Bowling Alone, Bowling Together: Is Social Capital Priced in Bank Loans?

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Abstract

We investigate whether the societal-level social capital enjoyed by firms affects the cost of their bank loans. Employing a measure of societal-level social capital for U.S. counties, we find that firms with higher societal-level social capital are associated with lower loan spreads. To further identify causality, we explore two events: Using a sample of firms that relocate their headquarters for tax reasons, we find that firms that move to lower (higher) social capital counties experience a higher (lower) cost of bank loans following relocations. The second event was the terrorist attack on September 11, 2001. After the disaster, social capital in affected counties—mainly in the State of New York, the State of Virginia, and adjacent counties—increased through social capital building efforts. We show that firms headquartered in the affected counties experience significantly lower loan spreads than other firms after the attack. Our findings contribute to the understanding of how societal-level social capital promotes economic development through its impact on financing costs.

Keywords

loan spreads, societal level, social norms and networks, private debt

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Introduction

Business does not exist in a vacuum. Rather, firms operate in a society with interactions and associations in numerous dimensions. Viewing social capital as the norms and social connections that enhance growth, many recent accounting and finance studies have explored the economic benefits of firm-level social capital (e.g., a CEO's social and political connections, etc.). While we believe that firm-level social capital *per se* is important, in this study, we emphasize the importance of *societal-level* social capital in capital raising beyond firm-level social capital. Specifically, we examine the effect of social capital, at the societal level, on the cost of bank loans. To the extent that private loans issued by banks represent an important source of corporate financing and that loan contracts are very costly, social capital can add great value to the society if it can reduce the cost of borrowing.[1]

Our investigation from the societal perspective is in part motivated by research in sociological sciences and social economics. Defined as features of social organization, such as *norms* and *networks* that can improve the efficiency of society by facilitating coordinated actions (Putnam, 1993), social capital has two key components: norms and networks. Societal-level social capital affects the cost of bank loans through the lending risk and information risk. Specifically, the *norms* component refers to social values such as altruism, honoring obligations, and mutual trust, and these social values promote mutual cooperation.

It may not be easy to posit specific economic factors that *directly* tie high corporate social capital to lower interest rates. We develop our hypothesis from the ''behavioral consistency theory'' (Cronqvist, Makhija, & Yonker, 2012). Specifically, the theory suggests that individuals behave consistently across situations. As people in high social capital areas honor obligations, they will exhibit the same norms when they use borrowed funds from banks. The *networks* component refers to the connections that a person uses as resources to achieve his interests. Information may be more easily verifiable with denser networks. To reduce information asymmetry, borrowers disclose firm-specific information to banks. In dense networks with trustworthy people, banks can verify the information with suppliers, customers, employees, and other stakeholders more easily. To the extent that more cross-verified firm-specific information reduces the information risks, we expect that firms with higher social networks have lower loan spreads.[2]

To construct our societal-level social capital from sociological surveys, we follow the strategy used in Jha and Chen (2015). We build our social capital index based on individuals' participation in associational community activities. Specifically, we employ survey data from Rupasingha and Goetz (2008), and calculate a principal component score of county-level counts of political votes, census response rates, social and civic associations, and nongovernment organizations to construct the societal-level social capital that the firms are endowed within U.S. counties. As argued in Jha and Chen (2015), this index captures exogenous social resources, through which social capital accrue to people via individuals' participation in community activities. Following prior studies (e.g., Graham, Li, & Qiu, 2008; Houston, Jiang, Lin, & Ma, 2014), we measure the cost of borrowing using the natural logarithm of loan spreads at the loan facility level.

Using a sample of firms with private bank loans from 1990 to 2009, we find that firms with higher societal-level social capital are associated with lower bank loan spreads.[3] In particular, a 1 standard deviation increase of social capital is associated with a reduction of 7.46 basis points in loan spreads. Our results are robust to the inclusion of firm-level, loan-level, and geographic and demographic-level characteristics as well as loan purpose, loan-type, bank-type, industry, and state-year fixed effects. We interpret our findings as high societal-level social capital reducing the cost of borrowing.

We next perform several cross-sectional variation tests to examine whether certain conditions moderate the effect of societal-level social capital on the cost of bank loans. These tests rest on the prediction that other information in the lending–borrowing relation may ''crowd out'' the effect of societal-level social capital. When a lender has previous loan contracts with the borrower, private knowledge about the borrower's creditworthiness can be inferred from the lender's prior interactions with the borrower. As such, the lender is less likely to rely on societal-level social capital to assess default risk when they initiate new loans. Similarly, when the geographic distance between the lender and the borrower is closer, the lender can gather information about the borrower's creditworthiness from alternative sources, for example, local newspapers, and so on. We predict and find that the effect of societal-level social capital on the cost of bank loans is more pronounced for firms that have no previous relation with the lenders and firms that are geographically far away from their lenders.

We conduct several additional analyses and robustness tests: First, to mitigate the concern that our results are driven by the effect of social capital through financial reporting quality, we repeat our main regression by adding several different measures of accounting quality. Second, to assess the sensitivity of our results to the linear interpolation method, we repeat our analysis using only survey-year observations.

Finally, to further identify causality, we take advantage of two events to investigate the effect of societal-level social capital on the cost of bank loans. We first study a subsample of firms that experience changes in social capital due to headquarter relocations. Using a sample of firms that relocate their headquarters due to state-level tax policy changes, we find that firms that move to lower (higher) social capital counties experience higher (lower) cost of bank loans after the relocation. The second event is the terrorist attack on September 11, 2001. The Federal Emergency Management Agency classifies the State of New York and the State of Virginia as ''Major Disaster Declaration—Terrorist Attack,'' and the local governments have taken a series of actions to facilitate social capital building. Consequently, the levels of political consciousness, engagement, and trust are substantially higher than the levels before the attack in the two affected states. Utilizing a difference-in-differences design, we find that firms headquartered in affected counties have significantly lower loan spreads than other firms after the attack.

Our study contributes to the literature in several ways: First, we extend the understanding of the economics of societal-level social capital. Prior research documents that higher social capital is associated with more investment in stocks (Guiso, Sapienza, & Zingales, 2004), more favorable access to institutional credit by households (Guiso et al., 2004), a lower level of earnings management and more transparent financial reports (Jha, in press), and lower audit fees (Jha & Chen, 2015). Extending from their studies, we focus on the ''social economics'' dimension of debt contracting. Specifically, by focusing on the contracting role of societal-level social capital, we explore how informal institutions such as societal-level social capital enhance mutual trust between the borrower and the lender, and how this is reflected in the cost of bank loans. In other words, our study provides insights into the microfoundation for the benefits of societal-level social capital in promoting economic development.

A concurrent study by Hasan, Hoi, Wu, and Zhang (2017) also finds the negative relation between cost of debt and social capital. However, an important question is how this relation works independently from the measures of information quality. Many studies (e.g., Francis, LaFond, Olsson, & Schipper, 2005) show that better earnings quality leads to lower cost of debt. Moreover, Jha (in press) finds that social capital improves earnings quality. Hence, it is likely that the effect of social capital on cost of debt is due to its effect on earnings quality. Hasan, Hoi, Wu, and Zhang report insignificant relation between earnings quality and the cost of debt; they have only one earnings quality measure, and the insignificant association between their earnings quality measure and cost of debt can still imply that their relation between social capital and cost of debt captures the information quality. To fix this, we include several measures of earnings quality, and show that while all earnings quality measures have the predicted effect on the cost of bank loans, the effect of social capital is still economically and statistically significant. These findings imply that the effect of social capital on the cost of bank loans is not likely going through information quality but more likely going through trust. To further show that the relation is going through trust, we examine the role of societal-level social capital versus private trust between the borrower and the bank. We find that the effect of societal social capital is smaller when private trust is stronger. We also suggest several additional control variables and the important endogeneity tests. When we include state-year fixed effects, the economic significance is twice as high as in Hasan, Hoi, Wu, and Zhang. We use tax-motivated relocations as the relocation decision itself may be correlated with corporate borrowing. In addition, we use a natural experiment (i.e., the September 11 event) to establish causality. Our study contributes to the existing literature by showing that the ''trust'' element (in addition to information quality) is essential in the bank loan decisions, suggesting that the societal-level social capital is an important measure of trust. Moreover, we provide improvements in methodologies. More research in this area can let managers be aware of the importance of the societal-level social capital and help them improve their performance through improving trust.

Second, our article contributes to the emerging literature on the association between firm-level ties and loan pricing. For example, Houston et al. (2014) find that firms that have board members with political ties enjoy lower cost of bank loans. Different from their study, we highlight the importance of the ''social evaluation'' of the borrower. In other words, we emphasize that the accumulation of societal-level social capital is an important element beyond firm-level connections in explaining the cost of bank loans.

Finally, our results complement studies using county-level, geographic information to investigate firms' investing, financing, and financial reporting behavior (e.g., Mcguire, Omer, & Sharp, 2012). In particular, we show that when writing loan contracts, banks have typically reacted to their perceived firm behavior, as implied by the societal-level social capital.

