Social Capital and Bank Misconduct

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ABSTRACT

I use enforcement actions issued by US bank regulators to show that banks headquartered in counties with higher levels of social capital (as captured by civic norms and social networks) are less likely to be involved in misconduct. This result holds in a range of robustness and endogeneity tests and is supported by an analysis of the level of social capital of the place where bank executives grew up. The effect of local levels of social capital on misconduct is mostly significant for less geographically dispersed banks. I also show that, following misconduct revelation, sanctioned banks experience a greater decrease in deposit market-shares in counties with higher levels of social capital. Taken together, these findings indicate that social capital acts as an external monitoring mechanism preventing and punishing bank misconduct.

Keywords: banks, social capital, misconduct, market-share.
JEL Codes: G21, G28.

1. Introduction

Misconduct cases significantly deteriorate the image of banks (Thakor 2016). Even though cases concerning large banks attract more headlines, misconduct is present across banks of all sizes.[1] Previous literature documents that bank violations of laws and regulations have implications for financial stability (Jackson and Kotlikoff 2018), shareholder value (Armour et al. 2017, Köster and Pelster 2017), reputation and public confidence (Delis, Iosifidi, et al. 2019, Zingales 2015) and have negative real effects on local economies where sanctioned banks operate (Danisewicz et al. 2018). Given these negative consequences, it is important to study the factors that may determine misconduct in the banking sector.

The idea that managers may support, engage in, or conceal misconduct due to personal interests is supported by anecdotal[2] as well as empirical evidence (Bergstresser and Philippon 2006). The literature focuses on the role of internal governance and executive compensation in preventing or driving misconduct in the banking sector (Nguyen et al. 2016, Sakalauskaite 2018). However, there is little evidence about how decisions of bank managers regarding misconduct may also be influenced by factors that are external to the firm. Individuals have a propensity to behave in line with the expectations of social peers in their communities (Akerlof and Kranton 2005). Managers tend to have social interactions outside their firms, and social norms that emanate from those interactions influence what they do at work (Hilary and Hui 2009). In a cost-benefit analysis, the private benefits that can be obtained from misconduct[3] are subject to higher costs (i.e., a higher social penalty)[4] if peers perceive that behavior as inconsistent with their standards (Parsons et al. 2018). Therefore, social norms - *culture* - in the area where firm insiders are based may be an important driver of their decisions

[1] In this paper, I use 3,114 severe enforcement actions against US banks between 2001 and 2015. In 90% of these cases, an institution with less than $3 billion in total assets is involved.

[2] "Wells Fargo uncovers up to 1.4 million more fake accounts", CNN, August 31, 2017.

[3] Possible motivations to commit misconduct in banks are the following: diverting bank resources for private benefit, manipulating regulators/supervisors' views about the bank, or inflating short-run earnings. Some opportunistic behaviors managers may undertake in order to boost short-run profits are: assuming temporary extreme risks, delaying required provisions, setting loose internal controls and credit assessment methods, selling inappropriate financial products to customers, charging unfair commissions to customers, working with customers whose funds come from questionable, illegal or unethical sources, contribute to market manipulation to obtain short-term gains, etc.

[4] Social penalties can take the form of higher social stigmatization or physical costs such as psychological distress caused by peer pressure or the decision of deviating from the internalized social norms (Akerlof and Kranton 2005).

regarding opportunistic behaviors and, consequently, affect misconduct. In this paper, I focus on social capital as a source of social norms and examine whether social capital affects the probability that a bank is involved in misconduct and its consequences.

Social capital is defined as the civic norms and social networks that facilitate collective actions and enhance cooperation in a community (Guiso et al. 2004, Woolcock 1998, 2001). A central theme that emerges from the literature is that social capital restrains opportunistic behaviors, and enforces trust by setting common values and standards in a community and incurring reputational costs on those who violate social norms (e.g., Bloom et al. 2012, Buonanno et al. 2009, Fukuyama 1997, Putnam 1993, Spagnolo 1999). Following this evidence, recent papers document that social capital matters for corporations (e.g., Hasan et al. 2017b, a, Jha and Chen 2014). More specifically, managers in high social capital areas constrain self-serving practices and are more careful when taking actions that may turn-out over-confident and value destroying (Hoi et al. 2019, Huang and Shang 2019). Building on these assertions, I formulate two hypotheses.[5] Firstly, given that misconduct is likely to be viewed as incongruent with standards set by social capital, I hypothesize that banks headquartered in high social capital areas are less likely to be involved in misconduct. Secondly, consistent with higher stigmatization and social sanctions against deviant behaviors imposed by social capital, I conjecture that once a misconduct case is revealed, sanctioned banks would be subject to a harsher punishment by depositors in areas characterized by higher levels of social capital. I expect the latter conjecture to hold mostly during the last financial crisis and its aftermath, a period characterized by low trust in banks (Sapienza and Zingales 2012, Zingales 2015) and higher social concerns about misconduct (Chaly et al. 2017).

I test these hypotheses using the social capital measure provided by the Northeast Regional Center for Rural Development (NRCRD) at Pennsylvania State University.[6] The NRCRD social capital index is computed for each county in the US using the first principal component in an analysis of four variables: two variables to capture the strength of civic norms (the US Census response rate and voter turnout in the presidential elections) and two measures of the density of networks (the number of

[5] I further develop these hypotheses in section 2 of the paper.
[6] This variable is commonly used in the finance literature to measure local levels of social capital in the US (e.g., Hoi et al. 2019, Hasan et al. 2017 a, b).

social and civic associations and the number of non-government organizations scaled by population). I identify misconduct using enforcement actions issued by US banking regulators against banks that engage in unsafe, unsound or illegal practices. Enforcement actions are suitable for studying the relation between social capital and the probability that a bank is involved in misconduct due to two reasons: first, they provide an unambiguous external indicator of undesirable behavior in the industry (Nguyen et al. 2016), and second, they are publicly announced what allows bank stakeholders to be aware of them (Delis, Iosifidi, et al. 2019).

Using a sample of 101,669 bank-year observations during the period 2001-2015, I document a negative and statistically significant relationship between the level of social capital in the headquarters' area and the probability that a bank is involved in misconduct. The economic effect is sizeable. Relative to an average probability of misconduct equal to 3.1%, a one standard deviation increase in the measure of social capital corresponds to a reduction of the probability that a bank is involved in misconduct of 11.8%. I find that this result is caused by local preferences to behave according to an established standard. In particular, I document that the negative effect of social capital on misconduct is mostly significant for less geographically dispersed banks which are more likely to have local investors, local insiders and have decision-making and strategic functions more concentrated in the headquarters' area (Adhikari and Agrawal 2016, Alessandrini et al. 2009). This result can also be explained by the fact that cultural preferences from the headquarters are disseminated more easily within less geographically dispersed banks than in banks operating in the whole country or even internationally. In the latter type of banks, subcultures may arise and the social capital of the different decision centers may not be correlated (Thakor 2016).[7]

The negative and significant relationship between social capital and the probability that a bank is involved in misconduct is robust to controlling for bank and state-level unobserved heterogeneity, using organ donation as an alternative social capital measure and incremental to the effects of local religiosity. I also run regressions using the level of social capital of the state where bank executives

[7] Another possibility is that geographically dispersed banks are more likely to be publicly held so they may be subject to stronger monitoring by stock market actors (e.g. market supervisors, more sophisticated investors, etc) reducing the effect of social capital as a monitoring force. However, I find that the effect of social capital on the probability that a bank is involved in misconduct is significant for both publicly and privately held banks. I also find that this effect is significant for both banks with more than $1 billion of total assets and banks below that threshold.

grew up instead of the level of social capital in the county where a bank is headquartered. Using executives cultural traits is motivated by the fact that key decision-makers in a firm create and disseminate their cultural values within the organization (Liu 2016, Nguyen et al. 2018).This test is based on the idea that people are likely to be affected not only by the level of social capital of the place where they live, but also by the social capital of the place where they grew up (Guiso et al. 2004). For this test I use a smaller sample of banks for which I can identify the state where bank executives grew up. In line with the baseline results, I find that bank executives' social capital is negatively related to the probability that a bank is involved in misconduct.

One of the methodological challenges I face is that I can only observe detected misconduct (once an enforcement action against a financial institution has been issued). This poses a problem of partial observability since misconduct may occur even in the absence of an enforcement action. To address this aspect, I follow Nguyen et al. (2016) and run additional tests using a bivariate probit model (Poirier 1980) that allows me to separate the effect between misconduct commission and detection. This test shows that social capital reduces the probability of committing misconduct and has no effect on misconduct detection. Finally, I study possible channels through which higher social capital may lead to lower misconduct. I document that banks located in higher social capital areas are more prudent and are less likely to restate their accounts. These results are consistent with a lower propensity of managers in high social capital areas to take high risks for personal interests and a lower propensity to provide deficient reporting that could reflect financial misconduct (Karpoff and Lou 2010).

I address the potential endogeneity of social capital due to omitted variables or reverse causality using two-stage instrumental variable regressions. For this test, I follow Hoi et al. (2019) and build an instrument for social capital based on cultural values of people in a given county inherited from their ancestral origins. This instrument is based on Hofstede's score of national culture for power distance. In a separated instrumental variable test, I follow Hasan et al. (2017 a, b) and use racial homogeneity and the natural logarithm of the distance from the bank headquarters to the Canadian border as instruments for social capital. The instrumental variable regressions confirm that the negative relationship between social capital and bank misconduct is plausibly causal.

Lastly, I study whether banks involved in misconduct are subject to a harsher punishment in areas characterized by higher levels of social capital. To analyze this outcome, I use percentage changes in deposits market-share for each bank in each county and the level of social capital of the counties where banks have branches. I show that, following misconduct revelation, sanctioned banks experience a greater decrease in deposits market-share in counties with higher levels of social capital. When the social capital measure is one standard deviation above the mean, I find a decrease of 1.3% in deposits market-share (which represents roughly 11% of the average deposits market-share). Consistent with the idea that social capital exerts a harsher punishment over banks during periods of low trust, I find that this result is mostly significant for the last financial crisis period and its aftermath.

My paper makes relevant contributions. First, it contributes to the literature studying the determinants of bank misconduct. Previous papers provide evidence on bank-level determinants of misconduct. In particular, these papers focus on governance characteristics and compensation schemes (Nguyen et al. 2016, Sakalauskaite 2018). My article adds to this literature by providing empirical evidence about the existence of an external monitoring mechanism that constrains misconduct. Specifically, I show that social capital surrounding bank headquarters reduces the likelihood of misconduct in banks.

Second, my study is related to papers analyzing the impact of civic norms, trust and social networks surrounding headquarters on corporate behavior. Hasan et al. (2017b, a) show that social capital constrains corporate tax avoidance and facilitates debt contracting. Hoi et al. (2019) find that CEOs in high social capital areas tend to have a lower compensation, what is interpreted as lower rent extraction. Jha and Chen (2014) show that higher social capital increases trust between auditors and firms. Huang and Shang (2019) find that social capital lowers the need for corporate leverage as a means to alleviate agency issues. My findings are complementary to the above mentioned papers: they point that social capital reduces agency conflicts related to opportunistic behaviors. My paper adds to this literature by showing that social capital constrains misconduct in banks, a sector in which misconduct may be more prevalent due to its opacity (Jiang et al. 2016, Thakor 2015). In a related paper, Parsons et al. (2018) provide evidence on the cultural factors that contribute to misconduct. My

paper differs from the latter in two aspects; I address the role of social capital as a source of social norms and focus on misconduct in the banking sector.

Finally, my paper is related to the literature that analyzes the consequences of regulatory actions against banks due to violations of laws and regulations or fraud. These papers show sharp decreases in market values and performance (Armour et al. 2017, Köster and Pelster 2017), adverse reputational effects in the syndicated loans market (Delis, Iosifidi, et al. 2019), a significant decrease of bank deposits (Delis, Staikouras, et al. 2019), and a negative impact on income and employment in the area where sanctioned banks operate (Danisewicz et al. 2018). In line with these papers, Bertsch et al. (2019) document that bank customers switch to alternative lending platforms when they face misconduct. I contribute to this stream of the literature by documenting that, after misconduct revelation, sanctioned banks experience a decrease in deposit market-shares, with this effect more pronounced in higher social capital areas.

2. Hypothesis development

2.1. How social capital may affect bank misconduct

Social capital is an environmental factor affecting the behavior of individuals (Guiso et al. 2004, Rupasingha et al. 2006) and organizations (Bloom et al. 2012, La Porta et al. 1997). In their review of the literature, Guiso et al. (2011) argue that definitions of social capital used in the economic literature tend to be vague and very broad, and suggest a narrower definition that focuses on values and shared beliefs that help cooperation in a society. In line with this suggestion, I define social capital as the civic norms and social networks that facilitate collective actions and enhance cooperation in a community (Woolcock 2001).

A central idea that emerges in social capital studies is that the set of existing common beliefs and standards to judge behaviors make that civic norms facilitate actions that are consistent with the prescribed norms. At the same time, respect for civic norms constrains individual and organizational actions that are socially undesirable (Hasan et al. 2017a). How civic norms are spread and enforced depend on the interactions among people within a specific community. The existence of informal values or norms shared by the members of the community facilitates the creation of social ties through associative movements (i.e., social and civic associations) which increases trust and favors

cooperation (Putnam 1993). Frequent social interactions in a dense network lead to more information sharing what boosts communication, mutual trust and enforcement of social norms (Coleman 1988).

Given how social capital can shape the expectations and behaviors of people in a specific area, one could establish a natural (negative) link between social capital and the probability that a bank is involved misconduct. There is evidence that managers affect firm outcomes (Bertrand and Schoar 2003) and they are themselves influenced by the social environment surrounding companies' headquarters (Hilary and Huang 2015, Hilary and Hui 2009). Bank misconduct is undesirable from a social perspective (Group of Thirty 2015), so one should expect some social resistance against it. This resistance may even be stronger in higher social capital areas where higher trust and respect for civic norms increase the pressure from peers regarding civic and socially positive behaviors. As a consequence, managers in high social capital areas should anticipate higher social stigmatization (Cialdini and Trost 1998) and psychological distress (Akerlof and Kranton 2005) for improper behavior. [8] Thus, managers in high social capital areas would be less likely to take actions that benefit themselves at the expense of others and be more careful when taking actions that may turn-out to be over-confident or value destroying (Hoi et al. 2019, Huang and Shang 2019). Given these assertions, I formulate the following hypothesis:

Hypothesis 1a: *A bank headquartered in a county with a higher level of social capital has a lower probability of being involved in misconduct.*

By their nature, regionally oriented banks have their business activities more concentrated in a specific area (Hakenes et al. 2014, Ostergaard et al. 2015). The diffusion of social and cultural factors from the headquarters towards other parts of the firm in less geographically dispersed banks is easier since managerial controls can be easily implemented and, if needed, managers can walk through branches or subsidiaries and have conversations with local employees. Also, less geographically diversified banks are more likely to have local ownership and insiders. These factors can contribute to a higher pressure and incentives to avoid deviant behaviors coming from investors, bank workforce or directors in areas with higher social capital as the 'same social capital' aligns the incentives of bank

[8] When social norms become part of the persons' identity, breaching them may lead to psychological distress (Akerlof and Kranton 2005, Parsons et al. 2018). The more someone deviates from the self-imposed benchmark, the guiltier the person feels.

stakeholders and managers. As a consequence, less complex organizations can be more successful in spreading cultural values from the headquarters, affecting individual and group behavior within the organization. On the other hand, more complex and geographically diversified banks are more likely to develop subcultures in different divisions or areas, making more difficult the transmission of a uniform culture from the headquarters (Thakor 2016).

Consequently, endowed social and cultural factors surrounding bank headquarters are likely to exert a stronger influence on less geographically diversified banks. This assertion is consistent with the idea that the effect of social capital on corporate behaviors attenuates with geographical diversification (Hasan et al. 2017a, Jha and Cox 2015). In line with this argument, I conjecture the following:

Hypothesis 1b: *The negative relationship between social capital and the probability that a bank is involved in misconduct is mostly significant for less geographically dispersed banks.*

2.2. Social capital and punishment over banks involved in misconduct

There is evidence that enforcement actions against banks involved in misconduct have negative reputational effects (Delis, Iosifidi, et al. 2019). Banks affected by a reputational shock are subject to depositors discipline (Martinez Peria and Schmukler 2001). However, this discipline may not be common in all areas where banks operate. For instance, Homanen (2018) shows that banks involved in scandals are subject to greater depositor discipline in areas where their customers have higher concerns about bank malpractice. In higher social capital areas there is the expectation that institutions operating in the region behave honestly (Fukuyama 1997, Putnam 2000). Thus, bank misconduct is more likely to be viewed as incongruent with civic standards in high social capital areas. Consequently, after misconduct revelation, banks depositors would discipline banks more in higher social capital areas.

The discipline exerted by depositors over banks in high social capital areas may change over time. In periods of low incidence of misconduct, banks may enjoy higher levels of trust in high social capital areas as mutual trust attenuates the subjective probability of been deceived. Nonetheless, once multiple bank misconduct cases become publicly known, individuals adjust their subjective

probabilities of being deceived and trust in banks decreases (Guiso et al. 2008). As a consequence, the social penalty against norm-deviant banks is amplified, especially during periods of low trust. The last financial crisis and its aftermath is a period characterized by a drop of trust in financial institutions (Zingales 2015) and higher social concerns about bank misconduct (Chaly et al. 2017). Thus, the discipline exerted by depositors over banks in high social capital areas would be stronger during the last financial crisis period and its aftermath.

