SOCIAL CAPITAL AND MORTGAGES

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Abstract

We discover that the social capital of the community in which households live positively influences the likelihood that their mortgage applications are approved, the terms of approved mortgages, and the subsequent performance on those mortgages. The results hold when conditioning on household and community characteristics and an array of fixed effects, including individual effects data permitting, and when employing instrumental variables and propensity score matching to address identification and selection concerns. Concerning causal mechanisms, evidence suggests that social capital enhances lender screening and monitoring of borrowers and increases the social costs to borrowers from defaulting on their debts.

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"In measurable and well-documented ways, social capital makes an enormous difference in our lives."
– *Robert D. Putnam (2020, p.290).*

1. Introduction

Research suggests that access to mortgage credit shapes long-run wealth accumulation, the neighborhoods where families raise their children, and other components of household welfare (e.g., Campbell, 2006; Karlan and Zinman, 2010; Célérier and Matray, 2019; Bartlett, Morse, Stanton, and Wallace, 2022). This research naturally motivates questions about the factors determining access to mortgage credit, including determinants other than traditional measures of household income, wealth, and creditworthiness.

In this paper, we examine the question: Does the social capital of the community in which a family lives exert an independent impact on access to mortgage credit, the terms on approved mortgages, and subsequent performance on those mortgages? Consistent with an extensive literature, we define *social capital* as the networks, norms, and trust within groups that facilitate communication, cooperation, and coordination for mutual benefit (e.g., Putnam, 1997; Coleman, 1990). Research documents that social capital shapes aggregate economic performance (e.g., Fukuyama, 1995; Knack and Keefer, 1997; Routledge and Von Amsberg, 2003; Guiso, Sapienza, and Zingales, 2009), firm performance (e.g., Lins, Servaes, and Tamayo, 2017; Jha and Chen, 2015; Pevzner, Xie, and Xin, 2015; Hasan, Hoi, Wu, and Zhang, 2017a, 2017b; Gennaioli, La Porta, Lopez-de-Silanes, Shleifer, 2022), and household decisions (e.g., Guiso, Sapienza, and Zingales, 2004; Hong, Kubik, and Stein, 2004). However, we are unaware of previous research using loan-level data to explore how social capital shapes mortgages, which account for about 70% of total U.S. consumer debt.[1]

[1] See the Federal Reserve Bank of New York Quarterly Report on Household Debt and Credit, https://www.newyorkfed.org/microeconomics/hhdc.

Theory offers ambiguous predictions about the impact of social capital on mortgage credit. Greater social interconnectedness that spurs cooperation, trust, and communication can improve the effectiveness of lenders' decisions in at least two ways. First, social capital that reduces informational asymmetries can enhance lenders' screening and monitoring of borrowers (Nooteboom, Berger, and Noorderhaven, 1997; Lewicki, McAllister, and Bies, 1998). Second, social capital that fosters trust and strengthens social bonds will tend to increase the costs to borrowers from defaulting on their debts, especially to lenders within the community. In these ways, social capital can increase the approval rates of those who choose to apply for mortgages, the terms of approved mortgages, and the performance of those loans. However, social capital may impede efficient credit allocation if strong social connections induce loan officers to make lending decisions based on nepotism and cronyism rather than sound financial principles. Such favoritism could generate a negative relationship between social capital and borrower performance that also affects mortgage terms and credit availability. Thus, the effects of social capital on mortgage approval decisions, the terms on approved loans, and subsequent performance on those mortgages are open empirical questions.