The remainder of this article is organized as follows: The next section discusses the related literature and develops the main hypotheses. Section ''Research Design'' lays out the measures of social capital and the empirical design, and discusses the sample selection. Section ''Empirical Results'' reports the empirical results. Section ''Robustness Checks'' presents the robustness tests. Section ''Evidence From a Matched-Sample Analysis'' presents the matched-sample analysis. Section ''Evidence From Headquarter Relocations and the September 11 Shock'' presents the evidence from two events. The last section concludes.

Literature Review and Hypothesis Development

The Definition of Social Capital

In the economics literature, social capital is often viewed as social norms or mutual trust. For example, Guiso, Sapienza, and Zingales (2008a) define social capital as a set of beliefs and values that foster cooperation. These definitions regard social capital as shared informal norms that promote cooperation between two or more individuals. In the management literature, researchers attribute social capital to a set of networks with benefits. For example, Lin (1999) views social capital as the investment in social relations by individuals through which they gain access to embedded resources to enhance expected returns of instrumental or expressive actions. This view of social capital is predicated on the idea that a strong set of networks is a resource in itself, providing people with access to resources on preferential terms. Appendix A summarizes several definitions of social capital used by researchers.

More broadly, many researchers view social capital as both social norms and networks. For example, Helliwell and Putnam (1995) define social capital as features of social organizations, such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefits. We take this approach, and incorporate both norms and networks in our definition of social capital. In other words, we view norms and networks as not mutually exclusive. Social capital is viewed as a ‘‘good culture’’ that is the product of both dense networks and altruistic norms. Norms and networks reinforce with each other. This view is consistent with studies of Guiso et al. (2004), Guiso, Sapienza, and Zingales (2008b), Jha (in press), and Jha and Chen (2015). While the social norms enable people to build up networks, the dense networks provide people with opportunities to connect, leading to mutual trust and higher norms.

The Benefits of Social Capital

Social capital plays an important role in promoting economic growth through information sharing, mutual cooperation, and decision-making mechanisms. For example, using regional social capital data in Italy, Helliwell and Putnam (1995) find that per-capita GDP convergence is faster, and the equilibrium income levels are higher in regions with higher social capital. Using county-level social capital data in the United States and measuring social capital by the density of associational activity, crime index and the percentage of eligible voters participating in the federal election, Rupasingha, Goetz, and Freshwater (2000) document that social capital has a significantly positive effect on the per-capita income growth.

Social capital also facilitates the development of financial systems. Using survey data on Italian households, Guiso et al. (2004) show that in high social capital regions, households are more likely to use checks, invest more in stocks, and have higher access to loans from banks and other financial intermediaries. Using Dutch and Italian data, Guiso et al. (2008a) find that a lack of trust has a negative impact on stock market participation.

Taking a different perspective to study firm behaviors, Jha (in press) and Jha and Chen (2015) bring social capital to accounting research. Jha (in press) documents that firms headquartered in high social capital regions have less earnings management and more transparent financial reports as social capital constrains managers’ opportunistic behaviors. Jha and Chen (2015) find that firms with higher social capital pay lower audit fees. Another important market participant is private lenders who supply capital to firms in exchange for a fixed return. The lending contract between the firm (the borrower) and the bank (the lender) represents a typical financial obligation that the firm has to fulfill in the future. To the extent that public firms are the pillars of the economy, insights from the financing perspective can contribute to understanding how social capital leads to economic development.

The Role of Societal-Level Social Capital in Bank Loans

Bank loans represent an important source of corporate financing. In writing a loan contract, the lender lends money to the borrower, who promises to return the principal and interest in the future. The lender is exposed to two major types of risks: the lending risk and information risk. The societal-level social capital reduces the cost of bank loans through these two channels.

The norms component of social capital refers to a series of social values, such as altruism, honoring obligations, and mutual trust. In high social capital regions, people are more likely to trust and cooperate with each other, and fulfill their obligations. The ‘‘behavioral consistency theory,’’ that is, the notion that individuals behave consistently across situations, provides the theoretical basis (Cronqvist et al., 2012). As people in high social capital areas have strongly internalized norms, they will exhibit the same norms when they use borrowed funds from banks for operations. The strongly internalized norms discipline the manager's opportunistic behaviors and motivate the manager to work harder, shirk less, and assure sufficiently profitable operating outcomes to make on-time payment to banks. As the manager works harder, fundamentals improve, reducing lending risks.

In addition, the loan contract is an incomplete contract where the bank cannot always contract on a borrower's all future activities (Christensen, Nikolaev, & Wittenberg-Moerman, 2016). As such, the incomplete contract relies to a large extent on the lender's judgment of the borrower's trustworthiness (Guiso et al., 2004). When originating loans, the bank anticipates these beneficial management behaviors (i.e., less moral hazards) disciplined by high societal-level social norms and has less concern about the lending risk. To the extent that the lending risk is reflected in the cost of loans, we expect that firms with higher social norms have lower loan spreads.

The networks component refers to the social connection resources by which a firm is surrounded. To reduce information asymmetry, borrowers want to communicate firm-specific information to banks. However, the information communicated has to be verified by banks. The social networks play an important role in this verification process. In a dense network (and with trustworthy people), banks can obtain evidence from suppliers, customers, employees, and other stakeholders more easily and with better quality. To the extent that more high-quality firm-specific information will reduce the information risks, we expect that firms with dense social networks have lower loan spreads.[4]

Our hypothesis also rests on the idea that the firm headquartered in high social capital assimilates the high societal-level social capital by which it is surrounded. Theoretically, Schneider (1987) suggests that ‘‘attraction to an organization, selection by it, and attrition from it yield particular kinds of persons in an organization,’’ and that ‘‘these people determine organizational behavior’’ (p. 441). This is also consistent with recent empirical studies where researchers utilize firm headquarter geographic characteristics to investigate firms' investing, financing, and financial reporting behavior (e.g., Hilary & Hui, 2009; Mcguire et al., 2012). As corporate headquarters are close to corporate core business activities (Pirinsky & Wang, 2006), a firm headquartered in a high social capital region is endowed with high societal-level social capital.[5] To summarize, we hypothesize that firms headquartered in high social capital regions have lower cost of loans.

Research Design

Measures of Social Capital

To measure social capital, recent researchers use survey data on the level of trust (e.g., Guiso et al., 2008a; Whiteley, 2000), civic engagement (e.g., Guiso et al., 2004), and crime rates (e.g., Rupasingha et al., 2000). Appendix A summarizes several measures of social capital in the literature. In this study, we adopt the one recently used in accounting (i.e., Jha & Chen, 2015) to measure societal-level social capital at the county level.

Following Rupasingha and Goetz (2008) and Jha and Chen (2015), we calculate the societal-level social capital index as county-year-specific participation in associational community activities. This choice of independent variable rests on the fact that social capital manifests itself via individuals' participation in associational activities (Guiso et al., 2004). In particular, we use four input variables to calculate the social capital index: the voter turnout in presidential elections, the census response rate, the number of social and civic associations, and the number of nongovernment organizations in each county. We obtain all four input variables from the Northeast Regional Center for Rural Development (NERCRD). We describe each input in detail as follows.[6]

The *Voter turnout in presidential elections* and the *Census response rate* are two primitive indicators of social norms. Specifically, the *Voter turnout in presidential elections* is the number of votes casted scaled by the population above 18 years old (measured per 10,000 people). The *Census response rate* is the response rate to the Census Bureau's decennial census, an indicator of the citizen cooperation attitudes. These two measures are the most commonly used proxies for social norms (Guiso et al., 2004; Helliwell & Putnam, 1995; Jha & Chen, 2015). As there are no legal incentives for people to vote or respond to the census, people with high norms participate in voluntary civic engagement activities because they feel *obligated* to do so, representing strongly internalized norms. The higher values of these variables, the stronger the social norms.

The *Number of social and civic associations* and the *Number of nongovernment organizations* are two primitive indicators of social networks. Specifically, the *Number of social and civic associations* is the sum of religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, sport clubs, manager and promoter membership sports and recreation clubs (no data for 2005 or 2009), and membership organizations not elsewhere classified (no data for 2005 or 2009), divided by 12 (10 for 2005 or 2009) and scaled by the population of the county (measured per 10,000 people). The *Number of nongovernment organizations* is the sum of nongovernment organizations excluding the ones with an international focus, scaled by the population (measured per 10,000 people). As social capital manifests itself in individuals through their participation in associational activities and social capital is enhanced when people belong to voluntary groups, higher values of these variables represent higher social networks.

We calculate the four input variables each year in 1990, 1997, 2005, and 2009. To reduce dimensionality and extract the most relevant information out of the four inputs, we conduct a principal components analysis upon these four inputs to construct our primary social capital index: *Social Capital*. As the NERCRD survey data are only available for the years 1990, 1997, 2005, and 2009, we linearly interpolate the data to fill in the years between 1990 and 1997, the years between 1997 and 2005, and the years between 2005 and 2009.[7] We provide a more detailed description of variable definitions in Appendix B.

Finally, we match firms' county and state information using the zip codes reported in Compustat. As corporate headquarters are close to corporate core business activities (Pirinsky & Wang, 2006), we use a firm's headquarter to assign county-level social capital. As Compustat only keeps the most recent zip code of a firm's headquarter, we use the headquarter information contained in 10-K filings to determine a firm's historical zip codes. Specifically, we perform a textual analysis on firms' 10-K filings restored on Securities and Exchange Commission (SEC's) online EDGAR system, and extract the zip codes from their 10-K filings using the web-crawling technique. As such, we are able to construct a time series of headquarter zip codes for each firm in our sample. Similar to Hilary and Hui

(2009), we adopt the geography-based identification strategy and merge the county-year-level social capital index to financial data at the facility level using the dynamic zip code.

