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The Role of Social Connectedness: Evidence from Mergers and Acquisitions

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Abstract

Using a comprehensive dataset of social network ties between U.S. counties, we document higher announcement returns for acquirers that are more socially proximate to their targets. Our findings are robust to the inclusion of geographical proximity and withstand endogeneity concerns. Consistent with the information asymmetry hypothesis, we show that the effect of social connectedness is more pronounced when targets have high information opacity, as proxied by target status, analyst coverage, bid–ask spreads, R&D, and high-tech classifications. In addition, social connectedness lowers advisory fees, reduces deal premiums, and yields better acquirer long-term performance.

Keywords: *Social connectedness; merger and acquisition; information asymmetry*

JEL Classification: G34

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The Role of Social Connectedness: Evidence from Mergers and Acquisitions

Abstract

Using a comprehensive dataset of social network ties between U.S. counties, we document higher announcement returns for acquirers that are more socially proximate to their targets. Our findings are robust to the inclusion of geographical proximity and withstand endogeneity concerns. Consistent with the information asymmetry hypothesis, we show that the effect of social connectedness is more pronounced when targets have high information opacity, as proxied by target status, analyst coverage, bid–ask spreads, R&D, and high-tech classifications. In addition, social connectedness lowers advisory fees, reduces deal premiums, and yields better acquirer long-term performance.

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"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

I. 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 connections on economic outcomes. For example, Bailey et al. (2018a) find social connectedness to have a positive impact on patent citations and trade flow within the United States. Kuchler et al. (2020) show that social networks are the main driver of the investment decisions of institutional investors. In addition, Rehbein and Rother (2020) demonstrate a significant association between social connectedness and cross-county lending. Despite social connectedness being documented as a source of information in the literature (Bailey et al. (2018a), Diemer and Regan (2020), Kuchler et al. (2020)), we know surprisingly little about its role and effectiveness in addressing the problem of information asymmetry in mergers and acquisitions (M&As), one of the most important form of corporate investments. In this paper, we investigate the role of social connectedness in M&As by focusing on the performance of public acquirers in both the short and long term.

We obtain data on social connectedness from Facebook. This social connectedness 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. (2020), Facebook users in the United States typically use this platform to interact with their friends and acquaintances in the real world. This suggests that our measure of social connectedness, albeit derived from Facebook friendship ties, captures the exchange of information among friends beyond the Facebook platform and is extended to real-world connections and information exchange. Supported by Facebook's enormous scale, the social connectedness measure adopted in our study is expected to be representative of real-world friendship connections in the United States.[1] As information among friendship links enters as soft information in the decision-making process, strong social connections are likely to facilitate more efficient information transmission by lowering acquirers' costs and need for acquiring information about target firms as well as their local economic conditions.

[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).

We begin our empirical analysis by quantifying the impact of social connectedness on acquirers' announcement returns (hereafter acquirer returns). It is well documented in the literature that target information asymmetry has a strong impact on acquirer returns (see, e.g., Uysal, Kedia, and Panchapagesan (2008), Officer, Poulsen, and Stegemoller (2009), McNichols and Stubben (2015), Cai et al. (2016)). The lower the information asymmetry, the higher the acquirer returns (Uysal et al. (2008)). Since social networks facilitate information transmissions (see, e.g., Bailey et al. (2018a), Kuchler et al. (2020), and Rehbein and Rother (2020)), strong social connections could attenuate the acquirer-target information asymmetry and therefore, enhance acquirer returns.

Following Bailey et al. (2018a), we measure social connectedness as the natural logarithm of the social connectedness index, *Ln(SCI)*. We measure acquirer returns as the cumulative abnormal returns (CAR) over the seven-day period around the announcement date, *CAR(-3,3)*. Running a regression of social connectedness on acquirer returns, we find results consistent with our hypothesis. Specifically, the coefficient of *Ln(SCI)* is positive and statistically significant at the 5% level, suggesting that acquirers that are more socially proximate to their targets experience higher announcement returns. After controlling for all relevant deal characteristics, acquirer characteristics, and year and industry fixed effects, we find that a one-standard-deviation increase in *Ln(SCI)* leads to an increase of 52 basis points in *CAR(-3,3)*, ceteris paribus. Given that the average market capitalization of the acquirers four weeks before the announcement is $15.2 billion, a 52-basis-point increase in *CAR(-3,3)* translates to a significant increase in acquirers' market capitalization of approximately $79 million.

Since geographic proximity has been well documented in the literature as one of the information resolution factors, one might be skeptical that the impact of social connectedness on acquirer returns could be due to geographic proximity (see, e.g., Coval and Moskowitz (1999), (2001), Petersen and Rajan (2002), and Degryse and Ongena (2005)). We address this concern by re-estimating our baseline regression while controlling for geographic proximity. Our main results remain robust. More interestingly, we find that the impact of geographic proximity is subsumed when the model includes social connectedness. This finding complements the results of Bailey et al. (2018a), Diemer and Regan (2020), Kutchler et al. (2020), and Rehbein and Rother (2020), who find that geographic proximity is one of the determinants of social proximity. In other words, social proximity, or social connectedness, captures the impact of geographic proximity and extends to other dimensions.

There are two potential concerns with our main findings. First, our findings are not drawn from a natural experiment setting. One might be worried that M&A deals where acquirers and targets are located in counties with high social connectedness are fundamentally different from other deals, leading to higher acquirer returns. Second, there might be unobservable factors related to both the social connectedness between two counties and acquirer returns. We adopt an instrumental variable approach to address these endogeneity concerns. Following Rehbein and Rother (2020), we construct our instruments based on county-level highway connections data obtained from Baum-Snow (2007). This dataset includes data on the number of highways and the number of years since the commission of the first highway connecting the acquirer's and target's counties. Findings from these tests support the causal effect of social connectedness on acquirer returns.

We conduct further analyses to explore the channel through which social connectedness affects acquirer returns. First, following previous literature, we perform a subsample analysis by partitioning targets into public firms and private firms (Officer, Poulsen, and Stegemoller (2009)) and listed and non–listed firms (Faccio, McConnell, and Stolin (2006)). Second, we explore the impact of social connectedness on acquirer returns conditional on target information asymmetry proxied by analyst coverage, bid–ask spreads, and classifications of high-tech firms and R&D firms. We find that the positive impact of social connectedness on acquirer returns is more pronounced in more informationally opaque targets. Third, we examine the role of advisory fees on acquirer returns. It is well documented that financial advisors act as information producers by generating credible information about target firms, and the better the reputation of the financial advisors, the more effectively they can address the information asymmetry problem (Chemmanur and Fulghieri (1994)). In addition, financial advisors with better reputation charge higher fees (Fang (2005), Golubov, Petmezas, and Travlos (2012)). Therefore, we expect that social connectedness, by reducing asymmetric information, can lower advisory fees. In deals where advisory fees are higher, indicating lower information asymmetry, social connectedness plays a less important role. We document results consistent with these predictions. Finally, we examine the role of social connectedness on takeover premiums. Prior literature documents that takeover premiums are positively associated with the target's information asymmetry (Raman, Shivakumar, and Tamayo (2013), Cheng, Li, and Tong (2016)). In our context, we conjecture that acquirers that are socially connected with their targets have an information advantage about the true value of target firms and thus pay lower takeover premiums. Indeed, we obtain a negative and significant coefficient for *Ln(SCI)* in regression models of takeover premiums that is consistent with our prediction. Taken together, our results suggest that social connectedness improves acquirer returns by mitigating information asymmetry.

Next, we explore the role of social connectedness in post-merger performance. We document that, following the completion of M&A deals where acquirers and targets are socially connected, acquirers achieve a higher long-term buy-and-hold return, 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 among individuals and corporates (Bailey et al. (2018a), (2018b), (2019), Kuchler et al. (2020), Rehbein and Rother (2020)) and between acquirers and targets (Cai and Sevilir (2012)), improve long-term performance and contribute significantly to productivity and economic growth (Lucas (1988), Aghion and Howitt (1992)).

In our final avenue of inquiry, we examine if social connectedness, through its facilitation of information transmission, affects the likelihood of acquisition in the first place. To do so, in each announcement year, we identify all acquirers (m) and all targets (n) and create an $m \times n$ matrix of all possible acquirer–target pairs. We then construct a dummy variable, *Acquisition,* that indicates an actual transaction between an acquirer and a target and investigate the impact of social connectedness on the likelihood of an M&A deal using probit regressions. We find strong evidence supporting the positive relation between social connectedness and acquisition likelihood, even after controlling for physical distance. We also report the results from pseudo-analyses and robustness checks to ascertain support for our main findings.

Our study makes two important contributions to the literature. First, our research adds to the literature that focuses on the role of information in M&As. The research on M&As examines different factors that can reduce information asymmetry and, therefore, affect merger outcomes.[3] We contribute to this rich literature by exploring the impact of a new factor, which is social connectedness. While the value of social connectedness is documented in the M&A literature, the lack of comprehensive data on social connectedness has limited previous studies to qualitative analyses (Sarala et al. (2016)) or quantitative analyses where social connectedness was measured at the top management level (Ferris, Javakhadze, and Rajkovic (2017)). Our paper differs from those studies in the extent that our measure of social connectedness is constructed based on billions of active Facebook users, with an arguably representative sample of real-world friendships. Interestingly, not only do we find social connectedness to play an important role in acquirer returns, but also our findings suggest that physical

[3] 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)).

distance, which Uysal et al. (2008) have found to have a significant impact on acquirer returns, might just be one dimension of social connectedness, since its effect is subsumed by social connectedness when both of the factors are simultaneously considered in the regression equation.