To address these questions, we use data from the anonymized confidential loan-level HMDA data covering over 90% of all consumer mortgage applications and approval decisions in the U.S. and information on several consumer risk characteristics, such as income and the loan-to-income ratio. We also use the anonymized Federal Reserve merged HMDA-McDash data that track mortgage loan performance over time, contains comprehensive information on mortgage terms (e.g., interest rates and maturities), and provides details on consumer domiciles. We merge these datasets with county-level social capital data from the Northeast Regional Center for Rural Development (NRCRD) and the General Social Survey (GSS), respectively. To measure social capital, the NRCRD contains county-level information on presidential election voter turnout, the response rate to the decennial census, and the prevalence of social organizations and tax-exempt non-profit organizations. Besides examining these individual social capital indicators, we primarily follow prior research (e.g., Rupasingha, Goetz, and Freshwater, 2006; Hasan et al., 2017a, 2017b; Hoi, Wu, and Zhang, 2019) and use the first principal component of these individual indicators.

We discover that social capital exerts a positive and economically significant effect on mortgage approval rates. The baseline, ordinary least squares (OLS) regressions include bank-time fixed effects to control for the possibility that time-varying lender characteristics shape credit decisions and borrower traits that might influence mortgage approvals (e.g., debt, income, loan amount, gender, race, etc.). To isolate the role of a county's social capital, we include numerous county-level characteristics (e.g., average income, unemployment, population density, average credit scores, etc.) and state-time fixed effects to further control for changes in local economic conditions shaping mortgage markets. Besides indicating a robust, statistically significant positive relationship between social capital and approval rates, the estimates suggest the relationship is economically large. For example, consider a prospective borrower living in a county at the 90th percentile of the social capital distribution and an otherwise identical prospective borrower living in a county at the 10th percentile of the distribution. Our estimates suggest that moving the individual from the low to the high social capital county would increase the prospective borrower's probability of having the mortgage application approved by four percentage points, suggesting material influences of social capital on access to mortgages.

This finding is robust to using several statistical methods to address identification and selection concerns. First, we use instrumental variables (IV) to enhance identification. Hoi et al. (2019) develop an instrument for social capital based on the countries of ancestry of people living in U.S. communities. They show that the social characteristics of ancestral countries help explain cross-community differences in social capital. We use ancestral trust, i.e., the level of trust of the countries of ancestry, to identify social capital's impact on credit decisions. The resulting IV estimates indicate that social capital boosts loan approval rates. Second, we use propensity score matching (PSM) to address the concern that the nonrandom assignment of individuals across counties could interfere with identifying the impact of social capital on mortgage approvals. We construct artificial control groups by matching each treated loan application with non-treated loan applications having similar observable characteristics. We define a *treated* county as one with sufficiently high social capital. Consistent with the other analyses, the PSM results indicate that social capital boosts approval rates, reducing concerns that our findings reflect differences in the traits of high– and low–social capital counties rather than the effect of social capital on credit approval. Finally, we saturate the OLS, IV, and PSM regression models with additional county characteristics to reduce omitted variable concerns. All of the results hold with little change in the estimated coefficient on social capital.

We also explore potential mechanisms of how social capital influences mortgage approvals: enhancing interpersonal connections and trust. From this perspective, we should find that the relationship between social capital and loan approval weakens when studying lenders that rely less on interpersonal interactions with borrowers. We first conduct three falsification tests of this view. First, we examine mortgage decisions generated by automated underwriting systems (AUSs), which do not use interpersonal interactions in their decisions, and find no relationship between social capital and mortgage approval rates. Second, we focus on fintech lenders, which have fewer direct interactions with borrowers than traditional lenders, and find that the relationship between social capital and mortgage approval rates is weaker among fintech lenders. Third, we examine applications where the bank does not have a branch near the borrower. These are banks where interpersonal interactions are less likely to shape credit decisions. Consistent with the interpersonal connections mechanism, social capital has little effect on loan approval rates on these mortgages. Finally, we conduct a different test of the view that social capital shapes credit decisions by easing informational asymmetries. As a proxy for informational asymmetries between lenders and borrowers, we examine the time it takes lenders to screen mortgage applications and issue decisions. If social capital facilitates the acquisition and processing of information about borrowers, we expect that social capital will reduce screening time. Consistent with this conjecture, we find that higher levels of social capital are associated with shorter screening times.

