Social Capital and Bank Stability

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Abstract

Using a sample of public and private banks, we study how social capital relates to bank stability. Social capital, which captures the level of cooperative norms in society, is likely to reduce opportunistic behavior (Jha and Chen 2015; Hasan et al. 2016) and, therefore, act as an informal monitoring mechanism. Consistent with our expectations, we find that banks in high social capital regions experienced fewer failures and less financial trouble during the 2007–2010 financial crisis than banks in low social capital regions. In addition, we find that social capital is negatively associated with abnormal risk-taking and positively associated with accounting transparency and accounting conservatism in the pre-crisis period of 2000–2006, indicating that risk-taking, accounting transparency, and accounting conservatism are possible channels through which social capital affected bank stability during the crisis.

Keywords: Bank Stability; Social Capital; Bank Failure and Trouble;
Risk Taking; Accounting Transparency

Data Availability: Data are available from the sources identified in the text.

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1. Introduction

The 2007–2010 U.S. banking crisis occurred despite banks being subjected to strict regulations and other monitoring mechanisms, such as mandatory auditing, internal control reporting requirements, and other stipulations (e.g., the Sarbanes Oxley Act that applied to all publicly traded firms). After the savings and loans debacle in the 1980s, the Federal Deposit Insurance Corporation Improvement Act (FDICIA) was enacted to improve bank stability. FDICIA includes stricter requirements pertaining to capital adequacy, risk-based deposit insurance, and internal controls. However, some of these requirements do not apply to banks with less than $1 billion in assets ($500 million before 2005). Given that formal monitoring mechanisms such as stricter regulations and corporate governance failed to avert the banking crisis of 2007–2010, we focus on the role of informal institutions on bank stability.

Our objective is to examine the impact of social capital, an informal monitoring mechanism, on bank stability. We define social capital as a community's norms and networks. Social capital, which captures the level of cooperative norms in society, is likely to reduce opportunistic behavior (Jha and Chen 2015; Hasan et al. 2016). In addition, social capital is associated with better economic performance through less value-destroying opportunistic actions. Hasan et al. (2016) provide evidence that firms located in high social capital counties experience better financing conditions in both public and private lending markets. Jha and Chen (2015) provide evidence that firms whose headquarters are in high social capital counties pay lower audit fees.

Using a sample of public and private banks, we investigate whether social capital is associated with bank stability. As stated by Hasan et al. (2016), "debt holders, including banks and bond investors, could perceive social capital as constraining opportunistic firm behaviors." In our context, social capital can limit bank managers' excessive risk-taking, which may affect bank stability directly as well as dampen borrowers' opportunistic behavior, which could influence bank stability indirectly. Following these arguments, we examine whether banks in counties with high social capital experienced fewer failures and less financial trouble during the financial crisis.

Focusing on the banking industry has the following important benefits. Banks are highly regulated; therefore, if we find a positive association between social capital and bank stability, it will provide strong evidence on the impact of social capital as an informal monitoring device. In addition, the banking industry offers significant differences in monitoring requirements among banks. For instance, smaller banks (with less than $500 million in assets) are not required to hire an external auditor, and some of the FDICIA requirements are waived for banks with less than $1 billion in assets. Therefore, the banking industry offers a rich setting in terms of different levels of regulatory scrutiny. In addition, small banks are usually private and community-based. Given that these banks are subject to less formal internal and external monitoring, informal institutions such as social capital are likely to play a more important role in disciplining managers of small banks. Furthermore, network and social norm effects of social capital have the potential to play a more direct role in small, community-based banks than in large financial institutions that operate across multiple regions and countries. We posit that the relationship between social capital and bank stability is stronger for small, unaudited, private banks than for other banks.

We compute a social capital index for U.S. counties using the method and dataset from Rupasingha and Goetz (2008),[1] who use a principal component analysis of two measures of norms and two measures of networks to construct an index for each county for the years 1997, 2005, and 2009.[2] We then linearly interpolate and fill in the social capital data for the intervening years. We test whether the level of social capital in 2006 (just prior to the financial crisis) can predict bank stability during the 2007–2010 financial crisis.[3] In particular, we examine whether social capital in 2006 is negatively associated with bank failure and bank financial trouble during the financial crisis period. We obtain the data on bank failure from the FDIC's publicly available data on bank closures.[4] In the U.S., bank examiners use the CAMELS (which stands for Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Systematic risk) rating system, which relies on several financial ratios and management characteristics, to identify banks that may be in financial trouble. Because the CAMELS ratings used by bank examiners are not publicly available, we classify banks as troubled based on publicly available data that reflect capital adequacy, asset quality, and profitability. We classify a bank as troubled if it satisfied one or more of the following conditions in 2007–2010: 1) low Tier 1 capital ratio (less than 4%); 2) high ratio of loan loss provisions to total loans (greater than 1%); 3) low return on assets (less than -5%); and 4) listed as a failed bank on the FDIC website during the financial crisis.

[1] Anil Rupasingha and Stephan J. Goetz, "US County-Level Social Capital Data, 1990-2005." The Northeast Regional Center for Rural Development, Penn State University, University Park, PA, 2008.

[2] We construct the social capital variable by using the first factor from a principal component analysis of the following four measures: 1) 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, sports clubs, managers and promoters, membership sports, and recreation clubs; 2) the total number of nongovernment organizations, excluding those with an international focus; 3) the percentage of votes cast; and 4) the census response rate.

[3] It is generally accepted that the financial crisis in the U.S. started in the latter half of 2007 (Ryan 2008; Erkens et al. 2012). Therefore, we define the pre-crisis period as 2000–2006 and the crisis period as 2007–2010.

[4] https://www.fdic.gov/bank/individual/failed/banklist.html

Our results are consistent with expectations. During the financial crisis, social capital had a strong negative relationship with bank failure and bank financial trouble. These results hold for the full sample, the subsamples of public and private banks, and the subsample of small, unaudited, private banks. Our results are interesting because they indicate that, for smaller, unaudited, private banks that are subject to less external monitoring, informal institutions such as social capital can substitute as an effective and important monitoring mechanism. Our main results are robust to several sensitivity tests, including controlling for regional effects, subsample analyses within each region, an alternate proxy for social capital, an instrumental variable approach to address the potential concern that our baseline models are affected by the endogeneity of social capital, the use of different thresholds to define troubled banks, and subsample analyses for large and small banks with differential regulatory scrutiny.

In additional tests, we provide evidence of possible economic channels through which social capital may affect bank stability. In the pre-crisis period, our results indicate that private banks, especially small, unaudited, private banks, exhibit lower risk-taking behavior (as well as lower abnormal/excessive risk) when they are located in high social capital counties. These results provide evidence of a possible channel through which social capital enhances bank stability. Furthermore, we find that social capital is negatively associated with restatements and positively associated with bank accounting conservatism, as proxied by timely recognition of bad news (i.e., decline in earnings). Given the evidence in Lim et al. (2014) that banks more transparent in their financial reporting and utilizing conservative accounting are characterized by "more prudent, stable lending behavior in borrower selection," the greater financial reporting quality associated with higher levels of social capital could result in higher bank stability through the selection of higher quality borrowers. This is also reinforced by our evidence that social capital is negatively related to loan charge-offs (an indication of the higher quality of borrowers, leading to lower default) in the pre-crisis period.

Our study contributes to the literature in several important ways. By providing evidence that social capital can mitigate a bank's risk-taking behavior and improve its stability, we show that social capital can act as an external monitoring mechanism to control incentives for excessive risk-taking. In addition, we provide evidence that, even in a highly regulated industry, social capital can act as an informal monitoring mechanism during both normal economic times (before the financial crisis) and periods with higher uncertainty (during the financial crisis).

We also note that, whereas the prior literature on informal institutions focuses on public firms from unregulated industries, we study both public and private firms from a regulated industry. Two recent papers (Ostergaard et al. 2015; Hasan et al. 2016) also examine the role of social capital in the banking industry. Hasan et al. (2016) focus on firms that borrow from banks. They argue that, to the extent that borrowers are located in high social capital counties, they engage in less opportunistic actions, which are reflected in lower bank loan spreads. Ostergaard et al. (2015) document that, following the deregulation of the Norwegian banking sector in the 1980s, small savings banks from high social capital regions have a higher probability of survival. They also provide evidence that savings banks from high social capital regions raise more deposits from the local community, are more altruistic, and have branches that are more locally driven.

Our study differs from these two studies in several important ways. Whereas Hasan et al. (2016) focus on the borrowers in the lending process, we focus on the lenders (i.e., banks). Specifically, we examine the impact of social capital on the risk-taking and financial reporting behaviors of banks prior to the financial crisis (as possible channels for bank stability) as well as financial trouble and failure during the financial crisis. In this regard, the two studies provide complementary evidence on the role of social capital as an informal monitoring mechanism. Our study also differs from Ostergaard et al. (2015) in that they examine the impact of social capital following the deregulation of the banking system in Norway whereas we focus on the U.S. economy prior to and during the financial crisis. Furthermore, Ostergaard et al. (2015) do not find evidence that high social capital communities have an impact on the survival of commercial banks; we provide such evidence. Finally, in addition to investigating the implications of social capital for bank failure and financial trouble, we examine its impact on bank risk-taking and other channels that strengthen bank stability prior to the financial crisis.

The rest of this paper is organized as follows. We discuss the literature and develop our hypothesis on the relationship between social capital and bank stability in Section 2. We present the research design and describe the data in Section 3, discuss the results in Section 4, and offer conclusions in the final section.

2. Research Background and Hypothesis

Consistent with Woolcock (2001), we define social capital as the norms and networks that determine the performance of a society. In general, communities with high social capital are expected to face less opportunistic behavior. For example, Coleman (1998) argues that the strength of the relationship in a society with high social capital "makes possible transactions in which trustworthiness is taken for granted and trade can occur with ease." He also argues that high social capital should reduce self-interested actions. Similarly, Guiso et al. (2010) claim that high social capital, defined as civic capital, generates positive economic payoff and, in general, allows a community to overcome the free-rider problem.

We expect bank managers in a community with high social capital to behave less opportunistically. This expectation is consistent with Jha and Chen (2015), who find that a region with high social capital has people with a greater propensity to honor an obligation and a greater mutual trust within a much denser network, both of which act as a deterrent to opportunistic/self-serving actions and increase cooperation in the community (La Porta et al. 1997). Thus, communities with high social capital may experience fewer moral hazard problems than those with low social capital.

Ostergaard et al. (2015) document the impact of social capital on the survival of Norwegian savings institutions. Their study provides evidence that, after the deregulation of the banking industry, the probability of survival of savings banks facing higher competition from larger commercial banks is higher in high social capital communities.[5] Ostergaard et al. (2015) also show that savings banks from high social capital communities raise more deposits from the local community, are more altruistic, and have branches that are more locally driven. Using similar reasoning, we expect that banks located in high social capital counties experienced less financial trouble and failure during the financial crisis.