Second, the findings in this paper complement those of papers on the value of social connections in terms of real economic outcomes. Bailey et al. (2018a) document the positive relation between social connections and patent citations. Rehbein and Rother (2020) 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 (2021) theoretically show that sociability, self-enhancing transmission, and other communication features are associated with active investment strategies. Our paper offers new insights into the value of social connectedness in M&A outcomes. We demonstrate that social connections add economic value to acquirers in both the short and long term. Our paper also differs from other papers in the M&A literature that examine the relation between social ties and long-term performance (see, e.g., Cai and Sevilir (2012) and Ishii and Xuan (2014)), since our measure of social connections deviates from that at the top management level.[4] Instead, we focus on social networks at the county level, which are aggregated from individual friendships.

[4] 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.

The remainder of the paper is organized as follows. In Section II, we discuss the data collection and summary statistics. We present the main empirical results in Section III. Section IV provides evidence supporting the information channel for the relation between social connectedness and acquirer returns. We explore the role of social connectedness on post-merger performance in Section V. Section VI presents additional analyses and robustness checks. We offer concluding remarks in Section VII.

II. Data Collection and Summary Statistics

A. Data Collection and the Measurement of the Main Variables

We obtain a large sample of M&A transactions between 2007 and 2019 from the Thomson SDC database. 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 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 (e.g., street address and state of location) to identify the counties of both the target and the acquirer. Furthermore, we require acquirers to have stock price information in the CRSP, to calculate announcement returns, and 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, respectively.

1. Social Connectedness

We obtain data for the social connectedness index from Facebook.[5] The index is constructed based on the friendship links between anonymized Facebook users in different U.S. counties. Facebook is the world's most popular social network, with more than 2.7 billion active global users monthly as of September 30, 2020. 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. (2020), 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.[6]

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

[6] A large growing literature provides evidence that Facebook networks is reflections of real-world social networks (Bailey et al. (2018a), (2018b), Bailey et al. (2019), Kuchler et al. (2020), Rehbein and Rother (2020), and Bailey et al. (2021)).

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 relative 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. *Acquirer Returns*

We measure acquirer returns as cumulative abnormal returns over the event window of seven days, from day -3 to day 3, where day 0 is the announcement date.[7] Following Brown and Warner (1985), we measure abnormal returns using the market-adjusted model and CRSP value-weighted returns as the market benchmark. Brown and Warner (1980) suggest that the adjustment for systematic risk does not improve the accuracy of short-term abnormal return calculations. This measure is popular among M&A studies (e.g., Fuller, Netter, and Stegemoller (2002), Harford, Humphery-Jenner, and Powell (2012), and Austin, Harris, and O'Brien (2020)), and other literature utilizing the event study methodology (e.g., Chang, Cheng, and Yu (2007), Edwards and Shevlin (2011), Liu, Shu, and Wei (2017)).

[7] Results remain qualitatively the same when we employ other event windows.

B. Summary Statistics

Table 1 presents the summary statistics for the sample of 3,920 M&As over the sample period from 2007 to 2019. All continuous variables are winsorized at the 2.5th and 97.5th percentiles of their distribution.

{Insert Table 1}

As shown in Table 1, the acquirer's cumulative abnormal returns from day -3 to day 3, centered on announcement day 0, *CAR(-3,3)*, has a mean value of 1.1%, with a large standard deviation of 7.4%. The 25th and 75th percentiles are equal to -2.6% and 4.4%, respectively. Social connectedness, *Ln(SCI)*, deviates slightly from its mean of 9.003, with a standard deviation of 1.732, and the values of the 25th and 75th percentiles are close to the median value of 8.457. The variable *Ln(Deal value)*, the natural logarithm of the deal value (in millions of dollars), averages 4.912, with a standard deviation of 1.761. This evidence suggests that our sample covers large M&A transactions, even though a majority of transactions involve private targets (71.8%). In addition, 20.1% of the transactions in our sample involve acquirers and targets located in the same state, and the majority of transactions (58.3%) involve acquirers and targets in the same industry. Table 1 also shows that the average stock percentage as the method of payment is 10.6%. We note that 4.8% of the transactions, that is, 188 transactions, are tender offers. A large proportion of transactions in our sample (92.8%) were successfully completed. Overall, the statistics show that our sample is comparable to other M&A samples in the literature.

Table 1 also provides the descriptive statistics of acquirers, including their asset size (*Ln(AT)*), leverage (*Leverage*), return on total assets (*ROA*), and scaled capital expenditures (*Investment*). On average, acquirers are large. The mean of the natural logarithm of total assets, *Ln(AT),* equals 7.418, and, as an exponential, it equals $1.665 billion. The leverage ratio averages 0.217, and 75% of the acquirers in the sample have a leverage ratio equal to or below 33%, suggesting that they are not in financial distress before the announcement. Acquirers' *Q* is centered at 2.134, with the 25th and 75th percentiles equal to 1.380 and 2.490, respectively, indicating that, in most of our transactions, the acquirer's market value of assets is greater than its book value of assets.

III. Main Empirical Results

A. *Social Connectedness and Acquirer Returns*

To empirically test the relation between social connectedness and acquirer announcement returns, we estimate the following cross-sectional regression:

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

where the dependent variable, *CAR(-3,3)*, is the acquirer's cumulative abnormal returns between days -3 and 3, where day 0 is the announcement date; and *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. 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), and Li, Qiu, and Shen (2018)). We further control for common industry and year factors that could affect acquirer returns by including industry fixed effects (defined by the 49 Fama–French industries) and year fixed effects in all specifications.[8] The standard errors are robust to heteroskedasticity. The definitions of variables are provided in Table A.1 in the Appendix.

Table 2 reports the estimation results of Equation (1). As shown in Model (1), the coefficient of *Ln(SCI)* is positive at 0.003 and statistically significant at the 5% level, supporting our hypothesis that social connectedness addresses the information asymmetry problem and leads to higher acquirer returns. Using the coefficient of *Ln(SCI)*, β, to quantify the economic significance of social connectedness, we find that a one-standard-deviation increase in *Ln(SCI)* (1.732) leads to an increase of 52 basis points (i.e., 0.52%) in the acquirer's announcement returns. Since the average market capitalization of the acquirers four weeks before the announcement is $15.2 billion, the positive price reaction corresponds to an average increase in the acquirer's market capitalization of $79 million, emphasizing the economic significance of our results.

[8] 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. Besides, we re-estimate equation (1) using acquirer's county fixed effect to control for its population size and other invariant county-level characteristics.

{Insert Table 2}

We further show that *Ln(Deal value)* and *Within industry* are positively related to acquirer returns, consistent with the findings of Amihud and Lev (1981), Morck, Shleifer, and Vishny (1990), and Li et al. (2018). The coefficient of *Public* (i.e., the target's public status) is negative (-0.007) and statistically significant at the 5% level, supporting the view on a negative association between public target status and acquirer returns (Moeller, Schlingemann, and Stulz (2004), Faccio, McConnell, and Stolin (2006), and Uysal, Kedia, and Panchapagesan (2008)). The coefficient of *Stock ratio* is negative at -0.020 and statistically significant at the 1% level, indicating stock financing's negative impact on acquirer returns (Li et al. (2018)). The coefficients of the variables controlling for acquirer characteristics enter the regressions with the expected signs. More specifically, the acquirer's asset size reduces its returns (e.g., Moeller et al. (2004), Masulis et al. (2007), and John et al. (2015)), while the acquirer's leverage significantly increases its returns (Masulis et al. (2007), and John et al. (2015)). We also document that the acquirer's investment level before the announcement date is positively related to its returns. Overall, the findings for the control variables are generally consistent with the M&A literature, providing us with confidence in our findings of a positive relation between social connectedness and acquirer returns.

B. Social Connectedness, Physical Distance, and Acquirer Returns

We are concerned that geographical proximity can drive the effect of social connectedness on acquirer returns. 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.

To address this concern, we measure the precise physical distance (in miles) between the target and acquirer, based on the longitude and latitude of their locations' zip codes. We first illustrate whether high social connectedness is always associated with a short distance between the acquirer and its target. Figure 1 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, which is the county that received the highest number of bids in our sample. Higher degrees of social connectedness are denoted by a darker shade.

{Insert Figure 1}

As shown in Figure 1, counties socially connected with Santa Clara are mostly but not only those that are geographically close to Santa Clara. We further examine the four counties with the highest number of acquirers of Santa Clara targets and observe that these counties are highly socially connected with Santa Clara. Interestingly, although three of them 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 positively related to social connectedness but does not fully capture all the dimensions of social connectedness.