We next examine the impact of social capital on the terms of approved mortgages. We discover that social capital significantly improves lending terms. Specifically, borrowers in higher social capital counties obtain mortgages with lower interest rates and longer maturities than similar borrowers in other counties. Consistent with the view that social capital increases the social costs to borrowers from defaulting on their debts and the ability of lenders to screen and monitor borrowers, social capital enhances the terms of mortgages.

Moreover, we find that social capital boosts loan performance. To measure performance, we focus on loan delinquency, measured by whether the loan was ever 60 days past due during the three years after origination, and show the results are robust to using alternative performance metrics. Our work relates to Li, Ucar, and Yavas (2022), who find a negative relationship between social capital and loan delinquencies using county-level data. We use loan-level data, control for numerous borrower traits, lender-time and state-time fixed effects, and a much more extensive array of time-varying country traits to address omitted variable concerns and employ a PSM strategy to address selection concerns. We find a strong, negative relationship between social capital and mortgage delinquencies and show that this finding is robust to using OLS, IV, PSM, and saturating these regression analyses with borrower and county controls.

Finally, we use an alternative dataset that allows us to estimate loan performance regressions with individual fixed effects. The anonymized Federal Reserve Bank of New York's Consumer Credit Panel/Equifax (CCP) contains data at the individual-mortgage-quarter level. Thus, we have information on individuals who obtained mortgages in counties with different levels of social capital.

As a result, we can condition on individual fixed effects. By including individual fixed effects, we test whether an individual's performance on a mortgage differs when the person is in a higher or lower social capital county while also conditioning on the full array of other covariates. We find a strong, negative relationship between social capital and mortgage delinquencies. Since we cannot obtain such granular data on approvals or credit terms, we can only condition on individual fixed effects in the delinquency analyses.

Our research makes several unique contributions to the consumer finance literature. First, we believe we offer the first loan-level assessment of the impact of social capital on the largest component of the consumer credit market in the United States: household mortgages. Second, we provide a holistic treatment of the mortgage market that evaluates the effects of social capital on mortgage approval rates, the terms of approved mortgages, and repayment delinquencies. Third, exploiting the most granular data available on mortgage applications, approvals, terms, and performance, we employ an array of statistical methods to mitigate challenges to identifying the impact of social capital on mortgages. Fourth, we offer several tests of the mechanisms through which social capital influences mortgages. Our findings suggest that social capital boosts mortgage approval rates, loan terms, and loan performance by enhancing lender screening and monitoring of borrowers and increasing the social costs to borrowers from defaulting on their debts.

Furthermore, our findings have broad, policy-relevant implications. Our findings suggest that social capital shapes wealth accumulation, the neighborhoods where families can raise their children, and other factors shaping household welfare, as indicated by the work of Campbell (2006), Karlan and Zinman (2010), Célérier and Matray (2019), and Bartlett et al. (2022). Thus, beyond traditional metrics of creditworthiness, social capital affects families' economic horizons, advertising the importance of community engagements that build communication, cooperation, and coordination (Putnam, 2020). Our findings also indicate that fintech lenders could reduce the adverse effects of living in low social capital communities because they do not rely on social capital to make loans. While there are many concerns with the artificial intelligence processes underlying many fintech lenders, addressing those weaknesses could significantly benefit borrowers living in low social capital areas.

Our research relates to work on the role of soft information in credit decisions. Building on Stein (2002), extensive research finds that soft information, the information obtained through interpersonal interactions and familiarity with local economies and individuals, strongly influences informational asymmetries and lending decisions (e.g., Puri and Rocholl, 2008; Agarwal and Hauswald, 2010; An, Deng, and Gabriel, 2011; Heider and Inderst, 2012; Ergungor and Moulton, 2014; Rajan, Seru, and Vig, 2015; An, Do, Riddiough, and Yao, 2015; Agarwal, Chomsisengphet, Liu, Song, and Souleles, 2018). Our work is distinct in focusing on social capital as a form of soft information. We find that social capital—the networks, norms, and trust within communities—significantly affects the mortgage lending decisions, mortgage terms, and subsequent delinquency rates.