In addition to the impact on banks, high social capital is expected to provide banks with less opportunistic borrowers. For instance, using the arguments developed in Coleman (1988) and Guiso et al. (2010), Hasan et al. (2016) reason that borrowers in high social capital counties behave less opportunistically and act less in their self-interest. To the extent that these characteristics reduce moral hazard problems facing lenders, Hasan et al. (2016) argue that borrowers should enjoy a lower spread on their loans because the risks lenders face and the associated costs are lower. They find evidence consistent with this reasoning—that is, banks and

[5] Savings banks are governed by depositors, local governments, and employees. Unlike commercial banks, the objective of savings banks is not to maximize profits.

bond investors require a lower spread for borrowers that have their headquarters in high social capital counties. They also provide evidence that other lending terms such as collateral and covenants are less stringent for firms located in high social capital counties. In addition, Jha and Chen (2015) use similar arguments to document that auditors charge lower fees to firms headquartered in high social capital counties because they deem these firms to be more trustworthy. In our context, to the extent that borrowers are less risky and more trustworthy, banks are likely to experience greater financial stability in counties with high social capital.

Our context includes multiple channels through which social capital can improve bank stability. Following the definition of social capital as the norms and networks that facilitate collective action, we explore the influence of the social norms aspect of social capital on bank stability. Sunstein (1996) defines norms as "social attitudes of approval and disapproval, specifying what ought to be done and what ought not to be done." Society utilizes control mechanisms such as "open criticism" and the "withdrawal of social support" (Hechter and Opp 2001; Horne 2009) to punish violations of these norms. Conversely, individuals who comply with these norms may receive "higher levels of social recognition (public acknowledgement of their status, merits, or personality) and respect" (Stavrova et al. 2013). Unethical behavior (e.g., excessive risk-taking for personal gain) that could destabilize a bank clearly violates acceptable social norms. Therefore, the management of a bank located in a high social capital region would be less likely to violate a social norm because of the social sanctions and criticism that would ensue.

The foregoing discussion implies that high social capital reflects less opportunistic behavior in a community and can mitigate moral hazard problems. Moral hazard problems have always been viewed as a significant issue that could affect managers' actions, behaviors, and disclosures, including excessive risk-taking behavior for personal gain. To the extent that high social capital is associated with less opportunistic behavior, we expect higher bank stability in the form of fewer bank failures, less financial trouble, and less risk-taking for banks located in high social capital counties. This decrease in risk-taking behavior can be attributed to social capital linked to less self-interested actions, more transparency, and higher-quality accounting information (Nanda and Wysocki 2013; Garrett et al. 2014).

In summary, we suggest that social capital, which is related to the norms and networks that facilitate collective action that reduces both managers' propensity to take excessive risk as well as borrowing firms' inclination for opportunistic actions, is positively related to bank stability. Given this reasoning, we hypothesize the following (stated in alternate form):

Hypothesis: Social capital is positively related to bank stability.

3. Research Method and Data

Measures of Social Capital

Our measure of social capital (*SC*) is based on Rupasingha and Goetz (2008), who use a principal component analysis of two measures of social norms and two measures of social networks to construct an index for each county for the years 1997, 2005, and 2009. The social-capital index for each county and the underlying data used to construct the index are available at the Northeast Regional Center for Rural Development (NERCRD). Rupasingha and Goetz's (2008) approach to measure social capital at the county level is the most comprehensive approach and has been used by many researchers, including Putnam (2007), Deller and Deller (2010), Hopkins (2011), Jha and Chen (2015), and Hasan et al. (2016).

Following Rupasingha and Goetz (2008), we use voter turnout in presidential elections and the census response rate as the two measures of social norms. Higher values of these variables represent more social capital.[6] We use the number of social and civic associations and the number of nongovernmental organizations (NGO) in the county, as Rupasingha and Goetz (2008) do, as the two measures of social networks. Social and civic associations include physical fitness facilities, public golf courses, religious organizations, sports clubs, political organizations, professional organizations, business associations, and labor organizations in the county.[7] We normalize all the measures by the population of the county. We then extract the first principal component of these four measures and use it to construct an index of social capital for each county for the years 1997, 2005, and 2009. Because of the unavailability of data, and consistent with Jha and Chen (2015) and Hasan et al. (2016), we linearly interpolate the data to fill in the years 2000 to 2004 and 2006.

Measures of Bank Stability

We use two proxies to assess bank stability during the 2007–2010 crisis. The first measure is actual bank failure, where a bank is deemed failed if the FDIC closed it between 2007 and 2010. Second, we identify a group of banks described as financially troubled in 2007–2010. As discussed earlier, bank examiners use the CAMELS rating system, which is based on several financial ratios and management characteristics, to identify such troubled banks. Because this rating is not publicly available, we classify banks as troubled by using publicly available data that reflect profitability, asset quality, and capital adequacy if they meet at least one of the

[6] Alesina and La Ferrara (2000) use the percentage of people who voted in the 1996 presidential election as a component variable in the construct of a social-capital index. Knack (2002) uses the census response rate as a component measure of social capital.

[7] Knack (2002), Hopkins (2011), and Jha and Chen (2015) use these two measures of social networks as component measures of the social-capital index.

following four criteria in any year from 2007 to 2010: 1) low Tier 1 capital ratio (less than 4%); 2) high ratio of loan loss provisions to total loans (greater than 1%); 3) low return on assets (less than -5%); and 4) listed as a failed bank during the financial crisis by the FDIC. We delete banks classified as troubled in 2006 based on any of these criteria from our subsample so that our analysis is limited to banks that were healthy in 2006.

Empirical Model

We estimate the following equations (1) and (2) to investigate whether social capital measured in 2006 can predict bank stability in the financial crisis period (i.e., 2007–2010). Our test specifications closely follow the models of Lel and Miller (2008) and Beltratti and Stulz (2012). In these models, the dependent variables *FAILURE* and *TROUBLE* are two inverse proxies for bank stability.

$$FAILURE = \beta_0 + \beta_1\, SC + \beta_2\, SIZE + \beta_3\, CAP + \beta_4\, NPL + \beta_5\, LIQUIDITY + \beta_6\, ALL + \beta_7\, ROA + \beta_8 LOSS + \beta_9\, GROWTH + \beta_{10}\, POPULATION + \beta_{11}\, HOUSEHOLD\_INC + \beta_{12}\, EDUCATION + e \tag{1}$$

$$TROUBLE = \beta_0 + \beta_1\, SC + \beta_2\, SIZE + \beta_3\, CAP + \beta_4\, NPL + \beta_5\, LIQUIDITY + \beta_6\, ALL + \beta_7\, ROA + \beta_8\, LOSS + \beta_9\, GROWTH + \beta_{10}\, POPULATION + \beta_{11}\, HOUSEHOLD\_INC + \beta_{12}\, EDUCATION + e \tag{2}$$

where *FAILURE* equals 1 if the bank failed during the 2007–2010 financial crisis period and 0 otherwise; and *TROUBLE* equals 1 if the bank was in financial trouble during the 2007–2010 financial crisis and 0 otherwise. Our variables of interest are the measure of social capital (*SC*). We predict that social capital is positively (negatively) related to bank stability (*FAILURE* and *TROUBLE*). In other words, banks with headquarters in high social capital counties were less likely to experience financial trouble and failure during the financial crisis. We use year 2006 data for all the independent variables (including *SC* and the controls) to test this relationship. To control for the possibility that the error terms are correlated, we cluster standard errors at the county level.

The control variables are *SIZE* (natural logarithm of total assets), *CAP* (ratio of Tier 1 capital to risk-weighted assets), *NPL* (ratio of non-performing loans to total assets), *LIQUIDITY* (ratio of cash to total assets), *ALL* (ratio of loan loss allowance to total assets), *ROA* (ratio of net income to total assets), *LOSS* (an indicator variable that equals 1 if *ROA* is negative and 0 otherwise), *GROWTH* (change in total assets divided by beginning total assets), and *PUBLIC* (an indicator variable that equals 1 if it is a public bank and 0 otherwise). Based on prior studies, we expect a negative association between the control variables *CAP* and *LIQUIDITY* and the dependent variables *FAILURE* and *TROUBLE*. We expect a positive association between the control variables *NPL*, *ALL*, *GROWTH*, and *PUBLIC* and the dependent variables *FAILURE* and *TROUBLE*. As country-level economic and demographic factors could also influence bank stability, following Hasan et al. (2016) we include the population (*POPULATION*), median household income (*HOUSEHOLD_INC*), and total public school enrollment (*EDUCATION*) as additional controls. All variables are defined in the Appendix.

Data and Descriptive Statistics

The financial information used in our tests is obtained from the Call Reports (FFIEC 031 Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices and FFIEC 041 Consolidated Reports of Condition and Income for a Bank with Domestic Offices only). Banks must file Call Reports with the Federal Reserve, the FDIC, and the Office of Thrift Supervision. Consolidated financial statements, including banks' financial position and performance during the period, must be provided in the Call Reports for both public and private banks. This information has to be prepared in accordance with U.S. accounting standards (i.e., GAAP).

Our sample for the tests of bank failure and bank financial trouble comprises 5,537 bank observations.[8] It includes 236 observations for public banks, 5,301 observations for private banks, and 3,247 observations for unaudited private banks.

Table 1 provides descriptive statistics for the variables in models (1) and (2), showing that 4.9% of the observations experienced failure during the financial crisis period. During the same period, 16.5% of the observations were financially troubled based on the criteria discussed earlier. In general, sample banks have strong Tier 1 capital ratio as illustrated by the average CAP of 10.4% and are marginally profitable as indicated by the average ROA of 1.1%. Furthermore, 3.7% of the bank-year observations experienced a loss during 2006.

[Insert Table 1 here]

Table 2 presents the correlation matrix for the variables used in models (1) and (2). Of interest is the strong positive correlation of 0.51 between the variables *FAILURE* and *TROUBLE*. Also of interest are the negative and significant correlations between the dependent variables *FAILURE/TROUBLE* and social capital (*SC*). These univariate results are consistent with our hypothesis and indicate that banks with headquarters in high social capital counties experienced less failure and financial trouble during the crisis period.

[Insert Table 2 here]

Table 3 presents the univariate test results. Panel A presents the comparison between high and low social capital counties for the proportion of failed banks. Similarly, Panel B presents the comparison between high and low social capital counties for the proportion of troubled banks.

[8] The numbers are smaller when we focus on troubled banks due to the deletion of banks already classified as troubled in 2006.

Recall that our hypothesis predicts that banks headquartered in counties with higher social capital experienced less failure and financial trouble during the financial crisis. We use the above (below) median value of social capital in 2006 to classify banks into high (low) social capital counties. As indicated in Panel A, the mean failure rate for banks located in low social capital counties is 7.2%, compared to 2.7% for banks located in high social capital counties, and the mean difference, 4.5%, is significant at the 1% level. We document similar results for the subsamples of public and private banks—that is, the mean difference in bank failure rate is 15.4% between public banks located in low social capital counties and public banks located in high social capital counties and 4.0% between private banks located in low social capital counties and private banks located in high social capital counties. Both mean differences in failure rate are significant at the 1% level. Finally, the average failure rate of unaudited private banks is 6.2% for banks in low social capital counties and 2.4% for unaudited private banks in high social capital counties. The mean difference in failure rate, 3.7%, is significant at the 1% level. In Panel B, we report the results for mean difference in bank financial trouble. The results reported in Panel B are consistent with the earlier results reported in Panel A. Overall, the results of the univariate tests provide strong support for our hypothesis that social capital is negatively associated with bank failure/trouble.