We further perform an empirical test to ascertain this observation. In the spirit of Uysal et al. (2008), we construct a dummy variable, *Local*, that equals one if the physical distance between the acquirer and the target is less than 220 miles, and zero otherwise. We determine 220 miles as the threshold, because it represents the average distance of the top 10% shortest distances between counties.[9] We first remove *Within state* and *Ln(SCI)* from Equation (1) and control for geographical proximity, *Local.* The regression results are presented in Model (1) of Table 3. As shown in this model, the coefficient of *Local* is positive and statistically significant at 10%, which lends support to the local information transmission hypothesis of Uysal et al. (2008). Specifically, if the transaction is local, the acquirer returns increase by 50 basis points, ceteris paribus. In Model (2), we include both *Local* and *Ln(SCI)* and find that the coefficient of *Ln(SCI)* is positive at 0.002 and statistically significant. In contrast, the coefficient of *Local* becomes negative and statistically nonsignificant. This finding implies that the information transmission is more pronounced through social network interactions than through geographical proximity.[10]

{Insert Table 3}

C. Instrumented Regressions

There are two endogeneity concerns with our baseline results. First, the results are not drawn from a natural experiment setting. Therefore, one could be concerned that

[9] The data are collected from https://www.nber.org/research/data/county-distance-database.

[10] The coefficient of *Ln(SCI)* is qualitatively the same when we the control for the physical distance between the target and the acquirer (in thousands of miles).

M&A deals with a high degree of social connectedness might be fundamentally different from deals in the other counties, leading to higher acquirer returns. Second, there is a possibility that the social connections between two counties are associated with unobservable factors that affect acquirer returns.

To address these endogeneity concerns, we employ an instrumental variable approach. Following the historical travel cost argument of Rehbein and Rother (2020), we construct two instruments using Baum-Snow's (2007) highway data, which also include highway construction dates. Our first instrument, *Ln(1+N_highway)*, is the natural logarithm of the number of highways connecting the acquirer's county and the target's county, plus one. Our second instrument, *Ln(1+N_hwyears)*, is 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. The value of the instruments equals zero if there are no connecting highways between the target and the acquirer.

The intuition is that historical travel costs do not directly impact the performance of acquisitions today, but they shape social ties, some of which can persist for generations. The planning of the U.S. highways began in World War II, to enhance logistics for the war effort and support the relocation of resources during the Cold War. According to Rehbein and Rother (2020), the social connections developed along these highways are persistent and still present, and the founding fathers of the highway system were not motivated by current factors related to M&As. The instruments, therefore, meet the requirements of relevance and exclusion. It is noted that social connections indeed appear to have emerged along highways, and they are likely to do so slowly over time. To incorporate this idea, our second instrument measures the number of years that have passed since the construction of the highways connecting the counties.

{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+N_highway)* is employed as an instrument for *Ln(SCI)*, while Models (3) and (4) report the results when *Ln(1+N_hwyears)* is used as an instrument. As expected, social connectedness is greater for counties with higher numbers of connecting highways. The coefficient of *Ln(1+N_highway)* is positive and statistically significant at the 1% level in Model (1). 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 acquirer returns, even after we control for endogeneity concerns. The results remain robust in Models (3) and (4); that is, *Ln(1+N_hwyears)* is positively related to social connectedness, and the predicted value of *Ln(SCI), Ln(SCI)_hat2,* positively affects acquirer returns.[11]

IV. Social Connectedness, Information Asymmetry, and Acquirer Returns

[11] One might argue that our instruments are positively associated with the county size, i.e. larger counties are more likely to have more connecting highways or longer history since the construction of the first highway. To address this concern, we re-estimate both our instrumented regressions after removing observations of acquirers located in the largest three (and five) counties. We obtain consistent results.

Our principal argument is that social connectedness facilitates the transmission of information between the acquirer and the target, thus improving acquirer returns. In this section, we directly examine this information channel by investigating how a target's information asymmetry affects the relation between social connectedness and acquirer returns. Next, we provide evidence of the effect of social connectedness on deal-level information asymmetry proxies, including advisory fees and takeover premiums.

A. Social Connectedness, Target Status, and Acquirer Returns

Following prior literature, we partition the whole sample into different subsamples based on target status, including public versus private firms (Officer, Poulsen, and Stegemoller (2009)), listed firms versus unlisted firms (Faccio, McConnell, and Stolin (2006)), and we re-estimate Equation (1) to examine the relation between social connectedness and acquirer returns. The dependent variable in Models (1) to (4) is *CAR(-3,3)*. Our main independent variable is *Ln(SCI)*. Other control variables for the deal and firm characteristics are the same as those discussed in Section III.A. We present the estimation results in Table 5.

{Insert Table 5}

The first model of Table 5 corresponds to M&A deals with public target firms. We find that the coefficient of *Ln(SCI)* is positive but not statistically significant for this subsample. However, in Model (2) of Table 5, we re-examine the baseline model with all private target firms in the whole sample and find that the coefficient of *Ln(SCI)* is positive and statistically significant at the 10% level. This finding indicates that social connectedness has a stronger positive effect on acquirer returns for private firms than for public firms. This result is in line with our hypothesis that firms that acquire targets with a high level of information asymmetry would benefit more from social connectedness.

We find consistent results when partitioning the whole sample into listed and non-listed firms. The results for listed target firms are presented in Model (3), where the coefficient of *Ln(SCI)* is economically small at 0.001 and not statistically significant at all conventional levels. However, for the regression results using non-listed targets, presented in Model (4), we find that the coefficient of *Ln(SCI)* is 0.003 and statistically significant at the 5% level, suggesting that *Ln(SCI)* has a significant positive effect on acquirer returns when target firms are unlisted. Overall, the findings in Table 5 support the notion that social connectedness has a stronger effect on acquirer returns when the targets have a higher level of information asymmetry.

B. Social Connectedness, Target Information Asymmetry, and Acquirer Returns

We next examine the impact of social connectedness on acquirer returns conditional on target information asymmetry. Other than the status of targets that we have examined in the previous section, many proxies for target information asymmetry are exclusively available for public targets. We thus explore the role of information asymmetry by further partitioning the group of public targets into two subgroups based on their information asymmetry level and estimate the following equation:

$$(2) \quad CAR(-3,3)_{i,t} = \alpha + \beta Ln(SCI)_i + \theta_1 Public_{HighIA_{i,t-1}} + \theta_2 Public\_LowIA_{i,t-1} + \vartheta_1 [Ln(SCI)_i \times Public\_HighIA_{i,t-1}] + \vartheta_2 [Ln(SCI)_i \times Public\_LowIA_{i,t-1}] + \gamma Deal\ characteristics_{i,t-1} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

where $Public\_HighIA$ is a dummy variable that denotes a public target with high information asymmetry, $Public\_LowIA$ is a dummy variable indicating a public target with low information asymmetry, β measures the impact of social connectedness on acquirer returns when the targets are private, ϑ_1 reflects the difference between the impact of social connectedness on acquirer returns when the targets are public firms with high information asymmetry and the targets are private firms, and, similarly, ϑ_2 quantifies the difference in impact between the two groups of low–information asymmetry public targets and private targets. Since private targets are subject to high levels of information asymmetry, we expect social connectedness to play a significant role in these deals and, thus β to be positive. Just as we expected the difference in information asymmetry to be more evident between low–asymmetric information public targets and private targets, we expect social connectedness to play a weaker role in acquirer returns in the former group; that is, we expect a negative ϑ_2 value.

We first measure the information asymmetry of public target firms 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 prior to the announcement date. We then define low–information asymmetry 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 asymmetry. 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 asymmetry. The negative and statistically significant coefficient on *Ln(SCI)* × *Public_LowIA* in Models (1) and (2) in Table 6 indicates that the impact of social connectedness on acquirer returns is weaker when the target firms are public firms with low information asymmetry, compared to private targets. This result suggests that social connectedness is more valuable when information asymmetry is severe. We find a positive and significant coefficient for *Ln(SCI)*, suggesting a positive relation between social connectedness and acquirer returns when the target is private.

{Insert Table 6}

We further employ classifications of high-tech and R&D firms as other measures of information asymmetry. 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_LowIA* is negative and statistically significant in the last two models of Table 6. This result suggests that the impact of social connectedness is weakened when public targets are neither high-tech nor R&D firms, that is, public targets with low information asymmetry.

Overall, the results in Table 6 suggest that the impact of social connectedness on acquirer returns depends on the information asymmetry of the targets. Social connectedness is most valuable in M&A transactions with target firms that are informationally opaque.

C. Social Connectedness, Advisory Fees, and Acquirer Returns

We provide further evidence on the effect of target firms' level of information asymmetry on the positive relation between *Ln(SCI)* and *CAR(-3,3)* by examining the role of advisory fees. Prior literature documents that financial advisors act as producers of credible information about target firms (Chemmanur and Fulghieri (1994)), alleviating the negative impact of information asymmetry in financial markets (Booth and Smith (1986), and Titman and Trueman (1986)). In addition, the model by

Chemmanur and Fulghieri (1994) suggests that financial advisors with better reputation are more effective at addressing the information asymmetry problem. Reputable financial advisors are also found to charge higher fees (Fang (2005), Golubov, Petmezas, and Travlos (2012)). Therefore, we conjecture that i) social connectedness reduces advisory fees by attenuating the information asymmetry problem and ii) in M&A deals with high advisory fees implying less severe information asymmetry, social connectedness has a weaker impact on acquirer returns.