Furthermore, our work relates to research on how non-financial borrower metrics affect loan approval rates. Munnell, Tootell, Browne, and McEneaney (1996) find that White applicants with the same property and personal characteristics as minorities experienced lower rejection rates after controlling for borrower characteristics. Bartlett et al. (2022) show that approximately 1 million minority applications were rejected between 2009 and 2015 due to discrimination. Taste-based cultural affinity (e.g., Hunter and Walker, 1996; Bostic and Robinson, 2003) and fluctuations in local sunshine (Cortés, Duchin, and Sosyura, 2016) also affect mortgage lending decisions. Our paper provides evidence that the social capital of the communities in which individuals live shapes their access to mortgage credit, the terms of that credit, and repayment performance.

In the remainder of the paper, we discuss the data, sample construction, and econometric models in Section 2, present the findings on social capital and credit approvals in Section 3, examine how social capital shapes loan terms in Section 4, and evaluate the impact of social capital on credit performance in Section 5. Section 6 concludes.

2. Data and Empirical Approach

2.1 Social capital data

Extensive research defines social capital as the strength of secular social norms and the density of social networks that function through interpersonal relationships and a shared sense of identity, understanding, values, trust, cooperation, and reciprocity (e.g., Putnam, 2000). Accordingly, high social capital communities are more likely to induce cooperation and trust among community members and promote behaviors that conform to social norms. They are also more likely to punish conduct that deviates from social norms and deter opportunistic behavior (e.g., Coleman, 1994; Spagnolo, 1999; Buonanno, Montolio, and Vanin, 2009). Portes (1998) argues that such social norms are passed and internalized into society from generation to generation.

We use data from the NRCRD at the Pennsylvania State University to measure social capital.[3] This dataset contains information on four relevant features of U.S. counties in 1997, 2005, 2009, and 2014: *PVOTE* equals the percentage of eligible voters who voted in the last presidential election; *RESPN* equals the response rate to the Census Bureau's decennial census; *ASSN* equals the total number of 10 different types of social organizations in the local community divided by the population per 1,000; and *NCCS* equals the number of tax-exempt non-profit organizations divided by population per 10,000.

Following Rupasingha et al. (2006), Hasan et al. (2017a, 2017b), and Hoi et al. (2019), we combine these four indicators into an overall, county-level social capital index, *SK*, by computing the

[3] See https://aese.psu.edu/nercrd/community/social-capital-resources.

first principal component of *PVOTE*, *RESPN*, *ASSN*, and *NCCS*.[4] Past research suggests that these four indicators provide information on social capital. Specifically, without legal requirements or material incentives to vote or participate in census surveys, *PVOTE* and *RESPN* likely reflect the degree to which individuals respond to civic responsibilities (e.g., Knack, 1992; Guiso et al., 2004). Furthermore, Coleman (1988) and Putnam (1993) contend that the types of social networks that manifest in social and non-profit organizations—as captured by *ASSN* and *NCCS*—foster the cooperation and civic norms underlying social capital. Appendix Y contains more details on the social capital measure and its components.[5]

2.2 Loan data and sample construction

We obtain loan-level data starting in 1998 from the Federal Reserve System's confidential HMDA Loan Application Registry. The data cover about 90% of all mortgage loan applications in the U.S. and the majority of public and private mortgage lenders.[6] For each loan application, we obtain data on the decision (approved, declined, withdrawn, closed for incompleteness, etc.) and various consumer characteristics (income, race, ethnicity, gender, presence of a co-applicant), loan attributes (loan amount requested, purpose), and property location (state, county, census tract).[7] Although the publicly available version of HMDA only reports the year of mortgage origination, the confidential version that