[Insert Table 3 here]

4. Empirical Results

In this section, we report the results of the tests of our hypothesis using models (1) and (2). We predict that banks headquartered in high social capital counties were less likely to experience failure or financial trouble (i.e., were more stable) during the 2007–2010 financial crisis. Table 4 presents the regression results with *FAILURE* as the dependent variable (model 1). For our main variable of interest, *SC*, we report the regression coefficient, followed by the Wald statistic in parentheses and the marginal effect (in percentage) in square brackets. The marginal effect indicates the change in the probability of bank failure per standard deviation change in *SC* (holding other independent variables constant).[9] Column 1 presents the results for the full sample. As indicated in the table, the coefficient of *SC* is negative, as expected, and significant at the 1% level. Columns 2 and 3 of Panel A present the results for the public bank and the private bank subsamples, respectively. The coefficient of *SC* is negative and significant at the 1% level for both the public bank and the private bank subsamples. We further divide the private banks into audited and unaudited subsamples and examine the impact of social capital on bank failure for these subsamples. We present our findings in Columns 4 and 5. By their nature, the unaudited private banks are smaller and usually have a concentration of business activities in a specific county. Therefore, it is conceivable that these banks are more aware of the expectations of the local community regarding pro-social behavior. In other words, banks operating in high social capital counties are less likely to behave in an opportunistic or self-interested manner. Thus, social capital can be an effective monitoring mechanism for these unaudited, small private banks. The results strongly support our prediction. As reported in Column 4, the coefficient of *SC* is negative but not significant for the audited private bank subsample. In Column 5, the coefficient of *SC* is negative and significant at the 1% level for the unaudited private bank subsample, which is consistent with our regression results for the full sample. The findings reported in Table 4

[9] We thank an anonymous reviewer for pointing us in this direction. The marginal effect of bank failure per standard deviation (SD) change for the social capital variable, *SC*, is computed as p x (1-p) x β x SD, where p is the base rate (0.11) and β is the estimated coefficient from the logistic regression (Liao 1994).

indicate that social capital can significantly reduce the bank failure rate and improve bank stability, especially among unaudited, small private banks.[10]

The marginal effect of bank failure per standard deviation change in *SC* indicates that the economic significance of social capital is nontrivial. For example, Columns 1, 2, 3, and 5 show that the difference in propensity to fail per standard deviation change in *SC* is 1.77%, 6.42%, 1.52%, and 1.93% for the full sample, the public bank subsample, the private bank subsample, and the private unaudited bank subsample, respectively. Overall, the evidence indicates that banks located in high social capital regions have a lower probability of failing during the crisis period than do banks located in low social capital regions.

Regarding the control variables in the full sample regression, Tier 1 capital (*CAP*) and level of liquidity (*LIQUIDITY*) are negatively associated with bank failure, as expected. Conversely, non-performing loans (*NPL*), loan loss allowance (*ALL*), and growth in assets (*GROWTH*) are positively associated with bank failure, as expected. We observe similar results for the control variables when we focus the analyses on the private bank subsample (Columns 3 to 5).

[Insert Table 4 here]

Table 5 presents the results for the relationship between social capital and banks' financial trouble during the 2007–2010 financial crisis. For the main variable of interest, *SC*, we report the regression coefficient, followed by the Wald statistic in parentheses and the marginal effect (in percentage) in square brackets. The results are very similar to those presented in Table 4, where we study the effect of social capital on bank failure. For the full sample (Column 1), the estimated coefficient of *SC* is negative, as expected, and significant at the 1% level. For the

[10] We conduct an F-test to examine the difference between the coefficients of *SC* in Columns 4 and 5 of Table 4. The null hypothesis (that the two coefficients of *SC* are equal) is rejected at the 1% level ($F=23.74$, $p<0.01$).

public and the private banks (Columns 2 and 3), the coefficients of *SC* are negative and significant at the 10% and 1% levels, respectively. For the audited private banks (Column 4), the coefficient of *SC* is negative and significant at the 10% level. For the unaudited private banks (Column 5), the coefficient of *SC* is negative and significant at the 1% level. The important findings reported in Table 5 indicate that social capital can significantly reduce the bank financial trouble rate and improve bank stability, especially among unaudited private banks.[11]

The marginal effect of bank financial trouble per standard deviation change in *SC* indicates that the economic significance of social capital is nontrivial. For example, Columns 1, 2, 3, and 5 show that the difference in propensity of bank financial trouble per standard deviation change for *SC* is 1.53%, 3.14%, 1.49%, and 1.79% for the full sample, the public bank subsample, the private bank subsample, and the private unaudited bank subsample, respectively. Overall, the evidence indicates that banks located in high social capital regions have a lower probability of financial trouble during the crisis period than do banks located in low social capital regions.

[Insert Table 5 here]

Sensitivity Tests

One potential concern is that high social capital counties are concentrated in the Northeast and Midwest of the U.S. In order to mitigate this concern, we construct indicator variables that capture the regional effect. We separate the 50 states plus the District of Columbia into West (AZ, AK, CA, CO, HI, ID, MT, NM, NV, OR, UT, WA, WY), Northeast (CT, MA, ME, NH, NJ, NY, PA, RI, VT), South (AL, AR, DC, DE, FL, GA, KY, LA, MD, MS, NC, OK, SC, TN, TX, VA, WV), and Midwest (IA, IL, IN, KS, MI, MN, MO, ND, NE, OH, SD, WI) regions,

[11] We conduct an F-test to examine the difference between the coefficients of *SC* in Columns 4 and 5 of Table 5. The null hypothesis (that the two coefficients of *SC* are equal) is rejected at the 1% level ($F=49.40$, $p<0.01$).

based on the U.S. Census classifications. After controlling for the time-invariant regional effects, the significantly negative relationships between social capital and our dependent variables still hold.

We use organ donation rate as an alternate proxy for social capital. Following Guiso et al. (2004) and Buonanno et al. (2009), we obtain the organ donation data from OPTN to construct this alternate measure of social capital for each state and year.[12] Following Hasan et al. (2016), we define state-level per capita donor as the total number of organ donors in a state in a given year divided by the state's total population in that year. The results using organ donation rate as an alternate proxy for social capital are consistent with our main results.

Following Barton and Waymire (2004), Kim and Lu (2011), and Hasan et al. (2016), we adopt an instrumental variable approach and implement a two-stage regression as an alternative strategy to address the potential concern that our results from the baseline models are affected by the endogeneity of social capital due to omitted variables correlated with social capital and bank failure/trouble. Putnam (2001, p. 48) argues that "the best single predictor of the level of social capital in American states is distance to the Canadian border. Being closer to the Canadian border means more social capital." Hasan et al. (2016) find that *LOG(BORDER_DISTANCE)* is negatively correlated with social capital, where *LOG(BORDER_DISTANCE)* is defined as the natural logarithm of the closest distance between the Canadian border and the center point of the state in which a bank is headquartered. Therefore, we use *LOG(BORDER_DISTANCE)* as the first instrumental variable. In addition, Hasan et al. (2016) provide evidence that ethnic homogeneity increases social capital. Thus, we use *ETHNICITY_HOMOGENEITY* as the second instrumental variable. Following Hasan et al. (2016), we define *ETHNICITY_HOMOGENEITY*

[12] Organ donation data can be downloaded from OPTN's website (https://optn.transplant.hrsa.gov/data/view-data-reports/state-data/).

as the Herfindahl index calculated across four basic Census-tracked ethnic categories—White, Black, Hispanic, Asian, and others—for a county in a given year. In the first-stage regression, the dependent variable is *SC*, and the independent variables include the two instrumental variables and 11 control variables.[13] The untabulated first-stage regression results show that, consistent with Hasan et al. (2016), the coefficient of *LOG(BORDER_DISTANCE)* is negative and the coefficient of *ETHNICITY_HOMOGENEITY* is positive; both coefficients are significant at the 1% level. A valid instrumental variable in this setting should have no direct effect on the bank failure or bank trouble variables. We examine this condition by including the two instrumental variables as additional controls in the baseline models and find that they are uncorrelated with either the bank failure or the bank trouble variable. Results from this additional analysis are not tabulated.

In the second-stage regression, we modify the baseline models by using *FITTED_SC* in place of the original *SC* variable. *FITTED_SC* is the predicted value of the social capital variable based on the estimates obtained from the first-stage regression model. We find that the coefficient of *FITTED_SC* is negative and significant at the 1% level in the baseline models, indicating that endogeneity of social capital is unlikely to affect the relationship between the social capital and bank failure/trouble in the baseline models.

In another sensitivity test, we use different thresholds to define troubled banks. We change one of the three conditions and keep the other two conditions intact. We repeat the test with Tier 1 capital ratio less than 8%, the ratio of LLP to total loans greater than 5% and 10%,

[13] The 11 control variables include an indicator variable for affiliation with a multibank holding company, Tier 1 capital to total risk-weighted assets, nonperforming loans to total assets, natural logarithm of total assets, an indicator variable for public bank, national employment growth rate, state employment growth rate, natural logarithm of the median household income in a county in a year, natural logarithm of the population size of a county in a year, natural logarithm of the people 25 years old and older with a bachelor's degree in a county in a year, and natural logarithm of the median age of the residents in a county in a year.

and ROA less than -8% and -10%. Our regression results are robust to these modifications of the bank trouble definition.

We separate the sample of banks into FDICIA and non-FDICIA bank subsamples. Banks in the FDICIA subsample are subject to FDICIA internal control provisions if their total assets were greater than $500 million before 2005 and greater than $1 billion after 2005 (inclusive). Banks in the non-FDICIA subsample are not subject to FDICIA internal control provisions. We estimate two baseline models (bank failure and bank trouble) separately for the two subsamples and find that the negative relationship between social capital and bank failure/trouble is robust for both the FDICIA and the non-FDICIA bank subsamples.

Finally, the results of our main tests of the relationship between social capital and bank stability (reported in Tables 4 and 5) are based on interpolated values of social capital for the year 2006 based on the actual values for the years 2005 and 2009. To alleviate the concern that our results may be influenced by the use of interpolated data for social capital, we repeat our main tests using the actual year 2005 data for social capital (*SC*). The untabulated results are similar to those reported in Tables 4 and 5.

Tests of Possible Economic Channels

Our main results discussed in Section 4 are in the context of significant risk and uncertainty that marked the financial crisis. In developing our testable hypothesis, we argue that bank stability in the crisis period can be attributed to social capital linked to less self-interested actions in the pre-crisis period such as lower levels of excessive risk-taking, more transparency, and higher quality accounting information. In this section, we provide direct evidence on some of these channels.