We calculate *Advisory fees* as the total financial advisory fees paid by both acquirers and targets, normalized by the deal size. We examine the impact of *Ln(SCI)* on *Advisory fees* in Model (1) and the impact of *Ln(SCI)* on acquirer returns taking into account *Advisory fees* in Model (2). We also control for other factors that were discussed in the baseline model. The results are reported in Table 7.

{Insert Table 7}

In Model (1) of Table 7, the coefficient of *Ln(SCI)* is -0.025 and statistically significant at the 5% level. This indicates that high social connectedness leads to lower advisory fees, which is consistent with our conjecture. In Model (2), the coefficient of the interaction term between *Advisory fees* and *Ln(SCI)* is -0.002 and statistically significant at the 5% level. This indicates that higher advisory fees attenuate the positive relation between *Ln(SCI)* and *CAR(-3,3)*. In addition, the coefficient of *Advisory fees* is 0.021 and statistically significant at the 5% level, suggesting that advisory fees paid by both acquirers and target firms to financial advisors are positively associated with the acquirer returns. This finding is consistent with the positive relation between the reputation of the investment bankers and acquirer returns in prior literature (Golubov et al. (2012), Chemmanur et al. (2019)). Together with the coefficients of the other control variables, the coefficient of *Ln(SCI),* 0.003 and statistically significant at the 5% level, is consistent with the baseline regression result.

D. Social Connectedness and Takeover Premiums

In this section, we analyze whether social connectedness has any effect on takeover premiums. Prior literature documents a positive relation between takeover premiums and information asymmetry (Raman, Shivakumar, and Tamayo (2013), Cheng, Li, and Tong (2016)). Compared to other bidders, those that are socially connected to their targets have an information advantage regarding the true value of the target firms and therefore pay lower takeover premiums (Cai and Sevilir (2012)). We thus hypothesize that social connectedness, by lowering information asymmetry, reduces takeover premiums. We measure *Deal 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:

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

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 takeover premiums. This result is consistent with our prediction that social connectedness leads to less information asymmetry, which results in lower takeover premiums.

{Insert Table 8}

Since large targets exhibit less information asymmetry (Hasbrouck (1991), Leuz and Verrecchia (2000), and Yoon and Zoo (2011)), we expect the effect of social connectedness on takeover premiums to be less pronounced when the target size is larger. In Model (2) of Table 8, we include the interaction between *Ln(SCI)* and deal size, *Ln(Deal value)*. We expect the interaction term, *Ln(SCI)* × *Ln(Deal value),* to have a positive impact on takeover premiums. Our main results hold, since the coefficient of *Ln(SCI)* remains negative and statistically significant at the 5% level. The coefficient of the interaction term between *Ln(SCI)* and *Ln(Deal value)* is 0.005, which is statistically significant at the 10% level, indicates a less pronounced impact of *Ln(SCI)* on deal premiums for a large deal size. Overall, our findings suggest that acquirers tend to pay lower premiums when they are more informed about target firms through social connections

V. Social Connectedness and Post-Merger Performance

In Section IV, we provide evidence that supports the information channel through which acquirer–target social connectedness affects the acquirers' announcement returns.

If social connectedness attenuates the information asymmetry between acquirers and targets, socially proximate acquirers should be able to identify targets of high quality. Therefore, it is natural to ask if social connectedness generates superior post-merger performance. In this section, we examine the relation between social connectedness and post-merger performance as measured by i) long-term buy-and-hold abnormal returns (BHAR), and ii) long-term operating performance.

A. *Social Connectedness and Long-Term Buy-and-Hold Returns*

We examine the impact of social connectedness on acquirer returns over a long-term horizon for completed deals. 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:

$$BHAR_{i,t,T} = \prod_{t=1}^{T}(1 + R_{it}) - \prod_{t=1}^{T}(1 + R_{mt}) \quad (4)$$

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. 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 9.

{Insert Table 9}

As shown in Panel A, Table 9, the coefficient on *Ln(SCI)* is positive at 0.005 in the regression of the one-year *BHAR*, which is marginally statistically significant at the 10% level when market returns are measured using the CRSP value-weighted or equally weighted returns in Models (1) and (2), respectively, and statistically significant at 10% in Model (3) when the market benchmark is the S&P 500. Since the horizon to measure *BHAR* extends to two and three years in Panels B and C, respectively, the coefficient of *Ln(SCI)* becomes larger and more statistically significant, emphasizing the effect of social connectedness in the long term. Indeed, Panel C shows that a one-standard-deviation increase in *Ln(SCI)* increases the three-year abnormal returns by 2.6%, 2.4%, and 2.6% when the market returns are CRSP value-weighted, CRSP equally weighted, and S&P 500 returns, respectively. Overall, the evidence suggests that social connectedness, by addressing the information asymmetry problem and enhancing target selection, increases post-merger long-term BHAR.

B. Social Connectedness and Long-Term Operating Performance

We next examine how social connectedness affects the operating performance of acquirers in the long term. Prior literature documents that acquirers can benefit from knowledge and obtain an information advantage about the targets when information flow and communication between the targets and acquirers are improved (Cai and Sevilir (2012)).[12] Since social connectedness can mitigate information asymmetry between acquirers and targets, we expect that acquirers can search for high-quality

[12] Cai and Sevilir (2012) document that acquirers' long-term performance improves when they have a board connection with their targets.

targets, which, in turn, will generate better value in the long term. We employ the following regression to examine the impact of social connectedness on acquirers' long-term operating performance:

$$(5) \quad \Delta Performance(-1,3)_{i,t} = \alpha + \beta Ln(SCI)_i + \gamma Deal\ characteristics_{i,t-1} + \delta Acquirer\ characteristics_{i,t-1} + Industry\ FE + Year\ FE + \varepsilon_{i,t}$$

We use three different industry-adjusted proxies for the acquirer's long-term operating performance, including i) *ΔAdj_ROA(-1,3)*, ii) *ΔAdj_EBIT/Sales(-1,3)*, and iii) *ΔAdj_EBIT/MVE(-1,3),* where *MVE* is the acquirer's market value of equity, which equals the product of the number of shares and the share price at the end of the fiscal year immediately before the announcement date. 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 raw measure, that is, its ROA, EBIT over sales, and EBIT over the market value of equity, and the median value of other Compustat-listed firms in the same year and industry (as defined by their two-digit SIC codes).[13] We report the regression results in Table 10.

{Insert Table 10}

As shown in Table 10, the coefficient of *Ln(SCI)* is positive and significant across all model specifications. In terms of economic significance, a one-standard-deviation

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

increase in *Ln(SCI)* leads to increases of 0.52% in the change of the adjusted ROA, 1.04% in the change of the ratio of the adjusted EBIT to sales, and 1.21% in the change of the ratio of the adjusted EBIT to the market value of equity from year -1 to year 3, where year 0 is the M&A announcement year. These results indicate that social connectedness has a positive impact on the long-term operating performance of acquirers, supporting the notion that information flow and communication play a significant role in corporate investments and create value (Cai and Sevilir (2012)).

VI. Additional Analyses

A. Social Connectedness and Acquisition Likelihood

Since social networks facilitate information transmission, acquirers are more aware of targets in their socially proximate regions. Therefore, not only does social connectedness affect acquirer performance, but it also is expected to affect the acquisition likelihood in the first place.

To examine this conjecture, we construct a sample of all possible acquirer–target pairs drawn from our main sample as follows. In each announcement year, we identify all acquirers *(m)* and targets *(n)* and then create an $m \times n$ matrix of all possible matches between them. We then construct a dummy variable, *Acquisition,* indicating an actual transaction between an acquirer *i* and a target *j*, and we assign a value for each element of the matrix accordingly. Specifically, for each element *(i, j)* of the matrix, if an M&A transaction takes place that year between acquirer i and target j, *Acquisition* takes the value of one, and zero otherwise. We then append all year-specific matrices into a single matrix of random acquirer–target pairs from 2007 to 2019. We investigate the impact of social connectedness on the acquisition likelihood by estimating the following model using probit regressions:

$$Acquisition_{i,j,t} = \alpha + \beta Ln(SCI)_{i,j} + \gamma Acquirer\ FE + \delta Target\ FE + Industry\ FE + Year\ FE + \varepsilon_{i,j,t} \tag{6}$$

{Insert Table 11}

The estimation results of Equation (6) are presented in Table 11. As shown in Model (1), the coefficient of *Ln(SCI)* is positive at 0.143 and statistically significant at the 1% level, suggesting a positive effect of social connectedness on the likelihood of acquisition. In Model (2), we remove *Ln(SCI)* from our regression equation and use *Local* as our main independent variable. The results indicate that acquirers are more likely to acquire local targets. In particular, the coefficient of *Local* equals 0.373 and is statistically significant at the 1% level. However, in Model (3), when we include both *Ln(SCI)* and *Local*, we find that, while the coefficient of *Ln(SCI)* remains positive, the coefficient of *Local* becomes statistically nonsignificant, suggesting that social connectedness absorbs the effect of physical distance on the likelihood of acquisition. Overall, the results support our prediction that acquirers are more aware of and more likely to acquire socially connected targets, even after their physical distance is considered.

