Guy de Collongue, 69130 Écully, France
gnguyen@em-lyon.com

Thu Ha Nguyen
Department of Banking and Finance, Monash University
Caulfield East, Victoria 3145, Australia
hannah.nguyen@monash.edu

Hung Pham
Department of Banking and Finance, Monash University
Caulfield East, Victoria 3145, Australia
harry.pham@monash.edu

Abstract

Using a comprehensive dataset of social connectedness between U.S. counties, we document that an acquirer tends to select a target in its socially connected counties. The finding remains robust after controlling for the geographical proximity between the acquirer and the target and the social ties between their executives, and it withstands endogeneity concerns. Cross-sectionally, this impact is more pronounced when the target is less visible. We examine the deal characteristics and find that stock is preferred as the method of payment when the acquirer and the target are socially connected. Social connectedness reduces deal premiums and lowers advisory fees and the number of advisors. In addition, we find a positive association between social connectedness and the acquirer's short- and long-term performance, suggesting that social networks carry value-relevant soft information.

Keywords: *Social connectedness; acquisition likelihood; merger and acquisition; soft information.*

JEL Classification: G34

* We thank participants at the 2021 Monash Brown Bag Seminar (Melbourne, Australia), the 2022 Midwest Finance Association (MFA) annual meeting (Chicago, USA), Zhe An, Li Ge, Isaac Hacamo, Thanh Huynh, Anh Pham, John Vaz for helpful discussions and suggestions. We thank Yuelin Wang for her excellent research assistance.

Social connectedness and mergers and acquisitions

Abstract

Using a comprehensive dataset of social connectedness between U.S. counties, we document that an acquirer tends to select a target in its socially connected counties. The finding remains robust after controlling for the geographical proximity between the acquirer and the target and the social ties between their executives, and it withstands endogeneity concerns. Cross-sectionally, this impact is more pronounced when the target is less visible. We examine the deal characteristics and find that stock is preferred as the method of payment when the acquirer and the target are socially connected. Social connectedness reduces deal premiums and lowers advisory fees and the number of advisors. In addition, we find a positive association between social connectedness and the acquirer's short- and long-term performance, suggesting that social networks carry value-relevant soft information.

Keywords: *Social connectedness; acquisition likelihood; merger and acquisition; soft information.*

JEL Classification: G34

"In standard analyses of economic behavior, people interact only impersonally via trading orders and observation of market price. A missing chapter in our understanding of finance consists of the social processes that shape economic thinking and behavior."

—David Hirshleifer, Presidential Address of the American Finance Association, at the 2020 Annual Meeting in San Diego, California

1. Introduction

The new era of information technology has revolutionized the way people connect and interact with each other. A reliable measure of social connections, long sought in the literature, has recently become available with the emergence of big data coupled with technological development (Bailey, Cao, Kuchler, Stroebel, and Wong, 2018a; Bailey, Cao, Kuchler, and Stroebel, 2018b; Bailey, Dávila, Kuchler, and Stroebel, 2019). This has led to a growing body of research in the social finance field that examines the impact of social connectedness on economic outcomes. On one hand, previous literature has documented a positive impact of social connectedness on economic outcomes. For example, Bailey et al. (2018a) find that social connectedness has a positive impact on patent citations and trade flow within the United States. Rehbein and Rother (2022) demonstrate a significant association between social connectedness and cross-county lending. On the other hand, Kuchler et al. (2022) find that while increased awareness of socially connected firms is among the main drivers of institutional investment decisions, institutional investors do not obtain proprietary information from social networks. In this paper, we add to this literature by examining the role of social connectedness in one of the most significant forms of corporate investments, i.e., mergers and acquisitions (M&As). Specifically, we explore whether acquirers are more likely to choose targets in their socially connected counties, and the implications of this practice to transaction terms and acquisition outcomes.

We obtain data on the social connectedness index from Facebook. This index reflects the strengths of social connectedness between U.S. counties, constructed as the number of Facebook friendship links between two counties after adjusting for the number of Facebook users in each county. According to Bailey et al. (2018b) and Kuchler et al. (2022), Facebook users typically use this platform to interact with their friends and acquaintances in the real world. This suggests that the social connectedness index, albeit derived from Facebook friendship ties, captures the exchange of information among friends beyond the Facebook platform. It resembles real-world connections and information exchange more closely than other online platforms, for example, Twitter, where links to non-acquaintances (i.e., uni-directional links) are not uncommon. Moreover, the enormous scale of Facebook also makes the index representative of real-world social connections in the U.S., where the information exchange can occur online or in person.[1] Using this index, Kuchler et al. (2022) find that social connections raise institutional investors' awareness about potential investment targets. Rehbein and Rother (2022) highlight that soft information generated through social ties between lenders and borrowers enhances the credit intermediation process. Under this view, in the M&A context, social connectedness can raise the acquirer's awareness of potential targets and might enter the decision-making process as value-relevant soft information.

We begin our empirical analysis by investigating whether acquirers are more likely to choose targets located in their socially connected counties. To do so, we obtain data on both actual acquisition transactions and all firms (including both public and private firms) that can serve as potential targets in a given M&A transaction. We then construct a dummy variable, *Acquisition*, that indicates an actual transaction. Following Bailey et al. (2018a), we define social connectedness as the natural logarithm of the social connectedness index, *Ln(SCI)*. We find evidence supporting the positive relation between social connectedness and the likelihood of an actual acquisition. One-standard-deviation increase in social connectedness leads to an increase of 0.48% in the likelihood that a firm

[1] Facebook is the world's largest social networking provider, with over 2.74 billion monthly active users globally as of September 30, 2020 (https://www.facebook.com/iq/insights-to-go/2740m-facebook-monthly-active-users-were-2740m-as-of-september-30).

becomes an actual M&A target. This effect is approximately 65% of the unconditional mean of *Acquisition* (0.74%).

One may be concerned that physical distance can explain the impact of social connectedness on the likelihood of an acquisition. We address this concern by controlling for (i) the logarithm of the physical distance between the acquirer and the target, and (ii) a dummy variable equal to one if the acquirer-target physical distance is within 100 kilometers. Our main results remain robust after controlling for these physical distance measurements.

Next, we explore the conditional impact of social connectedness on targets' visibility. If the positive impact of social connectedness on acquisition likelihood is attributed to the heightened awareness of the socially connected acquirer about the target, we should observe a more pronounced effect when the target is less visible to the acquirer. We construct three proxies for targets' visibility, including *Private* (a dummy variable equal to one if the target's status is private, and zero otherwise), *Ln(T_Age)* (the natural logarithm of one plus the number of years from the target's founding year to the current year), and *Small* (a dummy variable indicating a small-sized target which equals one if the target's total assets are smaller than the 25th percentile value). Overall, the results imply that social connectedness is more important in facilitating an M&A transaction when the target has lower visibility.

To address the endogeneity concern that the social connectedness between two counties is associated with unobservable factors that affect the acquisition likelihood, we adopt an instrumental variable approach. Specifically, we use Baum-Snow (2007)'s national highway data and construct two instruments for social connectedness: (i) the number of highways connecting the acquirer's and target's counties and (ii) the number of years since the commission of their first connecting highway. Our empirical results support the causal effect of social connectedness on the acquisition likelihood.

We further explore the impact of social connectedness on transaction terms. We find that stock is preferred as the method of payment when the acquirer and the target are socially connected. We attribute this finding to the soft information transmitted in the social networks, which enhances the target's knowledge about the acquirer. This, in turn, leads to the preference for stock as the method of payment, consistent with the rational payment design hypothesis (Eckbo, Makaew, and Thorburn, 2018). Additionally, we observe lower transaction premiums in socially connected transactions. This evidence supports the conjecture that socially connected bidders, benefitting from soft information transmitted in the networks, possess an information advantage about the true value of the targets, thereby acquiring the targets at a more favorable price.[2] Our next findings on the lower number of advisors and lower advisory fees are consistent with the interpretation that social networks carry soft information and make both acquirers and targets informed, thus reducing their need for external advice.

In our third set of tests, we uncover the impact of social connectedness on acquisition outcomes. On one hand, social networks could lead to homophily bias (Gompers, Mukharlyamov, and Xuan, 2016), sub-optimally diversified portfolios (Kuchler et al. 2022), or poorer decision-making (Janis, 1982; McPherson, Smith-Lovin, and Cook, 2001) due to lower due diligence standards by acquirers and neglection towards non-socially connected merger candidates (Ishii and Xuan, 2014). On the other hand, social networks could facilitate soft information transmission (see, e.g., Bailey et al., 2018a; Rehbein and Rother, 2022), thus leading to better acquisition outcomes.[3] While our data does not allow us to track precisely information flows between the acquirer and the target via social networks, the tests on the impact of social connectedness on acquisition outcomes enable us to discern the dominating channel between the homophily bias channel and the information channel in the context of M&As. We find that, in the short run, acquirers who are more socially proximate to their targets experience higher announcement returns. The effect is more pronounced when targets have higher

[2] This finding is in line with Cai and Sevilir (2012) that takeover premiums are lower when the acquirer and the target share a common director.

[3] Rehbein and Rother (2022) provides an illustration of the soft information that a loan officer could receive from social ties within the society about a loan applicant. This illustration is applicable in our context.

informational opacity proxied by analyst coverage, bid-ask spread, and classifications of high-tech firms and R&D firms.

In our final avenue of inquiry, we explore the impact of social connectedness on post–merger performance. We find that, following the completion of M&A transactions where the acquirer and target are socially connected, the acquirer achieves higher long–term buy–and–hold returns, a higher adjusted return on total assets, a higher ratio of adjusted EBIT to sales, and a higher ratio of adjusted EBIT to the market value of equity. This evidence supports our conjecture that social connections, through facilitating the transmission of knowledge between the acquirer and the target, improve the acquirer's long–term performance.

Our study makes two important contributions. First, it contributes to the existing body of literature on the impact of social connections on real economic outcomes. Bailey et al. (2018a) identify a positive relationship between social connections and patent citations, while Rehbein and Rother (2022) focus on the loan market and provide evidence of more loans, higher GDP growth, and greater employment in counties that are socially proximate to bank capital. Han, Hirshleifer, and Walden (2022) theoretically show that sociability, self–enhancing transmission, and other communication features are associated with active investment strategies. Our research offers new insights into the value of social connectedness in the context of M&As. We demonstrate that social connectedness not only improves the likelihood of an acquisition, but also influences transaction terms, and ultimately contributes to the economic value realized by the acquirer in the short- and long-term. Our findings, while being consistent with Rehbein and Rother (2022) that social networks carry value-relevant information, diverge from that of Kuchler et al. (2022), who find no evidence of superior information disseminated through social networks in the context of institutional investments. Because investment targets in Kuchler et al. (2022) are public firms, whereas targets in the M&A context are relatively small and less-known firms, the difference in our findings suggests that soft information transmitted in social networks is particularly valuable when investments are provided to small and informationally opaque firms.

Second, we add to the literature on determinants of M&A outcomes.[4] We document that social connectedness affects the likelihood of an acquisition, transaction terms, and outcomes. We offer empirical evidence to the theoretical framework developed by Sarala, Junni, Cooper, and Tarba (2016) which highlights the role of interfirm linkages in M&A outcomes. Our paper is related to the works by Cai and Sevilir (2012) and Ishii and Xuan (2014) that examine the value of board connections in M&A transactions.[5] However, different from Cai and Sevilir (2012) and Ishii and Xuan (2014), which measure social connections at the board level, we focus on the broader type of social connectedness, which is aggregated at the county level from a representative sample of individuals' real–world friendship. Even when the acquirer and target board members do not possess any personal connection, acquirers might obtain soft information about, for example, the existence of a good potential target and its local economic environment, via this broader type of social connections. This, in turn, affects the acquisition likelihood and performance. We distinguish our findings from those of Cai and Sevilir (2012) and Ishii and Xuan (2014) by measuring and controlling for direct social ties of board members.