First, we study the relationships between social capital and bank risk-taking behavior during the pre-crisis period (i.e., 2000 to 2006). We argue that higher levels of risk-taking (in particular, excessive risk-taking) in the pre-crisis period could lead to lower bank stability in the crisis period; thus, the level of risk-taking in the pre-crisis period is a possible channel through which social capital relates to bank stability. Consistent with prior literature, we employ two commonly used risk measures in the banking industry (Laeven and Levine 2009; Houston et al. 2010; Kanagaretnam et al. 2014). The first measure, volatility of interest margin (*VOL_INT*), is computed as the standard deviation of annual interest margin divided by total loans over the 2000 to 2006 period. The second measure is *Z-SCORE*, defined as the natural logarithm of the ratio of ROA plus the capital ratio divided by the standard deviation of ROA from 2000 to 2006. *Z-SCORE* measures the distance from insolvency, so a higher *Z-SCORE* indicates that the bank is more stable.[14] For ease of interpretation and consistency with the other measure of risk-taking, we multiply *Z-SCORE* by negative one so that a higher value of negative *Z-SCORE* indicates more risk-taking (i.e., less bank stability). We label this transformed variable as *NEG_Z_SCORE*. Once again, we cluster standard errors at the county level. The empirical models for these risk-taking tests are:

$$VOL\_INT = \beta_0 + \beta_1 ASC + \beta_2 ASIZE + \beta_3 ACAP + \beta_4 ANPL + \beta_5 ALIQUIDITY + \beta_6 AALL + \beta_7 APOPULATION + \beta_8 AHOUSEHOLD\_INC + \beta_9 AEDUCATION + e \quad (3)$$

$$NEG\_Z\_SCORE = \beta_0 + \beta_1 ASC + \beta_2 ASIZE + \beta_3 ACAP + \beta_4 ANPL + \beta_5 ALIQUIDITY + \beta_6 AALL + \beta_7 APOPULATION + \beta_8 AHOUSEHOLD\_INC + \beta_9 AEDUCATION + e \quad (4)$$

The variable of interest is *ASC*, defined as the average value of the social capital measure *SC* from 2000 to 2006. We expect a negative coefficient of this variable—that is, we predict that social capital is negatively related to banks' risk-taking behavior prior to the financial crisis. The

[14] A third commonly used risk measure is the standard deviation of annual earnings before tax and loan loss provisions divided by total loans. We obtain similar results to those obtained for VOL_INT, when we use this alternate measure.

independent variables are similar to models (1) and (2), except that we use the average values for the 2000–2006 pre-crisis period.

As our prediction of a negative relationship between social capital and risk-taking applies mainly to excessive risk-taking for banks, we repeat our analyses employing two proxies for abnormal risk. Following the methodology of Cheng et al. (2015), we employ a two-stage analysis, where in the following first-stage models, we control for bank-level risk-taking (i.e., for normal risk) and use the residual from the first stage as the estimate of abnormal risk.

$$VOL\_INT = \gamma_0 + \gamma_1 SIZE + \gamma_2 REVG + \gamma_3 TOOBIG + \gamma_4 PUBLIC + \gamma_5 BANK\_TYPE + e \quad (5)$$

$$NEG\_Z\_SCORE = \gamma_0 + \gamma_1 SIZE + \gamma_2 REVG + \gamma_3 TOOBIG + \gamma_4 PUBLIC + \gamma_5 BANK\_TYPE + e \quad (6)$$

where *SIZE* is the natural logarithm of total assets; *REVG* is bank revenue growth rate; *TOOBIG* is an indicator variable reflecting whether a bank has more than 10% of the deposits; *PUBLIC* is defined as 1 if the bank is listed on a public stock exchange and 0 otherwise; *BANK_TYPE* is a series of indicator variables based on bank type analysis call item RSSD9425 that indicate the bank type (commercial bank, bank holding company, etc.).[15] Following Cheng et al. (2015), we use the residuals from the first-stage regressions as the estimate of Abnormal *VOL_INT* and Abnormal *NEG_Z_SCORE* and estimate the second-stage regressions after replacing the dependent variables in models (3) and (4), respectively, with the residuals.

The regression results using the volatility of interest margin (*VOL_INT*) are presented in Panel A of Table 6. For the full sample, the estimated coefficient of *ASC*, the measure of average social capital, is negative, as expected, and significant at the 1% level (Column 1). For public and private banks (Columns 2 and 3), the coefficient is negative and significant at the 5% and 1% levels, respectively. The coefficient is not significant at conventional levels for audited

[15] For example, bank type analysis call item RSSD9425 = (0,3,4) represents a commercial bank that is (1) not subject to special analysis, (2) a grandfathered nonbank bank, or (3) a credit card bank.

private banks (Column 4), but is significant at the 1% level for unaudited private banks (Column 5).

The regression results using the abnormal volatility of interest (*ABN_VOL_INT*) are presented in Panel B of Table 6. For the full sample, the coefficient of *ASC* is negative and significant at the 5% level (Column 1). The coefficient is not significant for public banks (Column 2), but it is negative and significant at the 5% level for private banks. The coefficient of *ASC* is not significant for audited private banks (Column 4), but it is negative and significant at the 5% level for unaudited private banks (Column 5). Consistent with our main results, the results reported in Panels A and B of Table 6 are stronger for unaudited private banks.[16]

Panel C of Table 6 presents the results for the second risk-taking variable (*NEG_Z_SCORE*) during the pre-crisis period. The results indicate that the estimated coefficient of *ASC* is significant at the 1% level for the full sample, for the private bank subsample, and for the unaudited private bank subsample. Panel D of Table 6 presents the corresponding pre-crisis period results for *ABN_NEG_Z_SCORE*. Again, the results indicate that the coefficient of *ASC* is significant at the 1% level for the full sample and for the private bank subsample and at the 5% level for the unaudited private bank subsample. In both Panel C and Panel D, the coefficient of *ASC* is not significant at conventional levels for the public bank subsample or the audited private bank subsample.[17]

In summary, these results show that both the risk-taking and the abnormal risk-taking measures in the pre-crisis period are lower for banks headquartered in high social capital

[16] We conduct an F-test to examine whether the coefficients of *ASC* in Columns 4 and 5 are different in Panels A and B of Table 6. The null hypothesis (that the two coefficients of *ASC* are equal) is rejected at the 1% level ($F=56.17$, $p<0.01$ in Panel A; $F=30.41$, $p<0.01$ in Panel B).

[17] We conduct an F-test to examine whether the coefficients of *ASC* in Columns 4 and 5 are different in Panels C and D of Table 6. The null hypothesis (that the two coefficients on *ASC* are equal) is at the 1% level ($F=106.97$, $p<0.01$ in Panel C; $F=76.44$, $p<0.01$ in Panel D).

counties, indicating that lower risk-taking in the pre-crisis period is one channel through which social capital could have affected bank stability during the crisis period.

[Insert Table 6 here]

Next we examine the relationship between social capital and bank accounting transparency. Morgan (2002) argues that the banking industry is more opaque than other industries despite the detailed financial reports that banks file. Institutions such as the Basel Committee on Banking Supervision, the International Monetary Fund, and the World Bank and bank regulators such as the FDIC in the U.S. and the Financial Services Authority in the U.K. have emphasized the importance of bank reporting transparency (e.g., Basel 1998, 2001; FDIC 2002; Flannery and Thakor 2006; FSA 2011). Furthermore, it is generally believed that the lax regulatory enforcement of financial reporting in the banking sector was a key contributor to the 2007–2009 financial crisis.[18]

Prior literature indicates that restatements reflect problems with the financial reporting system (e.g., Dechow et al. 2010). In addition, Doyle et al. (2007) find that restatements are indicative of weaknesses in the internal control system. Dechow et al. (2011) document that restatements are positively correlated with various measures of poor reporting quality, such as errors in accruals estimation. According to the analysis of Ng and Rusticus (2013), restatements indicate weaknesses in regulatory reporting. That is, restatements often occur because important adjusting entries and estimates of deferred taxes are not made in time for the filing of the report. This suggests that the restatement variable captures poor reporting quality due to either poor internal reporting systems or deliberate obfuscation.

[18] See, for example, The Financial Crisis Inquiry Report issued by the National Commission on the Causes of the Financial and Economic Crisis in the United States (FCIC 2011).

Based on the findings of the above studies, we use a measure of (poor) bank financial reporting transparency based on whether or not a bank is required to restate its prior financial reports. We use the information on restatements from the Call Reports (item RIAD B507: Cumulative Effect of Changes in Accounting Principles and Corrections of Material Accounting Errors) to identify banks with restatements during the year. Banks with restatements are regarded as having poor financial reporting transparency. During the sample period, the vast majority of banks (93%) had no restatements; the remaining 7% had one or more restatements. We use the following multivariate regression model for the test of accounting restatements:

$$RESTATEMENT = \beta_0 + \beta_1 SC + \beta_2 SIZE + \beta_3 CAP + \beta_4 NPL + \beta_5 LIQUIDITY + \beta_6 ALL + \beta_7 ROA + \beta_8 LOSS + \beta_9 GROWTH + \beta_{10} POPULATION + \beta_{11} HOUSEHOLD\_INC + \beta_{12} EDUCATION + e \qquad (7)$$

where the dependent variable *RESTATEMENT* is an indicator variable that equals 1 if RIAD B507 (restatements due to corrections of material accounting errors and changes in accounting principles) is either positive or negative for the bank year and 0 otherwise.

We report the relationship between social capital and bank accounting restatements during the pre-crisis period (i.e., 2000–2006) in Table 7. We find a significant negative relationship between *SC* and restatements for the full sample, the private bank subsample, and the unaudited private bank subsample.

[Insert Table 7 here]

We next examine the impact of social capital on bank accounting conservatism, which is another potential economic channel. The relationships among accounting conservatism, firm risk-taking, and firm stability have been widely studied for industrial firms. For example, Zhang (2008), Kirschenheiter and Ramakrishnan (2010), and Francis and Martin (2010), among others, have demonstrated that, by reducing reported income and assets, conservatism helps enhance net cash inflow. This is so because conservatism discourages cash distributions to contracting parties and increases cash flows from operating, investing, and financing sources by improving investment efficiency. Net cash enhancement reduces bankruptcy risk, which is a condition of cash insufficiency, by servicing debt and facilitating debt renegotiations (Kim et al. 1993; Campbell et al. 2008). In addition, accounting conservatism can deter opportunistic earnings management and reduce information asymmetries and conflicts of interest between managers and debt holders (Watts 2003; Kothari et al. 2009; Gao 2013). Improving the information environment through accounting conservatism can facilitate debt renegotiation to avoid bankruptcy (Giammarino 1989; Hotchkiss et al. 2008). Therefore, we argue that accounting conservatism is another viable channel through which social capital relates to bank stability.