B. Pseudo-Analyses

In this section, we conduct pseudo-analyses to ascertain the impact of social connectedness on acquirer returns documented in our earlier analyses. First, for each M&A deal, we randomly select a value of *Ln(SCI)* from the pool of all possible values of *Ln(SCI)* in our final sample. Second, for each M&A deal, we randomly choose a pseudo-announcement that satisfies the two following conditions: i) it is on a non-M&A announcement date and ii) it is on a trading day in the same announcement year. Third, on each actual announcement date, we randomly select a pseudo-acquirer from the pool of all acquirers. Finally, we simultaneously randomize the announcement date and the acquirer. We then rerun Equation (1) (i.e., the baseline regression) to obtain the coefficient β on *Ln(SCI).* We repeat this process 1,000 times and illustrate the distribution of the bootstrapped coefficient β in Figure 2.

{Insert Figure 2}

The results in Figure 2 suggest that the bootstrapped coefficients of *Ln(SCI)* in all the simulations are normally distributed and centered at zero. Table 12 reports the results of formal tests for the normality of the bootstrapped coefficients and comparisons with the actual coefficient of *Ln(SCI),* as obtained from the baseline regression.

{Insert Table 12}

As summarized in Table 12, the coefficients of *Ln(SCI)* in all four simulations have a mean of zero and a standard deviation of 0.001. The results of normality tests, including the Shapiro–Wilk, Shapiro–Francia, and skewness/kurtosis tests, suggest that the bootstrapped coefficients of *Ln(SCI)* are normally distributed. The coefficient of 0.003 for *Ln(SCI)* in our baseline model is on the far right of the distribution (between 2.83 and 4.26 standard deviations from the mean of the bootstrapped coefficients) in all the simulations. This result suggests that it is unlikely that the coefficient of *Ln(SCI)* in the baseline regression is obtained by chance.

C. *Alternative Measures for Acquirer Returns and Social Connectedness*

In this section, we perform several robustness checks using i) alternative risk-adjusted models to measure acquirer returns and ii) alternative measures of social connectedness. First, we re-estimate the acquirer returns using the market model (Model (1)); the Fama–French three-factor model, which includes the market risk premium, the size premium, and the value premium (Model (2)); and the Fama–French three-factor model plus momentum (Model (3)). Second, we re-estimate the baseline model of *CAR(-3,3)* on *SCI_5pct* (Model (4)), *SCI_10pct* (Model (5)), and *SCI_15pct* (Model (6)), respectively, where *SCI_5pct*, *SCI_10pct,* and *SCI_15pct* are dummy variables indicating high social connectedness using the thresholds of the fifth percentile, 10th percentile, and 15th percentile of *Ln(SCI)*. The results are presented in Table 13.

{Insert Table 13}

The coefficients of *Ln(SCI)* remain positive and statistically significant in Models (1) to (3) in Table 13, supporting our baseline results when the abnormal returns are calculated using different risk-adjusted models. Moreover, the coefficients of the alternative proxies for social connectedness in Models (4) to (6) are all positive and statistically significant at conventional levels. Overall, the results in Table 13 confirm our previous findings of the strong and positive impact social connectedness has on acquirer returns, and this relation is not subject to the models used to estimate acquirer returns or the measures of social connectedness.

VII. Conclusion

This paper examines the impact of social connectedness on M&As. We use a large dataset containing the interactions of Facebook users between U.S. counties to measure the social connectedness between targets and acquirers. We hypothesize that social connectedness, which can be understood as the number of ties and degree of connectedness of social networks, can reduce information asymmetry by helping acquirers gain access to the relevant information of targets and the corresponding local socioeconomical environment. Our study extends beyond the literature in the M&A field that focuses on geographical proximity and social ties between firms' top management levels.

Using a sample of 3,920 M&A transactions in the United States, we find that acquirers that are more socially proximate to their targets earn higher announcement returns. Our results are robust to the inclusion of the acquirer–target physical distance, mitigating the vital concern that our results are driven by geographic proximity, one of the common information resolution factors. More remarkably, we show that the negative effect of geographic proximity on acquirer returns can be explained by social connectedness.

We also find evidence that social connectedness increases acquirer returns more significantly when the target firms are subject to greater information asymmetry, as measured by their status and different proxies such as analyst coverage, bid–ask spreads, and high-tech and R&D firm classifications. We further document that social connectedness helps lower advisory fees, and the impact of social connectedness on acquirer returns is weaker in M&A deals with high advisory fees. This result is consistent with our hypothesis that social connectedness serves as an information channel between acquirers and targets.

Next, we show that acquirers offer lower premiums when the degree of social connectedness is high. This finding, by suggesting that strong social connectedness provides acquirers with more information about targets, thus reduces the likelihood of possible overvaluation and lends further support for the information channel. We also examine the effect of acquiring a socially connected target on the acquirer's post-merger performance in the long term. We find that short-term performance persists in the long term, as evidenced by the positive association of social connectedness and acquirers' long-term buy-and-hold returns and operating performance. This finding suggests that, when the information asymmetry between acquirers and targets is mitigated, acquirers can select high-quality deals that create better value in the long run. We further conduct an analysis of social connectedness and the likelihood of acquisition and find that acquirers tend to choose targets that are more socially connected. Our findings are robust to accounting for endogeneity and alternative measures for acquirer returns and social connectedness.

Overall, our study, drawn from a U.S. M&A sample, highlights the positive role that social connectedness plays in acquirer performance in the short and long term. Future work could further examine the value of social connections in cross-border M&As.

APPENDIX

Table A.1: Variable Definitions

Variable	Description	Data Sources
Main variables		
Ln(SCI)	The natural logarithm of the social connectedness index between the acquirer's county and the target's county.	Facebook, introduced by Bailey et al. (2018a), updated September 2020.
CAR(-3,3)	The acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date.	CRSP
Deal characteristics		
Ln(Deal value)	The natural logarithm of the deal value (in millions of dollars).	SDC M&A
Within industry	A dummy variable equal to one if the target and the acquirer operate in the same industry, and zero otherwise. Industries are defined by two-digit SIC codes.	SDC M&A
Public	A dummy variable equal to one if the target is a public firm, and zero otherwise.	SDC M&A
Stock ratio	The ratio of stock as the method of payment.	SDC M&A
Tender	A dummy variable equal to one if the deal is a tender offer, and zero otherwise.	SDC M&A
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
Acquirer characteristics		
Ln(AT)	The natural logarithm of the acquirer's total assets.	Compustat
Leverage	The ratio between the acquirer's total debt and total assets.	Compustat
ROA	The ratio between the acquirer's earnings before interest and taxes and total assets.	Compustat
Investment	The ratio between the acquirer's total expenditures and total assets.	Compustat
Tobin's Q	The ratio between the market value of assets and the book value of assets. The market value of assets is measured as the book value of debt plus market capitalization.	Compustat
Other characteristics		
Local	A dummy variable equal to one if the distance between the acquirer and the target is less than 220 miles, and zero otherwise.	Self-calculated
Advisory fees	Total financial advisory fees as a percentage of the deal size.	SDC M&A
Deal premium	The natural logarithm of the ratio between the offer price	SDC M&A

Variable	Description	Data Sources
	and the target's stock price one week before the announcement date.	
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. 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.	
ΔAdj_ROA(-1,3)	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. The acquirer's adjusted ROA is measured as the difference between the acquirer's ROA and the median ROA of other Compustat-listed firms in the same year and industry (defined by two-digit SIC codes).	Compustat
ΔAdj_EBIT/Sales(-1,3)	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. The acquirer's adjusted EBIT/Sales ratio is measured as the difference between the acquirer's EBIT/Sales ratio and the median EBIT/Sales ratio of the other Compustat-listed firms in the same year and industry (defined by two-digit SIC codes).	Compustat
ΔAdj_EBIT/MVE(-1,3)	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, where MVE is the acquirer's market value of equity. The acquirer's adjusted EBIT/MVE ratio is measured as the difference between the acquirer's EBIT/MVE ratio and the median EBIT/MVE ratio of the other Compustat-listed firms in the same year and industry (defined by two-digit SIC codes).	Compustat
Instrument variables		
Ln(1+N_highway)	The natural logarithm of the number of highways connecting the acquirer's county and the target's county, plus one.	Baum-Snow (2007)
Ln(1+N_hwyears)	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	Baum-Snow (2007)

Table A.2: Distribution of Mergers and Acquisitions across 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	Number of transactions	Average deal value ($ million)	Number of private targets	Number of public targets
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 across Industry

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

Industry code	Industry name	Number of transactions	Average deal value ($ million)
1	Agriculture	7	94
2	Food Products	80	1,291
3	Candy & Soda	10	1,364
4	Beer & Liquor	7	356
5	Tobacco Products	2	15,150
6	Recreation	16	144
7	Entertainment	28	579
8	Printing and Publishing	25	255
9	Consumer Goods	50	544
10	Apparel	42	248
11	Healthcare	103	545
12	Medical Equipment	219	433
13	Pharmaceutical Products	287	2,982
14	Chemicals	75	1,633
15	Rubber and Plastic Products	30	988
16	Textiles	2	90
17	Construction Materials	87	323
18	Construction	77	363
19	Steel Works Etc	71	351
20	Fabricated Products	5	255
21	Machinery	151	596
22	Electrical Equipment	71	328
23	Automobiles and Trucks	37	445
24	Aircraft	63	734
25	Shipbuilding, Railroad Equipment	12	133
26	Defense	13	1,138
27	Precious Metals	5	338
28	Non-Metallic and Industrial Metal Mining	16	1,394
29	Coal	13	608
30	Petroleum and Natural Gas	117	2,698
32	Communication	155	3,334
33	Personal Services	59	273
34	Business Services	451	540

35	Computers	136	910
36	Computer Software	522	558
37	Electronic Equipment	278	1,802
38	Measuring and Control Equipment	119	978
39	Business Supplies	29	834
40	Shipping Containers	15	767
41	Transportation	107	890
42	Wholesale	140	705
43	Retail	124	1,261
44	Meals	55	452
49	Other	9	51
	Total	3,920	49,757

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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.