The remainder of the paper is organized as follows. In section 2, we explore the impact of social connectedness on the acquisition likelihood. Section 3 examines the relation between social connectedness and transaction terms. We explore the role of social connectedness on acquisition outcomes in Section 4. We offer concluding remarks in Section 5.

[4] Some examples of these factors include geographic proximity (Uysal et al., 2008), accounting quality (Marquardt and Zur, 2014), options trading (Chan, Ge, and Lin, 2015), common auditors (Cai et al., 2016), and media connection (Hossain and Javakhadze, 2020).

[5] Cai and Sevilir (2012) find evidence that board connectedness leads to an improvement in the ROA of newly merged firms. Meanwhile, the results of Ishii and Xuan (2014) suggest that firms make bad M&A decisions when the directors and top executives of the targets and acquirers are socially connected.

2. Social connectedness and likelihood of an acquisition

2.1. *Data collection and measurement of variables*

2.1.1. *Social connectedness*

We obtain data for the social connectedness index from Facebook.[6] The index is constructed based on the friendship links between anonymized Facebook users in different U.S. counties. As of September 30, 2020, Facebook is the world's most popular social network, with more than 2.7 billion active global users monthly. It covers approximately 70% of the U.S. population, with 231 million active users. A recent survey by Duggan et al. (2016) shows that the use of Facebook by U.S.–based adult users is constant across income groups and levels of education, as well as among urban, rural, and suburban residents. According to Kuchler et al. (2022), Facebook users in the U.S. typically connect and friend users with whom they have social contacts in the real world, suggesting that Facebook is a place for real–world friends and acquaintances to exchange information online.[7]

According to Bailey et al. (2018a), the social connectedness index is measured using the geographic location information (county of residence) of Facebook users as identified by their regular IP addresses. More specifically, *(Social Connectedness Index)*$_{i,j}$ is measured as the ratio between the number of Facebook links between county i and county j, scaled by the product between the number of Facebook users in county i and county j. We then generate our main independent variable as the natural logarithm of the social connectedness index, *Ln(SCI)*$_{i,j}$.

2.1.2. *M&A transactions*

To examine the impact of social connectedness on the acquisition likelihood, it is essential to obtain data on real targets as well as data on pseudo firms that can serve as

---

[6] Data for social connectedness index can be found at https://dataforgood.fb.com/tools/social-connectedness-index.

[7] Literature suggests that Facebook networks is reflections of real-world social networks (Bailey et al. (2018a), (2018b), Bailey et al. (2019), Kuchler et al. (2022), Rehbein and Rother (2022), and Bailey et al. (2021)).

potential targets in a given M&A transaction. We utilize the Capital IQ database for this purpose as this platform provides access to comprehensive data on actual M&A transactions, encompassing both public and private M&As, and data on the universe of listed and unlisted firms.

We first collect data on actual M&A transactions from the Capital IQ database as follows:

1) Transactions are announced between 2007-2019.
2) The transaction status is either "closed" or "effective".
3) Transactions are classified as "majority", i.e., the acquisitions of the majority of ownership in target firms.
4) Both targets and acquirers are located in the U.S.
5) The transaction value is greater than $5 million.
6) The targets' industry information and location details are disclosed.

We then collect data on all U.S. firms in the same period as follows:

1) Firms are located in the U.S.
2) Firms' total assets are greater than $5 million in at least one year during the period 2007-2019.
3) Firms have information of industry and location.

For each real target firm identified in the former sample, we identify pseudo targets from the latter sample which satisfy two conditions: (1) The pseudo targets share the same industry (defined by the first 2 digits of the SIC code) with the real target; (2) the pseudo targets' information is available at the same M&A announcement year. We exclude transactions where pseudo targets are not identified. We present summary statistics for the actual transaction sample, the pseudo target sample, and the merged (actual and pseudo) sample in Panel A of Table 1.

{Insert Table 1}

As shown in Table 1, the sample with pseudo targets and the sample with actual targets have comparable acquirer characteristics. This is because we generate pseudo transactions by using acquirer information from an actual transaction and replace the information of the actual target by that of firms operating in the same industry and year. Our strategy is to maintain the same acquirer and examine how it navigates the target from a group of actual and pseudo targets through social connectedness. Real targets and pseudo targets are different in characteristics and performance. Specifically, pseudo targets are, on average, smaller in size (defined by the natural logarithm of total assets) than actual targets. Their operating performance is less negative. Pseudo targets have an average leverage ratio of 0.143, while this ratio is significantly higher for real targets (i.e., 0.385). These differences may exist because we allow all firms in the same industry and year of the actual target to serve as prospective targets. To address the differences, we control for target characteristics in our baseline regressions as well as conduct a robustness test using a sample created by stricter matching criteria, i.e., we match pseudo and actual targets by industry, year, and asset size.

2.2. *Social connectedness and the likelihood of an acquisition*

As acquirers are more aware of potential targets in their socially proximate regions thanks to information transmitted in social networks, we hypothesize that social connectedness increases the likelihood of an acquisition. We test if acquirers are indeed more likely to acquire firms located in their socially connected counties.

We first graphically demonstrate the relation between social connectedness and the likelihood of an acquisition. Figure 1 is the heatmap that depicts the values of *Ln(SCI),* measured as the natural logarithm of the social connectedness index between each U.S. county and Santa Clara county - the county that received the highest number of bids in our sample. Higher degrees of social connectedness are denoted by a darker shade. In this figure, Santa Clara is circled in red, whereas the four counties where the most bidders of Santa Clara's M&A transactions come from are circled in yellow. As shown in Figure

1, all four counties with the highest number of acquirers of Santa Clara targets are highly socially connected with Santa Clara.[8]

{Insert Figure 1}

We then conduct an empirical test of the relation between social connectedness and the likelihood of an actual acquisition using the matched sample of acquisitions with pseudo and realized targets. We construct a dummy variable, *Acquisition,* indicating an actual transaction between an acquirer *i* and a target *j* among all pseudo pairs with acquirer *i*. By design, the value of *Acquisition* is 1 for all actual transactions and 0 for all observations pertaining to the pseudo targets. We estimate the following model using linear regressions:

$$(1) \quad Acquisition_{i,j,t} = \alpha + \beta Ln(SCI)_{i,j} + \gamma Acquirer\ characteristics_{i,t} + \theta Within\ industry + Industry\ FE + Year\ FE + \varepsilon_{i,j,t}$$

where *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. We include acquirer characteristics that could affect the likelihood of an acquisition, including total assets (*Ln(A_AT)*), ROA (*A_ROA*) and leverage (*A_Leverage*). We further control for a dummy variable, *Within industry*, which is a binary variable indicating if the acquirer and the target operate in the same industry defined by CapitalIQ. Our model also includes industry and year fixed effects.[9] The standard errors are clustered at the acquirer industry. The definitions of variables are provided in Table A.1.

{Insert Table 2}

[8] Interestingly, while three of the four counties are geographically close to Santa Clara, the fourth is on the opposite side of the country from Santa Clara. This suggests that physical distance is related to social connectedness but does not fully capture all the dimensions of social connectedness.
[9] It is important to note that the social connectedness index already accounts for the difference in population across counties as it is scaled by the product of the number of Facebook users of pairwise counties.

The estimation results of Equation (1) are presented in Table 2. As shown in Model (1), the coefficient of *Ln(SCI)* is positive at 0.004 and statistically significant at the 1% level, suggesting a positive effect of social connectedness on the likelihood of being a takeover target. One-standard-deviation increase in social connectedness leads to an increase of 0.48% (= 0.004 × 1.2) in the likelihood that a firm becomes an actual takeover target. This effect is economically significant when comparing it with the unconditional mean of *Acquisition,* which is 0.70%.

We concern that geographical proximity can explain social connectedness between the acquirer and the target and simultaneously affect the acquisition likelihood, creating bias in the estimate of *Ln(SCI)*. To address this concern, we measure the precise physical distance between the acquirer and target based on the longitude and latitude of their locations' zip codes. In Model (2), we exclude *Ln(SCI)* from our regression equation and use the natural logarithm of distance (in miles) between the acquirer and the target, *Ln(Distance)*, as our main independent variable. The results indicate that acquirers are more likely to acquire physically proximate targets. In Model (3), we include both *Ln(SCI)* and *Ln(Distance)*. We find that the coefficient of *Ln(SCI)* reduces slightly in magnitude, but it remains statistically and economically significant. Meanwhile, the coefficient of *Ln(Distance)* becomes smaller in size, and is statistically weaker (i.e., it is statistically significant at the 10% level). This result suggests that physical distance can partly capture the impact of social connectedness on the acquisition likelihood. However, the impact of social connectedness extends beyond that of physical distance.[10]

Model (4) is a variation of Model (3) where we control for *Local*, a dummy variable equal to 1 if the distance between the acquirer and target is within 100 kilometers and zero otherwise. The coefficient of *Local* is 0.004 suggests an increase of 0.4% in the

[10] As illustrated in Figure 1, out of four counties exhibiting the highest number of acquirers of Santa Clara target firms, three are situated in close geographical proximity to Santa Clara. Strikingly, and the forth county is on the opposite side of the country from Santa Clara. This suggests that physical distance is related to social connectedness but does not capture all dimensions of social connectedness.

acquisition likelihood when the acquirer is within 100 kilometers of the target. *Ln(SCI)* remains positive and significant.

In Model (5), we further control for target characteristics, including total assets *(Ln(T_AT))*, ROA (*T_ROA)*, and leverage (*T_Leverage)*.[11] While the coefficient of *Ln(SCI)* falls to 0.001, it remains statistically significant at the 1% level suggesting an increase of 0.12% (= 0.001 × 1.2) in the likelihood of being a target if social connectedness raises by one standard deviation. The positive coefficient of *T_Leverage* implies that high-leveraged firms tend to be a target of an acquisition. Our results remain robust in Model (6) where we add acquirer fixed effects. Across all model specifications, the coefficient of *Same Industry* is positive and statistically significant at conventional levels, indicating the acquirer's preference for an acquisition of a target with similar technical operations, probably to reduce operational inefficiency and create synergies.

2.3. Target firms' visibility, social connectedness and likelihood of an acquisition

We attribute the positive impact of social connectedness on the likelihood of an acquisition to the increase in the awareness about targets located in socially proximate regions. If this holds true, we should observe a more pronounced effect when the target is less visible to the acquirer, i.e., when the target is a private, young, or small firm. We test this channel by introducing dummy variables measuring the target's visibility including private target, young (small in age) target, small (small in total assets) target, or immature (small in sales revenue) target and their interaction with *Ln(SCI)* to Equation (1). We report the regression results in Table 3.

{Insert Table 3}

We find evidence consistent with our conjecture. The negative and statistically significant coefficient of *Private* in Model (1) suggests that all else being equal, a private

[11] Palepu (1986) propose different variables to be included in the model of the acquisition likelihood including average excess return, accounting return on equity, growth-resources dummy, industry dummy, size, market-to-book, price-earnings ratio. Ambrose and Megginson (1992) extend Palepu (1986)'s model by incorporating measures of insider and institutional shareholdings. We are not able to include all recommended variables because our sample covers both public and private targets.

firm is less likely to be a target in an M&A transaction possibly because it is "less known" to the acquirer (Jensen, 2020). Meanwhile, the coefficient of *Ln(SCI)* × *Private* is positive and statistically significant at the 1% level. It indicates that social proximity enhances the target's visibility, leading to a greater likelihood of a private firm being a target of an acquisition.