The principle of (conditional) accounting conservatism is viewed as recognizing bad news faster than good news (Basu 1997), which results in asymmetric timeliness of recognition of accounting losses versus accounting gains. Our model for testing accounting conservatism using aggregate earnings follows from Ball and Shivakumar (2005) and Nichols et al. (2009):

$$\Delta NI_t = \beta_0 + \beta_1 D\Delta NI_{t-1} + \beta_2 \Delta NI_{t-1} + \beta_3 \Delta NI_{t-1}{*}D\Delta NI_{t-1} + \beta_4 SC + \beta_5 SC{*}D\Delta NI_{t-1} + \beta_6 SC{*}\Delta NI_{t-1} + \beta_7 SC{*}\Delta NI_{t-1}{*}D\Delta NI_{t-1} + \beta_8 SIZE + \beta_9 SIZE{*}D\Delta NI_{t-1} + \beta_{10} SIZE{*}\Delta NI_{t-1} + \beta_{11} SIZE{*}\Delta NI_{t-1}{*}D\Delta NI_{t-1} + \beta_{12} POPULATION + \beta_{13} HOUSEHOLD\_INC + \beta_{14} EDUCATION + e \quad (8)$$

where ΔNI_t denotes the change in net income from year *t*-1 to year *t*, divided by total assets at the end of year *t*-1, and $D\Delta NI_t$ is an indicator variable that equals 1 if ΔNI_t is negative and 0 otherwise. Model (8) relates current period change in earnings (ΔNI_t) to prior period change in earnings (ΔNI_{t-1}), and permits this autoregressive relation to differ for positive and negative values of ΔNI_{t-1} and for differing values of social capital index (*SC*). The model also controls for the effects of differences in total assets (*SIZE*) on the autoregressive relationships.

Under accounting conservatism, banks exhibit asymmetry in recognizing earnings decreases versus earnings increases (Nichols et al. 2009). Earnings increases are likely to be more persistent and less timely than earnings decreases, implying that β_3 should be negative. Our main prediction is that banks in high social capital counties have more conservative accounting. Specifically, we predict that the coefficient β_7 of $SC*\Delta NI_{t-1}*D\Delta NI_{t-1}$ is negative.

Table 8 shows the effect of social capital on accounting conservatism during the pre-crisis period (i.e., 2000–2006). As expected, the coefficient β_3 of $\Delta NI_{t-1}*D\Delta NI_{t-1}$ is negative and significant at the 1% level for the full sample, the private bank subsample, and the unaudited private bank subsample. More importantly, the coefficient β_7 of $SC*\Delta NI_{t-1}*D\Delta NI_{t-1}$ is negative and significant at the 1% level for the full sample, the private bank subsample, and the unaudited private bank subsample, indicating higher levels of accounting conservatism for banks in high social capital counties. These results imply that social capital can increase accounting conservatism by enhancing the timely recognition of earnings decreases versus earnings increases, especially for unaudited private banks.

[Insert Table 8 here]

The results reported in Tables 7 and 8 show that social capital is negatively associated with bank accounting restatements but positively associated with bank accounting conservatism. These results lend support to our argument that social capital improves financial reporting transparency, which could deter banks from taking excessive risks, thereby increasing their stability.

In our final test, we examine the effect of social capital on loan charge-offs (*LCO*). We expect a negative relationship between social capital and loan charge-offs because bank managers are more conservative in loan selection, resulting in higher quality loan portfolios. In addition, because bank clients in high social capital counties are more trustworthy, they are likely to exhibit lower default behavior. We estimate the following model to test this prediction:

$$CHGOFF = \beta_0 + \beta_1 SC + \beta_2 SIZE + \beta_3 CAP + \beta_4 NPL + \beta_5 LIQUIDITY + \beta_6 ALL + \beta_7 ROA + \beta_8 LOSS + \beta_9 GROWTH + \beta_{10} POPULATION + \beta_{11} HOUSEHOLD\_INC + \beta_{12} EDUCATION + e \tag{9}$$

where *CHGOFF* is loan charge-offs in the year, divided by beginning total assets.

We present the results of estimating this model in Table 9. The primary coefficient of interest is β_1, the coefficient of social capital (*SC*), which we expect to be negative. The results indicate a negative β_1 that is significant at the 5% level for the full sample, the private bank subsample, and the unaudited private bank subsample, but is not significant for the public bank subsample or the audited private bank subsample. These results indicate that social capital can effectively constrain bad loans for private banks, especially unaudited private banks.

[Insert Table 9 here]

5. Conclusion

Banks play a prominent role in the economy, which is why regulators have imposed stricter regulations to limit their risk-taking behaviors. Although banks operate in a highly regulated environment, the 2007–2010 financial crisis clearly demonstrates that these regulatory measures may not be sufficient to control banks' risk-taking incentives. In this study, we examine the impact of social capital, an informal monitoring mechanism, on bank stability. Social capital, which generally proxies the level of cooperative norms in a society, is likely to reduce opportunistic behavior. Therefore, it is conceivable that social capital can act as an informal monitoring mechanism that controls bank managers' opportunistic actions as well as borrowing firms' default actions.

We first investigate whether high social capital reduced bank failure and financial trouble during the years of the financial crisis. A bank failure occurs when the FDIC closes a bank. A bank is defined as being in financial trouble if it has a low level of Tier 1 capital, a high ratio of loan loss provisions to total loans, or a low return on assets or if it was listed by the FDIC as a failed bank during the financial crisis. The results are consistent with our expectations. We document that banks located in high social capital counties were more financially stable during the financial crisis period (i.e., 2007–2010) than banks located in low social capital counties. Thus, banks in high social capital counties experienced less failure and less financial trouble than banks in low social capital counties.

In additional tests, we provide evidence of possible economic channels through which social capital could affect bank stability. In the pre-crisis period, our results indicate that private banks, especially small, unaudited private banks, exhibit lower risk-taking behavior (as well as lower abnormal/excessive risk) when they are located in high social capital regions. Furthermore, we find that social capital is negatively associated with accounting restatements that may attract regulatory scrutiny but positively associated with accounting conservatism as proxied by the timely recognition of bad news (i.e., a decline in earnings). The greater financial reporting quality associated with higher levels of social capital could result in higher bank stability through the selection of higher quality borrowers. This finding is also reinforced by our results that social capital was negatively related to loan charge-offs in the pre-crisis period.

Consistent with the argument of Statman (2007) that social capital can be linked to ethics, fairness, trust, and freedom from corruption, our results show that social capital can mitigate a bank's risk-taking behavior and improve its financial stability. These results lend support to the notion that informal institutions such as social capital matter in constraining opportunistic actions such as excessive risk-taking, even in the highly regulated banking industry.

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Appendix

Variables	Description
Dependent Variables:	
FAILURE	This indicator variable equals 1 if the bank was closed by the FDIC in the years 2007-2010, and 0 otherwise.
TROUBLE	This variable is an indicator variable that equals 1 if the bank satisfies any of the following four conditions between 2007-2010: (1) Tier 1 capital ratio is less than 4%, (2) the ratio of loan loss provision to total loans is greater than 1%, (3) ROA is less than -5%, and (4) the bank is listed as a failed bank in the FDIC website during 2007-2010; and 0 otherwise. We delete troubled banks in 2006 from our troubled banks subsample so that our troubled banks subsample includes only banks that were healthy in 2006.
Dependent Variables for Supporting Tests:	
VOL_INT	This variable is the standard deviation of annual interest margin divided by total loans over the period 2000-2006.
NEG_Z_SCORE	This variable is the negative value of the natural logarithm of the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets over the pre-crisis period 2000-2006.
ABN_VOL_INT	Following Cheng et al. (2015), we use the residuals from the following regression as the estimate of Abnormal *VOL_INT*. $VOL\_INT=\gamma_0+\gamma_1 SIZE+\gamma_2 REVG+\gamma_3 TOOBIG+\gamma_4 PUBLIC+\gamma_5 BANK\_TYPE+e$
ABN_NEG_Z_SCORE	Following Cheng et al. (2015), we use the residuals from the following regression as the estimate of Abnormal *NEG_Z_SCORE*. $NEG\_Z\_SCORE=\gamma_0+\gamma_1 SIZE+\gamma_2 REVG+\gamma_3 TOOBIG+\gamma_4 PUBLIC+\gamma_5 BANK\_TYPE+e$
RESTATEMENT	This indicator variable equals 1 if RIAD B507 (Restatements due to corrections of material accounting errors and changes in accounting principles) is either positive or negative for the bank-year, and 0 otherwise.
Main Variable of Interest:	
SC	This variable is the measure of the social capital at the county level. It is constructed following Rupasingha and Goetz (2008). Specifically, the variable is constructed by using the first component from a principal component analysis that uses four different measures. For example, we use the following four measures: assn97, nccs97, pvote96, respn00 for 1997, where assn97 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, and membership organizations not elsewhere classified in 1997. We divide the total by 12 because there are 12 different categories. Further, we also divide it by the population of the county. We then multiply it by 10,000. The measure nccs97 is the total number of nongovernment organizations excluding the ones with an international focus in 1997 divided by the population multiplied by 10,000. The measure pvote96 is the number of votes casted divided by the population above 18 times 100. The measure respn00 is the census response rate. Then we use a principal component analysis and use the first component to construct the social capital index for each county. We use an analogous approach for 2005 and 2009. For each of these years, we use the presidential elections and census response closest to 2005 and 2009, respectively. We then linearly interpolate and fill the social capital data for the in-between years. *Source: Northeast Regional Center for Rural Development (NERCRD), Rupasingha and Goetz (2008)*

Firm-Level Controls used in the Regressions:	
SIZE	This variable is the natural logarithm of total assets.
CAP	This variable is the ratio of Tier 1 capital to total risk-weighted assets.
NPL	This variable is the ratio of non-performing loans to total assets.
LIQUIDITY	This variable is the ratio of cash to total assets.
ALL	This variable is the ratio of loan loss allowance to total assets.
ROA	This variable is the ratio of net income to total assets.
LOSS	This variable is an indicator variable that equals 1 if *ROA* is negative, and 0 otherwise.
GROWTH	This variable is the change of total assets divided by beginning total assets.
PUBLIC	This variable is an indicator variable that equals 1 if the firm is a public bank trading in a major exchange, and 0 otherwise.
POPULATION	The natural logarithm of total resident population in the county.
HOUSEHOLD_INC	The natural logarithm of median household income in the county.
EDUCATION	The natural logarithm of total public school enrollment in the county.
AUDITED	This variable is an indicator variable that equals 1 if the bank is audited by an auditor, and 0 otherwise.
UNAUDITED	This variable is an indicator variable that equals 1 if the bank is not audited by an auditor, and 0 otherwise.
ΔNI_t	This variable denotes the change in net income from year *t*-1 to *t*, scaled by total assets at the end of *t*-1.
$D\Delta NI_t$	This indicator variable equals 1 if ΔNI_t is negative, and 0 otherwise.
CHGOFF	Loan charge-offs, scaled by beginning total assets.
ASC	This variable is the average value of *SC* during the pre-crisis period 2000-2006.
ASIZE	This variable is the average value of *SIZE* during the pre-crisis period 2000-2006.
ACAP	This variable is the average value of *CAP* during the pre-crisis period 2000-2006.
ANPL	This variable is the average value of *NPL* during the pre-crisis period 2000-2006.
ALIQUIDITY	This variable is the average value of *LIQUIDITY* during the pre-crisis period 2000-2006.
AALL	This variable is the average value of *ALL* during the pre-crisis period 2000-2006.
APUBLIC	This variable is the average value of *PUBLIC* during the pre-crisis period 2000-2006.