Research Design

To test our main hypothesis, we use loan spreads to measure the cost of bank loans. Following the prior literature (e.g., Carey & Nini, 2007; Graham et al., 2008; Hertzel & Officer, 2012; C. Lin, Ma, Malatesta, & Xuan, 2011; C. Lin, Officer, Wang, & Zou, 2013), we use the all-in-drawn spread at the facility level from DealScan as the measure of the cost of bank loans. Specifically, the all-in-drawn spread is the sum of upfront fees, spread over the London Interbank Offered Rate (LIBOR), utilization fee, and annual fee specified in a facility at the inception of the facility. We employ the following model:

$$\begin{aligned}\mathrm{Log}(\mathit{Spread}) = \beta_0 + \beta_1 \mathit{Social\ Capital} + \mathit{Borrower\ characteristics} \\ + \mathit{Loan\ characteristics} + \mathit{Demographic\ and\ geographic\ controls} \\ + \mathit{Industry\ fixed\ effects} + \mathit{State} - \mathit{Year\ fixed\ effects} + \varepsilon,\end{aligned} \tag{1}$$

where the dependent variable is the natural logarithm of the all-in-drawn spreads (in basis points) measured at the origination of the loan. The independent variable of interest is the societal-level social capital of the county where the firm is headquartered. If lenders price societal-level social capital in loan contracts, we expect a negative relation between the loan spread and the borrower's societal-level social capital.

Financial reporting quality can affect the cost of debt. Specifically, Francis et al. (2005) find that firms with poorer earnings quality are associated with higher interest rates. As firms with better social capital are also associated with better earnings quality (Jha, in press), we isolate the effect of social capital on the cost of bank loans from the channel of financial reporting quality by including *Accounting Quality* (defined as negative one times the residual from the modified Dechow and Dichev, 2002, model) in our regression.[8] In the robustness tests, we repeat the analysis with other commonly used earnings quality measures. To the extent that firms with modified audit opinions are associated with higher loan spreads (Chen, He, Ma, & Stice, 2016), we include *MAO* (defined as the indicator variable that takes a value of 1 for nonunqualified audit opinions).

We control for firm-specific and loan-specific characteristics identified in prior research as determinants of loan spreads.[9] We include the logarithm of market value of equity (*Firm Size*), as creditors perceive larger firms as less risky (Anantharaman, Fang, & Gong, 2013; Blackwell, Noland, & Winters, 1998; Pittman & Fortin, 2004). We include the profitability (*ROA*), leverage ratio (*Leverage*), asset tangibility (*Tangibility*), default risk (*Altman's Z-score*), cash flow volatility (*Std* (*CFO*)), and sales volatility (*Std* (*Sales*)). These control variables capture the idea that profitable, less leveraged firms, firms with higher asset tangibility, distant from default and with more stable cash flows and sales have lower loan spreads. A high *BTM* ratio represents low growth opportunities and indicates lower risk, but a low *BTM* ratio could proxy for the liquidation value for creditors in default (e.g., Graham et al., 2008; C. Lin et al., 2013). Therefore, we do not have a clear prediction on the sign of the book-to-market ratio.

For loan characteristics, we include the loan maturity (*Loan Maturity*), loan size (*Loan Amount/TA*), the size of the lending syndication measured as the number of lenders (*No. of Lenders*), the number of covenants (*No. of Total Covenants*), the number of facilities in the package (*No. of Facilities*), the indicator variables of subordinate loan facilities, and the indicator variables of facilities using performance pricing. We also include the bank-type fixed effects (i.e., the indicator variables of bank types to differentiate whether at least one lead lender is an investment bank or a foreign bank; Anantharaman et al., 2013; Bradley & Roberts, 2004; Denis & Mihov, 2003), loan-type fixed effects (i.e., the indicator variables to differentiate term loan, revolvers greater than or less than 1 year, and 364-day facilities), and primary loan purpose fixed effects (i.e., the indicator variables to differentiate acquisitions, backup line, refinancing, working capital/corporate purposes, and other).[10] *Previous Relation* is an indicator variable that takes a value of 1 if at least one of the loan's lead lenders has been a lead lender of the borrower's previous loans in the past 5 years, and 0 otherwise. Finally, following Bushman and Wittenberg-Moerman (2012), for all regressions, we include industry fixed effects. These fixed effects control for any sample-wide systematic differences across industries.

To mitigate the concern that our social capital variable may be correlated with other geographic specific variables that may affect the cost of borrowing, we include a large set of geographic and demographic characteristics. Depending on data availability, these variables are either at the county level (if available) or at the state level. Specifically, we include *Population*, defined as the natural logarithm of a county's population; *Education*, defined as the percentage of population with a college education in a given county; *Religion*, defined as the percentage of religious adherents in a given county; and *Income*, defined as the natural logarithm of per-capita income adjusted by the consumer price index (CPI) in a given county. The education data at the county level are obtained from the Bureau of Economic Analysis (BEA). The religiosity data at the county level are obtained from the Association of Religion Data Archive (ARDA). To control for the general macroeconomic environment, we include *Unemployment*, defined as the unemployment rate expressed in the percentage rate for each county. We collect the county-level unemployment data from the Bureau of Labor Statistics (BLS). We also control for the local economic growth. In particular, we employ *Housing start* and *Income growth. Housing start* is the natural logarithm of the number of building permits each year for each state. We collect *Housing start* from the U.S. Census. *Income growth* is the growth rate of per-capita income each year for each county. We calculate *Income growth* using data from BEA. To control for the different political party strength, we include *Democratic vs. Republican*, defined as the ratio of the percentage of the popular votes received by the Democratic Party over the percentage of the popular votes received by the Republican Party for each state, scaled by 100.[11] The data are only available in 1996, 2000, 2004, 2008, and 2012. We apply the data from 1996 to the years prior to 1996, and we linearly interpolate the data to fill in the years between each survey year. To capture the difference in banking and financial development between regions, we employ *Banks*, defined as the number of bank branches in each state scaled by the total population (measured per 10,000) in each state, scaled by 100. We obtain these data from the Federal Deposit Insurance Corporation (FDIC). Finally, to further control for other unobserved geographical characteristics that also vary across years, we include state-year fixed effects. Appendix B provides a more detailed description of all control variables in the model.

Sample and Descriptive Statistics

We first construct our county-level social capital index using the procedures outlined in Section "Measures of Social Capital." We merge these data with the Compustat/CRSP merged data using the dynamic headquarter zip codes we constructed from EDGAR. Our data end in 2009 as this is the year when the last survey was conducted by NERCRD.

We then merge this initial database with bank loan data from Loan Pricing Corporation's (LPC) DealScan.[12] To execute the merge, we require that (a) the firm must have at least one bank loan issued within a fiscal year; (b) the loans are denominated in U.S. dollars; (c) the following information about the loans is available: all-in-drawn spreads, the lender characteristics, the performance pricing type, the maturity, the offering amount, loan type (i.e., term loan, revolver greater than 1 year, revolver less than 1 year, and 364-day facility), and the primary purpose; and (d) the firm has available information on its current and previous lenders. After removing firm-year observations with missing data on bank loans or with missing financial data, the final sample includes 16,451 loan facilities in 10,373 firm-year observations, covering the fiscal years between 1990 and 2009.[13] Panel A of Table 1 shows the sample selection procedure. All continuous variables are winsorized at the 1st and 99th percentiles to mitigate the effect of outliers.

Panel B and Panel C of Table 1 present the five states with the lowest and highest median social capital in our sample period, respectively. While Washington, D.C. has the highest societal-level social capital, the State of Arizona has the lowest societal-level social capital in our sample period. Correspondingly, the median loan spread received by firms in Washington, D.C. is 45 basis points, whereas the median loan spread received by firms in Arizona is 225 basis points.

Table 2 presents the summary statistics for our main variables. We report the summary statistics in four categories: social capital, firm characteristics, loan characteristics, and demographic and geographic characteristics. Similar to Jha (in press), the sample-wide average social capital (*Social Capital*) is –0.486. The mean ROA is 0.026, indicating that most of the firms in our sample are profitable. The mean spread is 178.38 basis points. The mean (median) number of lenders is 8 (5). These summary statistics are well aligned with recent studies (e.g., Valta, 2012). To describe social capital and loan spreads in a graphical way, we plot social capital and loan spreads at the state level in the online supplemental appendix.

Empirical Results

Main Results

Table 3 presents the ordinary-least-squares (OLS) regression results of Equation 1. The dependent variable is the natural logarithm of all-in-drawn spreads (in basis points). The independent variable of interest is the social capital index (*Social Capital*). Standard errors are White heteroskedasticity-robust and clustered by firm. Most importantly, the coefficient of *Social Capital* (β = –.0464, *t*-statistic = –2.05) is negative and statistically significant at the 5% level. This result suggests that higher social capital is associated with lower loan spreads. To mitigate the concern that the effect of social capital on the cost of bank loans goes through the channel of accounting quality, we control for *Accounting Quality* in column 2. When we include *Accounting Quality* as an additional control variable, the coefficient on *Social Capital* is negative and statistically significant (β = –.0467, *t*-statistic = –2.05). The effect of social capital on the loan spreads is also economically significant. As the dependent variable is the log of the loan spread, a 1 standard deviation increase in social capital (0.896) leads to a 4.2% (=0.896 $\times$ .0467) decline in the loan spread. We also assess the economic significance in basis points using the mean loan spreads. Applying the

Table 1. Sample Selection and Descriptive Statistics.