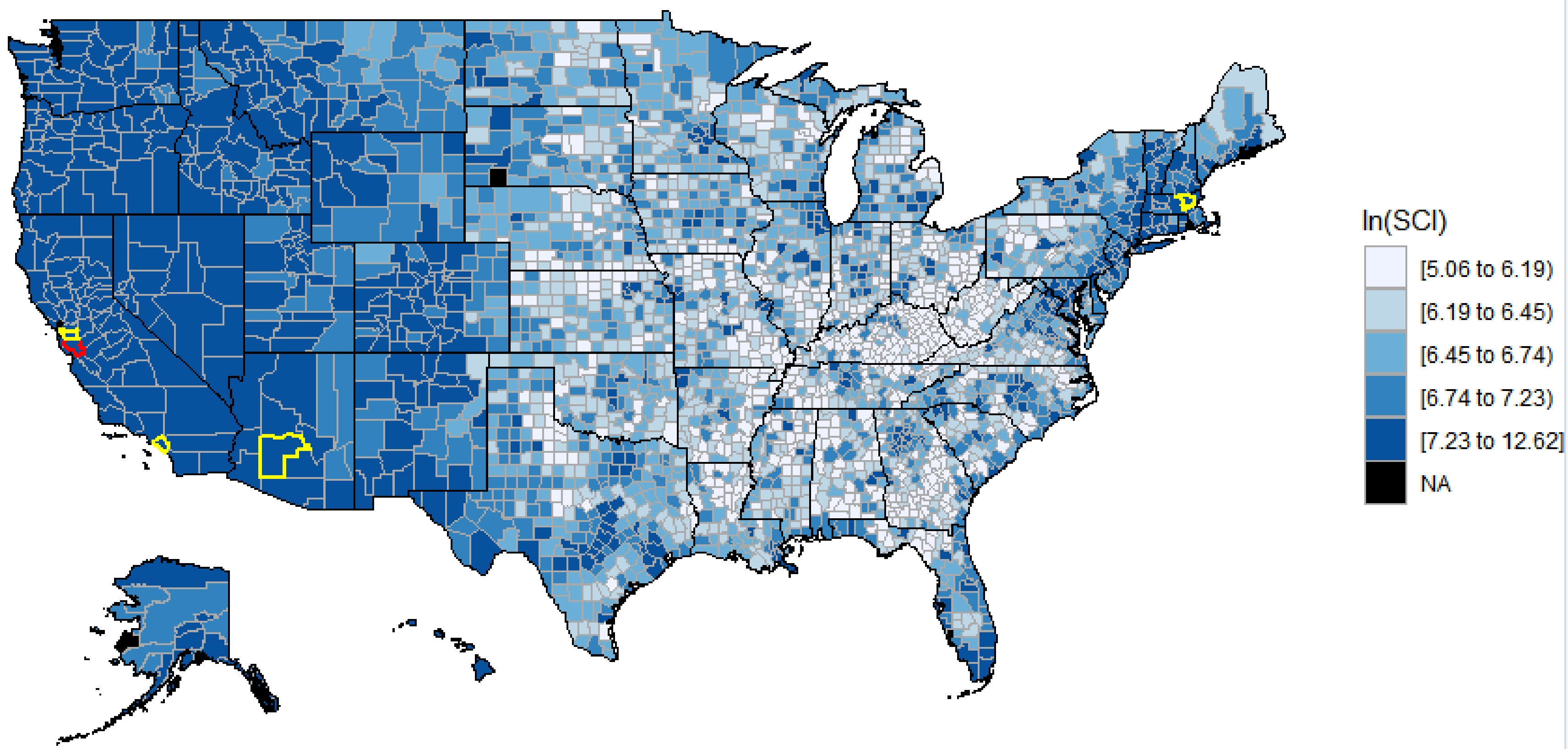
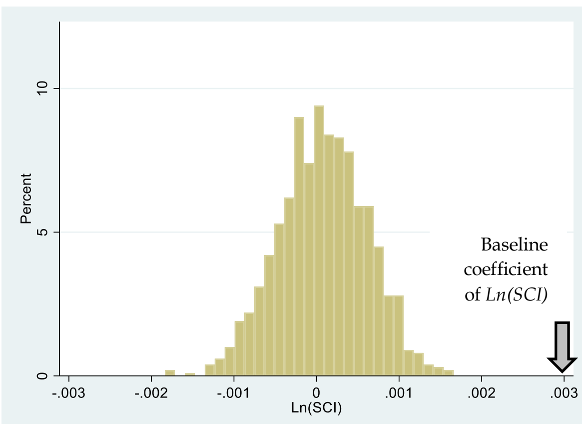


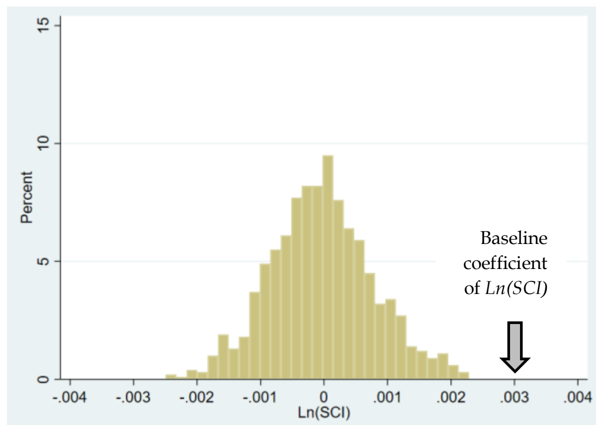
Figure 2: Bootstrapped Coefficients

This figure plots a histogram of the frequency distribution of bootstrapped coefficients of *Ln(SCI)*. In panel A, for each M&A deal, we randomly select a value of *Ln(SCI)* from the pool of all possible values of *Ln(SCI)* in our final sample. In panel B, for each M&A deal, we randomly choose a pseudo announcement, which satisfies the two following conditions: (i) being a non-M&A announcement date, and (ii) being a trading day in the same announcement year. In panel C, on each actual announcement date, we randomly select a pseudo acquirer from the pool of all acquirers. In panel D, we simultaneously randomize the announcement date and the acquirer. We then re-run the baseline regression to obtain the coefficient β on *Ln(SCI)*. We repeat this process 1,000 times to obtain 1,000 bootstrapped coefficients of *Ln(SCI)*.

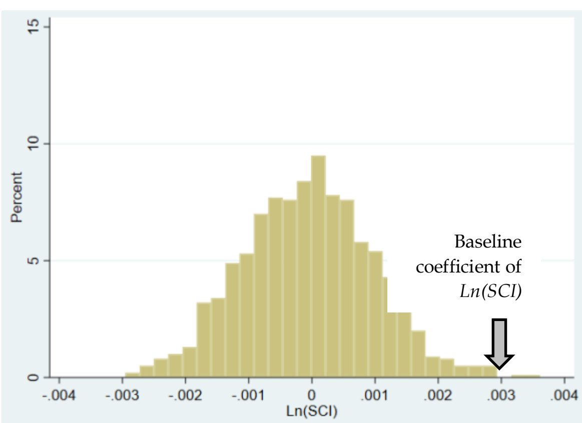
Panel A.



Panel B.



Panel C.



Panel D.