Given these assertions, I conjecture the following:

Hypothesis 2*: After misconduct revelation, deposit market-shares of sanctioned banks decrease more in higher social capital areas, especially when trust in banks is low (i.e., during the last financial crisis and its aftermath).*

3. Data and Methodology

3.1. Sample construction

I collect data on regulatory enforcement actions for the period 2001-2015 from the websites of the three main banking supervisors in the US: the Federal Reserve (Fed), the Federal Deposit Insurance Corporation (FDIC) and the Office of the Comptroller of the Currency (OCC). All insured commercial banks have one of the above agencies as their primary bank regulator. The supervisory bodies conduct full scope on-site examinations every 12 or 18 months depending on the size and financial condition of the bank.[9] This involves an audit process to evaluate the bank. If as a result of this process the supervisors find that the bank has breached any law or regulation, they issue an enforcement action.

Following Delis, Iosifidi et al. (2019) and Nguyen et al. (2016), I focus on bank enforcement actions that are related to technical aspects such as violations of capital adequacy and liquidity, asset quality, lending, provisions and reserves, and non-technical aspects such as failures of the bank's internal control and audit systems, risk management systems, anti-money laundering violations, violations of consumer protection laws (Federal Trade Commission Act, the Equal Credit Opportunity Act, etc.), breaches of the fitness and propriety of board members, senior managers or other persons

[9] Exams are conducted every 18 months for banks under a specific total assets threshold. This threshold has changed over time and is set at $500 million since 2007. The reader may refer to Agarwal et al. (2014) for further details. OCC supervises National Banks. State Banks are supervised by their chartering state banking departments, in conjunction with the FDIC for banks that are not members of the Federal Reserve System or the Fed for banks that are members of the Federal Reserve System. Agarwal et al. (2014) provides a detailed explanation on how banking supervision is organized in the US.

closely associated with banks and cases related to fraud and insider abuse. Either because they pose a risk to safety and soundness of the bank or because they tend to have media coverage, these kinds of breaches of the law and regulations have reputational effects and are of a great concern for both managers and supervisors (Delis, Iosifidi, et al. 2019).[10] In the next step, I match the enforcement actions using name, city and state with each bank that received an enforcement action using the Reports of Condition and Income (hereinafter Call Reports). If there are multiple enforcement actions related to a single misconduct case, I aggregate them so only one case is identified. My final sample contains 3,114 enforcement actions. 53% of these enforcement actions are of a technical nature and 47% of them are related to non-technical issues. I observe that the proportion of technical enforcement actions is higher during the financial crisis (2008 - 2010), while non-technical enforcement actions are more numerous after 2011 when Dodd-Frank regulations were enacted and right before the financial crisis in 2005 and 2006. The differences between these types of misconduct are detailed in Appendix 1 and 2. Even though I see some clusters, enforcement actions are not just a feature of the last financial crisis, as they spread over the sample period. Table 1 provides a detailed summary of the enforcement actions used in the paper.

[Table 1 about here]

I obtain balance sheet and income statement information from Call Reports. Banks (both public and private) must file every quarter their Call Reports. However, as I work with annual data, I keep the year-to-date information at the end of every fiscal year for the period 2000-2015. I remove from my sample banks that have fewer than two observations, banks that have negative equity values, no deposits or loans, failed (the year they fail) and acquired banks (the year they are acquired), banks that are non-insured or have been insured for less than 2 years, banks with no information on their primary regulator, banks whose federal regulator is the Office of Thrift Supervisor (OTS), and banks that are

[10] Other enforcement actions such as those related to Call Reports filing, Flood Insurance Act or Home Mortgage Disclosure Act, denials of Section 19 applications or prohibitions to open new branches are not considered in the analysis. These violations are considered as less severe and they have little reputational consequences according to the literature dealing with bank enforcement actions in the US (Danisewicz et al. 2018, Delis et al. 2017, Delis, Iosifidi, et al. 2019, Lambert 2017). Therefore, I do not consider them as bank misconduct.

not located in the continental territory of the US and Alaska.[11] My final sample contains 8,953 commercial banks.

Finally, I use some county-level variables. I obtain income per capita and employment from the Bureau of Economic Analysis and the median age, the percentage of people older than 25 years old with higher education and the percentage of rural population (to define the dummy variable *rural*) from the US Census. Continuous bank accounting and county-level socioeconomic variables are winsorized at the top and bottom 1% to avoid the impact of outliers. Table 2 provides descriptive statistics for the variables used in the paper.

[Table 2 about here]

3.2. Social capital measure

I use data from the Northeast Regional Center for Rural Development (NRCRD) at Pennsylvania State University to estimate the level of social capital in US counties in the years 1997, 2005, 2009 and 2014. The measure of social capital I use is based on Rupasingha and Goetz (2008) who use a principal component analysis (PCA) to construct a county-level index of social capital in the United States. The variables used for the computation of the social capital index (based on a PCA) are the number of non-profit organizations without including those with an international approach divided by population per 10,000 (NCCS), the number of social and civic associations[12] divided by population per 1,000 (ASSN), the voter turnout in presidential elections (PVOTE) and the census response rate (RESPN).[13] In line with the theoretical development, NCCS and ASSN capture the density of these networks at the county-level. PVOTE and RESPN are measures of civic norms. Higher values of these factors mean higher social capital levels. Because the social capital index is solely computed in the years 1997, 2005, 2009 and 2014, and consistent with other papers using county-level variables that

[11] Because I use distance from the Canadian border (in Km) as an instrumental variable, keeping banks located in remote (i.e. Alaska) or non-continental (e.g. Hawaii, Puerto Rico) areas could add unnecessary noise to my estimation.

[12] Associations included in this category are civic and associations, sports teams and clubs, bowling centers, physical fitness facilities, public golf courses, religious organizations, political organizations, business associations, professional associations and labor organizations in each county.

[13] Before computing the PCA, these four factors are standardized to have a mean of zero and a standard deviation equal to one.

are not measured every year (Hasan et al. 2017a, Hilary and Hui 2009, Jha and Cox 2015), I use linear interpolation to fill-in the data for the periods 2000-2004, 2006-2008, 2010-2013.

Figure 1 presents the spatial distribution of the variable *social capital* for all counties in the US in 2014. A darker shade represents higher social capital values. The map shows that social capital is higher in upper Midwest/Northwest counties and lower in Southern counties (with some exceptions). This map shows similar patterns to the ones reported in Rupasingha et al. (2006) for 1997 and Hasan et al. (2017a, b) for 2005. This explains the high correlation of the variable *social capital* over time (roughly 90% on average). This high correlation is consistent with the fact that social capital is highly persistent over time (Guiso et al. 2011).

[Insert Figure 1 about here]

3.3. Empirical design

I use the following probit model (or baseline model) to test Hypotheses 1a and 1b.

$$Prob(Y_{i,t} = 1) = F(\alpha + \beta_1 SocialCapital_{c,t-1} + \beta_2 X_{i,c,t-1} + \varphi_r + \varphi_t + \varepsilon_{i,t}) \quad (1)$$

Where, $Y_{i,t}$ is a variable indicating the presence of misconduct. This variable is a dummy variable equal to one if bank *i* receives an enforcement action for committing misconduct at time *t* and zero otherwise. α is a constant term, $SocialCapital_{c,t-1}$ is the main independent variable, $X_{i,c,t-1}$ contains a variety of variables including bank level covariates and a set of county-level variables. All these time-varying variables are measured at *t-1* in the baseline model. The bank level covariates used in the regressions include some proxies for capital strength, earnings, asset quality, liquidity and risk of the portfolio of assets. As a proxy for capital strength I use the equity over total assets ratio, I use the return on assets as a proxy for earnings, I use the allowance for loans and leases to control for asset quality, for liquidity I use the ratio of cash and cash equivalents over total assets and as a proxy for the risk of the asset portfolio the ratio risk-weighted assets over total assets. I also include other bank level variables such as deposit ratio, age, size and size squared, a proxy for competition, a dummy that takes the value one if the bank is publicly held and zero otherwise and a dummy that takes the value one if the bank is held by a bank holding company and zero otherwise. The county-level variables used in the

regressions are income per capita, employment rate, median age, percentage of people older than 25 years old with higher education and a dummy variable taking the value one if the county is rural (less than 50% of the county population living in urban areas) and zero otherwise[14]. I include these county-level control variables because they are highlighted in the literature as determinants of social capital. For instance, Rupasingha et al. (2006) highlights that more income leads people to join social groups and participate in non-income earning social activities. Also, it suggests that education and age are the most important determinants of social capital. Putnam (1995) states that employed people belong to more social groups than those outside the labor force. Putnam (1995) and Rupasingha et al. (2006) also show that urban communities present a lower level of civic engagement than rural counterparts. These variables may also play a role in the process of misconduct according to Parson et al. (2018). As I want to isolate the effect of social capital on bank misconduct from other county-level socioeconomic characteristics, it is important to include these control variables. I also include regulator fixed-effects (φ_r) to control for differences across regulatory agencies and time fixed-effects (φ_t) to control for the effect of aggregate shocks. In Appendix 1 I describe the construction of the variables used in the paper as well as the sources. Table 2 provides descriptive statistics. According to the statistics provided in Table 2, enforcement actions are a rare event since they only affect 3.1% of the observations. Probit models may underestimate the probability of rare events. To verify the robustness of my results, I follow King and Zeng (2001) 's recommendations and correct these downward biases by analyzing the data using a rare events logit model. The results delivered by this procedure are in line with the rest of the results of the paper (results are provided in Online Appendix, Table A.3.C.). However, I report probit models because it is a more conservative estimation. Standard errors are clustered by bank or county as indicated in the tables. Additionally, I follow Nguyen et al. (2016) and Wang et al. (2010) and address the potential partial observability problem associated to model (1) using a bivariate probit model. This model, described in Appendix 3, allows me to separate the detection process of misconduct from its commission. The results of this model are provided in Table 4.

[14] Definition of rural counties is provided by the US census in its rural lookup table https://www.census.gov/geo/reference/urban-rural.html. Counties with less than 50 percent of the population living in rural areas are classified as urban; 50 to 100 percent are classified as rural.

In final part of the paper, I assess the consequences of bank misconduct as stated in Hypotheses 2. In this case, I use a county-level measure of market-share for each bank in each county. I am interested in studying how market-share in each county changes when misconduct becomes public, depending on the level of social capital of the county. I run following OLS model for this test:

$$\begin{aligned} \%\Delta MarketShare_{\boldsymbol{i,c,t}} &= \gamma_0 + \gamma_1 ZSocialCapitalBranches_{c,t-1} + \gamma_2 misconduct_{i,t} \\ &+ \gamma_3 ZSocialCapitalBranches_{c,t-1} * misconduct_{i,t} + \gamma_4 X_{i,c,t-1} \\ &+ \varphi_r + \pi_{s,t} + u_{i,t} \end{aligned} \quad (2)$$

Where, $\%\Delta MarketShare_{\boldsymbol{i,c,t}}$ is the percentage change of deposits market-share of bank *i* in county *c* between time *t-1* and *t*. I compute $MarketShare_{\boldsymbol{i,c,t}}$ using branch level data available at the FDIC Summary of Deposits. These data are available annually and measured as of 30 June every year. I compute the share of deposits of each bank in each county every year using these data and then the annual percentage change. $ZSocialCapitalBranches_{c,t-1}$ is the standardized value of the social capital variable at *t-1* computed in each market (each county in which the bank operates), and $misconduct_{i,t}$ is a dummy variable taking the value one if bank *i* receives an enforcement action between year *t-1* and *t* and zero otherwise.[15] Therefore, the coefficient of interest is γ_3 and captures the impact of misconduct revelation on market-share changes when social capital is one standard deviation above the mean. In other words, this interaction term captures whether banks are more penalized in high social capital counties once misconduct is revealed. $X_{i,c,t-1}$ represents a vector of bank-level (equity ratio, allowance for loans and leases, ROA, liquidity, size, deposit ratio, age, publicly held dummy and bank holding company dummy) and county-level variables (bank competition measured at the county-level, income per capita, employment, age, education and the variable *rural*) measured for each county in which a bank is present. I follow other studies analyzing the effect of misconduct on investment flows (Giannetti and Wang 2016, Gurun et al. 2018) and

[15] Since market-shares using branch level data are measured as of June 30th every year, enforcement actions issued during the third and fourth quarter of *t-1* are moved to year *t*. Therefore, the variable $enforcement_{,i,t}$ takes the value one if an enforcement actions has been issued against bank *i* during third or fourth quarter of the fiscal year *t-1* or during the first or second quarter of the fiscal year *t*, and zero otherwise.

include the terms φ_r and $\pi_{s,t}$ that represent regulator and state-time fixed-effects[16], respectively. $u_{i,t}$ is an error term.

4. Results

4.1. Baseline results

In Table 3, I test the effect of *social capital* on the probability that a bank is involved in misconduct using the probit model detailed in (1). I provide the regression coefficients for each variable and the marginal effects of the main variable of interest in square brackets. Column 1 reports a probit regression of a bank misconduct dummy on *social capital* and year and regulator fixed-effects. I observe a negative impact of *social capital* on misconduct. The marginal effect of *social capital* is equal to -0.007 and significant at the 1% level. In Column 2, I show the result for the baseline model including the full set of control variables. I observe that the size of the coefficient for *social capital* decreases but remains negative and statistically significant at the 1% level. This result, in line with my predictions in Hypothesis 1a, shows that a higher level of social capital is associated with a lower probability that a bank is involved in misconduct. The economic effect is sizeable. I find that a one standard deviation increase in the county-level measure of social capital is associated with a statistically significant 0.36% (-0.003*1.201) lower probability of misconduct. Relative to an average probability equal to 3.1%, this corresponds to significant decrease in the probability that a bank is involved in misconduct of 11.8% (-0.0036/0.0305)[17]. In Column 3, I run the same regression but cluster the standard errors on the county-level. Given that the main dependent variable is measured at this level, it is advisable to test whether the results hold when applying this clustering in order to correct the standard errors for the non-independence of the observations within the same county. I show that the coefficient for the variable *social capital* remains statistically significant at the 1% level.

[Table 3 about here]

[16] State by year fixed-effects aim at controlling for state-level time-variant unobserved factors that could affect changes in deposit holdings from customers (e.g., state-level policies that make holding deposits les or more attractive).

[17] In Online Appendix, Table A.3.A I show that both networks and civic norms components of social capital have a negative and significant impact on the probability that a bank is involved in misconduct. In Table A.3.B, I show that the effect of *social capital* in my baseline regression is negative and significant for the pre-crisis, and crisis and post-crisis periods.

4.2. Bivariate probit model with partial observability, average over the sample period and lags of social capital

I employ regulatory enforcement actions issued by US bank regulators against banks that engage in unsafe, unsound and illegal banking practices to identify banks involved in misconduct. Generally, one can only observe detected misconduct (once an enforcement action is issued) but not the set of all committed cases of misconduct. That is, even in the absence of enforcement actions, a bank may have engaged in misconduct without being detected. This problem is known as partial observability. I follow Wang (2013), Wang et al. (2010), and Nguyen et al. (2016) and address this problem running a bivariate probit model (Poirier 1980). I describe the results of this test in section 4.2.1. Additionally, in section 4.2.2., I run some additional tests using mean values and lagged values of the main independent variable.

4.2.1. Bivariate probit model

To address the partial observability issue, I run the model detailed in Appendix 3. (7) states the function that is used for this model. Table 4 reports the estimation. Column 1 reports the prediction results for banks committing misconduct P(M=1) and Column 2 shows the prediction results for the detection of misconduct, conditional upon misconduct having occurred P(D=1 | M=1). In Column 1, the control variables are the same variables that I include in the baseline model. In Column 2, in order to capture the probability of misconduct detection, I modify the the set of control variables in the regression. I do not include the *equity ratio* and the proxy for earnings (*ROA*). I instead use the regulatory capital ratio and the Z-score. Since the regulatory capital ratio is one of the target ratios for regulators, a low level of this ratio will put the bank under the radar of supervisors. Similarly, Z-score is a proxy for bank stability. Low levels of this measure will indicate high earnings volatility and closeness to insolvency (e.g. Berger et al. 2017, Laeven and Levine 2009). Therefore, low values of these ratios will draw the attention of supervisors, increasing the probability of misconduct detection.

The coefficients for the variable *social capital* have the expected signs. In Column 1, I observe that the coefficient for *social capital* is negative and statistically significant. This result shows that a higher level of social capital is associated with a lower probability of committed misconduct. In Column 2, the estimated coefficient for *social capital* is positive. This suggests that social capital is positively

associated with misconduct detection. However, the coefficient is not statistically significant. These results are in line with the baseline results using a probit model. They confirm that banks located in high social capital areas are less likely to commit misconduct and that the effect is not driven by a lower probability of detection in high social capital areas.

4.2.2. Additional tests

In my study, I use enforcement actions issued against banks that commit misconduct. These data do not allow me to determine with enough certainty the exact date when misconduct has been committed for all cases. However, the measure of social capital is persistent and highly sticky. Due to this persistence, I argue that even if I do not measure misconduct at the time it is committed (but rather when there is an enforcement action), my empirical analysis is capturing a lower likelihood of receiving an enforcement action because misbehavior is lower in banks headquartered in counties with higher social capital levels. In this subsection, I run some additional tests that strengthen my argument.