In Model (2), we measure the target age, *Ln(T_Age),* as the natural logarithm of one plus the number of years from the founding year to the current year. Young firms often do not disclose much information to the public and do not get much media attention (Pittman and Fortin, 2004; Maskara and Mullineaux, 2011). Social networks, by transmitting information, can play a more important role in connecting acquirers to young and difficult-to-identify targets than in connecting acquirers to established and easy-to-identify firms. We document a negative and statistically significant coefficient of *Ln(SCI)* × *Ln(Age)* in Model (2) which supports our conjecture. In Model (3), we measure a firm's visibility by constructing a dummy variable *Small*, which equals one if the target's total assets are smaller than the 25^{th} percentile, and zero otherwise. We find supportive evidence that the interaction term, *Ln(SCI)* × *Small*, is positive (albeit statistically weak). Overall, the results in Table 3 suggest that social connectedness is most valuable in M&A transactions where target firms are less visible.

2.4. *Instrumented regression*

One could be concerned that the social connectedness between two counties is associated with unobservable factors that affect the acquisition likelihood. To address this endogeneity concern, we employ an instrumental variable approach. We construct two instruments for social connectedness using Baum–Snow's (2007) national system's interstate highways data. The highways were planned during World War II to improve logistics for the war efforts and were built in the aftermath of the war, partly to facilitate a quick relocation of resources during the Cold War. Our first instrument, *Ln(1+past_highways)*, is the natural logarithm of the number of highways connecting the acquirer's county and the target's county, plus one. Our second instrument measures the number of years that have passed since the construction of the first highway connecting the two counties. We define *Ln(1+first_highway_years)* as the natural logarithm of the number of years since the commission of the first highway connecting the acquirer's county and the target's county, plus one. As historical travel costs characterized by connecting highways may shape historical social ties, some of which can persist for generations, our instruments satisfy the relevance condition. Indeed, social connections appear to have emerged along highways, and they are likely to do so slowly over time. Moreover, it is unlikely that the visionary behind the establishment of the highway system which happened several decades ago were motivated by current factors driving M&A decisions today. The instruments, therefore, also satisfy the exclusion condition.

{Insert Table 4}

The regression results are presented in Table 4. Models (1) and (2) provide the first– and second–stage regression results, respectively, when *Ln(1+past_highways)* is employed as an instrument for *Ln(SCI)*, while Models (3) and (4) report the results when *Ln(1+first_highway_years)* is used as an instrument. As expected, social connectedness is greater for counties with a higher number of connecting highways. We then generate the predicted value of *Ln(SCI)* from Model (1), *Ln(SCI)_hat1*, and use it as the independent variable in Model (2). The positive and statistically significant coefficient of *Ln(SCI)_hat1* suggests that social connectedness increases the likelihood of an acquisition, even after we address the endogeneity concerns. The results remain robust in Models (3) and (4); that is, the number years since the first connecting highway is positively related to social connectedness, and the fitted value of *Ln(SCI), Ln(SCI)_hat2,* positively affects the likelihood of an acquisition.

2.5. *Additional analyses*

2.5.1. *Controlling for managerial social ties*

We further control for direct social ties between targets and acquirers in Equation (1). To construct proxies for direct social ties, we employ the BoardEx dataset. We first identify acquirers, targets, and their executives in BoardEx. We then define *Social ties* as the number of educational ties (i.e., the acquirer's executive attends the same academic institution with the target's executive in the past) and professional ties (i.e., the acquirer's executive shares the same past membership in a private or public corporate board with the target's executive, or they share the same membership in other institutions). We construct three measures of direct social ties, including (i) *Ln(Social ties),* the natural logarithm of one plus the number of social ties between the acquirer and target executives, (ii) *Social ties dummy*, a dummy variable that takes the value of one if there is at least one social tie between the acquirer and the target executives, and (iii) *Interlock,* a dummy variable equal to one if at least one executive of the target also serves as an executive of the acquirer, and zero otherwise. We control for three direct measures separately in our baseline regression and report estimation results in Table 5.

{Insert Table 5}

In all models of Table 5, the coefficient of *Ln(SCI)* is positive and significant at the 1% level, albeit its magnitude of 0.001, lower than that of 0.003 in the baseline regression. This suggests that direct social ties between the acquirer and the target only capture a portion of the impact of social connectedness on the acquisition likelihood.

2.5.2. Robustness tests

a) Alternative measures of social connectedness

We re-estimate our baseline model using alterantive measures of social connectedness: *SCI_5pct*, *SCI_10pct*, and *SCI_15pct*, which are dummy variables indicating high social connectedness using the thresholds of the top 5th percentile, 10th percentile, and 15th percentile of *Ln(SCI)*, respectively. The results are presented in the Appendix Table A.4. The coefficients of all alternative proxies for social connectedness are positive, monotonically decrease from 0.007 in Model (1) to 0.003 in Model (3), and are statistically significant at the 1% level. This evidence corroborates our previous finding that social connectedness increase the likelihood of an acquisition.

b) Alternative model specification

Due to the binary nature of the variable indicating an acquisition (*Acquisition*), one might be concerned that the linear probability model (LPM) that we employ to estimate our baseline results would generate fitted values outside the [0,1] range. We, therefore, re-estimate the baseline results using a logit model. The results in Table A.5 in the Appendix are consistent with the LPM regression results.

c) Stricter matching criteria

In the previous sections, we identify pseudo targets as firms that satisfy two conditions: i) firms operate in the same industry as the real target, and (ii) firms which have financial information at the same announcement year. One might argue that, practically, an acquirer would not consider all firms in the same industry as their prospect targets as those firms are vastly different in size. We address this concern by imposing an additional condition on the size of total assets of pseudo targets. Specifically, we require pseudo targets' total assets to be between 50% and 150% of the total assets of the actual target. This criteria leads to a significant reduction in the sample size, i.e., 39,824 observations. Due to a smaller number of pseudo targets, the unconditional mean of *Acquisition* increases to 5.67%, significantly larger than that of the previously merged sample (0.70%). The impact of social connectedness on the acquisition likelihood remains positive and statistically significant in all specifications in Table A.6. Our baseline results are not sensitive to the selection of pseudo targets.

d) Controlling for differences between acquirer and target counties

One might argue that when the acquirer and target counties share similar characteristics, an acquisition becomes more likely (Wang and Zajac, 2007). We re-estimate Equation (1) with additional control variables capturing differences between the acquirer and target counties. Specifically, we control for the absolute value of the difference between the GDP per capita of the acquirer's and the target's counties (*GDP per capita differential*) in Model (1), the natural logarithm of one plus the number of people migrating between the acquirer and the target counties (*Migration*) in Model (2), the unemployment rate difference between the acquirer's and the target's counties (*Unemployment differential*) in Model (3), and the aggregate absolute differences of industrial shares of the acquirer's and the target's counties GDP (*Industrial share differential*) in Model (4). We include all county-pair differences in Model (5). Estimation results are presented in Table 6.

{Insert Table 6}

In all models of Table 6, the coefficient of *Ln(SCI)* stays positive and significant in all specifications. This suggests that social connectedness positively affects the acquisition likelihood even when the county differences are controlled. The coefficients of variables on county differences are negative and statistically significant at conventional significant levels in Model (1) to Model (4), and negative but statistically weaker in Model (5). It suggests that the larger the difference between the acquirer and target counties in terms of GDP per capita, migration, unemployment rate, or industrial share, the less likely to observe an actual acquisition between the two counties.

Overall, the results support our conjecture that acquirers are more aware of, thus, more likely to acquire socially connected targets. Our results are robust to alternative measures of social connectedness, model specifications, stricter selection criteria for pseudo targets, and county-pair differences.

3. Social connectedness and transaction terms

In this section, we explore the impact of social connectedness on transaction terms. We start by obtaining data on actual M&A transactions between 2007 and 2019 from the Thomson SDC Platinum database.[12] We impose the following screening criteria on all M&A deals: 1) both the acquirer and the target are U.S. firms; 2) the acquirer is a public firm, while the target can be either public or private; 3) the transaction size is equal to or

[12] Compared with the Capital IQ database, Thomson SDC Platinum database provides more detailed financial information on M&A transactions. Besides, M&A data from Thomson SDC Platinum can easily be merged with CRSP and Compustat data to construct necessary variables for analyses at the transaction level.

greater than \$5 million; and 4) the transaction is not spinoff, recapitalization, self–tender, exchange offer, repurchase, acquisition of remaining interest or minority stake, or privatization, following Güner, Malmendier, and Tate (2008) and Chemmanur, He, He, and Nandy (2018). We then remove firms from the financial and utility industries, that is, those with Standard Industrial Classification (SIC) codes 4900 to 4999 and 6000 to 6999, respectively. We also remove targets missing location details (i.e., missing the zip code or address). We use zip code, zip code–county matched data, and detailed address information to identify acquirer and target counties. Furthermore, we require acquirers to have stock price information available in CRSP, to calculate announcement returns, and accounting information available in Compustat, to construct other necessary variables. Our final sample includes 3,920 transactions from 2007 to 2019. The sample distribution across years and industries is shown in Tables A.2 and A.3 in the Appendix.

3.1. Choice of payment methods

We first examine the association between social connectedness and methods of payment. Under the bidder opportunism hypothesis, stock is selected as the method of payment when the target overvalues bidder shares (Eckbo, Makaew and Thorburn, 2018). If social networks carry soft information, socially connected targets are more likely to know if bidder shares are overvalued, leading to a lower portion of stock payment. On the other hand, under the rational payment design hypothesis, when targets are more informed about bidders, they are less likely to undervalue the bidder shares, thus taking a larger stock portion (Eckbo, Makaew and Thorburn, 2018). We test the two hypotheses by estimating the following equation:

$$(2) \quad Payment\ method_{i,t} = \alpha + \beta Ln(SCI)_i + \gamma Deal\ characteristics_{i,t} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

where *Payment method* is proxied using *Stock_ratio* (The ratio of stock as the method of payment), *All_stock* (a dummy variable equal to one if the entire deal is paid with stock and zero otherwise), and *All_cash* (a dummy variable equal to one if the entire deal is paid with cash and zero otherwise). We control for deal characteristics, including *Ln(Deal value)*, *Within industry*, *Public*, *Tender*, and *Within state*, as well as acquirer characteristics, including *Ln(A_AT)*, *A_Leverage*, *A_ROA*, *A_Investment*, and *A_Q*. The definitions of variables are provided in the Appendix Table A.1. We also include industry fixed effects (defined by the 49 Fama–French industries) and year fixed effects in all specifications.

{Insert Table 7}

Table 7 shows a positive effect of *Ln(SCI)* on *Stock_ratio* and *All_stock* but a negative effect on *All_cash*, suggesting that transactions between socially connected acquirers and targets tend to use stock as the method of payment. Overall, the results are consistent with the rational payment design hypothesis that better-informed targets tend to choose stock as the method of payment.

3.2. Transaction premiums

We next analyze whether social connectedness has an impact on transaction premiums. We measure *Premium* as the natural logarithm of the ratio between the offer price and the target's stock price one week before the announcement date and estimate the following equation:

$$(3) \qquad Premium_{i,t} = \alpha + \beta Ln(SCI)_i + \gamma Deal\ characteristics_{i,t} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

{Insert Table 8}

Table 8 presents our estimation results. In Model (1), the coefficient of *Ln(SCI)* is -0.011 and statistically significant at the 10% level, suggesting that social connectedness reduces the premiums paid by acquirers. In terms of economic significance, a one–standard–deviation increase in *Ln(SCI)* leads to a decrease of 1.91% in premiums. The result suggests that bidders that are socially connected to their targets have an information advantage about the true value of the targets; therefore, they can acquire the targets at a more favorable price. The finding is consistent with the evidence in Cai and Sevilir (2012) that premiums are lower when there is a shared common director between the acquirer and the target.

In Model (2) of Table 8, we include the interaction between *Ln(SCI)* and deal size, *Ln(Deal value)*. Since large firms exhibit more information transparency (Chiang and Venkatesh, 1988; Hasbrouck, 1991; Leuz and Verrecchia, 2000), we expect the informational advantage of socially connected acquirers to be less pronounced when the target size is larger, i.e., the coefficient of the interaction term, *Ln(SCI)* × *Ln(Deal value)* to be positive. Results in Model (2) support our conjecture. The coefficient of the interaction term between *Ln(SCI)* and *Ln(Deal value)* is 0.005, statistically significant at the 10% level, indicating a less pronounced impact of *Ln(SCI)* on premiums for larger-size deals. Overall, our findings suggest that acquirers pay lower premiums when they are more informed about targets through social networks.