Panel A: Sample Selection.

Filters	Number of firm-year observations	Number of facilities
Compustat firms with available NERCRD data to construct social capital index over the period from 1990 to 2009	121,131	—
U.S. dollar loans issued over the 12-month period beginning from 6 months prior to each fiscal year-end in years 1990 to 2009	23,831	40,488
After elimination of facilities with missing loan and lender characteristics at issuance	16,730	26,801
After elimination of facilities with missing county and state characteristics	16,392	26,288
The final sample after elimination of facilities with missing firm-level financial data	10,373	16,451

Note. Panel A presents the sample selection procedure. Our final sample includes 10,373 firm-year observations and 16,451 loan facilities in the period 1990-2009. NERCRD = Northeast Regional Center for Rural Development.

Panel B: Five States With Lowest Social Capital.

States and territory	Rank of social capital	Number of loans	Median social capital	Median loan spreads
Arizona	1 (lowest)	214	−1.466	225
Georgia	2	428	−1.307	150
Texas	3	2,073	−1.181	150
Utah	4	59	−1.163	250
California	5	1,772	−1.002	175

Note. The panel presents the five states with the lowest median social capital in our sample period (1990-2009). We calculate the within-sample median social capital of all counties and the median all-in-drawn loan spreads of our sample firms in each state across years 1990-2009. The sample includes 46 states and Washington, D.C. with available loan data. The state with the lowest median social capital receives a rank of 1, and the one with the highest median social capital receives a rank of 46.

Panel C: Five States With Highest Social Capital.

States and territory	Rank of social capital	Number of loans	Median social capital	Median loan spreads
Minnesota	42	493	0.981	125
Iowa	43	79	1.017	140
South Dakota	44	30	1.070	150
North Dakota	45	14	1.171	50
District of Columbia	46 (highest)	63	2.726	45

Note. The panel presents the five states with the highest median social capital in our sample period (1990-2009). We calculate the within-sample median social capital of all counties and the median all-in-drawn loan spreads of our sample firms in each state/territory across years 1990-2009. The sample includes 46 states and Washington, D.C. with available loan data. The state/territory with the lowest median social capital receives a rank of 1, and the one with the highest median social capital receives a rank of 46.

Table 2. Summary Statistics.

	N	*M*	P25	Median	P75	Std.
Main variables						
Social Capital	10,373	–0.486	–1.176	–0.410	0.113	0.896
Firm-level variables						
Firm Size	10,373	6.606	5.109	6.648	8.049	2.087
ROA	10,373	0.026	0.007	0.038	0.070	0.092
BTM	10,373	0.581	0.292	0.479	0.743	0.632
Leverage	10,373	0.300	0.160	0.287	0.407	0.199
Tangibility	10,373	0.340	0.144	0.279	0.506	0.240
Altman's Z-score	10,373	3.549	1.929	4.395	4.795	2.351
Std (Sales)	10,373	0.264	0.091	0.175	0.321	0.316
Std (CFO)	10,373	0.059	0.027	0.045	0.076	0.049
Accounting Quality	10,373	0.000	–0.029	–0.002	0.024	0.068
Minus Accruals Quality	10,373	–0.049	–0.060	–0.035	–0.021	0.045
Minus Abs (DDresid)	10,373	–0.045	–0.056	–0.027	–0.011	0.055
MAO	10,373	0.422	0.000	0.000	1.000	0.494
Readability Index	8,720	26.599	24.003	26.637	29.315	4.094
Loan facility-level variables						
Log (Spread)	16,451	4.842	4.135	5.011	5.521	0.899
Spreads (Basis points)	16,451	178.380	62.500	150.000	250.000	138.274
Subordinate	16,451	0.001	0.000	0.000	0.000	0.031
Performance Pricing	16,451	0.476	0.000	0.000	1.000	0.499
Loan Maturity	16,451	3.571	3.178	3.807	4.094	0.713
Loan Amount/TA	16,451	0.174	0.056	0.120	0.234	0.173
Previous Relation	16,451	0.488	0.000	0.000	1.000	0.500
Loan package-level variables						
No. of Facilities	12,164	1.399	1.000	1.000	2.000	0.730
No. of Lenders	12,164	8.058	2.000	5.000	11.000	8.590
No. of Total Covenants	12,164	1.531	0.000	1.000	3.000	1.561
Log (No. of Facilities)	12,164	0.242	0.000	0.000	0.693	0.398
Log (No. of Lenders)	12,164	1.552	0.693	1.609	2.398	1.089
Log (1 + No. of Total Covenants)	12,164	0.722	0.000	0.693	1.386	0.657
Demographic and geographic variables						
Population	10,373	13.656	13.112	13.681	14.269	1.123
Education	10,373	0.310	0.251	0.287	0.374	0.093
Religion	10,373	0.539	0.456	0.547	0.601	0.111
Income	10,373	9.901	9.713	9.860	10.048	0.275
Income Growth	10,373	0.041	0.024	0.042	0.061	0.036
Unemployment	10,373	5.112	3.900	4.900	6.000	1.690
Housing Starts	10,373	10.441	9.984	10.453	11.198	0.966
Democratic vs. Republican	10,373	0.012	0.009	0.011	0.013	0.007
Banks	10,373	0.022	0.017	0.023	0.027	0.006

Note. This table presents the summary statistics for all the variables used in the article. The sample period is 1990 to 2009. Definitions of all variables are reported in Appendix B.

mean loan spreads (178.38 basis points), a 4.2% decline from the mean loan spread is equivalent to 7.46 basis points. We next assess the economic significance of social capital by comparing it with the effect of *ROA*, the common measure of profitability. The coefficient on *ROA* is –1.231. As such, a 1 standard deviation increase of social capital is equivalent to an increase of 0.034 (0.034 = 0.896 × .0467 / 1.231) in *ROA*. An increase of 0.034

Table 3. The Effect of Social Capital on Loan Spreads.

	(1)	(2)
	Log (spread)	
Social Capital	–.0464**	–.0467**
	(–2.05)	(–2.05)
Firm-level controls		
Accounting Quality		–.504***
		(–4.78)
Firm Size	–.198***	–.196***
	(–30.47)	(–30.37)
ROA	–1.018***	–1.231***
	(–12.09)	(–12.31)
BTM	–.00740	–.00863
	(–0.60)	(–0.72)
Leverage	.465***	.468***
	(10.06)	(10.27)
Tangibility	–.127***	–.119***
	(–3.32)	(–3.10)
Altman's Z-score	–.00861*	–.00783*
	(–1.84)	(–1.67)
Std (Sales)	.0556**	.0569**
	(2.39)	(2.38)
Std (CFO)	1.270***	1.250***
	(7.90)	(7.79)
MAO	.0586***	.0587***
	(4.18)	(4.22)
Loan characteristic controls		
Subordinate	.515**	.519**
	(2.03)	(2.03)
Performance Pricing	–.111***	–.110***
	(–7.12)	(–7.07)
Log (No. of Facilities)	.195***	.195***
	(11.47)	(11.47)
Loan Maturity	–.0589***	–.0580***
	(–4.61)	(–4.54)
Loan Amount/TA	–.0862**	–.0816**
	(–2.37)	(–2.24)
Log (No. of Lenders)	–.0259***	–.0249***
	(–3.17)	(–3.07)
Log (1 + No. of Total Covenants)	.119***	.119***
	(9.28)	(9.26)
Previous Relation	–.0231**	–.0234**
	(–2.10)	(–2.14)
Demographic and geographic controls		
Population	–.00307	–.00326
	(–0.27)	(–0.28)
Education	.271	.261
	(1.11)	(1.06)
Religion	–.125	–.135
	(–1.05)	(–1.12)

(continued)

Table 3. (continued)

	(1)	(2)
	Log (spread)	
Income	.00832	.0112
	(0.10)	(0.14)
Housing Starts	.0627*	.0622*
	(1.73)	(1.71)
Income Growth	.143	.138
	(0.44)	(0.42)
Unemployment	.0141	.0137
	(1.61)	(1.57)
Democratic vs. Republican	.0113	.0321
	(0.00)	(0.01)
Banks	–.0668	–.0256
	(–0.01)	(–0.01)
Fixed Effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects	
N	16,451	16,451
Adj. R^2	.6636	.6646

Note. Shaded variables are the variables of interest. This table presents the OLS regression of loan spreads on societal-level social capital. The dependent variable is the natural logarithm of the loan spread. The independent variable of interest is *Social Capital.* Definitions of all variables are reported in Appendix B. We include all firm-level characteristics, loan characteristics, demographic and geographic controls and loan purpose, loan-type, bank-type, industry, and state-year fixed effects. We provide the detailed definitions for the fixed effects in Appendix B. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

in *ROA* is fairly economically significant, given that the interquartile range of *ROA* is 0.063. As such, we conclude that the effect of social capital is not only statistically significant but also economically significant.