In Columns 3 and 4, given the high persistence of *social capital*, I run a cross-sectional probit regression using the mean values of the main independent variable and the rest of controls. I further distinguish between technical and non-technical cases to test whether the results hold for both types of misconduct. In Column 3, I run a probit regression of a dummy taking the value one if the bank is involved in technical misconduct over the sample period and zero otherwise on the mean value of *social capital* and the rest of independent variables I use in my baseline model. I show that the coefficient for *social capital* is negative and significant at the 1% level. I do the same exercise in Column 4 with non-technical enforcement actions. The coefficient for *social capital* is negative and statistically significant at the 1% level.

A potential concern in my study is that there may be some delay between the issuance of the enforcement action and the moment when the misconduct takes place. In this respect, I run two additional regressions taking 2 lags (in Column 5) and 3 lags (Columns 6) of the variable *social capital*[18]. The reported coefficients for *social capital* are negative and highly statistically significant.

[18] Parsons et al. (2018) indicate that, on average, misconduct is detected after 2 years with a median value of 3 years.

The results in this section support the idea that banks are less likely to commit misconduct if they are located in areas with higher social capital.

[Table 4 about here]

4.3. Robustness tests

In Table 5, I run several regressions to test the robustness of my results. I only show the coefficients and/or marginal effects of the variable *social capital* or other specific variables of interest for brevity. The control variables in this table are the ones I use in my baseline model. In Column 1, I run a robustness check that aims at testing whether bank-specific unobserved heterogeneity influences my results. I would ideally control for unobserved heterogeneity across banks in the model including bank fixed-effects. However, implementing such a model in my econometric setting poses two challenges. First, local levels of social capital tend to change very slowly, making impractical to implement a bank fixed-effects model to examine the relation between year-by-year variation in within bank social capital and misconduct. In this respect, Zhou (2001) notes that when temporal variation in the key dependent variable is small, firm fixed-effects eliminates too much of the variation in the variable to accurately estimate its coefficient. In order to get around this issue, Wintoki et al. (2012) suggests a sampling using period-spaced observations.[19] I follow this approach and use a sample using year intervals. To allow the maximum variation possible of *social capital*, I reduce the sample to the years in which this variable is measured in the NRCRD database (years 2005, 2009 and 2014) and the year 2001 which is the first year of my sample. The second challenge is that the estimation of the bank fixed-effects coefficients in a non-linear model could introduce an incidental parameters problem (Lancaster 2000, Neyman and Scott 1948). This problem of finding consistent estimators in non-linear models occurs because the number of bank fixed-effects grows without bound, but the amount of information for their estimation is limited. Both fixed-effects and coefficient estimates may become biased in such a setting. Even though the bias may get reduced as the number of periods in the panel increases, there is some uncertainty on whether it would disappear in my setting. It is also worth mentioning that in non-linear panels, taking first differences of the dependent

[19] Wintoki et al. (2012) study the effect of board structure on firm performance. Because board structure is highly persistent, introducing firm fixed-effects can reduce the power of any panel data estimator (Zhou 2001). To mitigate this concern, Wintoki et al. (2012) sample at two or three-year intervals instead of every year.

variable to get rid of fixed-effects is not possible. Given this challenge, I decide to go ahead with a linear probability bank fixed-effects model using a period-spaced sample. The result in Column 1 shows that the coefficient for *social capital* is negative and statistically significant at the 10% level. This result offers some assurance that unobserved heterogeneity at bank level is not driving the results.

In the baseline tests, I control for regulator and time fixed-effects. This choice follows previous papers using social capital or other variables measured at the county-level that have low time variation (Adhikari and Agrawal 2016, Hasan et al. 2017a, Hilary and Huang 2015, Hilary and Hui 2009, Jha and Cox 2015). A potential concern is the existence of a time-invariant regional heterogeneity that affects social capital and the probability that a bank is involved in misconduct. To alleviate this concern, I include state fixed-effects. However, there is low variation in the *social capital* variable within a state. The inclusion of state fixed-effects can take away part of the *social capital* variable effect on bank misconduct. Nonetheless, in Column 2, I show that the coefficient for *social capital* remains negative and statistically significant at the 5% level after running the baseline model with state fixed-effects. This result suggests that the baseline findings are not driven by omitted regional unobserved heterogeneity.

In Column 3, I exclude rural banks from the sample. I run a regression on a sample of banks that have at least one branch located in a Metropolitan Statistical Area (MSA), excluding all banks that have branches only in rural counties. This test allows me to rule out the possibility that my result is driven by differences in enforcement intensity between rural and urban banks.[20] The variable *social capital* remains negative and significant and the economic effect is close to my baseline results. In Column 4, instead of using linear interpolation to complete the data for missing years, I back-fill using estimates of the last year for which *social capital* data are available. For example, I fill-in missing data for *social capital* from 2001-2004 using social capital estimates in 1997. My main conclusions remain unchanged when I run this robustness test.

[20] Nguyen et al. (2016) show that bank enforcement intensity does not vary between rural and urban banks. However, they have a sample of publicly held banks that have a low number of rural banks. Therefore, I believe that it is convenient to run the baseline test using a sample of non-rural banks to rule-out any concern about differences in enforcement between these two types of banks.

Following Guiso et al. (2011) and Hasan et al. (2017b), I use organ donation as an alternative measure of social capital. Since donation of organs has no economic payoff and there is no legal obligation to donate, the decision to donate can be seen as a measure of how much people internalize the common good, providing a proxy for civic capital. I show in Column 5 the result of my baseline regression using *organ donation* as a proxy for social capital. The variable *organ donation* has a negative coefficient and is statistically significant at the 1% level.

In Column 6, I run a regression using a variable that captures the number of religion adherents at the county-level as in Hilary and Hui (2009). Religion has an effect on corporate decisions and is also a potential source of both moral values and an engine of socialization (Adhikari and Agrawal 2016, Dyreng et al. 2012, Guiso et al. 2011). I add the lagged variable *religion* together with the social capital measure and the set of control variables. My results show that *social capital* remains negative and highly significant while the variable *religion* is not statistically significant. This test shows that the measure of social capital captures the effect of altruistic and social values on bank misconduct beyond the effects of religion.

In Column 7, I add a proxy for less severe enforcement actions as a control variable. Less severe enforcement actions are related to violations of some reporting obligations or other laws less related to bank safety and soundness (see Appendix 1 for a more precise definition). These enforcement actions may be precursors to more severe bank problems and may trigger an increase of the attention of regulators on these banks, increasing the likelihood that an enforcement action is issued (Danisewicz et al. 2018). In order to be sure that omitting this variable does not lead to biased results, I use a variable that takes the value one if a bank receives a less severe enforcement action during the period *t-2* and *t*, and zero otherwise. I observe that the coefficient for less severe enforcement actions is positive and significant as predicted. The coefficient for *social capital* remains negative and statistically significant. This gives me confidence that my baseline result not biased due to an enhanced supervision from the bank's examiners/supervisors for institutions that received less severe enforcement actions.

[Table 5 about here]

As an addition to the robustness tests described above, I run a simulation exercise that works as a placebo test. I show the results of this exercise in Figure 2. The histogram plots the distribution of the coefficients of the variable *social capital* obtained from 1000 linear probability model regressions where the dependent variable is a dummy variable randomly simulated (taking the value one or zero), the main independent variable is the measure of social capital and the rest of control variables and fixed-effects are the same as those that I use in Table 3, Column 2. I generate 3,114 dummy variables every time, as this is the number of misconduct events identified in the baseline regressions. The vertical red line in Figure 2 represents the actual coefficient obtained for the variable *social capital* in the model estimated using a linear probability model (coefficient equal to -0.003).[21] The results show that, on average, the effect of social capital on false misconduct is zero. I observe that the point estimate of my actual result is never reached by the simulated coefficients. Finally, from the distribution of the t-statistics (not reported), I observe that in less than 5% of the cases the t-statistic is lower than -1.65. This result suggests that the likelihood of capturing pure spurious results in the actual estimates in Table 3 is statistically negligible.

[Figure 2 about here]

4.4. Evidence from the social capital level of the state where the CEO and other executives grew up

The baseline result of the paper shows that local levels of social capital are negatively related to the probability that a bank is involved in misconduct. This effect persists even after controlling for numerous county-level variables and state fixed-effects. Despite this, a potential concern is that the results I find might be driven by local area fixed-effects (unobserved heterogeneity) related to bank locations that are not captured by the variables and empirical settings I have used so far. As a consequence, I intend to alleviate concerns regarding local area fixed-effects by using the level of social capital of the CEO and other executives instead of the local level of social capital surrounding bank headquarters. The approach to measuring CEOs' and other executives personal social capital is motivated by the fact that people not only incorporate the values associated with the level of social

[21] I use a linear probability model because is less computationally demanding than a probit model. The coefficient of the baseline linear probability model is similar to the marginal effect obtained in the baseline test in Table 3.

capital of the place where they live, but also the level of social capital of the place where they grew up (Guiso et al. 2004). The key idea is that when individuals move to a different location, their cultural values (i.e., social capital) travel with them. Using executives cultural traits is consistent with the fact that key decision-makers in a firm create and disseminate their cultural values within the organization (Liu 2016, Nguyen et al. 2018).

I obtain data on the state where a CEO and other executives grew up for banking groups in the S&P 1500 from Scott Yonker.[22] The state where an executive grew up is identified as the state where an executive acquires her Social Security number. I calculate the mean value of *social capital* at the state-level using the level of social capital of each county within a state. As I am not able to measure the level of social capital in the state where an executive grew up at the time she was a child, I rely on the persistence of social capital over time (Guiso et al. 2011, 2016) and use the value of social capital in 1997 (which is the first year for which social capital can be computed in a reliable manner using NRCRD data).[23]

It is worth mentioning some features of the data I use for the analysis in Table 6. First, 47% of the bank-year observations present a CEO that is from the state where the largest bank within a bank holding company is located. This figure is similar to the one found by Adhikari and Agrawal (2016) for banks and larger than the 30% rate for non-financial firms found in the literature (Yonker 2017). For banks operating in two or fewer states this figure increases to 54% while for banks operating in five or more states the percentage of bank-year observations with a local CEO is 39%. This finding is consistent with the fact that less geographically diversified banks are more likely to have local CEOs. Second, as the data that identifies the state where a CEO and other executives grew up relies on the sample of banking groups available on Execucomp, I can only compute the level of social capital of the CEO and other executives for bank subsidiaries of banking groups present in the S&P 1500. This reduces the sample to fewer observations than my baseline model (2,326 bank-year observations) and for banks that are of a larger size (total assets roughly equal to $49 billion on average instead of $1.2

[22] In Israelsen and Yonker (2017), Jiang et al. (2018) and Yonker (2017), the authors use data on the state where the executives of a firm grew up. They identify the state of origin for the executives that appear on Execucomp. I thank Scott Yonker for sharing this data.

[23] NRCRD data provides social capital values for 1990. However, Hasan et al. (2017b) report in the appendix of the paper that they re-estimate the value of social capital in 1990 due to inconsistencies in the number of non-profit organizations reported in the NRCRD data. To avoid biases in the estimation, I use the value of social capital in 1997 as a proxy for the CEO level of social capital.

billion for the baseline sample). Also, banks in this group operate on average in more than three states while in the baseline sample the average is 1.3 states. These features may bias my results against finding significant results as I hypothesize that the effect of social capital is more important for less geographically diversified banks.

Despite these odds, in Table 6, Column 1, I run a probit regression of a dummy variable taking the value one in the presence of misconduct and zero otherwise on the social capital level of the state where the CEO of the banking group grew up (*CEO social capital*) and the set of bank and county-level variables that I use in the baseline test. I find a negative and statistically significant coefficient at the 5% level for the variable *CEO social capital*. In Column 2, I add some CEO-level control variables (*CEO tenure*, *CEO age*, *CEO delta* and *CEO total compensation*), and in Column 3, I add controls for board co-option, board size and board independence. In both Columns 2 and 3, I find negative and significant coefficients for the variable *CEO social capital.* Alternatively, in Column 4, I follow Liu (2016) and compute the average social capital of all executives with data available on Execucomp for each banking group to have a proxy for the average social capital of bank insiders (*Executive social capital).* I run a probit regression of the misconduct indicator on this variable and the baseline set of control variables. I obtain a coefficient that is negative and statistically significant at the 10% level.

The results from the level of social capital of the place where the CEO and other executives grew up alleviate the concerns about county-level (or local area) unobserved heterogeneity driving my main results. They also provide further evidence on how social capital, measured as a personal trait of the firm executives, can introduce cultural values in the bank that reduce the probability that the institution is involved in misconduct. This finding is consistent with the idea that managers are not only influenced by the social environment they live in, but also from the values related to social capital they acquired during their childhood.

[Table 6 about here]

4.5. Addressing endogeneity

I study social capital as an external factor that exerts exogenous pressure through social mechanisms reducing the incentives to commit misconduct in the banking sector. Even if *social capital* is exogenously determined, my empirical analysis may be affected by endogeneity due to

omitted variables that are correlated with *social capital* and the probability that a bank is involved in misconduct. Furthermore, since headquarters are not exogenously determined, my analysis could be biased because banks more prone to be involved misconduct could seek to locate in low social capital areas. These two endogeneity concerns could question the causality of the findings presented in the paper. Therefore, I use two-stage instrumental variable regressions to address these endogeneity concerns.[24]

To build an instrument for social capital, I use an epidemiological approach (e.g., Guiso et al. 2004, Hoi et al. 2019) based on the cultural values of the peoples' countries of ancestry. There is evidence showing that cultural preferences are persistent (Fernández 2011). Parent's attitudes and values are good predictors of the values and behavior of their descendants. Based on this approach, I use ancestry data from the US Census and Hoftesde's scores for power distance within a country. Specifically, I use Hotesde's data from https://www.hofstede-insights.com/ , and US Census first ancestries' country of origin data reported by the residents of each US county. I use the latter data to calculate the percentages of peoples' countries of ancestry within a county. Then, I construct the variable *power distance* for each county. I use a weighted average method that combines the percentage of peoples' countries of ancestry with the Hoftesde's scores for power distance based on peoples' countries of ancestry. Power distance views power as distributed unevenly, according to a hierarchy of authority. This uneven distribution of power is associated with an attitude towards lower tolerance (Hofstede 2001). According to Putnam (2000), communities with greater tolerance for equality tend to have higher social capital levels. As a consequence, I conjecture that the instrument I use is relevant since power distance of ancestors' countries of origin in a specific county should be negative and significantly related to social capital levels. Moreover, power distance of peoples' country of ancestry should not exert a direct influence on firm outcomes the probability that a bank is involved in misconduct.[25] If there is any influence, the effect would go through external pressure from the community to behave according to a standard (i.e., social capital).

[24] As an additional piece of evidence, I run a test (Online Appendix, Table A.3.E) that exploits bank headquarters relocations to other counties, resulting in either a decrease or increase in social capital. Using these relocations, I find that social capital-increasing relocations lead to a lower probability that a bank is involved in a misconduct case. This result further corroborates that my results are unlikely to be plagued by endogeneity.

[25] It could be the case that managers in an area are more likely to have similar ancestors than the people in the same county. As a consequence, they would be directly influenced by the cultural factors of their ancestors.

Table 7, Column 1 reports two-stage least squares estimate of a linear model. Panel B, Column 1 reports the first stage of the instrumental variable regression. *social capital* is the dependent variable in this model. *Power distance* is the instrument and main regressors in the first stage. Since the dependent variable in the first stage and the instrument, *power distance*, are measured at the county-level, I use within county clustering for the standard errors in the two stages.[26] Along with the instrumental variables, I include all control variables specified in the baseline model. The coefficient for *power distance* is negative and highly significant in the first stage. The F-statistics (testing for weak instruments) are well above the critical cutoff of 10 stated in Stock et al. (2002) and Stock and Yogo (2002). The second-stage regression is based on the baseline model, except that the key independent variable is the fitted value of *social capital* obtained from the first-stage regression. The coefficient for this variable is negative and statistically significant at the 10% level. In Column 2, I fit an IV probit model using Maximum Likelihood Estimation. This method of estimation fits a probit model when at least one of the regressors is affected by endogeneity. This model is an alternative to two-stage least square estimations when the outcome variable is binary. I observe that the instrument is negative and highly significant in the first-stage and the coefficient for *social capital* in the outcome regression is negative and significant at the 1% level. These results suggest that the effect of social capital on the probability that a bank is involved in misconduct is plausibly causal.

Additionally, I perform an additional instrumental variable analysis following the approach of Hassan et al. (2017 a, b). Putnam (2007) provides evidence showing that ethnic homogeneity increases cooperation and social solidarity, which implies that social capital is higher in racially homogenous areas. Thus, I compute an index of racial homogeneity (*HHI race*) at the county-level using race data from the US Census and use this variable as an instrument for social capital. This variable is computed every year for every county as a Herfindahl index calculated across the US Census ethnic categories of Hispanic, non-Hispanic black, non-Hispanic white, Asian and a category for other races. I conjecture that this variable is positive and significantly related to social capital. Regarding the exclusion restriction, I find no prior theoretical argument or empirical evidence that relates directly racial

However, Nguyen et al. (2018) find that cultural dimensions from ancestors that revolve around attitudes towards hierarchy such as Power Distance have no effect on strategic-decision making by bank managers or bank outcomes in general. According to this finding, the exclusion restriction requirement of the instrument *Power Distance* would not be violated in my setting.

[26] I obtain similar significance levels if I cluster the standard errors at the bank level.

homogeneity and the probability that a bank is involved in misconduct (if any it would affect misconduct through the social preferences of the area, i.e., social capital). Therefore, I consider that *HHI race* satisfies the two requirements of an instrumental variable. I use a second instrumental variable used in Hasan et al. (2017a, b), the natural logarithm of the distance from the bank headquarters to the Canadian border. The reasoning for this instrument is based on Putnam (2001, p48) who states that the distance to the Canadian border is the best single predictor of social capital in American states and discusses that this is because "slavery as a system and the post-slavery reconstruction period were institutionally designed to destroy social capital." As a consequence I expect a negative and significant impact of this variable on social capital.