3.3. *Advisory service*

We next explore the impact of social connectedness on advisory fees and a number of advisors. We calculate *Ln(Advisory fees)* as the natural logarithm of the total financial advisory fees paid by both acquirers and targets, normalized by the deal size, and *Ln(Advisors)* as the natural logarithm of the total number of advisors. We examine the impact of *Ln(SCI)* on *Ln(Advisory fees)* in Model (1) and on *Ln(Advisors)* in Model (2). We also control for other factors as discussed in section 3.1 and section 3.2. The results are reported in Table 9.

{Insert Table 9}

We obtain negative and significant coefficients of *Ln(SCI)* in both models of Table 9. It indicates that acquisitions between more socially connected acquirers and targets have lower advisory fees and fewer advisors. Prior literature documents that financial advisors act as producers of credible information about M&A targets (Chemmanur and Fulghieri, 1994). They alleviate the negative impact of information asymmetry in financial markets

(Booth and Smith, 1986; Titman and Trueman, 1986). Therefore, when acquirers obtain soft information about the targets through social networks, they rely less on the input from financial advisors, thus require less advisors and pay lower advisory fees.

4. Social connectedness and acquisition outcomes

The literature on homophily shows that if an investment is driven by heightened awareness rather than superior information about the targets, it might lead to sub-optimally diversified portfolios (Kuchler et al., 2022), or poorer decision-making (Janis, 1982; McPherson, Smith-Lovin, and Cook, 2001; Gompers, Mukharlyamov, and Xuan, 2016). In the context of M&As, the acquirer may lower due diligence standards or neglect non-socially connected yet valuable targets (Ishii and Xuan, 2014). However, if the investment is driven by soft information obtained through social networks (Bailey et al., 2018a; Rehbein and Rother, 2022), we should expect to observe better outcomes. We test whether social connectedness impacts the short-term and long-term acquisition performance. We first focus on cumulative abnormal returns (CARs), then expand the analyses to long-term buy–and–hold returns and long-term operating performance. Results from these tests allow us to identify the dominating channel between the homophily bias channel and the information channel in the context of M&As.

4.1. Social connectedness and acquirer returns

4.1.1. Social connectedness and announcement returns

We measure acquirer performance in the short term as CARs over the event window of seven days, from day -3 to day 3, where day 0 is the announcement date.[13] Following Brown and Warner (1985), we measure abnormal returns using the market–adjusted model and CRSP value-weighted returns as the market benchmark.[14] We estimate the following cross-sectional regression:

---

[13] Results remain qualitatively the same when we employ other conventional event windows. Results are available upon request.

[14] This measurement is popular among M&A studies (e.g., Fuller, Netter, and Stegemoller, 2002; Harford, Humphery–Jenner, and Powell, 2012; Austin, Harris, and O'Brien, 2020), as well as other studies utilizing

$$(4) \quad CAR(-3,3)_{i,t} = \alpha + \beta Ln(SCI)_i + \gamma Deal\ characteristics_{i,t} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

where the dependent variable, *CAR(-3,3)*, is the acquirer's CARs between days -3 and 3, given day 0 is the announcement date. We follow the M&A literature to control for deal characteristics that determine the acquirer returns, including *Ln(Deal value), Within state, Public, Stock ratio, Tender,* and *Within industry* (Masulis, Wang, and Xie, 2007; Ishii and Xuan, 2014; and John, Knyazeva, and Knyazeva, 2015). We also include acquirer characteristics that could affect acquirers' announcement returns, including *Ln(AT), Tobin's Q, Leverage, Investment,* and *ROA* (McConnell and Muscarella, 1985; Masulis et al., 2007; Li, 2013; John et al., 2015; Schmidt, 2015; Lee, Mauer, and Xu, 2018; Li, Qiu, and Shen, 2018). We control for industry and year fixed effects in all specifications. The definitions of variables are provided in the Appendix Table A.1.

{Insert Table 10}

Table 10 reports the estimation results of Equation (4). As shown in Model (1), the coefficient of *Ln(SCI)* is positive at 0.003 and statistically significant at the 5% level, suggesting that information transmitted through social networks is value-relevant. Specifically, a one–standard–deviation increase in *Ln(SCI)* leads to an increase of 52 basis points (= 0.003 x 1.732) in the acquirer's announcement returns.

In Model (2), we further control for the impact of geographical proximity by adding a control variable *Local*, which is a dummy variable equal to one if the physical distance between the acquirer and the target is less than 100 kilometers. Uysal et al. (2008) find that geographical proximity supports target–acquirer soft information transmission through managers' interactions in social, community, and business meetings, as well as through common stakeholders, including customers, suppliers, banks, and information intermediaries. The coefficient of *Ln(SCI)* in Model (2) is unchanged after controlling for

the event study methodology (e.g., Chang, Cheng, and Yu, 2007; Edwards and Shevlin, 2011; Liu, Shu, and Wei, 2017).

Local. This evidence means that the positive impact of social connectedness is not driven by the physical distance. In Model (3), we incorporate *Completion* to capture the impact of unsuccessful deals. The findings remain robust, emphasizing the value-relevant impact of social connectedness in the short-term.

4.1.2. Heterogeneous impact of social connectedness

We further explore heterogeneity in the effect of social connectedness on acquirer returns along target characteristics. If social connectedness indeed carries soft information that is relevant to the transaction, we should observe a more pronounced impact on the group of targets that are more informationally opaque. We utilize four different measures of information opacity. As the measures are only available for public targets, we partition the group of public targets into two subgroups based on their information opacity and estimate the following equation:

$$\begin{aligned}
(5)\qquad CAR(-3,3)_{i,t} &\\
&= \alpha + \beta Ln(SCI)_i + \theta_1 Public_HighOpacity_{i,t-1} \\
&+ \theta_2 Public_LowOpacity_{i,t-1} \\
&+ \vartheta_1 \left[Ln(SCI)_i \times\ Public_HighOpacity_{i,t-1}\right] \\
&+ \vartheta_2 \left[Ln(SCI)_i \times\ Public_LowOpacity_{i,t-1}\right] \\
&+ \gamma Deal\ characteristics_{i,t} + \delta Acquirer\ characteristics_{i,t-1} \\
&+ Industry\ FE + Year\ FE + \varepsilon_{i,t}
\end{aligned}$$

where *Public_HighOpacity* is a dummy variable that denotes a public target with high level of information opacity, *Public_LowOpacity* is a dummy variable indicating a public target with low information opacity, β measures the impact of social connectedness on acquirer returns of the base group (i.e., when the targets are private), ϑ_1 reflects the difference in the impact of social connectedness when the targets are public firms exhibiting a high level of information opacity and the base group, and, similarly, ϑ_2 quantifies the difference in the impact between the two groups of low information opacity public targets and the base group. Since private targets, compared with public targets, are more informationally opaque, we expect social connectedness to play a significant role in these deals and, thus β to be positive. In a similar vein, we argue that ϑ_1 and ϑ_2 should be both negative, but the magnitude of ϑ_2 is larger than that of ϑ_1.

We first measure the information opacity of public targets using the median level of analyst coverage. Since financial analysts aggregate and present complex information in an accessible manner, as well as provide information that might not be widely known in the market, they play an important role in mitigating information asymmetry (Chang, Dasgupta, and Hilary, 2006; Li, Lin, and Zhan, 2019). Firms with high (low) analyst coverage are informationally transparent (opaque). We obtain data for analyst coverage from the Institutional Brokers' Estimate System (I/B/E/S) database. In the spirit of D'Mello and Ferris (2000), we measure analyst coverage as the median number of analysts following the firm during the one–year period before the announcement date. We then define low information opacity public targets as those targets with analyst coverage in the top decile. Second, following Guo et al. (2004) and Chung and Zhang (2014), we use the average daily bid–ask spread as another proxy for information opacity of public targets. We obtain daily stock returns from the CRSP database and construct the average daily bid–ask spreads during the one-year period prior to deal announcements. Public targets with average bid–ask spreads in the bottom decile are classified as having low information opacity. The negative and statistically significant coefficient on *Ln(SCI)* × *Public_LowOpacity* in Models (1) and (2) in Table 11 indicates that the impact of social connectedness on acquirer returns is weaker when the target firms are public firms with low information opacity, relative to private targets. This result suggests that social connectedness is more valuable when targets are more informationally opaque.

{Insert Table 11}

We further employ classifications of high–tech and R&D firms as other measures of information opacity. Following Francis and Schipper (1999), we classify target firms as high-tech if their three–digit SIC codes are among the following: 357, 737, 283, 873, 366, 481, 360, 361, 362, 363, 364, 365, 366, and 367. Similarly, we define target firms as R&D

firms if their two-digit SIC codes are among the following: 28, 35, 36, 37, and 38 (Lev and Sougiannis, 1996). We document consistent results. The coefficient on *Ln(SCI)* × *Public_LowOpacity* is negative and statistically significant at the 5% and 10% levels in Model (3) and (4), Table 11.

Overall, the results in Table 11 provide robust evidence that social connectedness is most valuable when targets are informationally opaque, suggesting that social connectedness contains soft information that is beneficial to the M&A decision-making process.

4.2. Social connectedness and post-merger performance

4.2.1. Social connectedness and long-term buy-and-hold returns

We examine the impact of social connectedness on acquirer returns over a long-term horizon after deal completion. We use acquirers' BHAR over the one-year, two-year, and three-year holding periods following the transaction announcement. Following Ferris and Sainani (2021), we calculate the BHAR as:

$$BHAR_{i,t,T} = \prod_{t=1}^{T}\left(1 + R_{i,t}\right) - \prod_{t=1}^{T}\left(1 + R_{m,t}\right) \tag{6}$$

where $BHAR_{i,t,T}$ is the excess return for acquirer i over the holding period from month t to month T, $R_{i,t}$ is the realized return on the common stock of acquirer i in month t, and $R_{m,t}$ is the market return in month t. We measure R_{mt} as CRSP value-weighted market returns, CRSP equally weighted market returns, as well as returns on the Standard & Poor's (S&P) 500 composite index. We report the results of the regression of long-term buy-and-hold returns on social connectedness in Table 12.

{Insert Table 12}

As shown in Panel A of Table 12 where *BHAR* is measured over the one-year holding period, the coefficient on *Ln(SCI)* is positive in all three models but only marginally statistically significant at the 10% level in Model (3). As the horizon to measure *BHAR* extends to two and three years (as shown in panels B and C), the coefficient of *Ln(SCI)* becomes more significant economically and statistically. This suggests that soft information transmitted via social networks is value-relevant in the long term.

4.2.2. Social connectedness and long–term operating performance

In our final avenue of inquiry, we examine how social connectedness affects the operating performance of the acquirer in the long term. We estimate the following equation:

$$(7) \quad \Delta Performance(-1,3)_{i,t} = \alpha + \beta Ln(SCI)_i + \gamma Deal\ characteristics_{i,t} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

We use three industry–adjusted proxies for the acquirer's long-term operating performance, $\Delta Performance(-1,3)_{i,t}$, including i) *ΔAdj_ROA(-1,3)*, ii) *ΔAdj_EBIT/Sales(-1,3)*, and iii) *ΔAdj_EBIT/MVE(-1,3).* Specifically, *ΔAdj_ROA(-1,3)*, *ΔAdj_EBIT/Sales(-1,3)*, and *ΔAdj_EBIT/MVE(-1,3)* are measured as the difference between the acquirer's corresponding unadjusted measures (i.e., ROA, EBIT over sales, and EBIT over the market value of equity) and the median value of other firms in the same year and industry.[15] We report the regression results in Table 13.