As expected, in column 2, the coefficient on *Accounting Quality* (β = –.504, *t*-statistic = –4.78) is negative and statistically significant, consistent with prior studies (e.g., Francis et al., 2005) that good accounting quality reduces the cost of bank loans. This suggests that *Social Capital* and *Accounting Quality* affect the cost of bank loans through different channels.

Table 3 also reveals that control variables generally have the expected effect on loan spreads. We find that larger firms (*Firm Size*), more profitable firms (*ROA*), and firms that are distant from default (*Altman's Z-score*) tend to have lower loan spreads. Firms with higher leverage (*Leverage*), more volatile sales (*Std* (*Sales*)), and cash flow (*Std* (*CFO*)) tend to have higher loan spreads. Regarding loan characteristics, loans with shorter maturity, smaller loans have higher loan spreads. Consistent with the finding in Bushman, Williams, and Wittenberg-Moerman (2017), the coefficient on *No. of Total Covenants* is positive and statistically significant at the 1% level. Turning to the county- and state-level demographic and geographic control variables, the coefficients on *Population Education, Religion, Income, Income Growth, Unemployment, Democratic vs. Republican*, and *Banks* are not significantly different from 0 at conventional levels. The coefficient on *Housing Starts* is significantly positive. Overall, we conclude from Table 3 that social capital reduces the cost of bank loans after controlling for accounting quality, firm-level, loan-specific, and county- and state-level variables.

The Moderating Effect of Alternative Information

We next consider whether certain conditions mitigate the effect of societal-level social capital on bank loans. To the extent that the private loan is a contract between the lender and the borrower, we specifically focus on the information asymmetry between the two parties. The first condition we consider is the previous lending–borrowing relation. When the lender has recently interacted with the borrower through past transactions, the lender can gather information from past experience with the borrower to assess the likelihood of default and information risk. When the private knowledge about the default risk is more available, the banks are less likely to rely on societal-level social capital to assess information risks when they initiate new loans. The second condition we consider is the geographic proximity between the lender and the borrower. When the geographic distance between the lender and borrower is close, the lender can gather information about the borrower's creditworthiness from alternative sources, for example, local media and newspapers, and so on. As such, information from other readily available channels due to geographic proximity may supplant the role of societal-level social capital. While the previous lending–borrowing relation captures the private knowledge about the borrower along the time horizon, the distance between the borrower and the lender captures the private information advantage along the geographical horizon.

We present the results in Table 4. In Panel A, we estimate the main regression on two subsamples; that is, the subsample with at least one previous transaction between the borrower and lender over the past 5 years in column 1, and a subsample with no previous relation between the borrower and lender in the past 5 years in column 2, respectively. In column 1, the coefficient on *Social Capital* is negative but statistically insignificantly different from 0 at conventional levels. In column 2, the coefficient on *Social Capital* is negative and statistically significant at the 5% (β = –.0553, *t*-statistics = –2.30). This finding is consistent with social capital playing a less important role in reducing loan spreads when a borrower has previous lending–borrowing relations with the lender. Although the estimated coefficient on *Social Capital* in column 1 is one half larger than that provided in column 2, the difference is less statistically significant.

In Panel B, we estimate the main regression on two subsamples; that is, the subsample of borrowers that are geographically close to their lead lenders (column 1) and the subsample of borrowers that are relatively far from their lead lenders (column 2). We split the sample by the median distance between the lender and the borrower. If a borrower's headquarter is located within (further than) the median distance from its lead lenders' principal executive offices, it is classified as a borrower that is proximate (distant) to its lender. In column 1, the coefficient on *Social Capital* is negative but statistically insignificantly different from 0 at conventional levels. In column 2, the coefficient on *Social Capital* is negative and statistically significant at the 5% (β = –.0720, *t*-statistics = –2.01). The difference is also statistically significant. This finding is consistent with the idea that the impact of social capital on loan spreads is less pronounced when the lender is geographically close to the borrower. Overall, we interpret the findings in Table 4 as suggesting that the effect of social capital on the cost of bank loans is more pronounced among firms with less available alternative information about the borrower.

Table 4. The Role of Social Capital: When Private Knowledge About the Borrower Is Less Available.

Panel A: Borrower–Lender Relationship: Lending History.

	Log (spread)	
	(1) With previous relation	(2) With no previous relation
Social Capital	–.0361	–.0553**
	(–1.29)	(–2.30)
Firm-level controls	Yes	Yes
Loan characteristic controls	Yes	Yes
Demographic and geographic controls	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects	
N	8,021	8,430
Adj. R^2	.6985	.6259
H_1: $\beta^1_{Social\ Capital} > \beta^2_{Social\ Capital}$	p value = .235	

Note. Panel A presents the OLS regression of loan spreads on social capital in subsamples based on the lending history. The dependent variable is the natural logarithm of the loan spread. Column 1 presents the results for a subsample with a previous relation between the borrower and lender in the past 5 years. Column 2 presents the results for a subsample with no previous borrower–lender relation in the past 5 years. We include all firm-level characteristics, loan characteristics, and demographic and geographic controls and loan purpose, loan-type, bank-type, industry, and state-year fixed effects. Definitions of all variables are reported in Appendix B. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel B: Borrower–Lender Relationship: Geographic Proximity.

	Log (spread)	
	(1) Proximate	(2) Distant
Social Capital	–.0191	–.0720**
	(–0.67)	(–2.01)
Firm-level controls	Yes	Yes
Loan characteristic controls	Yes	Yes
Demographic and geographic controls	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects	
N	6,491	6,490
Adj. R^2	.6937	.6893
H_1: $\beta^1_{Social\ Capital} > \beta^2_{Social\ Capital}$	p value = .092	

Note. Panel B presents the OLS regression of loan spreads on social capital in subsamples based on the geographic proximity. Column 1 presents results for a subsample of borrowers whose headquarters are located within the median distance (534.9 miles) of their lead lenders' principal executive offices. Column 2 presents results for a subsample of borrowers whose headquarters are located further than the median distance from their lead lenders' principal executive offices. We include all firm-level characteristics, loan characteristics, and demographic and geographic controls and loan purpose, loan-type, bank-type, industry, and state-year fixed effects. Definitions of all variables are reported in Appendix B. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Robustness Checks

Alternative Measures of Financial Reporting Quality

In Equation 1, we use the residual term from the modified Dechow and Dichev (2002) model as a proxy for financial reporting quality to isolate the effect of social capital on the cost of bank loans from the effect of financial reporting quality. Panel A of Table 5 presents the results after controlling for alternative financial reporting quality measures. Specifically, we use *Minus Accruals Quality* (defined as negative 1 times the standard deviation of the firm-level residuals from the modified Dechow and Dichev, 2002, model over the 5-year rolling window), *Minus Abs* (*DDresid*; defined as negative 1 times the absolute value of the firm-level residual from the modified Dechow and Dichev, 2002, model), and *Readability Index* (calculated as 206.835 – 1.015 × (No. of words / No. of sentences) – 84.6 × (No. of syllables / No. of words)). Higher *Minus Accruals Quality, Minus Abs* (*DDresid*), and *Readability Index* represent higher financial reporting quality. We continue to find a negative association between social capital and loan spreads. This result suggests that the effect of social capital on loan spreads is not driven by financial reporting quality.

Using Survey Years Only

The NERCRD conducts four waves of survey in 1990, 1997, 2005, and 2009. As such, the primitive input variables (the *Voter turnout in presidential elections*, the *Census response rate*, the *Number of social and civic associations*, and the *Number of nongovernment organizations*) are only available in these 4 years. Following many studies using survey data, we linearly interpolate the data to fill in the years between 1990 and 1997, the years between 1997 and 2005, and the years between 2005 and 2009. To assess the sensitivity of our results to this linear interpolation approach, we repeat our analysis using only survey-year observations. Specifically, we estimate the baseline regression only for the years 1990, 1997, 2005, and 2009. We tabulate the results in Panel B of Table 5. As before, the coefficient on *Social Capital* is negative and statistically significant at the 5% level ($\beta = -.0610$, t-statistic = –2.34).

Evidence From a Matched-Sample Analysis

To further shed light on the effect of societal-level social capital on the cost of bank loans, we perform a matched-sample analysis. Specifically, for each year, we first rank firms into the low, medium, and high social capital terciles. Then for each firm in the high social capital tercile, we match it with a firm from the low social capital tercile using various criteria. We tabulate the results in Table 6. In column 1, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest firm size measured as the natural logarithm of market value of equity. In column 2, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest ROA. In column 3, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest leverage. In Columns 4 through 6, we repeat the matching in Columns 1 through 3 but require that the matching firm is from the same or an adjacent state. This additional requirement in matching further controls for the similar financial and economic conditions shared by contiguous regions. We use the indicator variable *High Social Capital*

Table 5. The Effect of Social Capital on Loan Spreads: Robustness Tests.

Panel A: Alternative Measures of Accounting Quality.