Table 7, Column 3 reports two-stage least square estimates of a linear model and Column 4 the results of an IV probit model. In both columns, the first stage of the instrumental variable regression reports a positive (negative) and highly significant impact of *HHI race* (*distance to Canadian border*) on social capital. The F-statistic shows that the instruments are relevant. In the second-stage regressions, the fitted value of *social capital* is negative and statistically significant at the 5% level in both Column 3 and Column 4. These results again provide evidence that the effect of social capital on the probability that a bank is involved in misconduct is plausibly causal.

[Table 7 about here]

4.6. Social capital and bank policies

In this section, I investigate some potential mechanisms through which social capital can reduce bank misconduct cases. Exploring these channels is challenging since the behaviors that lead to misconduct cannot be easily observed. Therefore, in this section I intend to identify some aspects that may partially explain the negative relationship between endowed social capital and bank misconduct cases.

Technical misconduct tend to occur when risk indicators increase significantly (Nguyen et al. 2016). Managers in high social capital areas are more likely to exhibit a higher pro-social behavior. As a consequence, they will be less prone to take risks for personal benefit (Hoi et al. 2019) and be more careful when taking actions that may turn-out to be over-confident or value destroying (Huang and Shang 2019). Thus, banks headquartered in high social capital areas should have more prudent

business models over time, which will explain a lower probability of technical misconduct. Moreover, higher social capital is related higher financial reporting transparency (Jha and Chen 2014). As a consequence, banks headquartered in high social capital areas will be less likely to report low quality accounts and have a lower propensity to provide deficient reporting that could hide other activities related to misconduct (Karpoff and Lou 2010). The latter would explain, at least partially, the lower incidence of non-technical misconduct in areas with higher social capital.

I test these channels in Table 8. Ideally, I would use market measures of risk to study bank risk levels. However, as I have publicly and privately held banks in my sample, I rely on accounting based measures of risk. As proxy for risk taking I use the Z-score and the volatility of earnings (volatility of ROA). The Z-score is considered to be a measure of default risk and the volatility of ROA a measure of operating risk (e.g., Berger et al. 2017, Kanagaretnam et al. 2019, Laeven and Levine 2009). I take the natural logarithm of these variables. In Column 1, I document positive impact of *social capital* on the Z-score and in Column 2, a negative impact on earnings volatility. Since lower Z-scores and higher earnings volatility imply higher risk, my results are consistent with the fact that banks in higher social capital areas are less risky. Additionally, I look at the evolution of the loan portfolio to assess risk. Managers may have incentives to grow their bank loan portfolio quickly to gain benefits in the short-run (Rajan 1994). Fahlenbrach et al. (2017) shows that, in the short-run, faster growing banks have a higher ROA than banks growing more slowly. This paper also shows that faster loan portfolio growth is related to greater risk and more loan provisioning in the long-run. Given this association, I expect that banks headquartered in high social capital areas have a lower loan growth as managers will have a lower propensity to seek for short-term gains. Also, since deficient provisioning and low credit standards may lead to sanctions, lower loan growth will explain a lower incidence of misconduct due to a lower need for provisioning and stronger credit standards. Consistent with these arguments, in Columns 3 and 4 of Table 8, I show that social capital is negatively associated with unused commitments growth and loan growth. Finally, I test the argument saying that banks in higher social capital areas tend to have better quality reporting. I use accounting restatements as a proxy for the quality of reporting. Prior literature indicates that restatements reflect weaknesses of the reporting system (Dechow et al. 2010, Doyle et al. 2007). In Column 5, I document that banks located in higher social capital areas are less likely to restate their accounts. Taken together, the results of this

subsection provide, to a certain extent, an explanation about the channels through which banks in areas with higher social capital are less likely to be involved in misconduct.

[Table 8 about here]

4.7. Geographically dispersed banks, size and publicly held status

The negative relationship between social capital and the probability that a bank is involved in misconduct could significantly attenuate for banks that are geographically diversified as I hypothesize in section 2. I use data from the FDIC summary of deposits and determine the number of states in which a bank has branches to measure geographical dispersion.

I test Hypothesis 1b in Table 9. In Column 1, I run a probit regression of the probability of misconduct on *social capital* and the rest of control variables I use in the baseline tests. I restrict the sample to those banks that are geographically diversified (i.e., banks having branches in more than 5 states). Hasan et al. (2017) and Jha and Cox (2015) determine geographical dispersion using a similar threshold. I find that the coefficient for *social capital* is not statistically significant. In Column 2, I run the same regression that I run in Column 1 but using the sample of banks with branches in less than 5 states. I find a coefficient for *social capital* that is negative and statistically significant at the 1% level. These findings confirm hypothesis 1b as the impact of social capital on misconduct is mostly significany for less geographically dispersed banks.

Regressions in Columns 3 to 6 provide further evidence on the fact that the findings in Columns 1 and 2 are explained by geographical diversification and not by other forces such as banks being publicly held or size. I run these tests on the sample of less geographically dispersed banks (i.e., banks with branches in less than five states). In Column 3, I run a probit regression on the sample of banks with more than $1 billion of total assets. This threshold is typically used in the banking literature to distinguish between larger and smaller banks (e.g., Berger et al. 2017, Berger and Bouwman 2013). I find a negative and statistically significant coefficient for *social capital* (p-value equal to 0.054). In Column 4, I run the same test on the sample of banks that have less than $1 billion of total assets. I find a coefficient for *social capital* that is negative and statistically significant. These results document that within the group of banks that are less geographically dispersed, the effect of social capital on the probability of being involved in misconduct is negative and significant for larger and smaller banks. In

Columns 5 and 6, I provide further evidence on whether the effect of social capital on the probability that a bank is involved in misconduct is different for publicly and privately held banks. The motivation to run this test comes from the fact that publicly held banks may be subject to stricter monitoring from investors (i.e. institutional investors) and the stock market (i.e. market regulators, analysts, auditors) what may reduce the effect of social capital as an external monitoring force. I use the information provided in call reports and the bank relationships database available at the National Information Center website to identify the banks' top holding company. I merge the call reports with CRSP using the RSSD-PERMCO file available at the New York Fed website. I then determine whether a bank (or its bank holding company) is publicly held if I find stock price information on CRSP for each bank-year observation.[27] I run separate regressions for publicly (Column 5) and privately (Column 6) held banks. In both cases I find a negative and significant impact of social capital on misconduct. Taken together, the results shown in Table 9 reinforce the argument that the effect of social capital on the probability that a bank is involved in misconduct attenuates due to geographical diversification and not only because of size or publicly held status.

[Table 9 about here]

4.8. Consequences of bank misconduct and the role of social capital

Hypothesis 2 states that in high social capital areas civic norms and networks are such that there is a greater punishment for deviant behavior. I perform a formal test of this hypothesis in Table 10. I use the model described in (2) for which the level of observation is bank-county. I include regulator and state by year fixed-effects in the model. In unreported tests I find that the results are similar to those reported in Table 10 if I include year (to control for common shocks in the period) and state (to control for unobserved fixed factors at state level) fixed-effects separately. The outcome variable is *%ΔMarket-share of deposits* and the variable of interest in this model is the interaction term *misconduct * Z social capital branches* that is capturing the incremental effect that social capital may

[27] A manual inspection of the data related to foreign owned commercial banks (agencies or branches of foreign banks are not included in the dataset) reveals that some of them belong to foreign publicly held banking institutions. As an example, since 2007 the Spanish listed bank Banco Popular fully owned the Florida based Total Bank. Therefore, banks owned by a publicly held foreign bank institution (according to variable rssd9325) are classified as publicly held in this test.

have on the percentage change of deposits market-shares after misconduct revelation. In Column 1, I document that the coefficient for the variable *misconduct * Z social capital branches* is negative and statistically significant. This result shows that deposits market-share decreases more in higher social capital areas after misconduct is revealed. This finding is consistent with the conjecture in Hypothesis 2.

As the last financial crisis and its aftermath is a period characterized by a decrease of trust in corporations, and especially in banks (Lins et al. 2017, Sapienza and Zingales 2012, Servaes and Tamayo 2017), I also conjecture in Hypothesis 2 that the effect of social capital on deposits market-share after misconduct is revealed is more important after 2008. In Columns 2 and 3, I divide the sample into pre-crisis (2001 to 2007) and crisis and post-crisis (2008 to 2015) periods and run model (2) for each period separately. In Column 2, the coefficient for the key interaction term is not statistically significant. In Column 3, the coefficient for the interaction term is statistically significant (at the 1% level). These results are consistent with the idea that the incremental effect of social capital in punishing banks involved in misconduct is mostly significant for the financial crisis period and its aftermath. The economic interpretation of the result is the following: during the crisis and its aftermath, deposits market-shares decrease, on average, 1.11% once misconduct is revealed (this is given by the coefficient for *misconduct*). The coefficient equal to -0.62 for the interaction term implies that a decrease of 1.73% in deposits market-share occurs upon misconduct revelation when the social capital measure is one standard deviation above the mean. This represents, in absolute value, roughly 14% of the average deposits market-share for a bank in a given county. The addition of the two coefficients (-1.11 + -0.62) is statistically significant (p-value=0.00, not reported).

So far, the result in Table 10 suggests that banks involved in misconduct are subject to a harsher punishment by customers in high social capital areas. Delis et al. (2019) shows that after banks receive an enforcement action related to violations of safety and soundness provisions, deposits of sanctioned banks decrease significantly. They find that demand-side effects (i.e., banks shrink assets) and not depositors' withdrawals drive this result. The latter finding may suggest an alternative interpretation of my result in Table 10: the findings reported could be showing that banks' demand for deposits is lower in higher social capital areas after enforcement actions are public. In order to rule out this explanation, I rely on another key result of the paper Delis et al. (2019) who document that enforcement actions

unrelated to technical aspects do not cause a change in deposits growth. In Table A.3.H. (in the online appendix), I run a test similar to the one in Table 10 using only non-technical enforcement actions to identify misconduct. In line with Delis et al. (2019), I find that banks involved in non-technical misconduct do not experience a decrease of deposit market-shares on average. However, the interaction term *misconduct * Z social capital branches* has a negative and significant coefficient. This result is consistent with the fact that, after a case of non-technical misconduct is revealed, banks experience a decrease in deposits market-share in higher social capital areas. This result supports the idea that customers punish banks in higher social capital areas after misconduct revelation and allows me to rule-out the fact that the effect documented in Table 10 may stem from banks demanding less deposits after an enforcement action is issued against them.

[Table 10 about here]

5. Conclusions

Why do some banks engage in misconduct and others do not? This question has attracted substantial interest among academics and researchers, especially since the last financial crisis. While some papers provide evidence showing that internal governance mechanisms explain bank misconduct, I shed more light on this issue by studying how social capital provides external pressure deterring misconduct in the banking sector.

Using regulatory enforcement actions issued against US banks to identify bank misconduct and a social capital construct specifically designed to capture secular social influences arising from civic norms and networks surrounding bank headquarters, I document a negative relationship between local levels of social capital and the probability that a bank is involved in misconduct. This result is mostly significant for less geographically dispersed banks for which local preferences and moral values of investors and other stakeholders are more likely to influence bank internals' behavior.

Additionally, I study the consequences of bank misconduct and the impact of social capital. I measure social capital in the counties where banks have branches and show that, following misconduct revelation, sanctioned banks experience a greater decrease in deposits market-share in counties with higher levels of social capital. Consistent with the idea that social capital exerts a harsher punishment over banks during periods of low trust, I find that this result is mostly significant for the last financial

crisis period and its aftermath. The latter findings provide evidence of higher stigmatization and social sanctions against 'deviant' banks in areas characterized by higher social capital levels, mostly when trust in banks is low.

These results provide interesting implications about how social capital contributes to create a social environment surrounding bank headquarters that deter undesirable behaviors such as bank misconduct. They also show that bank organizations that engage in misconduct are more disciplined in areas that are more likely to perceive misconduct as incongruent with the moral values of the local population (i.e., areas with higher social capital levels).

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Figure 1 Spatial distribution of social capital in 2014

Figure 1 presents the spatial distribution for the variable *social capital* in the United States. For brevity, I use social capital data in 2014. The counties with higher social capital are displayed with a darker shade, whereas the counties with lower social capital are displayed with a lighter shade.

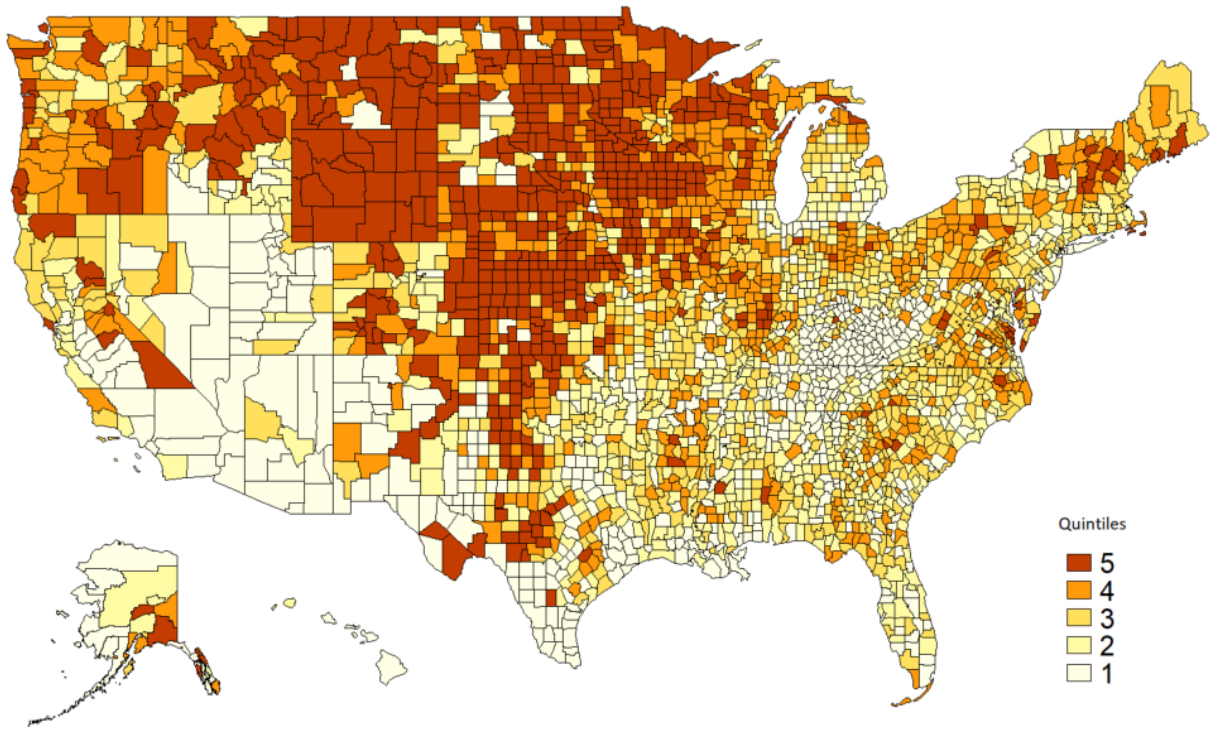

Table 1 Summary of misconduct cases

This table reports the bank enforcement actions issued by the three main banking regulators in the US (FDIC, OCC and FRB) each year. Technical enforcement actions refer to those enforcement actions related to violations of capital adequacy and liquidity, asset quality, lending, provisions, and reserves. Non-technical enforcement actions are related to failures of the bank's internal control and audit systems, risk management systems, anti-money laundering violations, violations of consumer protection laws (Federal Trade Commission Act, the Equal Credit Opportunity Act, etc.), breaches of the requirements concerning the fitness and property of board members, senior managers and closely related parties and cases related to fraud and insider abuse.

Year	All	Technical (%)	Non-Technical (%)	FDIC	OCC	FRB
2001	95	53%	47%	37	51	7
2002	118	61%	39%	47	64	7
2003	121	49%	51%	53	52	16
2004	127	43%	56%	70	48	9
2005	148	21%	79%	81	61	6
2006	142	24%	76%	86	50	6
2007	125	34%	66%	74	37	14
2008	202	53%	47%	89	87	26
2009	391	76%	24%	221	125	45
2010	577	78%	22%	351	152	74
2011	334	61%	39%	233	77	24
2012	254	50%	50%	186	47	21
2013	184	32%	68%	128	37	19
2014	150	24%	76%	101	36	13
2015	146	14%	86%	94	34	18
Total	3114	53%	47%	1851	958	305

Table 2 Descriptive statistics

This table reports descriptive statistics for the main variables of the empirical analysis. Appendix 1 provides variable definitions and details about their computation. The last column reports the mean difference between banks without misconduct and banks with misconduct. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively.