Table 1
Descriptive Statistics for Variables in the Main Tests

Descriptive statistics for variables in the main tests

	N	Mean	Median	Q1	Q3	Standard Deviation
FAILURE	5,537	0.049	0	0	0	0.216
TROUBLE	5,441	0.165	0	0	0	0.371
SC	5,537	0.009	-0.073	-0.817	0.667	1.150
SIZE	5,537	11.885	11.809	11.057	12.617	1.195
CAP	5,537	0.104	0.094	0.082	0.115	0.034
NPL	5,537	0.002	0.0002	0	0.002	0.005
LIQUIDITY	5,537	0.042	0.032	0.023	0.047	0.033
ALL	5,537	0.008	0.008	0.006	0.010	0.004
ROA	5,537	0.011	0.010	0.007	0.014	0.010
LOSS	5,537	0.037	0	0	0	0.189
GROWTH	5,537	0.091	0.058	0.012	0.126	0.139
PUBLIC	5,537	0.040	0	0	0	0.195
UNAUDITED	5,537	0.610	1.000	0	1.000	0.488
POPULATION	5,537	0.043	0	0	0	0.202
HOUSEHOLD_INC	5,537	11.317	10.953	9.973	12.719	1.814
EDUCATION	5,537	9.534	9.198	8.198	10.955	1.809

Variables are defined in the Appendix.

Table 2
Pearson Correlations for Variables in the Main Tests

Pearson correlations for variables in the main tests

	Variable	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	*FAILURE*	**0.51**	**-0.11**	**0.09**	**-0.06**	**0.03**	**-0.08**	**0.09**	-0.01	**0.04**	**0.19**	**0.07**	**0.13**	**0.06**	**0.13**
2	*TROUBLE*	**1.00**	**-0.12**	0.01	-0.01	**0.09**	**-0.03**	**0.18**	**-0.10**	**0.18**	**0.21**	**0.03**	**0.07**	**-0.03**	**0.07**
3	*SC*		**1.00**	**-0.29**	**0.05**	**0.07**	0.01	**0.06**	**-0.04**	-0.02	**-0.16**	**-0.06**	**-0.46**	-0.01	**-0.48**
4	*SIZE*			**1.00**	**-0.33**	**-0.18**	**-0.29**	**-0.05**	**0.08**	**-0.10**	**0.18**	**0.30**	**0.43**	**0.28**	**0.43**
5	*CAP*				**1.00**	**0.10**	**0.10**	**0.04**	**0.16**	**0.04**	**-0.13**	**-0.07**	**-0.07**	**-0.06**	**-0.07**
6	*NPL*					**1.00**	**0.04**	**0.07**	-0.01	0.01	**-0.12**	**-0.04**	**-0.13**	**-0.12**	**-0.13**
7	*LIQUIDITY*						**1.00**	-0.03	0.01	-0.01	**-0.07**	**-0.07**	**-0.07**	**-0.11**	**-0.07**
8	*ALL*							**1.00**	0.06	**0.03**	0.01	-0.01	**-0.09**	**-0.08**	**-0.09**
9	*ROA*								**1.00**	**-0.39**	**-0.11**	-0.02	**-0.06**	**-0.10**	**-0.07**
10	*LOSS*									**1.00**	**0.14**	-0.01	**0.10**	**0.08**	**0.10**
11	*GROWTH*										**1.00**	**0.04**	**0.20**	**0.16**	**0.21**
12	*PUBLIC*											**1.00**	**0.12**	**0.20**	**0.14**
13	*POPULATION*												**1.00**	**0.55**	**0.98**
14	*HOUSEHOLD_INC*													**1.00**	**0.60**
15	*EDUCATION*														**1.00**

Variables are defined in the Appendix.

Table 3
Univariate Tests

Panel A: The Mean Difference in Proportion of Failed Banks between Banks Located in High Social Capital Counties and Banks Located in Low Social Capital Counties for Different Samples

Sample (number of bank-years)	Mean *FAILURE* for Banks Headquartered in High Social Capital Counties (number of banks)	Mean *FAILURE* for Banks Headquartered in Low Social Capital Counties (number of banks)	Difference (t-value)
Full Sample (5,537)	0.027 (2,785)	0.072 (2,752)	-0.045*** (7.78)
Public Banks (236)	0.034 (119)	0.188 (117)	-0.154*** (3.89)
Private Banks (5,301)	0.027 (2,673)	0.067 (2,628)	-0.040*** (7.01)
Private and Unaudited Banks (3,247)	0.024 (1613)	0.062 (1,634)	-0.037*** (5.41)

Panel B: The Mean Difference in Proportion of Troubled Banks between Banks Located in High Social Capital Counties and Banks Located in Low Social Capital Counties for Different Samples

Sample (number of bank-years)	Mean *TROUBLE* for Banks Headquartered in High Social Capital Counties (number of banks)	Mean *TROUBLE* for Banks Headquartered in Low Social Capital Counties (number of banks)	Difference (t-value)
Full Sample (5,441)	0.124 (2,745)	0.207 (2,696)	-0.083*** (8.35)
Public Banks (236)	0.109 (119)	0.299 (117)	-0.190*** (3.71)
Private Banks (5,205)	0.124 (2,633)	0.203 (2,572)	-0.079*** (7.73)
Private and Unaudited Banks (3,200)	0.120 (1,599)	0.195 (1,601)	-0.075*** (5.84)

Table 3 reports the univariate test results for the mean bank's failure and bank's financial trouble variables. Panel A shows the results for the mean value of bank's failure for banks located in high social capital counties versus banks located in low social capital counties for full sample, public banks subsample, private banks subsample, private and audited banks subsample, and private and unaudited banks subsample. Panel B shows the results for the mean value of bank's financial trouble for banks located in high social capital counties versus banks located in low social capital counties for full sample, public banks subsample, private banks subsample, private and audited banks subsample, and private and unaudited banks subsample. We define banks located in high (low) social capital counties if the social capital index is above or equal to (below) the median social capital index in the sample. Panel A also shows the mean difference in proportion of banks' failure banks located in high social capital counties versus banks located in low social capital counties. Panel B also shows the mean difference in proportion of banks' financial trouble for banks located in high social capital counties versus banks located in low social capital counties. We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of all the continuous variables. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 4
The Effect of Social Capital on Bank Failure

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *FAILURE*	Dependent Var. = *FAILURE*	Dependent Var. = *FAILURE*	Dependent Var. = *FAILURE*	Dependent Var. = *FAILURE*
Variable	Coefficient (Wald Chi-Square) (1)	Coefficient (Wald Chi-Square) (2)	Coefficient (Wald Chi-Square) (3)	Coefficient (Wald Chi-Square) (4)	Coefficient (Wald Chi-Square) (5)
Intercept	-5.126*** (7.49)	-4.561 (0.52)	-4.841*** (7.43)	-0.375 (0.02)	-8.691*** (18.87)
SC	-0.157*** (14.91) [1.77%]	-0.570*** (10.73) [6.42%]	-0.135*** (10.17) [1.52%]	-0.062 (0.85) [0.70%]	-0.171*** (8.35) [1.93%]
SIZE	-0.027 (0.49)	-0.126 (0.90)	-0.047 (1.26)	-0.040 (0.46)	-0.046 (0.93)
CAP	-7.000*** (20.77)	-9.238 (2.25)	-7.068*** (18.08)	-8.667*** (13.80)	-5.119** (6.42)
NPL	27.188*** (11.55)	44.847 (1.33)	26.742*** (11.27)	35.980*** (11.66)	19.948** (5.11)
LIQUIDITY	-7.144*** (16.79)	-9.359 (0.79)	-7.159*** (16.59)	-6.163*** (8.10)	-8.234*** (10.14)
ALL	57.784*** (51.01)	108.000* (3.42)	56.586*** (46.44)	66.557*** (23.61)	50.130*** (28.15)
ROA	1.375 (0.20)	11.202 (0.12)	1.741 (0.35)	-2.952 (0.55)	7.707 (2.11)
LOSS	0.069 (0.16)	0.270 (0.08)	0.064 (0.13)	-0.203 (0.59)	0.369 (1.93)
GROWTH	1.752*** (80.10)	1.164* (3.02)	1.806*** (82.05)	2.203*** (64.13)	1.514*** (37.03)
POPULATION	0.216*** (8.25)	0.567 (1.40)	0.154* (3.80)	0.244 (1.90)	0.099 (1.16)
HOUSEHOLD_INC	0.248 (1.87)	0.255 (0.20)	0.250 (2.20)	-0.227 (0.55)	0.637*** (11.50)
EDUCATION	-0.132* (2.71)	-0.492 (0.89)	-0.065 (0.59)	-0.112 (0.39)	-0.046 (0.21)
Log-Likelihood	-923.8	-66.7	-848.5	-373.1	-466.9
Pseudo-R^2	0.177	0.241	0.175	0.213	0.154
Percent Concordant	80.1	78.8	80.2	83.0	78.0
# of Observations	5,537	236	5,301	2,054	3,247

Table 4 (Cont'd)

Table 4 reports the results for the logistic regression models with standard errors clustered by counties. The dependent variable *FAILURE* is defined as one if the bank failed during the crisis period 2007-2010, and zero otherwise. The research variable *SC* is the measure of the social capital index at the county level that we constructed following Rupasingha and Goetz (2008). We report the marginal effect (in percent) to represent economic significance for the social capital variable *SC* in square brackets. The marginal effect indicates the change in the probability of bank failure per standard deviation change in *SC* (holding other independent variables constant). The marginal effect per standard deviation (SD) change for *SC* is computed as $p \times (1 - p) \times \beta \times$ SD, where p is the base rate (0.11) and β is the estimated coefficient from the logistic regression (Liao 1994). We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of each continuous variable. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 5
The Effect of Social Capital on Bank Financial Trouble

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *TROUBLE*	Dependent Var. = *TROUBLE*	Dependent Var. = *TROUBLE*	Dependent Var. = *TROUBLE*	Dependent Var. = *TROUBLE*
Variable	Coefficient (Wald Chi-Square) (1)	Coefficient (Wald Chi-Square) (2)	Coefficient (Wald Chi-Square) (3)	Coefficient (Wald Chi-Square) (4)	Coefficient (Wald Chi-Square) (5)
Intercept	0.919 (0.48)	3.964 (0.52)	0.881 (0.46)	4.524** (4.58)	-2.130 (1.81)
SC	-0.136*** (21.41) [1.53%]	-0.279* (3.65) [3.14%]	-0.132*** (20.06) [1.49%]	-0.088* (2.71) [0.99%]	-0.159*** (18.34) [1.79%]
SIZE	-0.017 (0.38)	-0.023 (0.03)	-0.027 (0.80)	-0.099* (3.45)	0.013 (0.21)
CAP	-1.109 (1.91)	-2.500 (0.23)	-1.158 (1.89)	-2.147 (2.52)	-0.035 (0.01)
NPL	32.369*** (56.70)	29.392 (0.63)	32.384*** (56.36)	36.479*** (27.93)	30.212*** (33.42)
LIQUIDITY	-0.870 (1.27)	-9.049 (1.27)	-0.777 (0.98)	-0.537 (0.17)	-0.706 (0.53)
ALL	86.564*** (199.93)	205.100*** (11.58)	84.156*** (189.49)	95.242*** (77.21)	75.397*** (96.63)
ROA	-13.259*** (10.75)	-29.175 (1.03)	-12.766*** (9.46)	-3.780 (0.41)	-21.061*** (12.36)
LOSS	0.645*** (25.12)	0.123 (0.03)	0.649*** (24.24)	0.607*** (9.86)	0.706*** (14.31)
GROWTH	1.722*** (120.81)	1.597** (4.66)	1.727*** (119.89)	2.399*** (114.15)	1.195*** (23.75)
POPULATION	0.150* (3.28)	0.330** (6.53)	0.109 (1.65)	0.241** (4.53)	-0.004 (0.03)
HOUSEHOLD_INC	-0.284** (4.48)	-0.603 (1.58)	-0.263** (4.21)	-0.585*** (8.63)	0.020 (0.02)
EDUCATION	-0.118 (2.24)	-0.320* (3.19)	-0.077 (0.89)	-0.188 (2.66)	0.023 (0.09)
Log-Likelihood	-2,140.5	-93.4	-2,039.8	-765.5	-1,254.1
Pseudo-R^2	0.174	0.309	0.170	0.239	0.144
Percent Concordant	73.1	79.7	72.9	77.2	70.7
# of Observations	5,441	236	5,205	2,005	3,200