	(1)	(2) *Log (Spread)*	(3)
Social Capital	–.0450**	–.0464**	–.0587**
	(–1.98)	(–2.05)	(–2.24)
Minus Accruals Quality	–.662***		
	(–3.67)		
Minus Abs (DDresid)		–.187	
		(–1.38)	
Readability Index			–.00806***
			(–3.87)
Firm-level controls	Yes	Yes	Yes
Loan characteristic controls	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects		
N	16,451	16,451	13,764
Adj. R^2	.6642	.6636	.6758

Note. Panel A presents the OLS regression of loan spreads on social capital after controlling for other measures of financial reporting quality, that is, *Minus Accruals Quality, Minus Abs (DDresid)*, and *Readability Index*. The dependent variable is the natural logarithm of the loan spread. We include all control variables and fixed effects in the baseline test. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Panel B: Using Survey Years Only.

	Log (Spread)
Social Capital	–.0610**
	(–2.34)
Firm-level controls	Yes
Loan characteristic controls	Yes
Demographic and geographic controls	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects
N	2,813
Adj. R^2	.6841

Note. Panel B presents the OLS regression of loan spreads on social capital using only survey years. The dependent variable is the natural logarithm of the loan spread. The independent variable of interest is *Social Capital*. We only keep observations in survey years; that is, 1990, 1997, 2005, and 2009. Definitions of other variables are reported in Appendix B. We include all control variables and fixed effects in the baseline test. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

to differentiate the firm in the high social capital tercile from the matched firm. In all columns, the coefficient on *High Social Capital* is negative and statistically significant at the 10% level or better, consistent with firms with higher social capital having lower loan spreads.

Table 6. Evidence From the Matched-Sample Analysis.

	Log (Spread)					
Matching based on	(1) Closest *Size* and same industry	(2) Closest *ROA* and same industry	(3) Closest *Leverage* and same industry	(4) Closest *Size* and same industry in the same or adjacent states	(5) Closest *ROA* and same industry in the same or adjacent states	(6) Closest *Leverage* and same industry in the same or adjacent states
High Social Capital	–.145***	–.118**	–.112**	–.140***	–.110**	–.102*
	(–2.97)	(–2.31)	(–2.15)	(–2.90)	(–2.12)	(–1.94)
Firm-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Loan characteristic controls	Yes	Yes	Yes	Yes	Yes	Yes
Demographic and geographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects					
N	10,289	10,182	10,193	7,205	7,180	7,104
Adj. R^2	.7013	.6966	.6811	.7067	.7047	.7035

Note. This table presents the result of a matched-sample analysis. For each year, we rank firms into the low, medium, and high social capital terciles. Then for each firm in the high social capital tercile, we match it with a firm from the low social capital tercile using various criteria. In column 1, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest firm size measured as the natural logarithm of market value of equity. In column 2, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest ROA. In column 3, we match each firm in the high social capital tercile with a firm from the low social capital tercile in the same industry with the closest leverage. In Columns 4 to 6, we repeat the matching in Columns 1 to 3, but require that the matching firm is from the same or an adjacent state. We use the indicator variable *High Social Capital* to differentiate the firm in the high social capital tercile from the matched firm. The dependent variable is the natural logarithm of the loan spread. We include all firm-level characteristics, loan characteristics, demographic and geographic controls and loan purpose, loan-type, bank-type, industry, and state-year fixed effects. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm.

Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Evidence From Headquarter Relocations and the September 11 Shock

Evidence From Firms That Move Their Headquarters

To further guard our findings against the possibility of omitted correlated variables, we perform an analysis on a subsample of firms that experience changes in social capital due to headquarter relocations. Specifically, we take advantage of the headquarter relocation events due to state-level tax policy changes. To construct the sample, we first extract each firm's headquarter from EDGAR's online 10-K filings using the web-crawling technique. We then identify a sample of firms that moved their headquarters from one county to a different county.[14] The first year a firm reports its headquarter in the 10-K filing that is different from headquarters reported in prior years is identified as the year of relocation. We then identify headquarter relocations due to state-level tax policy changes. We designate a headquarter relocation as tax motivated if the state of the new headquarter has a tax cut or the state of the old headquarter has a tax rise at the time of relocation. We track the state-level tax policy change using the lists provided by Heider and Ljungqvist (2015). We further verify our classification by manually reading the 10-K filing for each case, and make sure that the corporate tax rate in the new state (after the move) is lower than the old state (before the move). For each firm that moves its headquarter for tax-motivated reasons, we keep 5 years before the relocation and 5 years after the relocation. As such, using this subsample of tax-motivated headquarter relocations, we investigate whether a move from a high social capital region to a lower social capital region results in higher cost of debt after the move and vice versa. Specifically, we employ the following equation:

$$\begin{aligned}\text{Log}(\textit{Spread}) = \beta_0 + \beta_1 \textit{Post} &+ \textit{Borrower characteristics} + \textit{Loan characteristics} \\ &+ \textit{Demographic and geographic characteristics} + \textit{Industry fixed effects} \\ &+ \textit{State} - \textit{year fixed effects} + \varepsilon.\end{aligned} \tag{2}$$

The indicator variable *Post* takes a value of 1 for years after a firm has moved and 0 otherwise. We compare social capital before and after the relocation, and designate firms into the ''relocation to lower social capital'' subsample and the ''relocation to higher social capital'' subsample.[15] We then estimate Equation 2 for the two subsamples separately. As before, we include all borrower characteristics, loan characteristics, geographic and demographic characteristics as well as industry and state-year fixed effects.

Panel A of Table 7 reports the regression results of Equation 2. For the sake of brevity, we include all control variables in the regression but only report the coefficient on *Post*. Consistent with our prediction, for firms that relocate into lower social capital counties due to tax motives, the coefficient on *Post* in column 1 is positive and statistically significant at the 5% level using the two-sided test. This suggests that firms that move to lower social capital counties experience higher cost of bank loans after the relocation. In contrast, for firms that relocate into higher social capital counties, the coefficient on *Post* in column 2 is negative and statistically significant at the 5% level. This indicates that firms that move to higher (lower) social capital counties for tax-motivated reasons experience lower (higher) cost of bank loans after the relocation.

Table 7. Evidence From Two Events.

Panel A: Evidence From Firm Headquarter Relocations

	(1) Relocation to lower social capital counties	(2) Relocation to higher social capital counties
	Log (Spread)	
Post	.155**	−.178**
	(2.46)	(−2.34)
Firm-level controls	Yes	Yes
Loan characteristic controls	Yes	Yes
Demographic and geographic controls	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and state-year fixed effects	
N	321	275
Adj. R^2	.654	.646
H_1: $\beta^1_{Social\ Capital} > \beta^2_{Social\ Capital}$	p value $< .01$	

Note. Panel A reports the OLS regression of loan spreads on the indicator variable *Post* using a sample of firms that relocate their headquarters due to state-level tax rate change. The dependent variable is the natural logarithm of the loan spread. The first year a firm reports its headquarter in the 10-K filing that is different from headquarters reported in prior years is identified as the year of relocation. We designate a headquarter relocation as tax motivated if the state of the new headquarter has tax cut or the state of the old headquarter has tax rise at the time of relocation. We track the state-level tax policy change using the lists provided in Heider and Ljungqvist (2015). We further verify our classification by manually reading the 10-K filing for each case, and confirm that the corporate tax rate in the new state is lower than that in the old state. For each firm that moves its headquarter for tax-motivated reasons, we keep 5 years before the relocation and 5 years after the relocation. We designate firms into the "relocation to lower social capital" subsample if their social capital is higher after the relocation than before the relocation, and designate firms into the "relocation to higher social capital" subsample if their social capital is lower after the relocation than before the relocation. The independent variable of interest is *Post*. *Post* is an indicator variable that takes a value of 1 after a firm has moved and 0 otherwise. Definitions of all other variables are reported in Appendix B. We include all firm-level characteristics, loan characteristics, and demographic controls and loan purpose, loan-type, bank-type, industry, and state-year fixed effects. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. OLS = ordinary least squares; WTC = World Trade Center.
Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

Evidence From the September 11 Shock

The second exogenous shock we investigate is the terrorist attack on September 11, 2001. After the attack, the Federal Emergency Management Agency classifies the State of New York and the State of Virginia as "Major Disaster Declaration—Terrorist Attack." Subsequently, the local governments have taken a series of actions to facilitate social capital building. As a result, studies show that in affected states, the levels of political consciousness and engagement are substantially higher than those before (Putnam, 2002; Sander & Putnam, 2010). Trust in government, trust in the police, and interest in politics are all higher than that observed before the attack. For example, Americans are more likely to have attended a political meeting or to have worked on a community project after the disaster.

This unexpected disaster offers a natural experiment to identify causality. The State of New York and the State of Virginia experience a sharp increase in social capital after the attack, while the exogenous shock affects other states to a lesser degree. To empirically implement the test, we employ a difference-in-differences design. *9/11 Affected Counties* is

Table 7. (continued)

Panel B: Evidence From the September 11 Shock.