Variables	N	mean	sd	p25	p50	p75	Misconduct=0 - Misconduct=1
misconduct	101669	0.031	0.172	0	0	0	-
social capital	101669	0.004	1.201	-0.823	-0.133	0.638	0.327***
equity ratio	101669	10.668	3.276	8.493	9.883	11.923	1.031***
allowance loan lease	101669	1.517	0.792	1.044	1.316	1.747	-0.584***
ROA	101669	1.081	1.012	0.673	1.187	1.648	1.191***
liquidity	101669	6.713	6.435	2.841	4.432	7.914	-0.324**
RWA	101669	67.515	13.235	58.988	68.265	76.838	-4.272***
deposit ratio	101669	83.239	7.105	80.123	84.856	88.316	0.195
age (ln)	101669	3.641	0.935	3.178	4.19	4.277	0.181***
size (ln)	101669	11.88	1.265	11.023	11.749	12.564	-0.625***
size sq	101669	142.74	31.444	121.517	138.048	157.845	-16.10***
competition	101669	0.193	0.119	0.111	0.158	0.236	0.015***
BHC	101669	0.796	0.403	1	1	1	-0.016*
publicly held	101669	0.091	0.288	0	0	0	-0.064***
income pc (ln)	101669	10.399	0.285	10.195	10.379	10.579	-0.085***
employment	101669	56.317	13.956	46.137	55.791	64.955	-1.866***
education	101669	21.37	9.981	13.777	18.5	27.2	-2.89***
median age (ln)	101669	2.091	0.112	2.079	2.079	2.197	0.018***
rural	101669	0.414	0.492	0	0	1	0.134***
Other variables used							
Z score (ln)	97744	3.865	1.049	3.249	3.91	4.54	1.005***
regulatory capital	101645	17.118	7.321	12.372	14.961	19.189	2.834***
loans growth	101669	5.34	15.202	-3.138	3.1	10.362	9.334***
unused comm growth	88364	16.56	54.586	-11.182	7.12	29.55	18.560***
sd(ROA) (ln)	99871	-1.424	1.003	-2.067	-1.46	-0.817	-0.985***
accounting restatements	101669	0.045	0.207	0	0	0	-0.014***
religion	100402	61.739	17.508	49.73	60.079	71.766	3.761***
less severe	101669	0.029	0.167	0	0	0	-0.036***
organ donation	68330	0.375	0.361	0.195	0.276	0.433	0.059***
Executives & board-level variables							
CEO social capital	2326	-0.121	0.761	-0.689	-0.193	0.347	0.209***
Executives social capital	2326	-0.061	0.601	-0.498	-0.193	0.258	0.159***
CEO age (ln)	2260	4.032	0.111	3.970	4.025	4.094	-0.00323
CEO tenure (ln)	1907	1.907	0.881	1.386	2.079	2.565	0.245***
total compensation (ln)	2300	7.822	1.321	6.928	7.691	8.710	-0.463***
CEO delta (ln)	2174	5.263	1.735	4.060	5.204	6.540	-0.257*
CEO vega (ln)	2128	3.795	2.680	2.640	3.666	5.435	-0.709***
co-opted directors	1749	38.638	25.477	15.789	36.364	61.538	1.254
board size (ln)	1444	2.663	0.234	2.565	2.708	2.803	-0.0796***
board independence	1444	69.854	16.782	58.333	72.727	81.818	3.187**
Instrumental variables							
power distance	101668	39.643	3.574	37.46	38.538	40.808	-
HHI race	101669	0.694	0.199	0.518	0.725	0.879	-
distance to Canadian border (ln)	101359	6.441	0.836	5.985	6.568	7.058	-
Bank-county-level variables							
%ΔMarket-share of deposits	321332	6.512	32.736	-5.631	0.331	7.793	-
Z social capital mkt	321332	0	1	-0.665	-0.118	0.503	-
county competition	321332	0.215	0.135	0.128	0.178	0 .258	-

Table 3 Baseline regressions

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and some control variables. I report the marginal effect of *social capital* in square brackets. All independent variables are lagged one period. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1.

	(1)	(2)	(3)
	No control variables	Baseline	Cluster by county
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.096***[-0.007]**	**-0.056***[-0.003]**	**-0.056***[-0.003]**
	(0.009)	(0.012)	(0.013)
equity ratio		-0.032***	-0.032***
		(0.004)	(0.004)
allowance loan lease		0.157***	0.157***
		(0.011)	(0.010)
ROA		-0.268***	-0.268***
		(0.009)	(0.011)
liquidity		0.000	0.000
		(0.002)	(0.002)
RWA		0.008***	0.008***
		(0.001)	(0.001)
deposit ratio		0.001	0.001
		(0.002)	(0.002)
age		0.042***	0.042***
		(0.011)	(0.011)
size		-0.505***	-0.505***
		(0.101)	(0.103)
size sq		0.025***	0.025***
		(0.004)	(0.004)
competition		0.105	0.105
		(0.098)	(0.106)
BHC		-0.019	-0.019
		(0.026)	(0.025)
publicly held		-0.066*	-0.066*
		(0.035)	(0.036)
income pc		-0.119*	-0.119
		(0.071)	(0.074)
employment		0.002	0.002
		(0.001)	(0.001)
education		0.002	0.002
		(0.002)	(0.002)
median age		-0.052	-0.052
		(0.111)	(0.116)
rural		0.009	0.009
		(0.027)	(0.026)
Constant	-2.071***	1.097	1.097
	(0.043)	(0.924)	(0.956)
Regulator FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Cluster	Bank	Bank	County
Pseudo-R2	0.054	0.168	0.168
Observations	101669	101669	101669

Table 4 Bivariate probit with partial observability and alternative settings

This table reports the results of the estimated relations between social capital and committing misconduct (M=1) in Column 1 and detection given misconduct (D=1 | M=1) in Column 2. In Column 3, the dependent variable is *technical misconduct* taking the value one if a bank receives a technical enforcement action during the sample period and zero otherwise. The independent variables are measured at the mean value for each bank. In Column 4, the dependent variable is *non-technical misconduct* taking the value one in the presence of non-technical misconduct over the sample period and zero otherwise. The independent variables are measured at their mean value for each bank. The main dependent variable (*social capital*) is lagged 2 and 3 years in Columns 5 and 6, respectively. The rest of the independent variables remain lagged 1 period in these columns. Standard errors (in parentheses) are clustered by bank and are robust to heteroscedasticity. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. I report the marginal effect of *social capital* in square brackets. Definitions for all variables are provided in Appendix 1.

	(1)	(2)	(3)	(4)	(5)	(6)
	Bivariate probit with partial observability		Technical EA	Non-technical EA	2 years lag	3 years lag
Dependent var. :	P(M=1)	P(D=1 | M=1)	P(Technical Misconduct=1)	P(Non-technical Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.084***[-0.002]**	**0.047[0.001]**	**-0.098***[-0.016]**	**-0.085***[-0.016]**	**-0.048***[-0.002]**	**-0.044***[-0.002]**
	(0.030)	**(0.034)**	**(0.023)**	**(0.022)**	**(0.012)**	**(0.012)**
Z score		-0.116***				
		(0.014)				
regulatory capital		-0.003				
		(0.004)				
equity ratio	-0.019***		-0.104***	-0.000	-0.030***	-0.029***
	(0.007)		(0.011)	(0.008)	(0.004)	(0.004)
ROA	-0.242***		-0.729***	-0.229***	-0.274***	-0.275***
	(0.021)		(0.036)	(0.027)	(0.009)	(0.010)
allowance loan lease	0.103***	0.031	0.541***	0.198***	0.150***	0.148***
	(0.032)	(0.031)	(0.036)	(0.029)	(0.012)	(0.012)
liquidity	-0.001	0.001	0.007	0.001	-0.000	-0.001
	(0.004)	(0.004)	(0.005)	(0.004)	(0.002)	(0.002)
RWA	0.003	0.004	0.031***	0.005***	0.008***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)
deposit ratio	-0.004	0.005	-0.008**	0.006*	0.001	0.001
	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
age	0.025	0.002	0.225***	0.195***	0.021*	0.009
	(0.039)	(0.042)	(0.024)	(0.022)	(0.012)	(0.013)
size	0.254	-2.875***	1.139***	-0.431**	-0.518***	-0.517***
	(0.384)	(0.310)	(0.236)	(0.180)	(0.101)	(0.103)
size sq	0.016	0.094***	-0.046***	0.028***	0.026***	0.026***
	(0.016)	(0.011)	(0.009)	(0.007)	(0.004)	(0.004)
competition	0.139	-0.084	0.187	0.029	0.112	0.103
	(0.250)	(0.283)	(0.191)	(0.183)	(0.098)	(0.099)
BHC	-0.092	0.076	0.105*	0.132**	-0.025	-0.030
	(0.072)	(0.081)	(0.058)	(0.052)	(0.026)	(0.027)
publicly held	-0.201*	0.085	-0.348***	-0.162**	-0.068*	-0.064*
	(0.113)	(0.087)	(0.079)	(0.066)	(0.035)	(0.036)
income pc	0.213	-0.248	-0.052	0.266*	-0.121*	-0.133*
	(0.216)	(0.229)	(0.145)	(0.141)	(0.072)	(0.072)
employment	-0.001	0.002	-0.000	0.004**	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
education	-0.001	0.000	0.004	-0.007*	0.002	0.002
	(0.006)	(0.006)	(0.004)	(0.004)	(0.002)	(0.002)
median age	0.129	-0.199	0.077	-0.221	-0.084	-0.100
	(0.317)	(0.339)	(0.247)	(0.236)	(0.112)	(0.114)
rural	-0.063	0.094	0.001	0.028	0.010	0.012
	(0.059)	(0.066)	(0.051)	(0.051)	(0.026)	(0.026)
Constant	-7.457**	22.918***	-8.863***	-4.268**	1.387	1.569*
	(2.992)	(2.932)	(1.904)	(1.673)	(0.931)	(0.943)
athrho	-0.994***	-0.994***	-	-	-	-
	(0.150)	(0.150)				
Regulator dummies	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	-	-	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
Log-Likelihood	-10930.68	-10930.68	-2920.986	-3188.799	-11407.58	-11167.98
Pseudo-R2	-	-	0.250	0.083	0.168	0.168
Observations	97720	97720	8952	8952	99740	97850

Table 5 Robustness tests

This table reports the results of regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and some control variables. In Column 1, I run a linear probability model with bank fixed-effects sampling in 2001, 2005, 2009 and 2014. In Columns 2 to 7 I run probit regressions. In Column 2, I add state fixed-effects to the baseline model. In Column 3, I remove rural banks from the sample. In Column 4, I use the social capital variable without applying linear interpolation. In Column 5, I use the variable organ donation (measured as the number of organ donors divided by county population per 10,000) obtained from United Network for Organ Sharing (UNOS) as a proxy for social capital. In Column 6, I add the religion variable as a regressor. In Column 7, I add a proxy for less severe enforcement actions as a regressor. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. I report the marginal effect of the variable *social capital* and *organ donation* in square brackets. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity.

	(1) Linear Bank FE	(2) State FE	(3) No-rural	(4) SC without interpolation	(5) Organ donation	(6) Religion	(7) Less severe EA
Dependent var. :	Misconduct	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.006***	**-0.038**[-0.002]**	**-0.056***[-0.003]**	**-0.049***[-0.002]**		**-0.055***[-0.002]**	**-0.057***[-0.003]**
	(0.003)	**(0.015)**	**(0.015)**	**(0.011)**		**(0.012)**	**(0.012)**
organ donation					**-0.130***[-0.007]**		
					(0.043)		
religion						-0.000	
						(0.001)	
less severe							0.209***
							(0.042)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	No	No	No
Bank FE	Yes	No	No	No	No	No	No
Cluster	Bank	Bank	Bank	Bank	Bank	Bank	Bank
Adj. R2	0.054						
Pseudo-R2		0.173	0.155	0.167	0.159	0.168	0.168
Observations	27302	101669	65970	101669	68502	100402	101669

Figure 2 Placebo Test

This histogram reports the distribution of the coefficients for the variable social capital obtained from 1000 linear probability model regressions in which the dependent variable is a dummy variable randomly simulated, and the main independent variable is the measure of social capital. The rest of independent variables, fixed-effects and clustering of standard errors are those that I use in Table 3, Column 2. I generate 3,114 dummy variables every time, as this is the number of misconduct events in the baseline regressions. The vertical red line in the graph represents the actual coefficient obtained for the variable *social capital* in the baseline model estimated using a linear probability model (coefficient equal to -0.003). In less than 5% of the cases the t-statistic is smaller than -1.65.

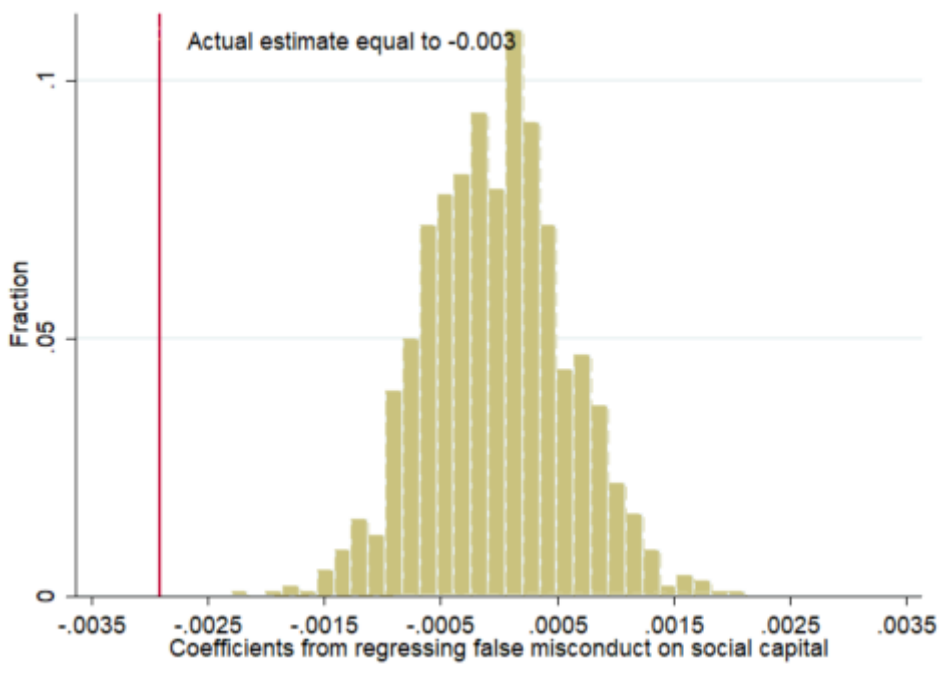

Table 6 Evidence from the social capital level of the state where the CEO and other executives grew up

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and some control variables. In Column 1, the main dependent variable is *CEO social capital* which is the average level of the social capital measure in 1997 in the state where the CEO of a banking group grew up. In Column 2, I add some CEO-level control variables. In Column 3, I add board-level variables. In Column 4, I compute a social capital measure for all executives of the bank reported on Execucomp (usually the top 5 earners). The sample I use in these tests is determined by the availability of the state where an executive grew up in the data provided by Scott Yonker and used in Israelsen and Yonker (2017), Jiang et al. (2018) and Yonker (2017). This sample only includes bank subsidiaries that belong to banking groups present in the S&P 1500. In all columns, I use the same control variables that I use in the baseline model in Table 3 except *BHC* and *publicly held* because all banks in this smaller sample are held by publicly traded bank holding companies. All independent variables are lagged one period. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. I report the marginal effect of the variable *social capital* in square brackets. Definitions for all variables are provided in Appendix 1.

	(1) CEO SC	(2) CEO variables	(3) Board variables	(4) Executives SC
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
CEO social capital	**-0.182**[-0.012]**	**-0.273***[-0.009]**	**-0.258*[-0.023]**	
	(0.078)	**(0.096)**	**(0.134)**	
Executives social capital				**-0.187*[-0.013]**
				(0.107)
equity ratio	-0.005	-0.020	0.003	-0.006
	(0.017)	(0.019)	(0.022)	(0.017)
allowance loan lease	0.106*	0.097	0.112*	0.107*
	(0.058)	(0.060)	(0.066)	(0.060)
ROA	-0.051	-0.089*	-0.099	-0.050
	(0.042)	(0.054)	(0.067)	(0.043)
liquidity	-0.001	-0.009	-0.024**	-0.001
	(0.007)	(0.008)	(0.010)	(0.007)
RWA	0.003	0.010**	0.005	0.003
	(0.004)	(0.004)	(0.006)	(0.004)
deposit ratio	-0.004	-0.001	-0.000	-0.003
	(0.006)	(0.007)	(0.008)	(0.006)
age	0.070	0.098	0.015	0.072
	(0.079)	(0.092)	(0.102)	(0.081)
size	-0.837	-0.794	0.192	-0.897
	(0.788)	(0.877)	(1.046)	(0.801)
size sq	0.039	0.035	0.002	0.041
	(0.027)	(0.031)	(0.036)	(0.028)
competition	-0.220	-0.648	-1.195*	-0.144
	(0.516)	(0.579)	(0.696)	(0.513)
income pc	-0.545	-1.256**	-1.540**	-0.546
	(0.466)	(0.567)	(0.667)	(0.470)
employment	0.021***	0.028***	0.032***	0.021***
	(0.005)	(0.006)	(0.008)	(0.005)
education	-0.002	0.003	0.004	-0.001
	(0.012)	(0.014)	(0.017)	(0.012)
median age	0.543	1.031	1.313	0.565
	(0.618)	(0.769)	(0.878)	(0.621)
rural	0.208	0.257	0.395	0.188
	(0.199)	(0.215)	(0.251)	(0.203)
CEO age		-0.182	0.597	
		(0.718)	(0.937)	
CEO tenure		-0.225**	-0.449***	
		(0.094)	(0.117)	
total compensation		-0.026	-0.030	
		(0.044)	(0.049)	
CEO delta		0.019	0.064	
		(0.075)	(0.078)	
CEO vega		0.126**	0.131**	
		(0.057)	(0.060)	
board co-option			0.006*	
			(0.004)	
board size			-0.033	
			(0.367)	
board independence			0.012*	
			(0.007)	
Constant	3.941	12.402	1.556	4.321
	(7.233)	(8.294)	(9.765)	(7.379)
Regulator FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank
Pseudo-R2	0.218	0.261	0.27	0.215
Observations	2326	1594	1055	2326

Table 7 Endogeneity

This table reports the estimates from IV regressions explaining the likelihood of a bank being involved in misconduct. Panel A shows the results of the second stage regressions of misconduct on social capital and a set of bank and county-level control variables. In Columns 1 and 3, I report the results of a 2SLS regression. In Columns 2 and 4, I report the results from IV probit regressions using Maximum Likelihood Estimation. I use the variable *Power distance* in the regressions in Column 1 and 2 as an instrument and *HHI race* and the natural logarithm of *distance to Canadian border* as instruments in Columns 3 and 4. Panel B shows the first stage regressions. In all columns, the dependent variable in the first stage is *social capital*. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered as indicated in the table. Independent variables are lagged one period. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. I report the marginal effect of the variable *social capital* in square brackets. Constant terms are included in the regression although they are not shown in the table for brevity.