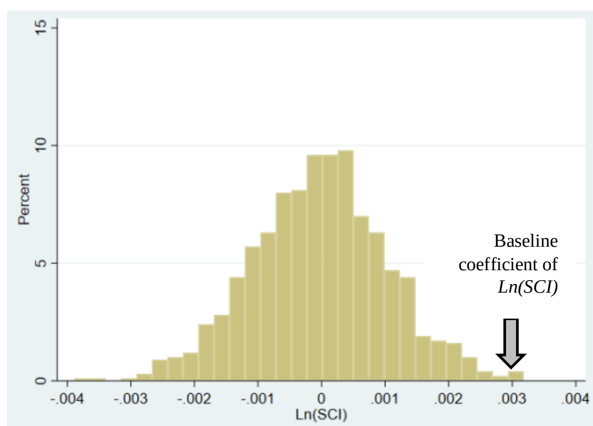


Table 1: Descriptive Statistics

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. *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 (in millions of dollars). *Within industry* is a dummy variable equal to one if the target and the acquirer operate in the same industry, 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(AT)* is the natural logarithm of the acquirer's total assets. *Leverage* is the ratio between the acquirer's total debt and total assets. *ROA* is the ratio between the acquirer's earnings before interest and taxes and total assets. *Investment* is the ratio between the acquirer's total expenditures and total assets. *Tobin's Q* is the ratio between the market value of assets and the 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
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(AT)	3,920	7.418	1.823	6.108	7.275	8.612
Leverage	3,920	0.217	0.188	0.038	0.199	0.330
ROA	3,920	0.087	0.082	0.050	0.091	0.133
Investment	3,920	0.036	0.033	0.014	0.025	0.045
Tobin's Q	3,920	2.134	1.095	1.380	1.809	2.490

Table 2: Social Connectedness and Acquirer Returns

The table reports regression results of acquirer 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. Definitions of other variables 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)	(4)
Ln(SCI)	0.003**	0.003**	0.003**	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Deal value)	0.005***	0.005***	0.005***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)
Within industry	0.007***	0.007***	0.007***	0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Public	-0.007**	-0.007**	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)
Stock ratio	-0.020***	-0.020***	-0.019***	-0.019***
	(0.007)	(0.007)	(0.007)	(0.007)
Tender	-0.002	-0.003	-0.002	-0.003
	(0.005)	(0.005)	(0.005)	(0.006)
Within state	-0.005	-0.005	-0.007	-0.009
	(0.005)	(0.005)	(0.006)	(0.006)
Ln(AT)	-0.008***	-0.008***	-0.008***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.028***	0.028***	0.030***	0.032***
	(0.008)	(0.008)	(0.008)	(0.009)
ROA	0.039**	0.039**	0.044**	0.036*
	(0.019)	(0.019)	(0.020)	(0.021)
Investment	0.042	0.042	0.048	0.061
	(0.050)	(0.050)	(0.052)	(0.058)
Tobin's Q	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.002)
Completion		0.006		
		(0.005)		
Constant	0.057	0.051	0.105*	0.007
	(0.038)	(0.039)	(0.062)	(0.042)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	No	Yes
State FE	Yes	Yes	Yes	No

Observations	3,920	3,920	3920	3920
R^2	0.05	0.05	0.06	0.14

Table 3: Social Connectedness, Physical Proximity, and Acquirer Returns

The table reports regression results of acquirer returns on geographical proximity 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. *Local* is a dummy variable equal to one if the distance between the acquirer and the target is less than 220 miles, and zero otherwise. Definitions of other variables 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)
Ln(SCI)		0.002*
		(0.001)
Local	0.005*	-0.001
	(0.003)	(0.005)
Ln(Deal value)	0.005***	0.005***
	(0.001)	(0.001)
Within industry	0.007***	0.007***
	(0.003)	(0.003)
Public	-0.007**	-0.007**
	(0.003)	(0.003)
Stock ratio	-0.019***	-0.020***
	(0.007)	(0.007)
Tender	-0.002	-0.003
	(0.005)	(0.005)
Ln(AT)	-0.008***	-0.008***
	(0.001)	(0.001)
Leverage	0.028***	0.028***
	(0.008)	(0.008)
ROA	0.039**	0.040**
	(0.019)	(0.019)
Investment	0.042	0.041
	(0.050)	(0.050)
Tobin's Q	-0.002	-0.002
	(0.001)	(0.001)
Constant	0.077**	0.062*
	(0.036)	(0.037)
Year, Industry FE	Yes	Yes
Observations	3,920	3,920
R^2	0.05	0.05

Table 4: Instrumented Regressions

The table reports instrumented regression results of acquirer 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. *Ln(SCI)* is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. *Ln(1+N_highway)* is the natural logarithm of the number of highways connecting the acquirer's county and the target's county, plus one. *Ln(1+N_hwyears)* is 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. Definitions of other variables 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(SCI) First-stage	*CAR(-3,3)* Second-stage	*Ln(SCI)* First-stage	*CAR(-3,3)* Second-stage
	(1)	(2)	(3)	(4)
Ln(1+N_highway)	1.404***			
	(0.100)			
Ln(SCI)_hat1		0.004*		
		(0.002)		
Ln(1+N_hwyears)			0.557***	
			(0.030)	
Ln(SCI)_hat2				0.004**
				(0.002)
Ln(Deal value)	-0.010	0.005***	-0.010	0.005***
	(0.012)	(0.002)	(0.012)	(0.002)
Within industry	0.017	0.007**	0.005	0.007**
	(0.041)	(0.003)	(0.037)	(0.003)
Public	0.010	-0.007**	0.012	-0.007**
	(0.044)	(0.003)	(0.044)	(0.003)
Stock ratio	0.201**	-0.020***	0.179**	-0.020***
	(0.079)	(0.007)	(0.077)	(0.007)
Tender	-0.040	-0.002	-0.057	-0.002
	(0.074)	(0.005)	(0.071)	(0.005)
Within state	2.552***	-0.009	2.435***	-0.009
	(0.111)	(0.008)	(0.103)	(0.007)
Ln(AT)	0.017	-0.008***	0.019	-0.008***
	(0.014)	(0.001)	(0.014)	(0.001)
Leverage	-0.140	0.028***	-0.161	0.028***
	(0.130)	(0.007)	(0.128)	(0.007)
ROA	-0.134	0.039	-0.159	0.039
	(0.225)	(0.024)	(0.200)	(0.024)
Investment	-0.099	0.043	0.065	0.043

	(0.593)	(0.048)	(0.602)	(0.048)
Tobin's Q	0.017	-0.002	0.019	-0.002
	(0.018)	(0.001)	(0.018)	(0.001)
Constant	7.780***	0.048***	7.825***	0.048***
	(0.089)	(0.013)	(0.088)	(0.012)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,920	3,920	3,920	3,920
R^2	0.74	0.05	0.75	0.05

Table 5: Social Connectedness, Target Status and Acquirer Returns

The table reports regression results of acquirer announcement returns on social connectedness using subsamples of target firms that are public, private, listed, and non-listed. *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. Definitions of other variables 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)			
	Public targets	Private targets	Listed targets	Non-Listed targets
	(1)	(2)	(3)	(4)
Ln(SCI)	0.002	0.003*	0.001	0.003**
	(0.002)	(0.001)	(0.003)	(0.001)
Ln(Deal value)	0.001	0.007***	-0.005*	0.006***
	(0.002)	(0.001)	(0.003)	(0.001)
Within industry	0.012**	0.006*	0.009	0.007***
	(0.005)	(0.003)	(0.007)	(0.003)
Stock ratio	-0.026***	-0.005	-0.006	-0.020**
	(0.010)	(0.010)	(0.013)	(0.008)
Tender	-0.001	0.01	0.003	-0.003
	(0.006)	(0.032)	(0.007)	(0.011)
Within state	-0.005	-0.004	-0.001	-0.005
	(0.011)	(0.006)	(0.014)	(0.006)
Ln(AT)	-0.006***	-0.009***	-0.002	-0.008***
	(0.002)	(0.001)	(0.003)	(0.001)
Leverage	0.029*	0.030***	0.040	0.025***
	(0.017)	(0.009)	(0.025)	(0.008)
ROA	0.085**	0.034	0.107	0.035*
	(0.043)	(0.022)	(0.066)	(0.020)
Investment	0.066	0.032	0.007	0.039
	(0.100)	(0.058)	(0.147)	(0.053)
Tobin's Q	-0.003	-0.002	-0.001	-0.002
	(0.003)	(0.002)	(0.005)	(0.002)
Constant	-0.022	0.080*	-0.016	0.064
	(0.027)	(0.048)	(0.036)	(0.045)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	1,107	2,813	591	3,329
R^2	0.10	0.05	0.16	0.05

Table 6: Social Connectedness, Information Asymmetry, and Acquirer Returns

The table reports regression results of acquirer 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_LowIA* is a dummy variable that equals one if targets are public firms with low level of information asymmetry, and zero otherwise. *Public_HighIA* is dummy variable that equals one if targets are public firms with high level of information asymmetry, and zero otherwise. Definitions of other variables 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_HighIA	-0.015	-0.003	-0.014	-0.007
	(0.019)	(0.018)	(0.021)	(0.020)
Public_LowIA	0.044	0.079	0.027	0.025
	(0.046)	(0.052)	(0.017)	(0.018)
Public_HighIA × Ln(SCI)	0.000	-0.001	0.001	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Public_LowIA × Ln(SCI)	-0.008*	-0.011**	-0.004**	-0.003*
	(0.004)	(0.006)	(0.002)	(0.002)
Ln(Deal value)	0.006***	0.005***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)
Within industry	0.006**	0.006**	0.007***	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Stock ratio	-0.011	-0.011	-0.019***	-0.019***
	(0.007)	(0.007)	(0.007)	(0.007)
Tender	0.005	0.005	-0.002	-0.001
	(0.006)	(0.006)	(0.005)	(0.005)
Within state	-0.002	-0.003	-0.005	-0.005
	(0.006)	(0.006)	(0.005)	(0.005)
Ln(AT)	-0.008***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.033***	0.035***	0.029***	0.028***
	(0.008)	(0.008)	(0.008)	(0.008)
ROA	0.042**	0.041**	0.042**	0.041**
	(0.020)	(0.020)	(0.019)	(0.019)
Investment	0.053	0.048	0.044	0.043
	(0.054)	(0.054)	(0.050)	(0.050)

Tobin's Q	-0.002	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.079*	0.068*	0.050	0.050
	(0.046)	(0.041)	(0.039)	(0.039)
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Observations	3,432	3,481	3,920	3,920
R^2	0.05	0.05	0.05	0.05

Table 7: Social Connectedness, Advisory Fees, and Acquirer Returns

The table reports regression results of acquirer returns on social connectedness conditional on the fees paid as the percentage of deal size. *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. *Advisory fees* is total financial advisory fees measured as a percentage of the deal size. Definitions of other variables 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.