9/11 Affected counties defined as	(1) NY and VA counties	(2) Counties that are close to the Pentagon or the WTC
	Log (Spread)	
Post 9/11	.0722	.0791*
	(1.53)	(1.68)
9/11 Affected counties	.224***	.102**
	(3.34)	(2.31)
9/11 Affected counties × *Post 9/11*	–.150***	–.0986***
	(–2.59)	(–2.63)
Firm-level controls	Yes	Yes
Loan characteristic controls	Yes	Yes
Demographic and geographic controls	Yes	Yes
Fixed effects	Loan purpose, loan-type, bank-type, industry, and year fixed effects	
N	10,308	10,308
Adj. R^2	.6725	.6711

Note. Panel B reports the effect of social capital on loan spreads using a difference-in-differences design. The sample period is 1996-2006, which spans 5 years before to 5 years after September 11, 2001. We remove firms that are partially destroyed by the attack and firms that experienced rebuilding/received funding or donation. We require that loan information is available in both Pre- and Post-9/11 periods for each county. We use two definitions for *9/11 Affected counties*. In column 1, *9/11 Affected counties* is an indicator variable that takes a value of 1 for firms headquartered in the State of New York and the State of Virginia. In column 2, *9/11 Affected counties* is an indicator variable that takes a value of 1 for firms headquartered in counties that are within 100 miles of the Pentagon (Arlington, Virginia) or the World Trade Center (Manhattan, New York City, New York). The dependent variable is the natural logarithm of the loan spread. *Post 9/11* is an indicator variable that takes a value of 1 if the loan facility's start date is within 5 years after the 9/11 attack, and 0 otherwise. The independent variable of interest is the interaction term of 9/11 States and Post 9/11. We include all firm-level characteristics, loan characteristics, demographic and geographic controls and loan purpose, loan-type, bank-type, industry, and year fixed effects. Definitions of all other variables are reported in Appendix B. The *t*-statistics are presented underneath the coefficient estimates. Standard errors are White heteroskedasticity-robust and clustered by firm. Significance at the 10%, 5%, and 1% level is indicated by *, **, and ***, respectively.

the indicator variable for affected counties. *Post 9/11* is the indicator variable for observations after the attack. The interaction term *9/11 Affected Counties* × *Post 9/11* is the variable of interest. If the social capital building after the attack results in an increase in societal-level social capital, we expect a negative coefficient on *9/11 Affected Counties* × *Post 9/11*. Specifically, we estimate

$$\begin{aligned}\text{Log}(\textit{Spread}) = {} & \beta_0 + \beta_1 \textit{Post}9/11 + \beta_2 9/11\ \textit{Affected Counties} \\ & + \beta_3 9/11\ \textit{Affected Counties} \times \textit{Post}9/11 + \textit{Borrower characteristics} \\ & + \textit{Loan characteristics} + \textit{County characteristics} + \textit{Fixed effects} + \varepsilon.\end{aligned} \tag{3}$$

We first validate the increase in social capital in the two affected states in our societal-level social capital data. The mean *Social Capital* in the two affected states—the State of New York and the State of Virginia—has increased from –0.441 in the survey conducted in

1997 to –0.308 in the survey conducted in 2005 (untabulated). In contrast, the mean *SocialCap* in other states appears stable (–0.172 in the survey conducted in 1997 and –0.153 in the survey conducted in 2005, respectively, untabulated).[16]

In addition, to further mitigate the impact of rebuilding and reliefs due to this disaster, we exclude firms that are partially destroyed by the attack and firms that experienced rebuilding/received funding or donation. We manually collect data to exclude these firms using two procedures: First, we extract the list of tenants in the World Trade Center (both Tower 1 and Tower 2) to identify firms that are attacked. We designate firms whose offices are destroyed as firms that need rebuilding after the attack. Second, we manually inspect firms' disclosure in 10-K filings after the attack. We identify firms who disclose that some of their properties are (partially) destroyed during the attack as firms that need rebuilding/may receive reliefs after the attack. In the final sample for this natural experiment, we remove firms identified from the above two procedures from the sample.

Panel B of Table 7 reports the results. For the sake of brevity, we include all control variables in the regression but only report the difference-in-differences variables. In column 1, *9/11 Affected counties* is an indicator variable that takes a value of 1 for firms headquartered in the State of New York and the State of Virginia, which are the two states classified by the Federal Emergency Management Agency as ''Major Disaster Declaration—Terrorist Attack'' following the 9/11 attacks. In column 1, the coefficient on *9/11 Affected counties* × *Post 9/11* is negative and statistically significant at the 1% level (β = –.150, *t*-statistic = –2.59). This suggests that firms headquartered in New York and Virginia have significantly lower loan spreads than *other* firms *after* the attack. To further probe the possibility that counties located in other states but close to the places of the attack also experience social capital building, we define *9/11 Affected counties* differently in column 2. Specifically, in column 2, *9/11 Affected counties* is an indicator variable that takes a value of 1 for firms headquartered in counties that are within 100 miles of the Pentagon or the World Trade Center. The coefficient on *9/11 Affected counties* × *Post 9/11* is negative and statistically significant at the 1% level (β = –.0986, *t*-statistic = –2.63), consistent with firms that experience large increase in social capital subsequent to the attack are issued less costly bank loans.

Conclusion

Our study investigates whether and how societal-level social capital affects the cost of bank loans. We document that the borrower's societal-level social capital significantly reduces the cost of debt after controlling for firm-specific, loan-specific, and geographic- and demographic-specific characteristics. To further identify causality, we study a subsample of firms that experience changes in social capital due to tax-motivated headquarter relocations. We find that firms that move to lower (higher) social capital counties for tax reasons experience higher (lower) cost of bank loans after the relocation. Finally, we utilize the exogenous shock of the September 11 attack which significantly increases societal-level social capital in the State of New York and the State of Virginia (and possibly adjacent counties) through social capital building after the disaster. We show that affected firms experience significantly lower loan spreads than other firms after the attack.

We make a number of contributions to the finance and accounting literature. Our study provides evidence that informal institutions such as societal-level social capital play an important role in loan contracting. We also contribute to social economics by showing that individual characteristics implied by regional, societal-level, social capital affect anticipated firm behaviors.

Appendix A Summary of the Prior Literature.

Study	Research question	The definition of social capital	Social capital is defined as	The measure of social capital
Helliwell and Putnam (1995)	Why do some Italian regions establish and maintain higher levels of output per capita?	Features of social organizations such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit.	Social norms and networks	Helliwell and Putnam (1995) measure social capital using three measures: An index of the extent of civic community, an index of various direct measures of the effectiveness of regional government, and surveys of satisfaction with their regional government.
N. Lin (1999)	Review of the social capital literature	Investment in social relations by individuals through which they gain access to embedded resources to enhance expected returns of instrumental or expressive actions	Networks	N. Lin (1999) suggests that social capital can be measured as the valued resources (e.g., wealth, power, and status) of others accessed by individuals in their networks and ties.
Rupasingha, Goetz, and Freshwater (2000)	Does social capital affect economic growth in the United States?	Features of social organizations such as networks, norms, and social trust that facilitate coordination and cooperation for mutual benefit.	Social norms and networks	Rupasingha et al. (2000) measure social capital using three measures: The density of associational activity, the crime index, and the percentage of eligible voters participating in the federal election.
Whiteley (2000)	Does social capital affect economic growth?	Willingness of citizens to trust others, including members of their own family, fellow citizens, and people in general.	Social norms	Whiteley (2000) uses a principal components analysis of three trust variables—The level of trust on members of one's own family, the level of trust on fellow nationals, and the level of trust on people in general. These variables are from the World Value Survey.

(continued)

Appendix A (continued)

Study	Research question	The definition of social capital	Social capital is defined as	The measure of social capital
Guiso, Sapienza, and Zingales (2004)	Does social capital affect financial development?	The mutual level of trust and altruistic tendency in a society.	Social norms	They use two variables to measure a region's social capital: Electoral participation and blood donation.
Guiso, Sapienza, and Zingales (2008a)	Social capital and long-term persistence	A set of beliefs and values that foster cooperation.	Social norms	Using the World Value Survey data, social capital is measured using the answers to the following question: "Generally speaking, would you say that most people can be trusted or that you can't be too careful in dealing with people?"
Jha (in press)	Does social capital affect financial reporting quality?	The norms and networks that facilitate collective action.	Social norms and networks	Jha (in press) conducts a principal component analysis of four input variables: The voter turnout in presidential election, the census response rate, the number of social and civic associations, and the number of nongovernment organizations in each county.
Jha and Chen (2015)	Does social capital affect audit fees?	They define social capital as the norms and networks that facilitate collective action.	Social norms and networks	Jha and Chen (2015) conduct a principal components analysis of four input variables: The voter turnout in presidential election, the census response rate, the number of social and civic associations, and the number of nongovernment organizations in each county.

Appendix B Variable Definition.