Panel A : Second Stage	(1) 2SLS	(2) IVprobit	(3) 2SLS	(4) IVprobit
Dependent var. :	social capital	social capital	social capital	social capital
Instrumented social capital	**-0.005***	**-0.113*****	**-0.004****	**-0.062****
	(0.003)	**(0.034)**	**(0.002)**	**(0.029)**
Controls (Table 3)	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
Observations	101668	101668	101359	101359
Panel B : First Stage				
Dependent var. :	social capital	social capital	social capital	social capital
power distance	-0.090***	-0.090***		
	(0.006)	(0.006)		
HHI race			2.145***	2.145***
			(0.116)	(0.116)
distance to Canadian border (ln)			-0.074***	-0.074***
			(0.021)	(0.021)
Controls (Table 3)	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Cluster	County	County	County	County
Observations	101668	101668	101359	101359
F test of weak instruments (Kleibergen-Paap)	203.16	-	255.53	-
Effective F- statistic (Montiel-Pflueger)	203.24		258.77	
p -Value of Hansen test	-	-	0.37	-

Table 8 Bank policies

This table reports the results of OLS regressions explaining several bank level variables. In Column 1 the dependent variable is the natural logarithm of the Zscore, in Column 2 the natural logarithm of the standard deviation of the Return on Assets, in Column 3 the annual growth of unused commitments, in Column 4 the annual growth of gross loans, in Column 5 an indicator variable taking the value one if the bank restated its accounts during the year and zero otherwise. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1.

	(1)	(2)	(3)	(4)	(5)
Dependent var. :	Zscore	sd(ROA)	Unused commitments growth	Loans growth	Accounting Restatements
social capital	**0.090*** **	**-0.088*** **	**-1.336*** **	**-0.388*** **	**-0.005*** **
	(0.006)	**(0.006)**	**(0.212)**	**(0.075)**	**(0.001)**
equity ratio	0.052***	0.020***	0.693***	0.285***	0.001*
	(0.002)	(0.002)	(0.079)	(0.030)	(0.000)
allowance loan lease	-0.255***	0.248***	-2.602***	-2.601***	-0.000
	(0.007)	(0.007)	(0.324)	(0.103)	(0.001)
ROA	0.325***	-0.244***	0.252	0.706***	-0.006***
	(0.006)	(0.006)	(0.263)	(0.098)	(0.001)
liquidity	-0.002**	0.002***	-0.007	0.036***	0.000
	(0.001)	(0.001)	(0.040)	(0.012)	(0.000)
RWA	-0.011***	0.011***	-0.185***	0.030***	0.000
	(0.000)	(0.000)	(0.017)	(0.006)	(0.000)
deposit ratio	0.004***	-0.004***	-0.049	0.020*	-0.000
	(0.001)	(0.001)	(0.030)	(0.011)	(0.000)
age	0.110***	-0.108***	-2.776***	-3.586***	0.006***
	(0.007)	(0.007)	(0.224)	(0.098)	(0.001)
size	0.476***	-0.479***	-22.073***	-3.254***	-0.064***
	(0.060)	(0.060)	(2.154)	(0.718)	(0.012)
size sq	-0.018***	0.018***	0.800***	0.140***	0.003***
	(0.002)	(0.002)	(0.086)	(0.029)	(0.000)
competition	-0.174***	0.193***	5.774***	3.073***	0.014
	(0.050)	(0.049)	(1.763)	(0.590)	(0.009)
BHC	-0.051***	0.044***	0.045	0.758***	-0.016***
	(0.014)	(0.014)	(0.529)	(0.181)	(0.003)
publicly held	-0.093***	0.091***	1.681***	1.315***	0.001
	(0.021)	(0.021)	(0.636)	(0.288)	(0.003)
income pc	-0.053	0.053	2.219*	4.719***	0.001
	(0.038)	(0.038)	(1.245)	(0.480)	(0.007)
employment	-0.001**	0.001**	0.012	0.011	0.000***
	(0.001)	(0.001)	(0.019)	(0.007)	(0.000)
education	-0.005***	0.005***	-0.001	-0.043***	-0.000
	(0.001)	(0.001)	(0.031)	(0.012)	(0.000)
median age	0.048	-0.073	-1.675	-3.463***	0.003
	(0.063)	(0.062)	(2.132)	(0.755)	(0.012)
rural	0.031**	-0.028**	0.446	0.236	0.001
	(0.014)	(0.014)	(0.445)	(0.165)	(0.003)
Constant	0.896*	0.736	173.806***	-7.115	0.354***
	(0.527)	(0.524)	(17.721)	(6.406)	(0.096)
Regulator FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank
Adj. R2	0.309	0.244	0.040	0.123	0.015
Observations	99764	99871	88364	101669	101669

Table 9 Geographically and less geographically dispersed banks

This table reports the results of probit regressions of a dummy variable taking the value one when a bank is involved in misconduct and zero otherwise on a social capital variable and a set of controls for different subsamples. In Column 1, I keep the banks that have branches in more than 5 states. In Column 2, I keep banks that have branches in less than 5 states. In Column 3, I keep banks that have branches in less than 5 states and have total assets equal or more than $1 billion. In Column 4, I keep banks that have branches in less than 5 states and have total assets lower than $1 billion. In Column 5, I keep banks that have branches in less than 5 states and are publicly held (either because the bank is listed or is held by a publicly listed BHC). In Column 6, I keep banks that have branches in less than 5 states and are privately held. Control variables are those that I use in the baseline regressions. Control variables are lagged one period. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity. I report the marginal effect of the variable *social capital* in square brackets.

	(1)	(2)	(3)	(4)	(5)	(6)
Sample :	>5 states	<5 states	>$1 Bill & <5 states	<$1 Bill & <5 states	Publily held & <5 states	Privately held & <5 states
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**0.108**	**-0.060*** **	**-0.089***	**-0.058*** **	**-0.098** **	**-0.057*** **
	[0.019]	**[-0.003]**	**[-0.009]**	**[-0.002]**	**[-0.006]**	**[-0.002]**
	(0.220)	**(0.012)**	**(0.046)**	**(0.013)**	**(0.047)**	**(0.013)**
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Bank	Bank	Bank	Bank	Bank	Bank
Pseudo-R2	0.224	0.164	0.079	0.180	0.134	0.174
Observations	456	100956	6868	94088	9412	91544

Table 10 Consequences of bank misconduct and the role of social capital

This table reports the results of OLS regressions of a variable that measures the annual percentage change of the market-share of deposits for each bank in each county from June 30th of year *t-1* to June 30th of year *t* on *misconduct* (a variable that takes the value one the year a bank is subject to an enforcement action an zero otherwise), a standardized measure of social capital measured in each market (i.e. counties in which the bank has branches), the interaction term *misconduct * Z social capital branches* and a subset of bank level and county-level control variables. The unit of observation is the county-bank level. In Column 1, I use the whole sample (2001-2015), in Column 2, I use the pre-crisis period sample (2001-2007), and in Column 3, I use the crisis and post-crisis period sample (2008-2015). Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. County-level variables are measured for each county in which a bank is present. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. All variables are defined in Appendix 1.

	(1)	(2)	(3)
Sample :	All	Pre-Crisis	Crisis & Post-crisis
Dependent var. :		%ΔMarket-share of deposits	
misconduct	-0.998***	-2.662***	-1.111***
	(0.223)	(0.547)	(0.245)
Z social capital branches	-1.047***	-1.683***	-0.549***
	(0.119)	(0.172)	(0.155)
misconduct * Z social capital branches	**-0.303***	**0.607**	**-0.621*****
	(0.184)	**(0.482)**	**(0.201)**
equity ratio	-0.117***	-0.085*	-0.154***
	(0.031)	(0.049)	(0.039)
allowance loan lease	-2.627***	-3.064***	-2.206***
	(0.112)	(0.192)	(0.134)
ROA	0.301***	-1.790***	1.249***
	(0.095)	(0.183)	(0.109)
liquidity	-0.010	-0.122***	0.033**
	(0.014)	(0.028)	(0.016)
RWA	0.058***	0.112***	0.037***
	(0.007)	(0.012)	(0.009)
deposit ratio	0.002	0.014	-0.023
	(0.013)	(0.018)	(0.018)
age	-3.097***	-3.130***	-2.833***
	(0.127)	(0.196)	(0.159)
size	0.294***	0.130	0.498***
	(0.074)	(0.118)	(0.089)
BHC	1.572***	2.800***	0.467
	(0.255)	(0.377)	(0.316)
publicly held	-2.333***	-2.382***	-2.243***
	(0.260)	(0.423)	(0.308)
county competition	0.671	2.429**	-0.237
	(0.696)	(1.106)	(0.837)
income pc	4.946***	5.809***	3.827***
	(0.600)	(1.012)	(0.697)
employment	-0.009	0.011	-0.026***
	(0.008)	(0.013)	(0.010)
education	0.144***	0.185***	0.135***
	(0.014)	(0.027)	(0.015)
median age	-4.418***	-3.950***	-4.794***
	(0.843)	(1.437)	(0.990)
rural	1.664***	1.920***	1.493***
	(0.201)	(0.311)	(0.242)
Constant	-30.309***	-41.437***	-17.716**
	(6.140)	(9.938)	(7.339)
Regulator FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Cluster	Bank-county	Bank-county	Bank-county
Adj. R2	0.032	0.033	0.034
Observations	321360	139439	181921

Appendix 1 Variable definitions

Variables	Definitions	Source
social capital	The first principal component based on data from the Northeast Regional Center for Rural Development (NRCRD) at Pennsylvania State University. Data on the level of social capital in US counties is available for the years 1997, 2005, 2009 and 2014. The measure of social capital I use is based on Rupasingha and Goetz (2008) who use a principal component analysis (PCA) to construct a county-level index of social capital in the United States. The variables used for the computation of the social capital index are the number of non-profit organizations without including those with an international approach divided by population per 10,000 (NCCS), the number of social and civic associations divided by population per 1,000 (ASSN), the voter turnout in presidential elections (PVOTE) and the census response rate (RESPN). In line with the theoretical development, NCCS and ASSN are measures of networks and capture the density of these networks at the county-level. PVOTE and RESPN are measures of civic norms. Higher values of these factors mean higher social capital levels. Because the social capital index is solely computed in the years 1997, 2005, 2009 and 2014, and consistent with other papers using county-level variables that are not measured every year (Hasan et al. 2017a, Hilary and Hui 2009, Jha and Cox 2015), I use linear interpolation to fill-in the data for the periods 2000-2004, 2006-2008, 2010-2013.	NRCRD (Northeast Regional Center for Rural Development)
equity ratio	The ratio of total equity divided by total assets (in percentage)	Call reports
allowance loan lease	The loan and lease allowance scaled by total loans (in percentage)	Call reports
ROA	The ratio of the pre-tax income over total assets (in percentage)	Call reports
liquidity	The ratio of cash and cash equivalents divided by total assets (in percentage)	Call reports
RWA	The ratio of risk weighted assets over total assets (in percentage)	Call reports
deposit ratio	The ratio of total deposits over total assets (in percentage)	Call reports
age	The natural logarithm of the number of years since the bank is an FDIC insured institution	Call reports
size	The natural logarithm of total assets	Call reports
size sq	The variable *size* squared	Call reports
BHC	A binary variable taking the value one if the bank is held by a bank holding company, and zero otherwise	Call reports
publicly held	A binary variable taking the value one if the bank is publicly held or held by a bank holding company that is publicly held, and zero otherwise	Call reports
competition	The bank-level Herfindahl-Hirschman Index (HHI) of deposit concentration for the local markets in which the bank is present. I define the local market as the Metropolitan Statistical Area (MSA) or non-MSA county in which the bank branches are located. I weight the local market measure of competition by the portion of bank total deposits that each bank has in each local market to obtain a bank-level variable	FDIC summary of deposits
income pc	The natural logarithm of income per capita measured at the county-level	Bureau of Economic Analysis
rural	Dummy variable taking the value one if the county is a rural county, and zero otherwise	US Census
median age	Natural logarithm of the median age group per county according to the age groups provided by the US Census	US Census
employment	The total number of jobs in the county divided by total population (in percentage)	Bureau of Economic Analysis
education	Number of people older than 25 years old that have a bachelor degree or higher divided by total population in the county (in percentage)	US Census
Z score	The natural logarithm of the Z score. The Z score is computed as the average mean of the equity ratio plus the mean of the ROA divided by the standard deviation of the ROA. The mean values and the standard	Call reports

	deviation are computed over a three years period	
regulatory capital	Tier 1 capital divided by risk-weighted assets (in percentage)	Call reports
loans growth	The year on year growth of gross loans (in percentage)	Call reports
unused comm growth	The growth rate of unused commitments. Unused commitments are measured using the following call reports variables: RCFD3814 + RCFD3816 + RCFD3817 + RCFD3818 + RCFD6550 + RCFD3411	Call reports
sd(ROA)	The natural logarithm of the standard deviation of ROA computed over a three years period	Call reports
Accounting Restatements	It is an indicator variable that equals 1 if the call report variable RIAD B507 (Restatements due to corrections of material accounting errors and changes in accounting principles) is either positive or negative for the bank-year observation, and 0 otherwise.	Call reports
religion	Number of religion adherents at the county-level divided by total population of the county (in percentage)	Association of Religion Data Archives (ARDA)
less severe	A binary variable taking the value one if the bank receives a less severe enforcement action related to a reporting issue (Call report, HDMA disclosure, etc.) or a violation of Flood Insurance requirements between *t-2* and *t*, and zero otherwise	Regulators'websites
organ donation	Number of organ donations in a county divided by county population per 10,000	Obtained by email from Network for Organ Sharing (UNOS)
CEO social capital	The social capital level of the state where the CEO of each banking group grew up. This is measured using the state-level value of *social capital* in 1997. The state-level value of *social capital* is computed using the mean value of the social capital index of all counties in a state. I use data of all the CEOs of each banking group reported on Execucomp for which the state where they grew up is identified in Scott Yonker's data	Scott Yonker and own calculations
Executives social capital	The social capital level of the state where the executives of each banking group grew up. This is measured using the state-level value of *social capital* in 1997. The state-level value of *social capital* is computed using the mean value of the social capital index of all counties in a state. Then I calculate a bank-level variable using the mean values of *social capitla* for all executives in the bank. I use data of all the executives of each banking group reported on Execucomp for which the state where they grew up is identified in Scott Yonker's data	
CEO tenure	The natural logarithm of the number of years the CEO is served in the position	Execucomp
CEO age	The natural logarithm of the CEO age	Execucomp
CEO total compensation	The natural logarithm of the CEO total compensation	Execucomp
CEO delta	The natural logarithm of the expected dollar change in CEO wealth for a 1% change in stock price	Lalitha Naveen website
CEO vega	The natural logarithm of the Dollar change in wealth associated with a 0.01 change in the standard deviation of the firm's returns	Lalitha Naveen website
Board co-option	Number of co-opted independent directors divided by board size	Lalitha Naveen website
Board independence	The fraction of directors that are outsiders	MSCI Directors database (only available as from 2001)
Board size	The natural logarithm of the number of directors sitting on the board	MSCI Directors database (only available as from 2001)
misconduct	It is a binary variable taking the value one in the presence of bank misconduct and zero otherwise. Misconduct cases are identified using bank enforcement actions issued by bank regulators in the US. They can	Regulators'websites

	be cease and desist orders, prompt corrective actions, written agreements or prohibitions from banking.	
technical misconduct	It is a binary variable that takes the value one in the presence of misconduct related to bank violations of capital adequacy and liquidity, asset quality, lending, provisions, and reserves, and zero otherwise.	Regulators'websites
non-technical misconduct	It is a binary variable that takes the value one in the presence of misconduct related to failures of the bank's internal control and audit systems, risk management systems, anti-money laundering violations, violations of consumer protection laws (Federal Trade Commission Act, the Equal Credit Opportunity Act, etc.), breaches of the requirements concerning the fitness and property of board members, senior managers and closely related parties and cases related to fraud and insider abuse, and zero otherwise.	Regulators'websites
Instrumental variables		
power distance	This is the county-level weighted average Hofstede's score for power distance (high power distance view power as distributed unevenly, according to a hierarchy of authority, what implies lower tolerance for equality). The weights to obtain a county-level variable are the percentage of people with first ancestry information as reported in Census ancestry data	Hofstede's score data (https://www.hofstede-insights.com/)and US Census
HHI race	The Herfindahl index calculated across the Census Bureau ethnic categories of Hispanic, non-Hispanic black, non-Hispanic white, Asian and other races for a county in a given year. This is a measure of ethnic homogeneity	US census
distance to Canadian border (ln)	Natural logarithm of the distance in kilometers from the bank headquarters to the closest point of the Canadian border	www.internationalboundarycommission.org/fr/
Variables added in Table 10		
%ΔMarket-share of deposits	Annual percentage change of the share of deposits of a bank in a county. Branch deposits are measured as of June 30th every year. Therefore, this variable is the change in market-share between June 30th of year *t-1* and June 30th of year *t*.	FDIC summary of deposits
misconduct (modified)	To be consistent with the measurement of the dependent variable in Table 10 (*%ΔMarket-share of deposits*), this variable takes the value one in year *t* if a bank is subject to an enforcement action and the enforcement is issued in the first two quarters of the year, or in year *t+1* if the enforcement action is issued in the last two quarters of the year. For bank-years when there is no enforcement action, this variable takes the value zero.	Regulators'websites
Z social capital branches	Standardized value of *social capital* computed for the counties where bank branches are located.	NRCRD (Northeast Regional Center for Rural Development) and FDIC summary of deposits
county competition	The county-level Herfindahl-Hirschman Index (HHI) of deposit concentration. I compute the market-share of each bank in each county and compute the county-level HHI based on those market-shares	FDIC summary of deposits