[4] Consistent with these earlier papers, we fill in missing data from 1998 to 2004 using available data in 1997, and from 2006 to 2014 using data in 2005. For 2015, we use data from 2014. Following prior research (e.g., Hasan et al., 2017a, 2017b), we also address data reporting inconsistencies across years by excluding: i) data on social associations for which NRCRD does not provide consistent reporting over time, which excludes memberships in sports and recreation (*MEMSPT*) organizations and organizations not elsewhere classified (*MEMNEC*), and ii) data for Alaska and Hawaii, which only became available in 2014. The results hold when we do not address these data reporting inconsistencies.

[5] Results are robust to using alternative methods to construct *SK:* i) using only the years when NRCRD has social capital data (2005, 2009, and 2014) or ii) generating *SK* for missing years using linear interpolation. Finally, results also hold using a social capital measure based on county-level voter turnout in the general election using data from the Cooperative Congressional Election Study (*CCES Turnout*). Appendix X, Panel D of Table X.2 and Table X.8 show that each of these three alternative social capital constructs is significantly associated with higher credit approval rates and lower delinquency rates, respectively.

[6] As of 2007, the median year in our sample, HMDA requirements stipulate that depository institutions with the home office or at least one branch office in a metropolitan statistical area (MSA) must report their HMDA loans if they made either home purchase loans on a one- to four-unit dwelling or refinanced home purchase loans, and if they have total assets greater than $36 million (https://www.ffiec.gov/hmda/reportde2007.htm; https://www.ffiec.gov/hmda/reporterhistory.htm). Thus, these requirements apply for the vast majority of the depository institutions.

[7] See https://www.ffiec.gov/hmda/history2.htm.

we employ includes the exact dates when the consumer submitted the application and when the loan officer issued a decision.

To analyze the performance of originated mortgage loans, we use the merged, anonymized HMDA-McDash dataset, as HMDA only includes data on mortgage applications, not the subsequent performance of approved loans. The raw McDash data provided by Black Knight Data & Analytics, LLC aggregates information from loan servicers. It includes information on loan performance, consumer risk (e.g., FICO credit score), and loan characteristics (e.g., loan amount, interest rate, maturity, property location, type, and loan-to-value ratios). The McDash data cover about two-thirds of all mortgages (e.g., Cortés et al., 2016). The Federal Reserve merged the HMDA and McDash datasets to create a loan-level data set with information on loan performance and other borrower characteristics.

Our sample construction process begins with a 20% random sample of mortgage applications from the confidential HMDA and a 20% random sample of approved mortgage loans from HMDA-McDash, from 1998 to 2015. The unit of observation is a mortgage-application day. We begin our sample in 1998 to accommodate HMDA-McDash performance data, which are better populated from 1998 onward (Cortés et al., 2016). We end in 2015 because the Federal Reserve has only merged the HMDA and McDash datasets through 2015.

Following the literature (e.g., Duchin and Sosyura, 2014; Chu and Zhang, 2022), we apply several data filters: 1) we retain only applications that are either approved or denied (e.g., we exclude applications that were withdrawn or closed for incompleteness before the decision); 2) we exclude observations with missing decision action dates or those that fall on non-workdays; 3) we retain only conventional mortgage applications (e.g., we exclude government-insured mortgages, such as FHA (Federal Housing Administration), VA (Veterans Affairs), FAS (Farm Service Agency), or RHS (Rural

Housing Service) mortgages); 4) we retain only home purchases, and exclude refinancing and home improvement loans because we are interested solely in home-purchase mortgage originations; 5) we exclude loans sold upon origination because they have relatively little effect on the originating lender's portfolio risk;[8] and 6) we retain only owner-occupied properties to ensure that consumers live at the property and are thus subject to the local social norms and networks.