{Insert Table 13}

As shown in Table 13, the coefficient of *Ln(SCI)* is positive and significant across all model specifications. This evidence is consistent with the conjecture that acquirers obtain value-relevant information from social networks, thus can search for high-quality targets, which, in turn, gain better performance in the long-term. This finding supports Cai and Sevilir (2012) in that acquirers have better long-term performance when they share a common director with their targets. It is in line with Rehbein and Rother (2022)'s conclusion that social connectedness is a source of soft information.

---

[15] We obtain quantitatively similar results (available upon request) when using the unadjusted measurements of ROA, EBIT to sales, and EBIT to the market value of equity.

5. Conclusion

Using social connectedness data from Facebook, we show that acquirers are more likely to acquire targets in their socially connected counties. This impact is more pronounced when targets are more visible to acquirers. We provide supportive evidence using alternative measurements of the targets' visibility, including their private/public status, age, and total asset size. Our results are robust to the inclusion of the acquirer–target physical distance, instrumented variables, additional control variables, model specifications, as well as alternative measures of social connectedness.

Next, we investigate transaction terms when the acquirer and the target are socially connected. We document a greater proportion of stock payment, lower premiums, lower number of advisors and advisory fees when the degree of social connectedness is higher. The results provide indicative evidence that social networks carry soft information that allows the acquirer and the target to know more about each other, leading to a larger proportion of stock payment, more accurate valuation of the target, and decreased reliance on external advisory services.

Finally, our study uncovers the positive impact of social connectedness on acquisition performance. Notably, social connectedness not only boosts the acquirer returns in the short term, but also contributes to the enhanced long–term buy–and–hold returns and operating performance.

Overall, our findings indicate that social connectedness facilitates M&A transactions by increasing the acquirers' awareness about potential targets as well as carries value-relevant soft information.

Appendix

Table A.1: Variable definitions

Panel A: The Capital IQ sample

Variable	Description	Data Sources
Ln(SCI)	The natural logarithm of the social connectedness index between the acquirer's county and the target's county.	Facebook & Bailey et al. (2018a)
Acquisition	A dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise.	CapitalIQ
Ln(Distance)	The natural logarithm of the distance (in miles) between the acquirer's and the target's zip code.	CapitalIQ
Local	A dummy variable equal to one if the physical distance between the acquirer and the target is less than 100 kilometers, and zero otherwise	CapitalIQ
Ln(A_AT)	The natural logarithm of the acquirer's total assets ($ million).	CapitalIQ
A_ROA	The ratio between the acquirer's earnings before interest and taxes and its total assets.	CapitalIQ
A_Leverage	The ratio between the acquirer's total debt and its total assets.	CapitalIQ
Ln(T_AT)	The natural logarithm of the target's total assets ($ million).	CapitalIQ
T_ROA	The ratio between the acquirer's earnings before interest and taxes and its total assets.	CapitalIQ
T_Leverage	The ratio between the acquirer's total debt and its total assets.	CapitalIQ
Within industry	A dummy variable equal to one if the target and the acquirer operate in the same primary industry, and zero otherwise. Industries are defined by CapitalIQ.	CapitalIQ
Private	A dummy variable equal to one if a firm's status is private, and zero otherwise.	CapitalIQ
Ln(T_Age)	The natural logarithm of one plus the number of years from the target's founding year to the current year.	CapitalIQ
Small	A dummy variable indicating a small-sized firm which equals one if the target's total assets are smaller than the 25^{th} percentile value, and zero otherwise.	CapitalIQ
Ln(Social ties)	The natural logarithm of one plus the number of social ties between the acquirer and the target board executives	BoardEx
Social ties dummy	A dummy variable equal to one if there is at least one social tie between the acquirer and the target board executives, and zero otherwise.	BoardEx
Interlock	A dummy variable equal to one if at least one executive of the target serves as an executive of the acquirer, and zero otherwise.	BoardEx
Instrument variables		
Ln(1+ past_highways)	The natural logarithm of one plus the number of past highways connecting the acquirer's county and the target's county.	Baum–Snow (2007)

Ln(1+ first_highway_years)	The natural logarithm of one plus the number of years since the commission of the first highway connecting the acquirer's county and the target's county.	Baum–Snow (2007)
County-level pairwise variables		
GDP per capita differential	Absolute value of the difference in GDP per capita of the acquirer and the target's counties.	U.S. Bureau of Economic Analysis (GDP) U.S. Census Bureau (population)
Migration	The natural logarithm of one plus the gross migration between the acquirer and the target's counties.	U.S. Census Bureau.
Unemployment differential	Absolute value of the difference in the unemployment rate of the acquirer and the target's counties.	U.S. Bureau of Labor Statistics.
Industrial share differential	The sum of the absolute differences in industry shares between the acquirer and the target's counties.	U.S. Bureau of Economic Analysis

Panel B: The SDC M&A sample

Variable	Description	Data Sources
Stock ratio	The ratio of stock as the method of payment.	SDC M&A
All_stock	A dummy variable equal to one if the entire deal is paid with stock, and zero otherwise.	SDC M&A
All_cash	A dummy variable equal to one if the entire deal is paid with cash, and zero otherwise.	SDC M&A
Premium	The natural logarithm of the ratio between the offer price and the target's stock price one week before the announcement date.	SDC M&A
Ln(Deal value)	The natural logarithm of the deal value ($ million).	SDC M&A
Ln(Advisory fees)	The natural logarithm of the total financial advisory fees paid by both acquirers and targets, normalized by the deal size.	SDC M&A
Ln(Advisors)	The natural logarithm of the total number of advisors	SDC M&A
CAR(-3,3)	The acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date.	CRSP
BHAR	The acquirer's buy–and–hold abnormal returns, calculated as $BHAR_{i,t,T} = \prod_{t=1}^{T}(1+R_{it}) - \prod_{t=1}^{T}(1+R_{mt})$, where $BHAR_{i,t,T}$ is the excess return for acquirer i over the holding period from month t to month T, R_{it} is the realized return on the common stock of acquirer i in month t, and R_{mt} is the market return in month t.	CRSP
Within industry	Same definition as in Panel A. Industries are defined by two–digit SIC codes.	SDC M&A
Public	A dummy variable equal to one if the target's status is public, and zero otherwise.	SDC M&A
Tender	A dummy variable equal to one if the deal is a tender offer, and zero otherwise.	SDC M&A

Variable	Description	Data Sources
Within state	A dummy variable equal to one if the target and the acquirer are located in the same state, and zero otherwise.	SDC M&A
Completion	A dummy variable equal to one if the deal is completed, and zero otherwise.	SDC M&A
Ln(A_AT)	Same definition as in Panel A.	Compustat
A_Leverage	Same definition as in Panel A.	Compustat
A_ROA	Same definition as in Panel A.	Compustat
A_Investment	The ratio between the acquirer's total expenditures and its total assets.	Compustat
A_Q	The ratio between the acquirer's market value of assets and its book value of assets. The market value of assets is measured as the book value of debt plus market capitalization.	Compustat
ΔAdjusted_ROA(-1,3)	Change in the acquirer's adjusted ROA from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3.	Compustat
ΔAdj_EBIT/Sales(-1,3)	is the change in the acquirer's adjusted EBIT/Sales ratio from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3.	Compustat
ΔAdj_EBIT/MVE(-1,3)	change in the acquirer's adjusted EBIT/MVE ratio from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3	Compustat

Table A.2: Distribution of mergers and acquisitions by year

The table shows the distribution of 3,920 M&A transactions across year. The sample is collected from Thomson SDC database during the 2007–2019 period. The acquirer and the target are U.S. firms. The acquirer is a public firm, while the target is either a public or a private firm.

Year	# transactions	Average deal value ($ m)	# private	# public
2007	476	415	347	129
	(12.14%)	(2.69%)	(72.90%)	(27.10%)
2008	362	519	255	107
	(9.23%)	(3.37%)	(70.44%)	(29.56%)
2009	243	1,206	155	88
	(6.20%)	(7.83%)	(63.79%)	(36.21%)
2010	330	456	229	101
	(8.42%)	(2.96%)	(69.39%)	(30.61%)
2011	308	581	230	78
	(7.86%)	(3.78%)	(74.68%)	(25.32%)
2012	337	418	251	86
	(8.60%)	(2.71%)	(74.48%)	(25.52%)
2013	269	730	201	68
	(6.86%)	(4.75%)	(74.72%)	(25.28%)
2014	359	1,411	271	88
	(9.16%)	(9.17%)	(75.49%)	(24.51%)
2015	327	2,116	218	109
	(8.34%)	(13.75%)	(66.67%)	(33.33%)
2016	251	1,811	175	76
	(6.40%)	(11.77%)	(69.72%)	(30.28%)
2017	243	1,867	180	63
	(6.20%)	(12.13%)	(74.07%)	(25.93%)
2018	240	1,341	174	66
	(6.12%)	(8.72%)	(72.50%)	(27.50%)
2019	175	2,520	127	48
	(4.46%)	(16.38%)	(72.57%)	(27.43%)
Total	3,920	15,390	2,813	1,107
	(100%)	(100%)	(71.76%)	(28.24%)

Table A.3: Distribution of mergers and acquisitions by industry

The table shows the distribution of M&A transactions by acquirer industry (defined by Fama–French 49 industry groups). The sample includes 3,920 M&A transactions from Thomson SDC database during the 2007–2019 period.

Industry	Industry name	#	Avg. deal value ($ m)	Industry	Industry name	#	Avg. deal value ($ m)
1	Agriculture	7	94	23	Automobiles and Trucks	37	445
2	Food Products	80	1,291	24	Aircraft	63	734
3	Candy & Soda	10	1,364	25	Shipbuilding, Railroad Equipment	12	133
4	Beer & Liquor	7	356	26	Defence	13	1,138
5	Tobacco Products	2	15,150	27	Precious Metals	5	338
6	Recreation	16	144	28	Non–Metallic and Industrial Metal Mining	16	1,394
7	Entertainment	28	579	29	Coal	13	608
8	Printing and Publishing	25	255	30	Petroleum and Natural Gas	117	2,698
9	Consumer Goods	50	544	32	Communication	155	3,334
10	Apparel	42	248	33	Personal Services	59	273
11	Healthcare	103	545	34	Business Services	451	540
12	Medical Equipment	219	433	35	Computers	136	910
13	Pharmaceutical Products	287	2,982	36	Computer Software	522	558
14	Chemicals	75	1,633	37	Electronic Equipment	278	1,802
15	Rubber and Plastic Products	30	988	38	Measuring and Control Equipment	119	978
16	Textiles	2	90	39	Business Supplies	29	834
17	Construction Materials	87	323	40	Shipping Containers	15	767
18	Construction	77	363	41	Transportation	107	890
19	Steel Works Etc	71	351	42	Wholesale	140	705
20	Fabricated Products	5	255	43	Retail	124	1,261
21	Machinery	151	596	44	Meals	55	452
22	Electrical Equipment	71	328	49	Other	9	51
	Total	3,920	49,757				

Table A.4: Alternative measures for social connectedness

The table reports robustness test results using alternative proxies for social connectedness. We re-estimate the baseline model of an actual acquisition on *SCI_5pct* (Model 1), *SCI_10pct* (Model 2), and *SCI_15pct* (Model 3) where *SCI_5pct, SCI_10pct,* and *SCI_15pct* are dummy variables that indicate high social connectedness using the 5-percentile, 10-percentile, and 15-percentile *Ln(SCI)* as thresholds, respectively. Control variables are the same as those in Table 2, and their definition is shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by CapitalIQ. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition		
	(1)	(2)	(3)
SCI_5pct	0.007***		
	(0.001)		
SCI_10pct		0.004***	
		(0.001)	
SCI_15pct			0.003***
			(0.001)
Observations	1,420,811	1,420,811	1,420,811
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.004	0.004	0.004