Appendix 2 Examples of enforcement actions

Type	Sub-classification	Description (Date, Regulator, Bank, Text)
Technical	violations of capital adequacy and liquidity	**September 2011, OCC, Citizens First National Bank** : "…(1) The Bank shall achieve within ninety (90) days of the date of this Order and thereafter maintain the following capital levels (as defined in 12 C.F.R. Part 3): (a) Total risk-based capital at least equal to twelve percent (12%) of risk-weighted assets; and 6 (b) Tier 1 capital at least equal to eight percent (8%) of adjusted total assets,.1 (2) The requirement in this Order to meet and maintain a specific capital level means that the Bank may not be deemed to be "well capitalized" for purposes of 12 U.S.C. § 1831o and 12 C.F.R. Part 6 pursuant to 12 C.F.R. § 6.4(b)(1)(iv)..."
	asset quality and lending	**March 2009, FDIC, Heartland Bank**: "…The FDIC and the OSBC considered the matter and determined that they had reason to believe that the Bank had engaged in unsafe or unsound banking practices. The FDIC and the OSBC, therefore, accepted the CONSENT AGREEMENT and issued the following: IT IS HEREBY ORDERED, that the Bank, its institution affiliated parties, as that term is defined in section 3(u) of the Act, 12 U.S.C. § 1813(u), and its successors and assigns, cease and desist from the following unsafe or unsound banking practices: … C. Operating with an excessive level of adversely classified assets and non-accrual loans; D. Engaging in hazardous lending and lax collection practices…"
	provisions and reserves	**February 2009, FRB, Sun American Bank**: "…Within 60 days of this Agreement, the Bank shall review and revise its allowance for loan and lease losses ("ALLL") methodology consistent with relevant supervisory guidelines…"
Non-Technical	bank's internal control and audit, risk management or IT systems	**June 2014, FRB, Regions Bank**: "…The Federal Reserve Board on Wednesday announced that Regions Bank, Birmingham, Alabama, will pay a $46 million penalty for misconduct related to the process followed by the bank for identifying and reporting non-accrual loans. The Federal Reserve also issued a consent order requiring Regions Bank to continue to improve its relevant policies and procedures(…)The enforcement actions are based on deficiencies in the controls and procedures in place at Regions Bank …"
	anti-money laundering violations	**March 2008, FDIC, First Regional Bank**: "…IT IS HEREBY ORDERED, that the Bank, its institution-affiliated parties, as that term is defined in section 3(u) of the Act, 12 U.S.C. § 1813(u), and its successors and assigns, cease and desist from the following unsafe and unsound banking practices and violations of law and/or regulation, as more fully set forth in the FDIC's Report of Examination dated April 23, 2007: (a) operating in violation of section 326.8 of the FDIC's Rules and Regulations, 12 C.F.R. § 326.8, regarding a satisfactory Bank Secrecy Act ("BSA") and Anti-Money Laundering ("AML") compliance program with respect to Individual Retirement Accounts administered by third parties…"
	violations of consumer	**April 2011, FRB, 10 different banks**: The Federal

	protection regulations and laws	Reserve Board on Wednesday announced formal enforcement actions requiring 10 banking organizations to address a pattern of misconduct and negligence related to deficient practices in residential mortgage loan servicing and foreclosure processing. These deficiencies represent significant and pervasive compliance failures and unsafe and unsound practices at these institutions. The Board is taking these actions to ensure that firms under its jurisdiction promptly initiate steps to establish mortgage loan servicing and foreclosure processes that treat customers fairly, are fully compliant with all applicable law, and are safe and sound.
	compliance issues	**September 2011, FDIC, Northwest Savings Bank**: "…2. (a) The Bank shall develop and implement an effective CMS that is commensurate with the level of complexity of the Bank's operations and a comprehensive written compliance program ("Compliance Program"). (b) Within 60 days from the effective date of this ORDER, the Board shall submit to the Regional Director of the New York Regional Office of the FDIC ("Regional Director") for non-objection a Compliance Program that, at a minimum: (i) includes policies, controls, procedures, and processes that ensure consistent compliance with all consumer laws, regulations and regulatory guidance to which the Bank is subject…"
	breaches of the requirements concerning the fitness and propriety of the managers or board members	**November 2011, OCC, American Bank & Trust Company, N.A.:** "…the Currency of the United States of America ("Comptroller") intends to initiate prohibition, cease and desist, and civil money penalty proceedings against Harry S. Coin ("Respondent") pursuant to 12 U.S.C. §§ 1818(b), (e), and (i) on the basis of Respondent's activities while serving as chief executive officer…" "…the Comptroller of Respondent caused the Bank to purchase approximately twenty acres of land in Rock Island, Illinois ("Rock Island Property") without conducting any formal analysis or obtaining prior Board approval, as required by the Bank's Branching Policy…" "Respondent caused the Bank to deposit $970,000 in Bank funds into the Bank's account at a correspondent bank in exchange for receiving preferential terms on a personal loan from the correspondent bank, in violation of 12 U.S.C. § 1972(2)(A). The Bank sustained a lost opportunity cost of approximately $30,526 because the Bank's account did not earn any interest at the correspondent bank. Respondent received personal gain in the form of a lower interest rate on his personal loan, which resulted in lower payments…"
	cases related to fraud and insider abuse	**July 2009, FDIC, Harleysville Savings Bank**: "..The FDIC considered the matter and determined it had reason to believe that: (a) The Respondent has engaged or participated in violations, unsafe or unsound banking practices and/or breaches of fiduciary duty as an institution-affiliated party of Harleysville Savings Bank, Harleysville, Pennsylvania; (b) By reason of such violations, unsafe or unsound banking practices and/or breaches of fiduciary duty, the Bank has

		suffered financial loss or other damage, the interests of the bank's depositors have been prejudiced, and/or Respondent received financial gain or other benefit; and (c) Such violations, unsafe or unsound banking practices and/or breaches of fiduciary duty involve personal dishonesty on the part of the Respondent or demonstrate the Respondent's willful and/or continuing disregard for the safety or soundness of the Bank…"

Appendix 3 Bivariate Probit Model

As I try to estimate the probability of bank misconduct, I face an empirical challenge. Misconduct is not observed until it is detected. Therefore, the outcome I observe when studying regulatory enforcement actions is the product of the commission of misconduct and the detection of misconduct. As the process of detection is not perfect (misconduct may be committed and not detected), I face a problem of partial observability. In order to address this aspect, I run additional tests using a bivariate probit model (Poirier 1980). This methodology allows me to be sure that what I am detecting is a lower probability of committing misconduct and not lower chance of detection or enforcement. This model, initially created to address the partial observability problem studying crime (Becker 1968), and used in other papers studying corporate misconduct (e.g. Nguyen et al. 2016, Wang 2011, Wang et al. 2010), assumes that the probability of misconduct is determined by two sets of variables. The first set is derived from the benefit of committing fraud and the second is derived from the probability of being detected. Empirically, the bivariate probit model addressing partial observability separates detection from commission processes. Let $M_{i,t}$ and $D_{i,t}$ be whether bank *i* commits misconduct in year *t* and whether misconduct is detected, respectively:

$$M_{i,t}^{*} = X_{M,i,t-1}\beta_{M} + \varepsilon_{i,t} \quad (3)$$

$$D_{i,t}^{*} = X_{D,i,t-1}\beta_{D} + \mu_{i,t} \quad (4)$$

Where, $X_{M,i,t-1}$ is a vector of variables explaining the incentive to commit misconduct, and $X_{D,i,t-1}$ is a set of variables that explain the banks' likelihood of being detected by the regulator. These two vectors do not contain the same variables and one of them has one or more variables that are absent in the other. $X_{M,i,t-1}$ contains the same variables that I use in my baseline model. However, $X_{D,i,t-1}$ does not contain the *equity ratio* and the proxy for earnings (*ROA*). I instead use the regulatory capital ratio and the Z-score. Since the regulatory capital ratio is one of the target ratios for regulators, a low level of this ratio will put the bank under the radar of supervisors. Similarly, Z-score is a proxy for bank stability. Low levels of this measure will indicate high earnings volatility and closeness to insolvency (e.g. Berger et al. 2017, Laeven and Levine 2009). Therefore, low values of these ratios will draw the attention of supervisors, increasing the chances of misconduct detection. $\varepsilon_{i,t}$ and $\mu_{i,t}$ are the disturbances that I assume that follow a bivariate normal distribution.

I represent $M_{i,t} = 1$ if $M_{i,t}^{*} > 1$ and $M_{i,t} = 0$ otherwise. I denote $D_{i,t} = 1$ if $D_{i,t}^{*} > 1$ and $D_{i,t} = 0$ otherwise. As the realizations of $M_{i,t}$ and $D_{i,t}$ are not observed directly, I define a variable $Z_{i,t} = M_{i,t} * D_{i,t}$. $Z_{i,t} = 1$ if a bank engages in misconduct and is detected, and $Z_{i,t} = 0$ if a bank does not engage in misconduct or if it engages in misconduct and is not detected by the regulator.

If I denote ϕ the bivariate standard normal cumulative distribution function, ρ the correlation between $\varepsilon_{i,t}$ and $\mu_{i,t}$ from (3) and (4), then:

$$P\left(Z_{i,t} = 1\right) = P\left(M_{i,t} = 1, D_{i,t} = 1\right) = \phi(X_{M,i,t-1}\beta_M, X_{D,i,t-1}\beta_D, \rho) \tag{5}$$

$$\begin{aligned} P\left(Z_{i,t} = 0\right) &= P\left(M_{i,t} = 0, D_{i,t} = 0\right) + P\left(M_{i,t} = 1, D_{i,t} = 0\right) \\ &= 1 - \phi(X_{M,i,t-1}\beta_M, X_{D,i,t-1}\beta_D, \rho) \end{aligned} \tag{6}$$

Therefore, the log-likelihood function allowing me to estimate the coefficients of the model[28] is as follows:

$$L(\beta_M, \beta_D, \rho) = \sum \log\left(\mathrm{P}\left(Z_{i,t} = 1\right)\right) + \sum \log\left(\mathrm{P}\left(Z_{i,t} = 0\right)\right) \tag{7}$$

[28] The model includes bank regulator and time fixed-effects.

ONLINE APPENDIX

Online Appendix Supplementary results

A.3.A Variables used in the computation of the social capital index

In Online Appendix Table A.3.A, I present probit regressions in which I replace the social capital index as main independent variable by each of the variables used in the computation of the Principal Component. These variables are related to civic norms RESPN (US Census response rate) and PVOTE (voter turnout) and related to networks ASSN (number of associations divided by population per 1,000) and NCCS (number of non-profit organizations divided by population per 10,000). In Column 1, I use all variables in the regression and show that the effect of social capital on bank misconduct is driven by both networks and respect for civic norms. In Columns 2 to 5, I introduce each variable separately in the regression. I observe that all variables forming the social capital index are negative and have a significant impact on bank misconduct.

A.3.B Pre-crisis, Crisis and Post-crisis periods

In Online Appendix Table A.3.B, I present probit regressions in which the baseline test is run for the pre-crisis (2001-2006) and post-crisis (2011-2015) periods. I find negative and significant coefficients for the variable *social capital* in the three periods. This test allows me to show that the effect of social capital is not driven by the crisis period. The same regression run in the period 2008-2010 has a negative and significant coefficient for *social capital* (not reported for brevity).

A.3.C Rare events logit model

It is evident from the descriptive statistics that the cases of misconduct (3.1% of the total observations) are a rare event. Statistical procedures, such as probit regressions may underestimate the probability of rare events. To verify the robustness of my results, in Online Appendix Table A.3.C, I follow King and Zeng (2001) and correct this potential downward bias using a rare events logit procedure. The result of this test is in line with the baseline model.

A.3.D Different regulators

In Online Appendix, Table A.3.D, I intend to rule-out the possibility that my result is driven by a different degree of enforcement for State and National banks. The fact that some banks are subject to examinations by a state level body and other banks exclusively by a federal body may lead to

inconsistencies in enforcement and supervisory processes (Agarwal et al. 2014). In order to address this aspect, I run separate regressions for National Banks (regulated by the OCC and subject to examinations by this supervisory body) and State Banks (regulated by either FDIC or Fed and subject to examinations by state and federal regulators under a periodical rotation policy). In Columns 1 and 2, I include all banks and in Columns 3 and 4, only banks operating in less than four states (as I find that the effect of social capital is more important for less geographically dispersed banks). In all cases, I find results that are consistent with my baseline regressions. I find that the coefficient for *social capital* is negative and statistically significant in all cases.

A.3.E Headquarter relocations

In Online Appendix, Table A.3.E, I report a linear probability model of a dummy variable representing misconduct on a dummy (*SCincreasing*) taking the value one if a bank is relocating its headquarters to a county that has a higher level of social capital and zero otherwise, *post* that takes the value one the third, fourth and fifth year after the headquarter relocation event and zero otherwise, and an interaction term *SCincreasing* post.* I also include the bank and county-level controls that I use in the baseline model. I choose a linear probability model because using non-linear models such as logit or probit with interaction terms may be problematic (Greene 2010). I run this regression on a sample of banks that relocate their headquarters once during the sample period (292 banks are affected). I remove from the sample banks that relocate more than once as in Hasan et al. (2017b). I follow Parsons et al. (2018) that indicate that the median time of misconduct detection is 3 years (for the cases in my sample for which I can identify the year when the misconduct –mostly non-technical cases- is committed I find that the average period between commission and announcement of misconduct is roughly 3 years). Consequently, I remove the three first years after the relocation, and run the regression on the three years previous to the relocation (t-3, t-2 and t-1) and the third, fourth and fifth year (t+3, t+4 and t+5) after the relocation. I only use three pre- and post-event years to avoid the influence of other events as I get further away from the relocation event. I restrict the sample to relocation events taking place between 2002 and 2012 to have a sufficient number of pre- and post-event years. There are 141 relocation events that are related to social capital increasing relocations and 151 events related to social capital decreasing relocations.

The interaction term *SCincreasing* post* captures the effect of social capital on bank misconduct after a relocation event takes place. The coefficient for this interaction is negative and statistically significant (at the 10% level), showing that moving to a county with greater social capital reduces the probability that a bank is involved in misconduct.

A.3.F Different geographical areas

In Online Appendix, Table A.3.F, Panel A, I replicate the baseline regression for different geographical areas in the US. I run one regression for each geographical area to rule-out the possibility that the results I document in the paper are driven by banks located in a particular region of the country. I run separate regressions for northern states (Column 1), southern states (Column 2), eastern states (Column 3) and western states (Column 4). Panel B shows which states fall in the different geographical areas. The results of the four regressions report a negative and significant coefficient for *social capital*.

A.3.G Other county-level variables

The choice of the county level variables in the main tests of the paper are motivated by the choices made in other papers studying the role of social capital on firm outcomes (e.g., Hasan et al. 2017 a, b, Jha and Cox 2015, etc.). In Online Appendix, Table A.3.G, I add other county-level control variables to rule-out the possibility that missing county-level variables bias the coefficient for *social capital*. In Column 1, I add county-level variables that may have a significant impact in the process of misconduct and other related firm outcomes (e.g. Parsons et al. 2018, Hilary and Huang, 2015, Di Giuli and Kostovetsky 2014). Besides the control variables used in the baseline model, I add population growth, wages growth, the natural logarithm of total population, the natural logarithm of population density, number of banks located in the same county, the distance from the closest regulatory office in km (following the indications in Wilson and Veuger (2017))[29] political orientation (the variable *republican* is the percentage of republican voters in each presidential election) and the

[29] This variable is the natural logarithm of the linear distance from the bank headquarters to the closest bank regulator's office. The distance is measured in kilometers. For State Banks, the distance is computed from the headquarters of the bank to the closest state regulator office. For National Banks, the distance is computed from the headquarters of the bank to the closest OCC office in the state. Banks with total assets higher than $50 billion tend to have a team of examiners that work permanently on-site. Therefore, I set the value of this variable equal to one for these banks. The variable has been computed using data from FDIC Summary of deposits, Call reports, OCC website and Wilson and Veuger (2017).

percentage of religious people.[30] When I add all these variables to the model, the effect of social capital on bank misconduct remains negative and statistically significant. Including these additional variables at once in the model may be problematic because of multicollinearity issues (as some of the county-level variables are highly correlated with each other). Therefore, in Columns 2 to 8, I add each variable separately (except religion because I included it in the robustness test section). In all cases, the coefficient for *social capital* is negative and statistically significant.