Variables	Definitions
Dependent variables (*Source:* DealScan)	
Log (*Spread*)	The natural log of loan spreads. Loan spreads are all-in-drawn spread expressed in basis points. The all-in-drawn spread is the sum of upfront fees, spread over LIBOR, utilization fee, annual fee specified in a facility at the inception of the facility.
Variables of interest	
Social Capital	This variable is the measure of societal-level social capital at the county level. The variable is constructed as the first principal component of four inputs: *Assn, Nccs, Pvote*, and *Respn. Assn* is the sum of the religious organizations, civic and social associations, business associations, political organizations, professional organizations, labor organizations, bowling centers, physical fitness facilities, public golf courses, sport clubs, managers and promoters membership sports and recreation clubs (no data for 2005 or 2009), and membership organizations not elsewhere classified (no data for 2005 or 2009), then divided the number by 12 (10 for 2005 or 2009) and scaled by the population of the county (measured per 10,000 people). *Nccs* is the total number of nongovernment organizations excluding the ones with an international focus, scaled by the population (measured per 10,000 people). *Pvote* is the number of votes casted scaled by the population above 18 years old (measured per 10,000 people). *Respn* is the census response rate. As the NERCD surveys are only available for the years 1990, 1997, 2005, and 2009, we linearly interpolate and fill the social capital data for years between two adjacent surveys. (*Source:* NERCRD)
Demographic and geographic controls	
Population	The natural logarithm of population each year for each county. *Source: BEA*.
Education	The percentage of college graduates each year for each county. The education data are only available in 1990, 2000, 2010, 2011, and 2012. We linearly interpolate the data to fill in the years between each survey. *Source: BEA.*
Religion	The percentage of religious adherents each year for each county. The religiosity data at the county level are only available in 1990, 2000, 2010, and 2012. We linearly interpolate the data to fill in the years between each survey. *Source: ARDA*.
Income	The natural logarithm of the per-capita income each year for each county. *Source: BEA*
Housing starts	The natural logarithm of the number of building permits each year for each state. *Source: the U.S. Census*.
Income growth	The growth rate of per-capita income each year for each county. *Source: BEA.*
Unemployment	The unemployment rate expressed in percentage rate for each county. *Source: Bureau of Labor Statistics*.
Democratic vs. Republican	The ratio of the percentage of the popular votes received by the Democratic Party over the percentage of the popular votes received by the Republican Party for each state, scaled by 100. The data are available in 1996, 2000, 2004, 2008, and 2012. We apply the data from 1996 in years prior to 1996, and linearly interpolate the data to fill in the years between each survey year. *Source:* http://www.270towin.com.

(continued)

Appendix B (continued)

Variables	Definitions
Banks	The number of bank branches scaled by the total population (measured per 10,000 people) each year for each county, scaled by 100. *Source: FDIC.*
Firm-level controls (*Source:* Compustat, SEC's Edgar system)	
Firm Size	The natural logarithm of market value of equity.
ROA	Earnings before extraordinary items divided by the total assets.
BTM	The book value of shareholders' equity divided by market value of equity.
Leverage	The sum of long-term debt plus debt in current liabilities, divided by total assets.
Tangibility	Net property, plant and equipment divided by total assets.
Altman's Z-score	For manufacturing firms, Altman's *Z*-score = [4.34 + 0.08 × working capital / total assets − 0.04 × retained earnings / total assets + 0.1 × EBIT / total assets + 0.22 × market value of equity / book value of total liabilities − 0.06 × sales / total assets] (Hillegeist, Keating, Cram, & Lundstedt, 2004); for nonmanufacturing firms, Altman's *Z*-score = [6.56 × working capital / total assets + 3.26 × retained earnings / total assets + 6.72 × EBIT / total assets + 1.05 × book value of equity / book value of total liabilities] (Altman, 2000).
Accounting Quality	This variable is calculated as negative 1 times the residual from the modified Dechow and Dichev (2002) model. We estimate the following regression for each year and each industry: $\Delta WC_t = \beta_0 + \beta_1 CFO_{t-1} + \beta_2 CFO_t + \beta_3 CFO_{t+1} + \beta_4(\Delta Rev_{i,t} - \Delta AR_{j,t}) + \beta_5 PPE_{i,t} + \varepsilon$, where *CFO* is firms' cash flows from operations, *Rev* is sales, *AR* is the account receivable, and *PPE* is net PP&E, all scaled by lagged total assets.
Minus Accruals Quality	This variable is calculated as negative 1 times the standard deviation of a firm's residuals from the modified Dechow and Dichev (2002) model over the 5-year rolling window.
Minus Abs (*DDresid*)	This variable is calculated as negative 1 times the absolute value of the residual from the modified Dechow and Dichev (2002) model.
Readability Index	This variable captures 10-K readability and is calculated as 206.835 − 1.015 × (No. of words / No. of sentences) − 84.6 × (No. of syllables / No. of words).
Std (CFO)	The standard deviation of cash flow from operations scaled by lagged total assets over the 5-year rolling window.
Std (Sales)	The standard deviation of sales scaled by lagged total assets over the 5-year rolling window.
MAO	An indicator variable that takes a value of 1 if a firm received a nonunqualified audit opinion, and 0 otherwise.
Loan facility-level controls (*Source:* DealScan)	
Subordinate	An indicator variable that takes a value of 1 for subordinate debt, and 0 otherwise.
Performance Pricing	An indicator variable that takes a value of 1 if the loan facility uses performance pricing and 0 otherwise.
Loan Maturity	Natural logarithm of loan maturity (in months).
Loan Amount/TA	Offering amount of the loan facility, divided by total assets.
Previous Relation	An indicator that takes a value of 1 if at least one of the loan's lead lenders had been a lead lender of the borrower's previous loans in the past 5 years preceding the loan's issuance date, and 0 otherwise.

(continued)

Appendix B (continued)

Variables	Definitions
Loan package-level controls (*Source:* DealScan)	
Log (No. of Facilities)	The natural logarithm of the number of loan facilities in the package.
Log (No. of Lenders)	The natural logarithm of the number of loan lenders.
Log (1 + No. of Total Covenants)	The natural logarithm of 1 plus the number of total covenants at the inception of the loan package.
Loan purpose, loan-type, and bank-type fixed effects (*Source:* DealScan)	
Loan Purpose	Five indicator variables for the primary purposes of loans: acquisitions, backup line, refinancing, working capital/corporate purposes, and other, respectively.
Loan Type	Four indicator variables for term loan, the loan type of revolver greater than 1 year, the loan type of revolver less than 1 year, and the loan type of 364-day facility, respectively.
Bank Type	Two indicator variables for investment bank (if at least one lead lender is an investment bank) and foreign bank (if at least one lead lender is a foreign bank), respectively.

Note. LIBOR = London Interbank Offered Rate; NERCRD = Northeast Regional Center for Rural Development; BEA = Bureau of Economic Analysis; ARDA = Association of Religion Data Archive; FDIC = Federal Deposit Insurance Corporation; SEC = U.S. Securities and Exchange Commission; EBIT = Earnings before interest and taxes.

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Notes

1. Graham, Li, and Qiu (2008) report that over the past decade, the net debt security issuances are much larger than equity issuances and among the debt issuances, the amount of bank loans of corporations has been larger than that of public debt since 1980.
2. Our study is also motivated by anecdotal evidence from interviews with banks. For example, using field interviews, Ferrary (2003) reports that the social evaluation in which the subjective perception of the borrower by the financial counselors and the information gathered from social channels are important factors in the decision-making process.

3. Our sample is limited to these years as data used to calculate social capital are not available for each county prior to 1990 or after 2009.
4. In addition, in the presence of a dense network, the potential reputational loss resulting from default is greater. As such, a dense network also motivates managers to work harder to improve the fundamentals.
5. We perform the robustness test to assess this approach in Section ‘‘Evidence From a Matched-Sample Analysis.’’
6. See the detailed data collection procedures by Northeast Regional Center for Rural Development (NERCRD) at http://aese.psu.edu/nercrd/community/social-capital-resources/social-capital-variables-for-1990-1997-and-2005 and http://aese.psu.edu/nercrd/community/social-capital-resources/social-capital-variables-for-1997-2005-and-2009.
7. Linear interpolation is a method of curve fitting using linear polynomials. The use of linear interpolation to fill in the missing values of the in-between years is a common practice in the prior studies (Hilary & Hui, 2009; Kumar, Page, & Spalt, 2011).
8. We multiply the residual from the Dechow and Dichev (2002) model by negative one, so that high values indicate better accounting quality.
9. All firm-specific variables are measured in the same fiscal year as that of social capital.
10. We identify lead lenders using the keyword search of ‘‘administrative agent,’’ ‘‘book-runner,’’ ‘‘lead arranger,’’ ‘‘lead bank,’’ ‘‘lead manager,’’ ‘‘agent,’’ ‘‘arranger,’’ or ‘‘sole lender.’’
11. Following Cornaggia, Cornaggia, and Israelsen (2016), we collect this variable from http://www.270towin.com.
12. We match DealScan and Compustat using the linking file provided by Professor Michael Roberts at the Wharton School of the University of Pennsylvania.
13. On average, in a given year, a firm has 1.59 loans and a county has 4.60 loans (untabulated).
14. We do not study firms that moved their headquarters within a county as our social capital measure is at the county level.
15. In an untabulated test, we compare the tax benefits of firms that move to higher and lower social capital counties, respectively. For firms that relocate for tax purposes to a higher social capital region, their effective tax rate on average is reduced from 37.7% to 36.8%. For firms that relocate for tax purposes to a lower social capital region, their effective tax rate on average is reduced from 37.5% to 36.2%. In other words, compared with firms that relocate to higher social capital regions, firms that relocate to lower social capital regions on average earn a 0.4% saving in effective tax rate.
16. Over 20 years from 1990 to 2009, both groups (the treatment: that is, New York and Virginia and the control group: other states) experience a downward trend in social capital. This pattern is consistent with the observation in Putnam (2000) where he reports the declining social capital in the United States. Most importantly, we are interested in the social capital index around the September 11 attack. New York and Virginia (the affected states) experience a sharp hike, whereas other states only experience a slight increase in social capital. This observation is consistent with the follow-up study by Putnam (2000), in that the social capital of affected states increased substantially after the attack.

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