Table A.5: Logistic regressions

The table reports logistic regression results of an acquisition on social connectedness. *Acquisition* is a dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Ln(Distance)* is the natural logarithm of the distance (in miles) between the acquirer's and the target's zip code. *Within industry* is a dummy variable equal to one if the target and the acquirer share the same primary industry defined by CapitalIQ, and zero otherwise. Variables measuring acquirer characteristics include *Ln(A_AT), A_ROA*, and *A_Leverage*. Variables measuring target characteristics include *Ln(T_AT), T_ROA*, and *T_Leverage*. Their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Capital IQ database. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition				
	(1)	(2)	(3)	(4)	(5)
Ln(SCI)	0.358***		0.295***	0.315***	0.379***
	(0.014)		(0.023)	(0.039)	(0.044)
Ln(Distance)		-0.212***	0.004	0.023	0.045
		(0.014)	(0.018)	(0.028)	(0.035)
Within industry	0.320**	0.350**	0.342**	0.475***	0.569***
	(0.158)	(0.157)	(0.160)	(0.184)	(0.187)
Observations	1,426,818	1,420,811	1,420,811	1,390,755	680,409
Acquirer characteristics	Yes	Yes	Yes	Yes	Yes
Target characteristics	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No
Acquirer FE	No	No	No	No	Yes
Pseudo R-squared	0.058	0.042	0.046	0.092	0.131

Table A.6: Stricter matching criteria

The table reports linear regression results of an actual acquisition on social connectedness using a sample of 39,824 observations created by stricter matching criteria between actual and pseudo targets. The main dependent variable, *Acquisition* is a dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. Variables measuring acquirer characteristics include *Ln(A_AT), A_ROA*, and *A_Leverage.* Variables measuring target characteristics include *Ln(T_AT), T_ROA*, and *T_Leverage.* Their definitions are shown in Table A.1. Standard errors in parentheses are clustered at the acquirer's industry defined by CapitalIQ. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition				
	(1)	(2)	(3)	(4)	(5)
Ln(SCI)	0.031***		0.018***	0.014***	0.018***
	(0.003)		(0.002)	(0.002)	(0.003)
Ln(Distance)		-0.013***	-0.000	-0.001	0.001
		(0.002)	(0.002)	(0.002)	(0.002)
Within industry	0.009	0.010	0.009	0.001	0.002
	(0.010)	(0.009)	(0.009)	(0.007)	(0.009)
Observations	39,824	39,345	39,345	39,137	39,137
Acquirer characteristics	Yes	Yes	Yes	Yes	Yes
Target characteristics	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	No
Acquirer FE	No	No	No	No	Yes
R^2	0.057	0.031	0.034	0.057	0.074

References

Ambrose, B. W., and Megginson, W. L. (1992). The role of asset structure, ownership structure, and takeover defenses in determining acquisition likelihood. *Journal of Financial and Quantitative Analysis*, *27*(4), 575-589.

Austin, J., Harris, J., and O'Brien, W. (2020). Do the most prominent firms really make the worst deals? How selection issues affect inferences from M&A studies. *Journal of Banking and Finance*, *118*, 105888.

Bailey, M., Cao, R., Kuchler, T., Stroebel, J., and Wong, A. (2018a). Social connectedness: Measurement, determinants, and effects. *Journal of Economic Perspectives*, *32*(3), 259-280.

Bailey, M., Cao, R., Kuchler, T., and Stroebel, J. (2018b). The economic effects of social networks: Evidence from the housing market. *Journal of Political Economy*, *126*(6), 2224-2276.

Bailey, M., Dávila, E., Kuchler, T., and Stroebel, J. (2019). House price beliefs and mortgage leverage choice. *Review of Economic Studies*, *86*(6), 2403-2452.

Bailey, M., Gupta, A., Hillenbrand, S., Kuchler, T., Richmond, R., and Stroebel, J. (2021). International trade and social connectedness. *Journal of International Economics*, *129*, 103418.

Baum-Snow, N. (2007). Did highways cause suburbanization? *Quarterly Journal of Economics*, *122*(2), 775-805.

Booth, J. R., and R. L. Smith II (1986). Capital raising, underwriting and the certification hypothesis. *Journal of Financial Economics*, *15*(1-2), 261-281.

Brown, S. J., and Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics, 14*(1), 3-31.

Cai, Y., Kim, Y., Park, J. C., and White, H. D. (2016). Common auditors in M&A transactions. *Journal of Accounting and Economics*, *61*(1), 77-99.

Cai, Y., and Sevilir, M. (2012). Board connections and M&A transactions. *Journal of Financial Economics*, *103*(2), 327-349.

Chan, K., Ge, L., and Lin, T. C. (2015). Informational content of options trading on acquirer announcement return. *Journal of Financial and Quantitative Analysis*, 1057-1082.

Chang, E. C., Cheng, J. W., and Yu, Y. (2007). Short-sales constraints and price discovery: Evidence from the Hong Kong market. *Journal of Finance, 62*(5), 2097-2121.

Chang, X., Dasgupta, S., and Hilary, G. (2006). Analyst coverage and financing decisions. *Journal of Finance*, *61*(6), 3009-3048.

Chemmanur, T. J., and Fulghieri, P. (1994). Investment bank reputation, information production, and financial intermediation. *Journal of Finance*, *49*(1), 57-79.

Chemmanur, T., He, J., He, S., and Nandy, D. (2018). Product market characteristics and the choice between IPOs and acquisitions. *Journal of Financial and Quantitative Analysis*, *53*(2), 681-721.

Chiang, R., and Venkatesh, P. C. (1988). Insider holdings and perceptions of information asymmetry: A note. *Journal of Finance*, *43*(4), 1041-1048.

Chung, K. H., and Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *Journal of Financial Markets, 17*, 94-120.

D'Mello, R., and Ferris, S. P. (2000). The information effects of analyst activity at the announcement of new equity issues. *Financial Management*, *29*(1), 78-95.

Duggan, M., Greenwood, S., Perrin, A., 2016. Social media update 2016. Pew Research Center.

Eckbo, B. E., Makaew, T., and Thorburn, K. S. (2018). Are stock-financed takeovers opportunistic?. *Journal of Financial Economics*, *128*(3), 443-465.

Edwards, A., and Shevlin, T. (2011). The value of a flow-through entity in an integrated corporate tax system. *Journal of Financial Economics, 101*(2), 473-491.

Ferris, S. P., and Sainani, S. (2021). Do CFOs matter? Evidence from the M&A process. *Journal of Corporate Finance*, *67*, 101856.

Francis, J., and Schipper, K. (1999). Have financial statements lost their relevance? *Journal of Accounting Research*, *37*(2), 319-352.

Fuller, K., Netter, J., and Stegemoller, M. (2002). What do returns to acquiring firms tell us? Evidence from firms that make many acquisitions. *Journal of Finance, 57*(4), 1763-1793.

Gompers, P. A., Mukharlyamov, V., and Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, *119*(3), 626-644.

Guo, R. J., Lev, B., and Zhou, N. (2004). Competitive costs of disclosure by biotech IPOs. *Journal of Accounting Research, 42*(2), 319-355.

Güner, A. B., Malmendier, U., and Tate, G. (2008). Financial expertise of directors. *Journal of Financial Economics, 88*(2), 323-354.

Han, B., Hirshleifer, D., and Walden, J. (2022). Social transmission bias and investor behavior. *Journal of Financial and Quantitative Analysis*, *57*(1), 390-412.

Harford, J., Humphery-Jenner, M., and Powell, R. (2012). The sources of value destruction in acquisitions by entrenched managers. *Journal of Financial Economics, 106*(2), 247-261.

Hasbrouck, J. (1991). Measuring the information content of stock trades. *Journal of Finance*, *46*(1), 179-207.

Hirshleifer, D. (2020). Presidential address: Social transmission bias in economics and finance. *Journal of Finance*, *75*(4), 1779-1831.

Hossain, M. M., and Javakhadze, D. (2020). Corporate media connections and merger outcomes. *Journal of Corporate Finance*, *65*, 101736.

Ishii, J., and Xuan, Y. (2014). Acquirer-target social ties and merger outcomes. *Journal of Financial Economics*, *112*(3), 344-363.

Janis, I. L. (1982). *Groupthink: Psychological studies of policy decisions and fiascoes*. Houghton Mifflin School.

Jansen, M. (2020). Resolving information asymmetry through contractual risk sharing: The case of private firm acquisitions. *Journal of Accounting Research*, *58*(5), 1203-1248.

John, K., Knyazeva, A., and Knyazeva, D. (2015). Employee rights and acquisitions. *Journal of Financial Economics*, *118*(1), 49-69.

Kuchler, T., Li, Y., Peng, L., Stroebel, J., and Zhou, D. (2022). Social proximity to capital: Implications for investors and firms. *The Review of Financial Studies*, *35*(6), 2743-2789.

Lee, K. H., Mauer, D. C., and Xu, E. Q. (2018). Human capital relatedness and mergers and acquisitions. *Journal of Financial Economics, 129*(1), 111-135.

Leuz, C., and Verrecchia, R. E. (2000). The economic consequences of increased disclosure. *Journal of Accounting Research*, *38*, 91-124.

Lev, B., and Sougiannis, T. (1996). The capitalization, amortization, and value-relevance of R&D. *Journal of Accounting and Economics*, *21*(1), 107-138.

Li, K., Qiu, B., and Shen, R. (2018). Organization capital and mergers and acquisitions. *Journal of Financial and Quantitative Analysis, 53*(4), 1871-1909.

Li, X. (2013). Productivity, restructuring, and the gains from takeovers. *Journal of Financial Economics, 109*(1), 250-271.

Li, X., Lin, C., and Zhan, X. (2019). Does change in the information environment affect financing choices? *Management Science*, *65*(12), 5676-5696.

Liu, L. X., Shu, H., and Wei, K. C. J. (2017). The impacts of political uncertainty on asset prices: Evidence from the Bo scandal in China. *Journal of Financial Economics, 125*(2), 286-310.

Marquardt, C., and Zur, E. (2015). The role of accounting quality in the M&A market. *Management Science*, *61*(3), 604-623.

Maskara, P. K., and Mullineaux, D. J. (2011). Information asymmetry and self-selection bias in bank loan announcement studies. *Journal of Financial Economics, 101*(3), 684-694.

Masulis, R. W., Wang, C., and Xie, F. (2007). Corporate governance and acquirer returns. *Journal of Finance, 62*(4), 1851-1889.

McConnell, J. J., and Muscarella, C. J. (1985). Corporate capital expenditure decisions and the market value of the firm. *Journal of Financial Economics, 14*(3), 399-422.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology*, 27(1), 415-444.

Palepu, K. G. (1986). Predicting takeover targets: A methodological and empirical analysis. *Journal of Accounting and Economics*, *8*(1), 3-35.

Pittman, J. A., and Fortin, S. (2004). Auditor choice and the cost of debt capital for newly public firms. *Journal of Accounting and Economics, 37*(1), 113-136.

Rehbein, O., and Rother, S. (2022). *Social connectedness (and distance) in bank lending*. Working paper.

Sarala, R. M., Junni, P., Cooper, C. L., and Tarba, S. Y. (2016). A sociocultural perspective on knowledge transfer in mergers and acquisitions. *Journal of Management*, *42*(5), 1230-1249.

Schmidt, B. (2015). Costs and benefits of friendly boards during mergers and acquisitions. *Journal of Financial Economics, 117*(2), 424-447.

Titman, S., and Trueman, B. (1986). Information quality and the valuation of new issues. *Journal of Accounting and Economics*, *8*(2), 159-172.

Uysal, V. B., Kedia, S., and Panchapagesan, V. (2008). Geography and acquirer returns. *Journal of Financial Intermediation*, *17*(2), 256-275.