Table 5 (Cont'd)

Table 5 reports the results for the logistic regression models with standard errors clustered by counties. The dependent variable *TROUBLE* is defined as 1 if the bank had experienced financial trouble during the crisis period 2007-2010, and 0 otherwise. A bank has experienced financial trouble during 2007-2010 if the bank satisfied any of the following four conditions in 2007-2010: (1) Tier 1 capital ratio is less than 4%, (2) the ratio of loan loss provision to total loans is greater than 1%, (3) ROA is less than -5%, and (4) the bank is listed as a failed bank in FDIC website during 2007-2010. We delete troubled banks in 2006 from our troubled banks subsample so that our troubled banks subsample includes only the healthy banks in 2006. The research variable *SC* is the measure of the social capital index at the county level that we constructed following Rupasingha and Goetz (2008). We report the marginal effect (in percent) to represent economic significance for the social capital variable *SC* in square brackets. The marginal effect indicates the change in the probability of bank financial trouble per standard deviation change in *SC* (holding other independent variables constant). The marginal effect per standard deviation (SD) change for *SC* is computed as $p \times (1 - p) \times \beta \times$ SD, where p is the base rate (0.11) and β is the estimated coefficient from the logistic regression (Liao 1994). We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of each continuous variable. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 6
The Effect of Social Capital on Banks' Risking-taking during the Pre-Crisis Period 2000-2006

Panel A: The Effect of Social Capital on Banks' Volatility of Interest Margin during the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *VOL_INT*	Dependent Var. = *VOL_INT*	Dependent Var. = *VOL_INT*	Dependent Var. = *VOL_INT*	Dependent Var. = *VOL_INT*
Variable	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.008 (-1.42)	-0.001 (-0.25)	-0.008 (-1.45)	-0.020** (-2.24)	-0.001 (-0.29)
ASC	-0.0003*** (-3.35)	-0.0004** (-2.45)	-0.0003*** (-3.25)	-0.0002 (-1.23)	-0.0002*** (-3.94)
ASIZE	0.0001 (0.97)	-0.0003** (-2.41)	0.0001 (1.26)	0.0005* (1.76)	0.00001 (0.14)
ACAP	0.021*** (2.69)	0.013 (1.64)	0.021*** (2.68)	0.032*** (2.60)	0.013** (2.13)
ANPL	0.169*** (3.09)	-0.114** (-2.04)	0.170*** (3.12)	0.295*** (2.98)	0.078* (1.88)
ALIQUIDITY	0.009** (3.43)	0.004 (0.66)	0.009*** (3.47)	0.015*** (3.16)	0.006*** (2.63)
AALL	0.206*** (3.89)	0.161*** (3.61)	0.206*** (3.86)	0.313*** (3.49)	0.100*** (2.64)
APOPULATION	-0.0002 (-0.62)	0.001*** (3.68)	-0.0004 (-0.91)	-0.0001 (-0.17)	-0.0001 (-0.35)
AHOUSEHOLD_INC	0.0003 (0.67)	0.0002 (0.38)	0.0003 (0.68)	0.001 (1.12)	0.00001 (0.03)
AEDUCATION	0.001 (1.30)	-0.0004** (-2.11)	0.001 (1.56)	0.0005 (0.70)	0.0003 (0.94)
Adj. R^2	0.072	0.212	0.072	0.100	0.038
# of Observations	6,613	196	6,417	2,857	4,085

Table 6 (Cont'd)

Panel B: The Effect of Social Capital on Banks' Abnormal Volatility of Interest Margin during the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *ABN_VOL_INT*	Dependent Var. = *ABN_VOL_INT*	Dependent Var. = *ABN_VOL_INT*	Dependent Var. = *ABN_VOL_INT*	Dependent Var. = *ABN_VOL_INT*
Variable	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.010* (-1.77)	-0.012** (-2.31)	-0.010* (-1.71)	-0.016* (-1.85)	-0.004 (-0.84)
ASC	-0.0002** (-2.18)	-0.0003 (-1.53)	-0.0002** (-2.13)	-0.00001 (-0.03)	-0.0001** (-2.16)
ASIZE	-0.00001 (-0.11)	0.00002 (0.01)	-0.00001 (-0.12)	0.0003 (1.09)	-0.00004 (-0.03)
ACAP	0.012 (1.49)	0.017* (1.99)	0.012 (1.47)	0.020 (1.59)	0.007 (1.43)
ANPL	0.113** (2.08)	-0.136** (-2.16)	0.114** (2.09)	0.237*** (2.84)	0.056** (2.44)
ALIQUIDITY	0.005* (1.68)	0.001 (0.20)	0.005* (1.67)	0.013*** (2.65)	0.004* (1.76)
AALL	0.166*** (2.61)	0.165** (2.35)	0.165** (2.57)	0.263*** (2.95)	0.081** (2.15)
APOPULATION	-0.0002 (-0.43)	0.001*** (5.19)	-0.0003 (-0.82)	-0.0002 (-0.36)	-0.0003 (-1.02)
AHOUSEHOLD_INC	0.0005 (1.19)	0.0004 (0.87)	0.0005 (1.21)	0.0004 (0.68)	0.0001 (0.32)
AEDUCATION	0.0004 (0.92)	-0.001*** (-3.89)	0.001 (1.28)	0.001 (0.84)	0.0005 (1.41)
Adj. R^2	0.055	0.192	0.054	0.066	0.022
# of Observations	6,613	196	6,417	2,857	4,085

Table 6 (Cont'd)

Panel C: The Effect of Social Capital on Banks' Negative Z-Score during the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *NEG_Z_SCORE*	Dependent Var. = *NEG_Z_SCORE*	Dependent Var. = *NEG_Z_SCORE*	Dependent Var. = *NEG_Z_SCORE*	Dependent Var. = *NEG_Z_SCORE*
Variable	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.920 (-1.18)	6.085* (1.99)	-1.127 (-1.43)	-1.346 (-1.46)	-0.495 (-0.56)
ASC	-0.033*** (-2.83)	0.005 (0.06)	-0.034*** (-2.87)	-0.015 (-0.80)	-0.032*** (-2.72)
ASIZE	-0.279*** (-22.18)	-0.337*** (-4.80)	-0.278*** (-20.93)	-0.358*** (-22.42)	-0.250*** (-14.84)
ACAP	-3.782*** (-7.32)	-0.411 (-0.10)	-3.823*** (-7.31)	-4.954*** (-7.90)	-3.848*** (-6.32)
ANPL	12.848*** (4.79)	-25.522 (-0.60)	13.194*** (4.94)	11.093*** (3.20)	12.162*** (3.93)
ALIQUIDITY	1.203*** (3.27)	-5.344* (-1.97)	1.295*** (3.49)	0.454 (1.09)	0.957* (1.91)
AALL	33.850*** (12.19)	27.884 (1.12)	33.948*** (11.87)	36.448*** (9.44)	34.720*** (9.12)
APOPULATION	0.154** (2.03)	-0.454** (-2.07)	0.190*** (2.98)	0.228*** (2.64)	0.141** (2.01)
AHOUSEHOLD_INC	0.091 (1.09)	-0.393 (-1.49)	0.105 (1.22)	0.223** (2.29)	0.030 (0.31)
AEDUCATION	-0.016 (-0.21)	0.607*** (2.68)	-0.054 (-0.86)	-0.084 (-0.99)	-0.015 (-0.21)
Adj. R^2	0.167	0.238	0.164	0.212	0.138
# of Observations	6,154	169	5,985	3,035	4,269

Table 6 (Cont'd)

Panel D: The Effect of Social Capital on Banks' Abnormal Negative Z-Score during the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Banks Subsample	Private and Unaudited Banks Subsample
	Dependent Var. = *ABN_NEG_Z_SCORE*	Dependent Var. = *ABN_NEG_Z_SCORE*	Dependent Var. = *ABN_NEG_Z_SCORE*	Dependent Var. = *ABN_NEG_Z_SCORE*	Dependent Var. = *ABN_NEG_Z_SCORE*
Variable	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.947 (-1.15)	4.953 (1.14)	-1.170 (-1.42)	-2.526*** (-2.78)	-0.227 (-0.27)
ASC	-0.045*** (-3.58)	0.009 (0.09)	-0.046*** (-3.63)	-0.018 (-1.01)	-0.029** (-2.33)
ASIZE	-0.124*** (-8.93)	-0.128 (-1.38)	-0.123*** (-8.85)	-0.124*** (-8.29)	-0.126*** (-8.38)
ACAP	-3.918*** (-7.55)	1.624 (0.29)	-3.979*** (-7.64)	-5.461*** (-9.21)	-4.608*** (-8.59)
ANPL	8.077*** (2.75)	-46.075 (-1.08)	8.417*** (2.87)	9.424*** (2.71)	8.947*** (3.11)
ALIQUIDITY	1.403*** (3.43)	-5.668 (-1.65)	1.485*** (3.64)	0.271 (0.65)	0.598 (1.30)
AALL	26.568*** (8.49)	20.611 (0.57)	26.507*** (8.42)	33.904*** (8.55)	32.344*** (8.70)
APOPULATION	0.197*** (2.67)	0.464 (0.93)	0.192*** (2.65)	0.245*** (2.92)	0.132** (2.06)
AHOUSEHOLD_INC	0.086 (1.00)	-0.549 (-1.38)	0.109 (1.25)	0.223** (2.35)	0.042 (0.46)
AEDUCATION	-0.070 (-0.96)	-0.300 (-0.60)	-0.067 (-0.93)	-0.104 (-1.25)	-0.010 (-0.16)
Adj. R^2	0.116	0.111	0.118	0.150	0.107
# of Observations	6,154	169	5,985	3,035	4,269