A.3.H Consequences of bank misconduct and the role of social capital: counties with two or more banks

In Table A.3.H in the appendix, I run the same regression as in Table 10 of the paper but limiting the sample to those counties where at least two different banks have branches. Since there are counties where solely a single bank institution has branches, this test aims at making sure that my results are not driven by those counties. The results from the regressions are similar to the ones in Table 10.

A.3.I Consequences of bank misconduct and the role of social capital: non-technical cases

Delis et al. (2019) shows that after banks receive enforcement actions related to violations of safety and soundness provisions, deposits at sanctioned banks decrease significantly. They find that this reduction is mainly driven by a demand-side effect (i.e., banks shrink assets) and not by depositors' withdrawals. They also find that enforcement actions unrelated to technical aspects do not cause a change in deposits. In order to rule out the fact that the coefficient for the main interaction term is picking up the effect documented by Delis et al. (2019), I focus only on enforcement actions that are unrelated to safety and soundness provisions and run a test similar to the one in Table 10. I run this test in Table A.3.I in the Online Appendix. I modify the indicator *misconduct*. This variable only takes the value one for enforcement actions of non-technical nature, and zero otherwise. Non-technical misconduct is defined in Appendix 1 and examples are provided in Appendix 2. Whenever a bank is receiving a technical and a non-technical enforcement action in the same year, the enforcement action indicator takes the value zero. In this table, I report that the interaction term *misconduct * Z social*

[30] Population related variables are collected or computed using US Census data. Wage growth is computed using BEA data. The number of banks in a county is computed using call reports data. Political orientation of the county is obtained using the percentage of votes for the Republican Party in each US presidential election between 2000 and 2016 (I use linear interpolation to fill-in the gaps between elections). *Religion* is defined in Appendix 1.

capital branches has a negative value in Column 1, is non-significant for the pre-crisis period (Column 2) and significant for the crisis and post-crisis period (Column 3). This result is in line with the result documented in Table 10.

Table A.3.A Different components of social capital

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on the different variables used to compute *social capital* and control variables. I report the marginal effect of each variable of interest in square brackets. In Column 1, I add the four components of *social capital*. In Columns 2 and 3, I include the variables related to civic norms RESPN (US Census response rate) and PVOTE (voter turnout), respectively. In Columns 4 and 5, I include the variables related to networks ASSN (number of associations divided by population per 1,000) and NCCS (number of non-profit organizations divided by population per 10,000), respectively. All independent variables are lagged one period. Fixed-effects are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered by bank. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity.

	(1)	(2)	(3)	(4)	(5)
	All components	RESPN	PVOTE	ASSN	NCCS
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
RESPN	-0.262*[-0.012]	-0.383***[-0.017]			
	(0.152)	(0.137)			
PVOTE	0.010[0.001]		-0.221*[-0.010]		
	(0.139)		(0.127)		
ASSN	-0.111***[-0.004]			-0.121***[-0.005]	
	(0.028)			(0.024)	
NCCS	-0.000[-0.000]				-0.001**[-0.000]
	(0.001)				(0.001)
Controls (Table 3)	Yes	Yes	Yes	Yes	Yes
Regulator and Time FE	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.168	0.167	0.167	0.168	0.167
Observations	101669	101669	101669	101669	101669
p-value test : RESPN+PVOTE=ASSN+NCCS	0.41				

Table A.3.B Pre-crisis, Crisis and Post-crisis periods

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and control variables. I report the marginal effect of the variable *social capital* in square brackets. In Column 1, I run the baseline regression for the pre-crisis period (2001-2007). In Column 2, I run the baseline regression for the post-crisis period (2011-2015). All independent variables are lagged one period. Fixed-effects are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered by bank. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1.

	(1)	(é)
	Pre-crisis	Post-crisis
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.044**[-0.001]**	**-0.110***[-0.006]**
	(0.018)	**(0.024)**
equity ratio	-0.031***	-0.022***
	(0.007)	(0.007)
allowance loan lease	0.221***	0.125***
	(0.019)	(0.017)
ROA	-0.313***	-0.243***
	(0.017)	(0.015)
liquidity	0.001	0.003
	(0.003)	(0.002)
RWA	0.008***	0.006***
	(0.001)	(0.001)
deposit ratio	0.004	-0.001
	(0.003)	(0.003)
age	0.042**	0.063***
	(0.018)	(0.021)
size	-0.335**	-0.927***
	(0.142)	(0.167)
size sq	0.019***	0.043***
	(0.006)	(0.006)
competition	0.033	0.131
	(0.154)	(0.166)
BHC	0.010	-0.101**
	(0.044)	(0.042)
publicly held	-0.119**	0.075
	(0.059)	(0.060)
income pc	0.079	-0.156
	(0.128)	(0.122)
employment	-0.000	0.005***
	(0.002)	(0.002)
education	-0.005	0.001
	(0.003)	(0.003)
median age	-0.056	0.097
	(0.194)	(0.188)
rural	-0.031	0.022
	(0.042)	(0.047)
Constant	-1.944	3.673**
	(1.532)	(1.661)
Regulator and Time FE	Yes	Yes
Pseudo-R2	0.124	0.147
Observations	51263	30398

Table A.3.C Rare events logit model

This table reports the results of a non-linear regression of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and control variables. I report the marginal effect of the variable *social capital* in square brackets. I run a rare events logit model as suggested by King and Zang (2001). All independent variables are lagged one period. Fixed-effects are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered by bank. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1.

	(1) Rare events
Dependent var. :	P(Misconduct=1)
social capital	**-0.116***[-0.003]**
	(0.028)
equity ratio	-0.082***
	(0.009)
allowance loan lease	0.293***
	(0.025)
ROA	-0.532***
	(0.020)
liquidity	-0.001
	(0.004)
RWA	0.019***
	(0.002)
deposit ratio	0.002
	(0.004)
age	0.089***
	(0.024)
size	-1.022***
	(0.223)
size sq	0.051***
	(0.009)
competition	0.256
	(0.219)
BHC	-0.052
	(0.057)
publicly held	-0.157**
	(0.079)
income pc	-0.272*
	(0.155)
employment	0.003
	(0.002)
education	0.007*
	(0.004)
median age	-0.160
	(0.244)
rural	0.031
	(0.059)
Constant	2.261
	(2.029)
Regulator FE	Yes
Time FE	Yes
Observations	101669

Table A.3.D Different regulators

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and control variables. I report the marginal effects in square brackets. In Column 1, I run the baseline model on the sample of National banks (regulated by the OCC). In Column 2, I run the baseline model on the sample of State banks (regulated either by the FDIC or the Fed). In Column 3, I run the baseline model on the sample of National banks (regulated by the OCC) that are present in less than 5 states. In Column 4, I run the baseline model on the sample of State banks (regulated either by the FDIC or the Fed) that are present in less than 5 states. All independent variables are lagged one period. Fixed-effects are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered by bank. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity.

	(1)	(2)	(3)	(4)
Sample :	Banks regulated by OCC	Banks regulated by FDIC or Fed	Banks in <5 states regulated by OCC	Banks in <5 states regulated by FDIC or Fed
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.036*[-0.002]**	**-0.065***[-0.002]**	**-0.050**[0.003]**	**-0.067***[0.003]**
	(0.022)	**(0.015)**	**(0.022)**	**(0.01)**
Controls (Table 3)	Yes	Yes	Yes	Yes
Regulator FE	No	Yes	No	Yes
Time FE	Yes	Yes	Yes	Yes
Pseudo-R2	0.137	0.183	0.140	0.180
Observations	22164	79505	21814	79221

Table A.3.E Headquarter relocations

This table reports the results of a linear probability model. I run a regression of a dummy variable representing misconduct on a dummy (*SCincreasing*) taking the value one if a bank is relocating its headquarters to a county that has a higher level of social capital and zero otherwise, *post* that takes the value one the third, fourth and fifth year after the headquarter relocation and zero otherwise, and interaction term *SCincreasing*post*. I also add the rest of bank and county-level controls that I use in the baseline model. I run this regression on a sample of banks that relocate their headquarters once during the sample period (292 banks are affected). I remove from the sample banks that relocate more than once as in Hasan et al. (2017b). I follow Parsons et al. (2018) that indicate that the median time of misconduct detection is 3 years. Consequently, I remove the three first years after the relocation, and run the regression on the three years previous to the relocation (t-3, t-2 and t-1) and the third, fourth and fifth year (t+3, t+4 and t+5) after the relocation. I only use three pre- and post-event years to the influence of other events taking place as I get further away from the relocation event. I restrict the sample to relocation events taking place between 2002 and 2012 to have a sufficient number of pre- and post-event years. There are 141 relocation events that are related to social capital increasing relocations and 151 events related to social capital decreasing relocations. I use time and regulator dummies. Standard errors (reported in parentheses) are robust to heteroscedasticity. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1.

	(1) Relocations
Dependent var. :	Misconduct
SCincreasing	0.017
	(0.013)
post	0.040**
	(0.019)
SCincreasing *post	**-0.037***
	(0.022)
equity ratio	-0.001
	(0.002)
allowance loan lease	0.029***
	(0.011)
ROA	-0.036***
	(0.006)
liquidity	-0.001
	(0.001)
RWA	0.001
	(0.000)
deposit ratio	0.001
	(0.001)
age	0.004
	(0.008)
size	-0.070
	(0.052)
size sq	0.003
	(0.002)
competition	0.086
	(0.061)
BHC	-0.028
	(0.020)
publicly held	0.011
	(0.021)
income pc	0.047
	(0.037)
employment	-0.001
	(0.001)
education	-0.000
	(0.001)
median age	-0.093
	(0.076)
rural	-0.008
	(0.016)
Constant	0.013
	(0.507)
Regulator and time dummies	Yes
Adj-R2	0.095
Observations	1419

Table A.3.F Different geographical areas

This table reports the results of probit regressions of a dummy variable taking the value one in the presence of misconduct and zero otherwise on a social capital variable and control variables. I report the marginal effects in square brackets. In Column 1, I run the baseline model on the sample of banks located in the northern area of the US. In Column 2, I run the baseline model on the sample of banks located in the southern area of the US. In Column 3, I run the baseline model on the sample of banks located in the eastern area of the US. In Column 4, I run the baseline model on the sample of banks located in the western area of the US. Panel A shows the results of the regressions. Panel B shows the classification of the states into North, South, East or West. All independent variables are lagged one period. Fixed-effects are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity and clustered by bank. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity.

Panel A	(1)	(2)	(3)	(4)
Sample :	North	South	East	West
Dependent var. :	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)	P(Misconduct=1)
social capital	**-0.063***[-0.003]**	**-0.050**[-0.002]**	**-0.053***[-0.002]**	**-0.079***[-0.003]**
	(0.019)	**(0.020)**	**(0.015)**	**(0.021)**
Controls (Table 3)	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Pseudo-R2	0.165	0.171	0.173	0.168
Observations	53973	47696	68378	33291

Panel B

State	Columns (1) and (2)	Columns (3) and (4)
Alabama	south	east
Arizona	south	west
Arkansas	south	east
California	south	west
Colorado	south	west
Connecticut	north	east
Delaware	north	east
District of Columbia	north	east
Florida	south	east
Georgia	south	east
Idaho	north	west
Illinois	north	east
Indiana	north	east
Iowa	north	east
Kansas	south	west
Kentucky	south	east
Louisiana	south	east
Maine	north	east
Maryland	south	east
Massachusetts	north	east
Michigan	north	east
Minnesota	north	east
Mississippi	south	east
Missouri	north	east
Montana	north	west
Nebraska	north	west
Nevada	south	west
New Hampshire	north	east
New Jersey	north	east
New Mexico	south	west
New York	north	east
North Carolina	south	east
North Dakota	north	west
Ohio	north	east
Oklahoma	south	west
Oregon	north	west
Pennsylvania	north	east
Rhode Island	north	east
South Carolina	south	east
South Dakota	north	west
Tennessee	south	east
Texas	south	west
Utah	south	west
Vermont	north	east
Virginia	south	east
Washington	north	west
West Virginia	south	east
Wisconsin	north	east
Wyoming	north	west

Table A.3.G. Other county-level variables

This table reports the results of probit regressions of a dummy taking the value one in the presence of misconduct and zero otherwise on a subset of variables. In Column 1, I include the social capital variable, the same control variables that I use in Table 3 and a subset of county-level controls (population growth, wage growth, natural log of total population, percentage of people voting for the republican party, natural logarithm of the number of banks, natural logarithm of the distance of the bank headquarters from the closest regulatory office and percentage of religious adherents). In Columns 2 to 8, I add each county-level variable separately (except *religion*). I report the marginal effect of the variable *social capital* in square brackets. Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. Definitions for all variables are provided in Appendix 1. Constant terms are included in the regression although they are not shown in the table for brevity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	All	Pop gr	Wage gr	Pop	Pop Density	Republican	Nb of banks	Dist. to regulator
Dependent var. :	P(Misconduct=1)							
social capital	**-0.036****	**-0.051*****	**-0.056*****	**-0.039*****	**-0.038*****	**-0.055*****	**-0.054*****	**-0.054*****
	[-0.002]	**[-0.002]**	**[-0.003]**	**[-0.002]**	**[-0.002]**	**[-0.003]**	**[-0.002]**	**[-0.002]**
	(0.015)	**(0.012)**	**(0.012)**	**(0.014)**	**(0.013)**	**(0.012)**	**(0.012)**	**(0.012)**
population gr.	0.125	0.036						
	(0.107)	(0.098)						
wage gr.	0.000		-0.000					
	(0.004)		(0.004)					
population (ln)	0.012			0.027**				
	(0.020)			(0.011)				
pop density (ln)	0.020				0.031***			
	(0.016)				(0.010)			
republican	-0.001					-0.002**		
	(0.001)					(0.001)		
numb of banks (ln)	-0.013						0.010	
	(0.018)						(0.013)	
distance to regulator (ln)	-0.001							-0.010
	(0.001)							(0.001)
religion	0.000							
	(0.001)							
Baseline controls (Table 3)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.169	0.168	0.168	0.168	0.168	0.168	0.168	0.167
Observations	98843	99780	101669	101669	101669	101669	101669	101359

Table A.3.H. Consequences of bank misconduct using counties with 2 banks or more

This table reports the results of OLS regressions of a variable that measures the annual percentage change of the market-share of deposits for each bank in each county from June 30th of year *t-1* to June 30th of year *t* on *misconduct* (a variable that takes the value one the year a bank is subject to an enforcement action an zero otherwise), a standardized measure of social capital measured for each market (i.e. counties where banks have branches), the interaction term *misconduct * Z social capital branches* and a subset of bank level and county-level control variables. The sample includes those counties where two or more banks have branches. The unit of observation is the county-bank level. In Column 1, I use the whole sample (2001-2015), in Column 2, I use the pre-crisis period sample (2001-2007), and in Column 3, I use the crisis and post-crisis period sample (2008-2015). Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. County-level variables are measured for each county in which a bank is present. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. All variables are defined in Appendix 1.

	(1)	(2)	(3)
Sample : Counties with >=2 banks	All	Pre-Crisis	Crisis & Post-crisis
Dependent var. :		%ΔMarket-share of deposits	
misconduct	-0.995***	-2.671***	-1.111***
	(0.224)	(0.549)	(0.246)
Z social capital branches	-1.057***	-1.699***	-0.554***
	(0.121)	(0.174)	(0.157)
misconduct * Z social capital branches	**-0.305**	**0.608**	**-0.625*****
	(0.186)	**(0.488)**	**(0.204)**
Controls (Table 10)	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Cluster	Bank-county	Bank-county	Bank-county
Adj. R2	0.032	0.033	0.034
Observations	319622	138621	181001

Table A.3.I. Consequences of bank misconduct using non-technical enforcement actions

This table reports the results of OLS regressions of a variable that measures the annual percentage change of the market-share of deposits for each bank in each county from June 30th of year *t-1* to June 30th of year *t* on *misconduct* (a variable that takes the value one the year a bank is subject to an enforcement action an zero otherwise), a standardized measure of social capital measured for each market (i.e. counties where banks have branches), the interaction term *misconduct * Z social capital branches* and a subset of bank level and county-level control variables. The unit of observation is the county-bank level. In Column 1, I use the whole sample (2001-2015), in Column 2, I use the pre-crisis period sample (2001-2007), and in Column 3, I use the crisis and post-crisis period sample (2008-2015). Fixed-effects and the cluster level of standard errors are specified in the table. Standard errors (reported in parentheses) are robust to heteroscedasticity. All independent variables are lagged one period. County-level variables are measured for each county in which a bank is present. *, **, and *** represent significance levels of 0.10, 0.05 and 0.01, respectively. All variables are defined in Appendix 1.

	(1)	(2)	(3)
Sample :	All	Pre-Crisis	Crisis & Post-crisis
Dependent var. :		%ΔMarket-share of deposits	
Non-technical misconduct	0.497**	-1.042*	0.124
	(0.244)	(0.600)	(0.267)
Z social capital branches	-1.028***	-1.682***	-0.520***
	(0.119)	(0.172)	(0.155)
Non-technical misconduct * Z social capital branches	**-0.586*** **	**0.645**	**-0.967*** **
	(0.204)	**(0.553)**	**(0.223)**
Controls (Table 10)	Yes	Yes	Yes
Regulator FE	Yes	Yes	Yes
State x Year FE	Yes	Yes	Yes
Cluster	Bank-county	Bank-county	Bank-county
Adj. R2	0.032	0.033	0.034
Observations	321360	139439	181921