Wang, L., and Zajac, E. J. (2007). Alliance or acquisition? A dyadic perspective on interfirm resource combinations. *Strategic Management Journal*, *28*(13), 1291-1317.

Figure 1: Santa Clara's social connectedness

This figure depicts values of *Ln(SCI)* measured as the natural logarithm of social connectedness index between each U.S. county and Santa Clara county - the county that received the highest number of bids in our sample. Higher degrees of social connectedness are denoted by a darker shade. In this figure, Santa Clara is circled in red, whereas the four counties where the most bidders of Santa Clara's M&A deals come from are circled in yellow.

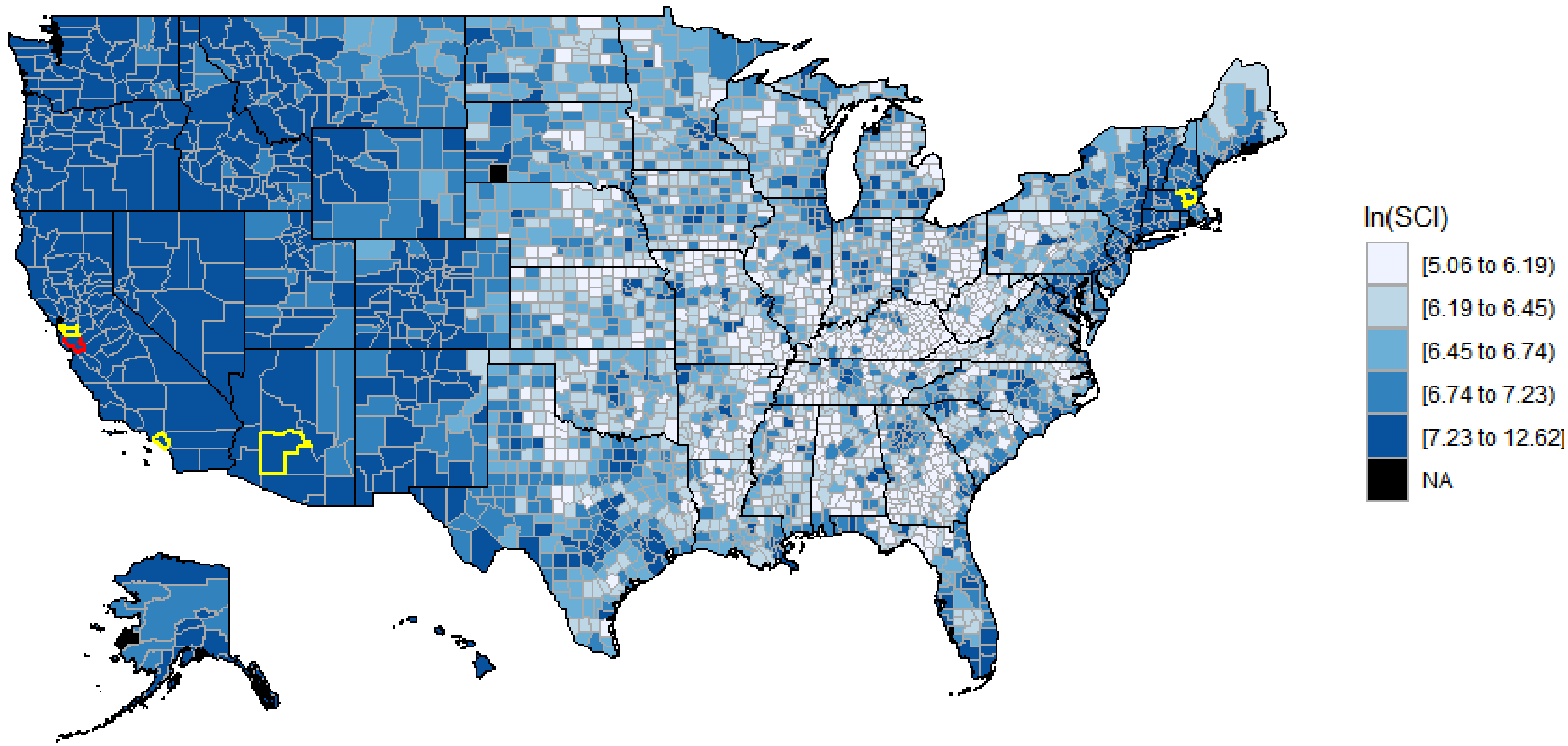

Table 1: Descriptive statistics

Panel A: The CapitalIQ sample

The table provides summary statistics for the sample of transactions announced between 2007 and 2019. *Acquisition* is a dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise. *Ln(A_AT)* is the natural logarithm of the acquirer's total assets. *A_ROA* is the ratio between the acquirer's earnings before interest and taxes and its total assets. *A_Leverage* is the ratio between the acquirer's total debt and total assets. *Ln(T_AT)* is the natural logarithm of the target's total assets. *T_ROA* is the ratio between the acquirer's earnings before interest and taxes and its total assets. *T_Leverage* is the ratio between the acquirer's total debt and total assets. *Ln(Distance)* is the natural logarithm of the distance (in miles) between the acquirer's and the target's zip code. *Within industry* is a dummy variable equal to one if the target and the acquirer share the same primary industry defined by CapitalIQ, and zero otherwise.

	The merged sample				*The sample of transactions with pseudo targets*				*The sample of actual transactions*			
	N	Mean	Std	Median	N	Mean	Std	Median	N	Mean	Std	Median
Acquisition	1,426,818	0.007	0.086	0.000	1,416,244	-	-	-	10,574	-	-	-
Ln(SCI)	1,426,818	8.475	1.200	8.266	1,416,244	8.469	1.191	8.264	10,574	9.238	1.900	8.617
Ln(A_AT)	1,426,818	7.068	2.134	7.178	1,416,244	7.068	2.134	7.173	10,574	7.112	2.128	7.259
A_ROA	1,426,818	0.023	0.252	0.062	1,416,244	0.023	0.252	0.062	10,574	0.028	0.247	0.060
A_Leverage	1,426,818	0.292	0.249	0.260	1,416,244	0.292	0.249	0.260	10,574	0.290	0.247	0.258
Ln(T_AT)	1,401,687	3.817	2.714	3.490	1,399,315	3.816	2.714	3.487	2,372	4.470	2.617	4.485
T_ROA	1,401,594	-0.112	0.434	0.000	1,399,325	-0.112	0.432	0.000	2,269	-0.190	0.994	0.051
T_Leverage	1,401,473	0.143	0.290	0.000	1,399,325	0.143	0.289	0.000	2,148	0.385	0.598	0.228
Ln(Distance)	1,420,811	6.552	1.330	6.846	1,410,829	6.555	1.325	6.847	9,982	6.034	1.801	6.595
Within industry	1,426,818	0.409	0.492	0.000	1,416,244	0.409	0.492	0.000	10,574	0.388	0.487	0.000

Panel B: The SDC Sample

The table provides summary statistics for the sample of 3,920 M&A transactions between 2007 and 2019. *CAR(-3,3)* is the acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date. *Premium* is measured as the natural logarithm of the ratio between the offer price and the target's stock price one week before the announcement date. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Ln(Deal value)* is the natural logarithm of the deal value. *Within industry* is a dummy variable equal to one if the target and the acquirer operate in the same industry defined by two–digit SIC codes, and zero otherwise. *Public* is a dummy variable equal to one if the target is a public firm, and zero otherwise. *Stock ratio* is the ratio of stock as the method of payment. *Tender* is a dummy variable equal to one if the deal is a tender offer, and zero otherwise. *Within state* is a dummy variable equal to one if the target and the acquirer are located in the same state, and zero otherwise. *Completion* is a dummy variable equal to one if the deal is completed, and zero otherwise. *Ln(A_AT)* is the natural logarithm of the acquirer's total assets. *A_Leverage* is the ratio between the acquirer's total debt and its total assets. *A_ROA* is the ratio between the acquirer's earnings before interest and taxes and its total assets. *A_Investment* is the ratio between the acquirer's total expenditures and its total assets. *A_ Q* is the ratio between the acquirer's market value of assets and its book value of assets.

	N	Mean	Standard deviation	25th	Median	75th
CAR(-3,3)	3,920	0.011	0.074	-0.026	0.007	0.044
Premium	759	0.316	0.203	0.176	0.288	0.422
Ln(SCI)	3,920	9.003	1.732	7.907	8.457	9.309
Ln(Deal value)	3,920	4.912	1.761	3.555	4.804	6.084
Within industry	3,920	0.583	0.493	0	1	1
Public	3,920	0.282	0.450	0	0	1
Stock ratio	3,920	0.106	0.255	0	0	0
Tender	3,920	0.048	0.214	0	0	0
Within state	3,920	0.201	0.401	0	0	0
Completion	3,920	0.928	0.258	1	1	1
Ln(A_AT)	3,920	7.418	1.823	6.108	7.275	8.612
A_Leverage	3,920	0.217	0.188	0.038	0.199	0.330
A_ROA	3,920	0.087	0.082	0.050	0.091	0.133
A_Investment	3,920	0.036	0.033	0.014	0.025	0.045
A_Q	3,920	2.134	1.095	1.380	1.809	2.490

Table 2: Social connectedness and likelihood of an acquisition

The table reports linear regression results of an actual acquisition on social connectedness. The main dependent variable, *Acquisition* is a dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. Definitions of other variables are shown in Table A.1. Standard errors in parentheses are clustered at the acquirer's industry defined by CapitalIQ. The coefficients and standard errors of *Ln(Distance)*, *Ln(A_AT)* and *Ln(T_AT)* are multiplied by 10^3. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition					
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(SCI)	0.004***		0.003***	0.003***	0.001***	0.001***
	(0.000)		(0.000)	(0.000)	(0.000)	(0.000)
Ln(Distance)		-0.205***	-0.033*		-0.010*	-0.004
		(0.023)	(0.018)		(0.005)	(0.007)
Local				0.004***		
				(0.001)		
Ln(A_AT)	-0.091	0.032	-0.002	-0.088	-0.059	-0.360***
	(0.057)	(0.054)	(0.056)	(0.058)	(0.036)	(0.124)
A_ROA	0.002	-0.001	0.002	0.002	-0.002	0.003
	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)	(0.006)
A_Leverage	-0.0001	-0.0003	-0.0002	-0.0000	-0.0002	-0.0006
	(0.0005)	(0.0004)	(0.0004)	(0.0005)	(0.0002)	(0.0005)
Ln(T_AT)					-0.016	-0.051
					(0.043)	(0.044)
T_ROA					0.004	0.004

					(0.005)	(0.005)
T_Leverage					0.004***	0.004***
					(0.0004)	(0.0004)
Within industry	0.002 *	0.002**	0.002*	0.002*	0.0008**	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0004)	(0.0004)
Observations	1,426,818	1,420,811	1,420,811	1,426,818	1,395,942	1,395,942
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	No
Acquirer FE	No	No	No	No	No	Yes
R^2	0.006	0.004	0.005	0.006	0.003	0.010

Table 3: Cross-sectional analyses

This table examines how the impact of social connectedness on the acquisition likelihood varies with target characteristics representing its visibility. The models control for dummies indicating private target, young target (low target age), small target (small in total assets), and their interaction with the social connectedness index. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Private* is a dummy variable equal to one if the target's status is private, and zero otherwise. *Ln(T_Age)* is the natural logarithm of one plus the number of years from the target's founding year to the current year. *Small* is a dummy variable indicating a small-sized target, which equals one if the target's total assets are smaller than the 25th percentile value, and zero otherwise. Other control variables are the same as those in Table 2, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by CapitalIQ. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition		
	(1)	(2)	(3)
Ln(SCI)	0.001*	0.005***	0.001***
	(0.000)	(0.001)	(0.000)
Private	-0.021***		
	(0.004)		
*Ln(SCI)*Private*	0.004***		
	(0.001)		
Ln(T_Age)		0.006***	
		(0.002)	
*Ln(SCI)*Ln(T_Age)*		-0.001***	
		(0.000)	
Small			-0.003*
			(0.002)
*Ln(SCI)*Small*			0.0004*
			(0.0002)
Observations	1,420,811	1,286,278	1,396,160
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.008	0.006	0.002