Table 6 reports the results for two OLS regression models that use bank risk-taking measures as the dependent variables. In Panel A, the dependent variable *VOL_INT* is the standard deviation of interest margin scaled by total assets over the period 2000-2006. In Panel B, the dependent variable *ABN_VOL_INT* is the abnormal portion of the standard deviation of interest margin scaled by total assets over the period 2000-2006. In Panel C, the dependent variable *NEG_Z_SCORE* is the negative average value of the natural logarithm of the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets over the period 2000-2006. In Panel D, the dependent variable *ABN_NEG_Z_SCORE* is the abnormal portion of the negative average value of the natural logarithm of the ratio of the return on assets plus the capital ratio divided by the standard deviation of the return on assets over the period 2000-2006. The research variable *SC* is the measure of the social capital index at the county level that we constructed following Rupasingha and Goetz (2008). *ASC* is the average social capital index at the county level during 2000-2006. We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of all the continuous variables. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 7
The Effect of Social Capital on Restatements During the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Subsample	Private and Unaudited Subsample
Variable	Dependent Var. = *RESTATEMENT*	Dependent Var. = *RESTATEMENT*	Dependent Var. = *RESTATEMENT*	Dependent Var. = *RESTATEMENT*	Dependent Var. = *RESTATEMENT*
	Coefficient (Wald Chi-Square) (1)	Coefficient (Wald Chi-Square) (2)	Coefficient (Wald Chi-Square) (3)	Coefficient (Wald Chi-Square) (4)	Coefficient (Wald Chi-Square) (5)
Intercept	-3.976*** (31.61)	-8.216*** (19.89)	-3.433*** (20.82)	-4.066*** (17.73)	-2.725*** (7.47)
SC	-0.061*** (18.37)	-0.070 (1.11)	-0.062*** (18.65)	-0.044 (2.69)	-0.064*** (13.75)
SIZE	0.093*** (38.03)	0.147*** (10.91)	0.080*** (26.98)	0.095*** (19.81)	0.070*** (11.39)
CAP	1.839*** (15.21)	5.232 (2.11)	1.812*** (15.18)	1.777*** (7.26)	1.803*** (9.73)
NPL	6.480*** (10.14)	14.481 (0.44)	6.412*** (9.57)	7.284** (4.96)	4.830* (3.78)
LIQUIDITY	0.425 (1.70)	2.830 (0.76)	0.379 (1.30)	0.544 (1.59)	0.181 (0.17)
ALL	-2.172 (0.37)	-39.964 (2.46)	-0.899 (0.07)	-0.437 (0.01)	-2.254 (0.29)
ROA	-5.436** (4.27)	-7.908 (0.77)	-5.254** (4.08)	-1.628 (1.98)	-12.784*** (17.68)
LOSS	0.194*** (6.86)	0.496* (3.08)	0.172** (5.04)	0.149* (3.14)	0.100 (0.97)
GROWTH	-0.223** (4.88)	-0.264 (0.45)	-0.214** (4.32)	-0.299** (5.09)	-0.120 (0.54)
POPULATION	0.035 (0.69)	-0.021 (0.41)	0.144** (5.93)	0.267*** (7.42)	0.086* (3.14)
HOUSEHOLD_INC	0.137** (3.85)	0.497*** (8.30)	0.078 (1.03)	0.105 (1.27)	0.043 (0.20)
EDUCATION	-0.065 (2.26)	-0.028 (0.31)	-0.171*** (8.77)	-0.297*** (8.92)	-0.118*** (6.87)
YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
Log-Likelihood	-9,223.6	-490.2	-8,708.6	-3,754.7	-4,921.7
Pseudo-R^2	0.018	0.058	0.016	0.014	0.021
Percent Concordant	58.0	65.8	57.6	56.2	58.9
# of Observations	32,432	1,047	31,385	12,333	19,052

Table 7 (Cont'd)

Table 7 reports the results for the logistic regression on restatements with standard errors clustered by counties for the pre-crisis period 2000-2006. Wald Chi-Squares are in the parentheses. The *RESTATEMENT* variable is defined as 1 if *RIADB507* (Restatements due to corrections of material accounting errors and changes in accounting principles) is either positive or negative for the bank-year, and 0 otherwise. We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of all the continuous variables. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 8
The Effect of Social Capital on Accounting Conservatism during the Pre-Crisis Period 2000-2006

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and audited Subsample	Private and Unaudited Subsample
	Dependent Var.=ΔNI_t	Dependent Var.=ΔNI_t	Dependent Var.=ΔNI_t	Dependent Var.=ΔNI_t	Dependent Var.=ΔNI_t
Variable	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.002 (-0.31)	0.020 (1.37)	-0.003 (-0.50)	0.001 (0.18)	-0.008 (-0.78)
$D\Delta NI_{t-1}$	0.002 (0.57)	-0.006 (-0.96)	0.002 (0.67)	0.007 (1.35)	0.002 (0.38)
ΔNI_{t-1}	0.482*** (2.78)	1.275* (1.96)	0.475*** (2.70)	0.814** (2.16)	0.374** (2.46)
$\Delta NI_{t-1}* D\Delta NI_{t-1}$	-1.625*** (-4.39)	-2.195 (-0.88)	-1.629*** (-4.39)	-0.466 (-0.36)	-1.796*** (-7.79)
SC	0.00001 (0.12)	0.0001 (0.58)	0.00002 (0.24)	0.001* (1.91)	-0.0001 (-0.34)
$SC* D\Delta NI_{t-1}$	-0.0004** (-2.43)	0.00005 (0.09)	-0.0004** (-2.49)	-0.001** (-2.06)	-0.0004* (-1.77)
$SC* \Delta NI_{t-1}$	0.004 (0.26)	-0.107 (-1.37)	0.004 (0.28)	-0.139** (-2.00)	0.032 (0.79)
$SC* \Delta NI_{t-1}* D\Delta NI_{t-1}$	-0.120*** (-3.05)	0.150 (0.60)	-0.120*** (-3.08)	0.071 (0.64)	-0.158*** (-3.03)
SIZE	0.001** (2.52)	0.00005 (0.25)	0.001** (2.46)	0.001*** (2.59)	0.001* (1.89)
$SIZE* D\Delta NI_{t-1}$	-0.0001 (-0.59)	0.0004 (0.90)	-0.0002 (-0.69)	-0.001 (-1.58)	-0.0001 (-0.35)
$SIZE* \Delta NI_{t-1}$	-0.031*** (-2.65)	-0.074 (-1.49)	-0.031** (-2.58)	-0.066** (-2.29)	-0.024** (-2.39)
$SIZE* \Delta NI_{t-1}* D\Delta NI_{t-1}$	0.103*** (3.36)	0.087 (0.45)	0.104*** (3.38)	-0.004 (-0.04)	0.122*** (6.74)
POPULATION	0.0001 (0.43)	0.0004 (1.12)	0.00003 (0.21)	-0.00004 (-0.16)	0.0001 (0.38)
HOUSEHOLD_INC	-0.0005 (-1.18)	-0.002 (-1.37)	-0.0004 (-0.99)	-0.001 (-1.84)	-0.00001 (-0.02)
EDUCATION	-0.0001 (-0.35)	-0.0004 (-1.13)	-0.00003 (-0.17)	0.0001 (0.40)	-0.0001 (-0.51)
YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
Adj. R^2	0.020	0.161	0.020	0.033	0.022
# of Observations	32,432	1,047	31,385	12,333	19,052

Table 8 (Cont'd)

Table 8 reports the results for the OLS regression on change of net income with standard errors clustered by counties for the pre-crisis period 2000-2006. *t*-statistics values are in the parentheses. ΔNI_t denotes the change in net income from year *t*-1 to *t*, scaled by total assets at the end of *t*-1. $D\Delta NI_{t-1}$ denotes an indicator variable that equals 1 if ΔNI_{t-1} is negative, and 0 otherwise. The variable *SC* is the measure of the social capital index at the county level that we constructed following Rupasingha and Goetz (2008). We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of all the continuous variables. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.

Table 9
The Effect of Social Capital on Loan Charge-Offs

	Full Sample	Public Banks Subsample	Private Banks Subsample	Private and Audited Subsample	Private and Unaudited Subsample
Variable	Dependent Var. = *CHGOFF*	Dependent Var. = *CHGOFF*	Dependent Var. = *CHGOFF*	Dependent Var. = *CHGOFF*	Dependent Var. = *CHGOFF*
	Coefficient (t-value) (1)	Coefficient (t-value) (2)	Coefficient (t-value) (3)	Coefficient (t-value) (4)	Coefficient (t-value) (5)
Intercept	-0.003 (-0.45)	0.018*** (4.44)	-0.004 (-0.60)	-0.012 (-1.15)	0.001 (0.28)
SC	-0.0002** (-2.35)	0.0001 (0.39)	-0.0002** (-2.34)	-0.0001 (-1.39)	-0.0002** (-1.97)
SIZE	0.001*** (3.57)	0.0002** (2.55)	0.001*** (3.56)	0.001*** (3.01)	0.001*** (2.99)
CAP	0.015 (1.59)	-0.010** (-2.32)	0.015 (1.61)	0.021 (1.50)	0.009 (1.25)
NPL	0.218*** (4.16)	0.041 (0.85)	0.218*** (4.17)	0.305*** (3.28)	0.152*** (3.38)
LIQUIDITY	0.002 (1.20)	0.002 (0.51)	0.002 (1.25)	0.003 (1.62)	0.001 (0.33)
ALL	0.568*** (6.00)	0.243*** (6.31)	0.572*** (5.98)	0.747*** (6.22)	0.439*** (5.34)
ROA	0.0003 (0.38)	-0.044* (-1.78)	0.0003 (0.37)	0.056** (2.16)	-0.0001 (-0.25)
LOSS	0.005*** (14.56)	0.001 (1.51)	0.005*** (14.75)	0.006*** (6.32)	0.007*** (13.15)
GROWTH	-0.001*** (-2.68)	-0.0004 (-0.86)	-0.001** (-2.55)	-0.002** (-2.25)	-0.0003 (-0.60)
POPULATION	0.0001 (-0.56)	-0.0001 (-1.49)	-0.0001 (-0.47)	-0.0002 (-0.62)	-0.0001 (-0.40)
HOUSEHOLD_INC	-0.001*** (-3.28)	-0.0002*** (-5.51)	-0.001*** (-2.96)	-0.001 (-1.14)	-0.001*** (-3.87)
EDUCATION	0.0002 (0.79)	0.0001 (1.36)	0.0002 (0.64)	0.0003 (0.67)	0.0001 (0.81)
YEAR FIXED EFFECTS	YES	YES	YES	YES	YES
Adj. R^2	0.186	0.217	0.188	0.248	0.153
# of Observations	34,408	1,166	33,242	13,295	19,947

Table 9 reports the results for the OLS regression models with standard errors clustered by counties. The dependent variable *CHGOFF* is defined as loan charge-offs scaled by beginning total assets. The research variable *SC* is the measure of the social capital index at the county level that we constructed following Rupasingha and Goetz (2008). We collect the data from the Commercial Bank Data Call Reports from the Federal Reserve Bank of Chicago (http://www.chicagofed.org/). We winsorize the top and bottom 1% of each continuous variable. *, **, *** indicate significance at the 10%, 5%, and 1% levels, respectively, based on a two-tailed test. Variables are defined in the Appendix.