We then use the link file developed by Robert Avery to identify banks and merge the HMDA data with other financial data from the Call Reports. Our baseline analyses focus on mortgage applications submitted to banks. We thus exclude non-bank lenders because they are less likely to interact face-to-face with borrowers. Using the annual FDIC Summary of Deposits data, which include locations for all bank branches, we remove broker-originated applications (those filed with lenders that do not have a branch in the county of the mortgaged property). These applications are typically sent to external processing centers, so we cannot infer the location of the loan officer.

We merge these data with social capital measures from the NRCRD and county-level controls from several sources, including the Internal Revenue Service (IRS), the Haver Analytics/BLS, the U.S. Census Bureau, CoreLogic Solutions, and the FRBNY Consumer Credit Panel/Equifax (CCP). Our final sample consists of 2,578,020 mortgage applications from 1998 to 2015, of which 2,118,673 were approved, and 459,347 denied, for an average denial rate of about 18%. The mortgage applications were submitted to 5,579 unique banks in 2,916 counties over 216 different monthly periods. Figure 1 shows the geographical distribution of social capital (*SK*) across U.S. counties in 2014. Table 1 reports summary statistics for the key variables in our analysis.[9]

[8] In particular, we identify purchaser type for sold mortgages, e.g., Fannie Mae, Ginnie Mae, Freddie Mac, Farmer Mac, private securitization, etc. We exclude all such sold loans except those where the purchaser is a commercial bank, savings bank, or savings association. Our results are robust if we exclude all sold loans, which usually leave the originating bank's books within 39 days of issuance (Rosen, 2011).

[9] To address the concern that lenders may exhibit year-end window-dressing behavior in HMDA data (e.g., Evanoff and Segal, 1997), we show that the results hold when excluding December of each year from the sample as shown in Appendix X, Table X.2, Panel E.

3. Social Capital and Consumer Credit Approval

3.1 Methodology

This section investigates the relationship between social capital and loan approvals. We follow the prior mortgage loan origination literature and estimate a linear probability model of loan approvals (e.g., Munnell et al., 1996; Bhutta, 2011; Puri, Rocholl, and Steffen, 2011; Duchin and Sosyura, 2014; Cortés et al., 2016). The outcome variable is a bank's decision to approve or deny the loan application. We estimate the following model:

$$\begin{gathered} Approved_{i,m,b,t} = \delta_0 + \delta_1 Social\ Capital_{m,t-1} + \delta_2 Borrower\ Controls_i + \\ \delta_3 County\ Controls_{m,t-1} + \alpha_{b,t} + \varphi_{s,t} + \varepsilon_{i,m,b,t}. \end{gathered} \tag{1}$$

Note that *i* indexes the mortgage application, *m* indexes the borrower county, *b* indexes the bank, and *t* indexes the month-year. *Approved* is a dummy variable that equals 1 if the loan application is approved (action_type = 1 or 2) and 0 if it is denied (action_type = 3). *Social Capital* is the level of social capital in the county of the borrower's property in the year immediately before the borrower applied for a mortgage as defined in Section 2.1.

We condition on borrower- (*Borrower Controls*) and county-level controls (*County Controls*). For *Borrower Controls*, we include: *Debt-to-Income*, the applicant's requested loan debt-to-income ratio; *Ln(Borrower Income)*, the natural logarithm of the applicant's income; *Minority* and *Female*, binary variables indicating the applicant's responses to questions about race and gender, respectively; *Co-Applicant*, a binary variable for whether there is a co-applicant; *Metro*, an indicator for whether the applicant's property is located in an MSA; *Ln(Loan Amount)*, the natural logarithm of the size of the mortgage loan; and *Ln(Loan Amount) Sq*, the square of *Ln(Loan Amount)*. To isolate the relationship between access to mortgage credit and social capital from county-level economic characteristics, we also use a vector of *County Controls*: *Ln(Cnty Income)*, the natural logarithm of county income; *Cnty Unemployment Rate*, the rate of unemployment in the county; *ΔCnty HPI*, the change in a county's house price index; *Population Density*, county population scaled by surface square miles; *Cnty Credit Score*, the average consumer credit score in the county; *Cnty Age*, the average of people in the county, and *Cnty Age Sq*, the square of *Cnty Age*, which captures the possible non-linear relationship between age and credit outcomes. All county controls are lagged by one quarter or one year (depending on the frequency of the original data) to reduce simultaneity concerns (e.g., Duchin, Ozbas, and Sensoy, 2010). We conduct robustness checks using additional local market characteristics.