Table 4: Instrumented regressions

This table reports the instrumented regression results of an actual acquisition. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Acquisition* is a dummy variable equal to one if a firm is a target of a real M&A transaction, and zero otherwise. *Ln(1+past_highways)* is the natural logarithm of one plus the number of past highways connecting the acquirer's county and the target's county. *Ln(1+first_highway_years)* is the natural logarithm of one plus the number of years since the commission of the first highway connecting the acquirer's county and the target's county. Other control variables are the same as those in Table 2, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined in Capital IQ database. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Ln(SCI)	*Acquisition*	*Ln(SCI)*	*Acquisition*
	(1)	(2)	(3)	(4)
Ln(1+past_highways)	0.818***			
	(0.051)			
Ln(SCI)_hat1		0.005***		
		(0.001)		
Ln(1+first_highway_years)			0.289***	
			(0.018)	
Ln(SCI)_hat2				0.005***
				(0.001)
Observations	1,420,811	1,420,811	1,420,811	1,420,811
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R^2	0.666	0.004	0.665	0.004

Table 5: Social connectedness, direct social ties, interlock, and likelihood of an acquisition

The table reports regression results of an actual acquisition on social connectedness controlling for managerial social ties the acquirer and the target. *Acquisition* is a dummy variable equal to one if a firm is a real target of an M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Ln(Social ties)* is the natural logarithm of the number of historical direct social ties between the acquirer and the target plus one. *Social ties dummy* is a dummy variable equal to one if there is at least one social tie between the acquirer and the target board executives. *Interlock* is a dummy variable equal to one if at least one director/executive of the target also serves as a director or an executive of the acquirer, and zero otherwise. Other control variables are the same as those in Table 2, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined in the Capital IQ database. The coefficients and standard errors of *Ln(Social ties)* and *Social ties dummy* are multiplied by 10^3. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition		
	(1)	(2)	(3)
Ln(SCI)	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)
Ln(Social ties)	0.096		
	(0.154)		
Social ties dummy		0.296	
		(0.249)	
Interlock			0.185***
			(0.017)
Observations	583,850	583,850	583,850
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.003	0.003	0.037

Table 6: Social connectedness, county differences, and likelihood of an acquisition

The table reports regression results of an actual acquisition on social connectedness controlling for county-pair differences. *Acquisition* is a dummy variable equal to one if a firm is a real target of an M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *GDP per capita differential* is absolute value of the difference in GDP per capita of the acquirer and the target's county. *Migration* is the natural logarithm of one plus the gross migration between the acquirer and the target's county. *Unemployment differential* is the absolute value of the difference in the unemployment rate of the acquirer and the target's county. *Industrial share differential* is the sum of the absolute differences in industry shares between the acquirer and the target's county. Other control variables are the same as those in Table 2, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined in the Capital IQ database. The coefficient and standard error of *Migration* are multiplied by 10^2. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition				
	(1	(2)	(3)	(4)	(5)
Ln(SCI)	0.003***	0.003***	0.003***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP per capita differential	-0.005***				-0.003
	(0.002)				(0.002)
Migration		-0.021**			-0.016*
		(0.009)			(0.009)
Unemployment differential			-0.020**		-0.032***
			(0.007)		(0.010)
Industrial share differential				-0.001*	-0.001*
				(0.000)	(0.000)
Observations	1,358,073	852,140	1,420,799	1,375,823	813,738
Control variables	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
R^2	0.005	0.004	0.005	0.005	0.004

Table 7: Social connectedness and methods of payment

The table reports regression results of methods of payment on social connectedness. *Acquisition* is a dummy variable equal to one if a firm is a real target of an M&A transaction, and zero otherwise. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Stock ratio* is the ratio of stock as the method of payment. *All_stock* is a dummy variable equal to one if the entire deal is paid with stock, and zero otherwise. *All_cash* is a dummy variable equal to one if the entire deal is paid with cash, and zero otherwise. Definitions of other variables are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined in the Capital IQ database. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Stock ratio	*All_stock*	*All_cash*
	(1)	(2)	(3)
Ln(SCI)	0.014***	0.011**	-0.007
	(0.005)	(0.005)	(0.010)
Ln(Deal value)	0.043***	0.014***	-0.004
	(0.004)	(0.002)	(0.008)
Within industry	-0.005	-0.006	0.014
	(0.008)	(0.007)	(0.015)
Public	0.127***	0.096***	0.076***
	(0.020)	(0.014)	(0.027)
Tender	-0.178***	-0.111***	0.288***
	(0.017)	(0.015)	(0.033)
Within state	-0.002	-0.017	0.009
	(0.018)	(0.019)	(0.047)
Ln(A_AT)	-0.039***	-0.017***	0.044***
	(0.003)	(0.003)	(0.007)
A_Leverage	0.081***	0.079***	-0.139**
	(0.030)	(0.023)	(0.055)
A_ROA	-0.729***	-0.365***	0.474***
	(0.069)	(0.074)	(0.104)
A_Investment	0.109	-0.009	-0.255
	(0.175)	(0.149)	(0.286)
A_Q	0.023***	0.008*	0.002
	(0.005)	(0.004)	(0.008)
Observations	3,920	3,920	3,920

Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.264	0.134	0.129

Table 8: Social connectedness and transaction premiums

The table reports regression results of deal premiums on social connectedness. *Premium* is measured as the natural logarithm of the ratio between the offer price and the target's stock price one week before the announcement date. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Ln(Deal value)* is the natural logarithm of the transaction value. Other control variables include *Stock ratio* and those in Table 7, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Fama-French 49 industry portfolios. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Premium	
	(1)	(2)
Ln(SCI)	-0.011*	-0.044**
	(0.005)	(0.018)
Ln(SCI) × *Ln(Deal value)*		0.005*
		(0.003)
Ln(Deal value)	-0.027***	-0.073***
	(0.005)	(0.022)
Observations	759	759
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.225	0.229

Table 9: Social connectedness, advisory fees and the number of advisors

The table reports regression results of advisory fees and the number of advisors on social connectedness. *Ln(Advisory fees) is* the natural logarithm of the total financial advisory fees paid by both acquirers and targets, normalized by the deal size. *Ln(Advisors)* is the natural logarithm of the total number of advisors. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. Control variables are the same as those in Table 8, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Fama-French 49 industry portfolios. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Ln(Advisory fees)	*Ln(Advisors)*
	(1)	(2)
Ln(SCI)	-0.025**	-0.016**
	(0.012)	(0.007)
Observations	3,920	3,920
Control variables	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
R^2	0.162	0.525

Table 10: Social connectedness and acquirer announcement returns

The table reports regression results of the acquirer's returns on social connectedness. *CAR(-3,3)* is the acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date. The main independent variable, *Ln(SCI)*, is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Local* is a dummy variable equal to one if the physical distance between the acquirer and the target is less than 100 kilometres, and zero otherwise. *Completion* is a dummy variable equal to one if the deal is completed, and zero otherwise. Other control variables are the same as those in Table 8, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Fama-French 49 industry portfolios. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	CAR(-3,3)		
	(1)	(2)	(3)
Ln(SCI)	0.003**	0.003*	0.003**
	(0.001)	(0.001)	(0.001)
Local		-0.0003	
		(0.007)	
Completion			0.006
			(0.006)
Observations	3,920	3,920	3,920
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.047	0.047	0.047

Table 11: Social connectedness, target opacity, and acquirer returns

The table reports regression results of the acquirer's announcement returns on the interaction between targets' level of information asymmetry and social connectedness. *CAR(-3,3)* is the acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Public_LowOpacity* is a dummy variable that equals one if targets are public firms with low level of information opacity, and zero otherwise. *Public_HighOpacity* is dummy variable that equals one if targets are public firms with high level of information opacity, and zero otherwise. Other control variables are the same as those in Table 8, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Fama-French 49 industry portfolios. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	CAR(-3,3)			
	Analyst coverage	*Bid-ask spread*	*High-tech firms*	*R&D firms*
	(1)	(2)	(3)	(4)
Ln(SCI)	0.003*	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Public_HighOpacity	-0.015	-0.003	-0.014	-0.007
	(0.019)	(0.018)	(0.021)	(0.020)
Public_LowOpacity	0.044	0.079	0.027	0.025
	(0.046)	(0.052)	(0.017)	(0.018)
Public_HighOpacity × *Ln(SCI)*	0.000	-0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Public_LowOpacity × *Ln(SCI)*	-0.008*	-0.011**	-0.004**	-0.003*
	(0.004)	(0.006)	(0.002)	(0.002)
Observations	3,432	3,481	3,920	3,920
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
R^2	0.054	0.052	0.048	0.048

Table 12: Social connectedness and acquirer buy-and-hold returns

The table reports regression results of the acquirer's buy-and-hold returns (BHAR) for completed deals on social connectedness. We measure acquirers' BHAR over the holding periods of one year, two years and three years following the transaction announcement. *BHAR* is calculated as $BHAR_{i,t,T} = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{mt})$, where $BHAR_{i,t,T}$ is the excess return for acquirer i over the holding period from month t to month T, R_{it} is realized return on the common stock of acquirer i in month t, and R_{mt} is the market return in month t. We measure R_{mt} as the value-weighted market return, the equally-weighted market return as well as the return on the S&P composite index. The main independent variable, *Ln(SCI)*, is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. Size fixed effects are controlled based on dummies indicating five quintiles of the acquirer's total assets. Control variables are the same as those in Table 8, and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at year and acquirer industry. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Buy-and-hold long-term returns		
	CRSP value-weighted	CRSP Equally-weighted	S&P 500
	(1)	(2)	(3)
Panel A: 12-month BHAR			
Ln(SCI)	0.005	0.005	0.005*
	(0.003)	(0.003)	(0.003)
Observations	3,506	3,506	3,506
R^2	0.045	0.046	0.050
Panel B: 24-month BHAR			
Ln(SCI)	0.012*	0.012*	0.013**
	(0.006)	(0.006)	(0.005)
Observations	3,152	3,152	3,152
R^2	0.047	0.055	0.055
Panel C: 36-month BHAR			
Ln(SCI)	0.015**	0.014**	0.015***
	(0.005)	(0.005)	(0.005)
Observations	2,776	2,776	2,776
R^2	0.059	0.063	0.066
Control variables	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes

Table 13: Social connectedness and acquirer long-term performance

The table reports regression results of the acquirer's long-term performance on social connectedness. *ΔAdjusted_ROA(-1,3)* is the change in the acquirer's adjusted ROA from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3. *ΔAdj_EBIT/Sales(-1,3)* is the change in the acquirer's adjusted EBIT/Sales ratio from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3. *ΔAdj_EBIT/MVE(-1,3)* is the change in the acquirer's adjusted EBIT/MVE ratio from the fiscal year immediately prior to the announcement date (fiscal year -1) to fiscal year +3. All three measures are industry adjusted, i.e., calculated as the difference between the acquirer's corresponding measure of performance and the median value of the other Compustat-listed firms in the same year and industry (defined by two-digit SIC codes). *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. Control variables are the same as those in Table 8, excluding *A_ROA,* and their definitions are shown in Table A.1. Standard errors in parentheses are clustered at acquirer industries defined by Fama-French 49 industry portfolios. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	ΔAdj_ROA(-1,3)	*ΔAdj_EBIT/Sales(-1,3)*	*ΔAdj_EBIT/MVE(-1,3)*
	(1)	(2)	(3)
Ln(SCI)	0.003*	0.006***	0.007**
	(0.002)	(0.002)	(0.003)
Observations	2,613	2,633	2,626
Control variables	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
R^2	0.126	0.071	0.043