	Advisory fees	*CAR(-3,3)*
	(1)	(2)
Advisory fees × *Ln(SCI)*		-0.002**
		(0.001)
Total fees		0.021**
		(0.009)
Ln(SCI)	-0.025**	0.003**
	(0.013)	(0.001)
Ln(Deal value)	-0.061**	0.005***
	(0.028)	(0.001)
Within industry	0.017	0.007***
	(0.044)	(0.003)
Public	0.702***	-0.008***
	(0.064)	(0.003)
Stock ratio	0.887***	-0.021***
	(0.246)	(0.007)
Tender	0.457***	-0.003
	(0.110)	(0.005)
Within state	0.053	-0.005
	(0.056)	(0.005)
Ln(AT)	0.019	-0.008***
	(0.016)	(0.001)
Leverage	0.207	0.027***
	(0.204)	(0.008)
ROA	0.169	0.039**
	(0.316)	(0.019)
Investment	-0.366	0.045
	(0.494)	(0.050)
Tobin's Q	-0.042***	-0.002
	(0.016)	(0.001)
Constant	-0.149	0.053
	(0.144)	(0.038)
Year FE	Yes	Yes
Industry FE	Yes	Yes

Observations	3,920	3,920
R^2	0.16	0.05

Table 8: Social Connectedness and Deal Premium

The table reports regression results of deal premiums on social connectedness conditional on deal value and stock ratio. *Deal 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. Definitions of other variables 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.

	Deal Premium	
	(1)	(2)
Ln(SCI)	-0.011*	-0.044**
	(0.006)	(0.019)
Ln(SCI) × Ln(Deal value)		0.005*
		(0.003)
Ln(Deal value)	-0.027***	-0.073***
	(0.007)	(0.025)
Within industry	-0.005	-0.005
	(0.016)	(0.016)
Stock ratio	-0.104***	-0.105***
	(0.024)	(0.024)
Tender	0.015	0.016
	(0.018)	(0.018)
Within state	0.047*	0.043
	(0.028)	(0.028)
Ln(AT)	0.017***	0.016**
	(0.006)	(0.006)
Leverage	-0.053	-0.053
	(0.048)	(0.048)
ROA	0.051	0.04
	(0.116)	(0.116)
Investment	0.536**	0.491**
	(0.251)	(0.250)
Tobin's Q	0.012	0.012
	(0.009)	(0.009)
Completion	-0.018	-0.019
	(0.021)	(0.021)
Constant	0.288***	0.605***
	(0.086)	(0.191)
Year FE	Yes	Yes
Industry FE	Yes	Yes
Observations	759	759

R^2	0.22	0.22

Table 9: Social Connectedness and Acquirer Buy-and-Hold returns

The table reports regression results of acquirer 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 acquirers' total assets. Definitions of other variables 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
Acquirer characteristics	Yes	Yes	Yes
Deal characteristics	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Table 10: Social Connectedness and the Acquirer's 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 and the median value of the other Compustat-listed firms in the same year and industry (defined by two-digit SIC codes). 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. Definitions of other variables are shown in Table A.1. The heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, 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)
Acquirer characteristics	Yes	Yes	Yes
Deal characteristics	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Observations	2,613	2,633	2,626
R^2	0.13	0.07	0.04

Table 11: Social Connectedness and Acquisition Likelihood

The table reports results for probit regressions of *Acquisition* on *Ln(SCI)*. All acquirers *(m)* and targets *(n)* in each announcement year are identified from our sample to create an $m \times n$ matrix of all possible matches between acquirers and targets. *Acquisition* is a dummy variable indicating an actual transaction between an acquirer and a target, and zero otherwise. Specifically, for each element *(i, j)* of the matrix, if there is indeed an M&A transaction in that year between acquirer *i* and target *j*, *Acquisition* takes the value of one, and zero otherwise. Definitions of other variables are shown in Table A.1. The heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	Acquisition		
	(1)	(2)	(3)
Ln(SCI)	0.143***		0.144***
	(0.004)		(0.006)
Local		0.373***	-0.005
		(0.013)	(0.021)
Constant	-4.089***	-2.953***	-4.096***
	(0.197)	(0.193)	(0.201)
Observations	1,051,099	1,051,099	1,051,099
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Acquirer FE	Yes	Yes	Yes
Target FE	Yes	Yes	Yes
Pseudo R^2	0.03	0.02	0.03

Table 12: Pseudo-Analyses of Social Connectedness and Acquirer Returns

This table reports the coefficients of *Ln(SCI)* in the regressions of acquirer returns based on pseudo-analyses. In the first row, we report the coefficient of *Ln(SCI)* in the baseline model to facilitate comparisons with results from the pseudo-analyses. In the second row, we report the averages and standard deviations of bootstrapped coefficients of *Ln(SCI)* for the four following pseudo analyses. In Column (1), for each M&A deal, we randomly select a pseudo value of *Ln(SCI)* from our final sample. In Column (2), we randomly choose a pseudo announcement date for each M&A deal. In Column (3), we randomly select a pseudo acquirer from the pool of all acquires in our sample. In Column (4), we simultaneously select a pseudo announcement date and acquirer. We then re-run our baseline regression to obtain the coefficient of *Ln(SCI)*. We repeat this process 1,000 times. We report results for normality tests for bootstrapped *Ln(SCI)* in the third row, and distances between the baseline *Ln(SCI)* and the mean of bootstrapped *Ln(SCI)* measured as the number of standard deviations of bootstrapped *Ln(SCI)* in the last row of the table.

	CAR(-3,3)			
	Pseudo *Ln(SCI)*	Pseudo Announcement date	Pseudo Acquirer	Pseudo Acquirer and Announcement date
	(1)	(2)	(3)	(4)
Baseline Ln(SCI)	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)
Bootstrapped Ln(SCI)	0.00007	-0.00004	-0.00006	-0.00003
	(0.00054)	(0.00081)	(0.00103)	(0.00107)
Normality tests of bootstrapped Ln(SCI)				
(1) Shapiro-Wilk p-value	0.626	0.067	0.442	0.760
(2) Shapiro-Francia p-value	0.595	0.110	0.475	0.692
(3) Skewness/Kurtosis p-value	0.380	0.254	0.389	0.559
Baseline coefficient of Ln(SCI) as the number of standard deviations from the mean of bootstrapped coefficients of Ln(SCI)	4.26	3.75	2.97	2.83

Table 13: Alternative measures for Acquirer Returns and Social Connectedness

The table reports robustness test results (i) using alternative types of risk-adjusted models to estimate acquirer returns, and (ii) alternative proxies for social connectedness. Acquirer returns, *CAR(-3,3),* are the acquirer's cumulative abnormal returns from day -3 to day 3, where day 0 is the announcement date, using alternative types of risk-adjusted models including market model in Model (1), Fama-French three factors in Model (2), and Fama-French plus Momentum model in Model (3). The main independent variable of Models (1)-(3), *Ln(SCI)*, is the natural logarithm of the social connectedness index between the acquirer's county and the target's county. In Models (4)-(6), we re-estimate the baseline model of *CAR(-3,3)* on *SCI_5pct* (Model 4), *SCI_10pct* (Model 5), and *SCI_15pct* (Model 6) where *SCI_5pct*, *SCI_10pct* and *SCI_15pct* are dummy variables that indicate high social connectedness using 5-percentile, 10-percentile, and 15-percentile *Ln(SCI)* as thresholds, respectively. Definitions of other variables are shown in Table A.1. The heteroskedasticity-consistent standard errors are presented in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% level, respectively.

	CAR(-3,3)					
	Market model	Fama-French 3-factor	Fama-French 3-factor + Momentum	SCI_5pct	SCI_10pct	SCI_15pct
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(SCI)	0.003**	0.002*	0.002*			
	(0.001)	(0.001)	(0.001)			
SCI_5pct				0.016**		
				(0.007)		
SCI_10pct					0.014***	
					(0.005)	
SCI_15pct						0.013**
						(0.006)
Control	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,920	3,920	3,920	3,920	3,920	3,920
R^2	0.04	0.04	0.04	0.05	0.05	0.05