Finally, we control for the possibility that time-varying characteristics of lenders and the state could shape credit decisions. Specifically, we include (1) *Bank* × *Month-Year* fixed effects ($\alpha_{b,t}$) to control for all time-varying bank characteristics (e.g., general bank financial health, risk management, operating capacity at a monthly frequency) and (2) *State* × *Month-Year* fixed effects ($\varphi_{s,t}$, respectively), to control for all other changes in local economic variables at a monthly frequency (including heterogeneity in borrower risk characteristics and local demand factors that are not already included in the set of county-level characteristics described above). We cluster standard errors at the county level to account for within-county correlation of residuals in loan approvals.

3.2 Main regression results

As shown in Table 2, social capital is positively related to mortgage loan approval when using a simple univariate regression that controls for the fixed effects specified in equation (1), i.e., bank-time and state-time fixed effects (column (1)) or a regression that also conditions on borrower and county controls (column (2)).[10, 11]

[10] The results hold across many different subsample tests in which we divide the sample at the median of several county and bank characteristics. Specifically, we differentiate by the following county traits: *Unemployment Rate, ΔCnty HPI, Cnty Credit Score,* and local market concentration of deposits and mortgages. We also differentiate by the following bank traits: size, capitalization, and bank-level local market concentration of mortgages. The results hold across all subsamples, as shown in Appendix Tables X.5 and X.6.

[11] In untabulated results, we also check how the effect of social capital on credit approval varies in the cross-section of borrowers,

The estimated relationship between social capital and loan approval is economically significant. Based on the specification in column (2), the coefficient estimate of 0.014 on *SK* suggests that a prospective borrower living in a "high" social capital county, defined as the 90th percentile of the distribution of *SK* across counties, has a 4.0% higher probability of loan approval (an increase from 80.5% to 83.7%) than a similar individual living in a "low" social capital county, defined as the 10th percentile of SK distribution. The monetized value can be sizable. Consider, for example, moving all counties below the 10th percentile of SK to the 90th percentile. Our estimates suggest that this would increase the number of loan approvals by 28,644, involving almost $5.85 billion in new loans per year.[12] These estimates suggest that cross-county differences in social capital can materially shape mortgage approval rates.[13]

Turning to the control variables, we find that lenders are more likely to approve mortgage applications from safer borrowers (lower *Debt-to-Income*, higher *Ln(Borrower Income),* and those with a *Co-Applicant* are more likely to have their credit approved. Furthermore, approval rates are higher among non-minorities, females, and applicants in metro areas. Loan amount exhibits a non-linear relation with approval, with *Ln(Loan Amount)* entering positively and *Ln(Loan Amount) Sq*

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given that prior research suggests certain groups may face greater difficulties in obtaining credit (e.g., Ambrose, Conklin, and Lopez, 2021; Begley and Purnanandam, 2021; Bhutta, Hizmo, and Ringo, 2022; Giacoletti, Heimer, and Yu, 2022). Our results show that the effects of social capital on credit approval are generally stronger for low-income and female applicants and have no significant effects for minorities. Thus, social capital may benefit certain (but not all) disadvantaged.

[12] Number of new loans is calculated as 4.0% × ((2,578,020 (20% random sample) × 5 (to get the full population))/18 years), while dollar value of new loans is calculated as 4.0% × ((2,578,020 (20% random sample) × 5 (to get the full population))/18 years) × 204.21 (average loan amount) × 1000.

[13] In Appendix X, Table X.4, we also examine (1) the individual subcomponents of the SK measure and (2) and a measure of social trust. Putnam (1993, p.35) defines social capital as "features of social organizations, such as networks, norms of reciprocity, and trust that facilitate action and cooperation for mutual benefit." Two subcomponents of the SK measure, *PVOTE* and *RESPN*, are closely aligned with Putnam's conception of social norms inducing individuals to engage voluntarily in actions that benefit the community. The other two subcomponents, *ASSN* and *NCSS*, are closely aligned with Putnam's conception of social networks as they gauge participation in community organizations that facilitate cooperation. We repeat the primary analyses while including the four subcomponents (standardized to have means of 0 and standard deviations of 1). As shown, each component enters positively and significantly, suggesting that social norms and networks shape the mortgage market. We also explore the role of trust, a key feature of many conceptions of social capital (e.g., Putnam, 1993; Fukuyama, 1995; Gambetta, 2000; Guiso, Sapienza, and Zingales, 2006, 2011). We use a proxy for county-level social trust derived from the GSS question: "Generally speaking, would you say that people can be trusted or that you can't be too careful in dealing with people?" We recode the response to 1 if a survey participant reports that most people can be trusted, and 0 otherwise. Then, we define our measure of social trust as the mean of the responses in each county-year. Appendix X, Table X.4 shows that social trust is also positively associated with loan approval.

negatively. At the county level, approval rates are higher in counties with higher average incomes, house price appreciation, and consumer credit scores.[14]

3.3 Instrumental variable analysis

One concern is that endogeneity may bias the OLS estimates of the impact of social capital on credit decisions. We mitigate this concern in Table 2 by saturating the model with consumer, lender, and local market controls and fixed effects. We now further address endogeneity concerns by using an IV approach to isolate the exogenous component of social capital and examine its relationship with credit outcomes.

Prior research develops an instrument for social capital based on the ancestral countries of U.S. communities' residents (e.g., Algan and Cahuc, 2010; Hoi et al., 2019). Past research shows that parents' attitudes, values, and behaviors are good predictors of those of their children (e.g., Rice and Feldman, 1997; Putnam, 2000; Algan and Cahuc, 2010). Related work suggests that the social characteristics of ancestral countries shape U.S. communities' current social preferences, norms, and behaviors (e.g., Becker, 1996; Guiso et al., 2006). Moreover, Hoi et al. (2019) show that the social characteristics of ancestral countries help explain cross-county differences in social capital and use this approach to identify the impact of social capital on corporate agency problems.

We follow this line of research and use "ancestral trust," which is the level of trust in the ancestral countries of county residents. As noted, past research suggests that ancestral trust is positively related to contemporaneous social capital in a community, as ancestral trust is the basis for current mutual trust and collective behavior and cooperation among people in the community. We measure trust across countries using the following question in World Values Survey (WVS): "Generally speaking, would

[14] The dependent variable in our main analyses measures mortgage approvals. Since mortgage approvals are different from mortgage originations, we conduct a robustness check using loan originations as the dependent variable. Specifically, we examine *Originated*, an indicator that equals 1 if the loan was originated (action_type = 1), and 0 otherwise. The results are robust, as shown in Appendix X, Table X.2, Panel C. Social capital is positively and significantly associated with mortgage origination.

you say that most people can be trusted or that you need to be very careful in dealing with people?" The WVS only allows for two answers: 1: "Most people can be trusted," and 0: "Can't be too careful." To construct ancestral trust at the U.S. county level (*Ancestral Trust*), we (1) use ancestry data from the U.S. Census' American Community Surveys (which report the first ancestry of residents in a county) to compute the percentage of each county's population from each country; and (2) link these data with the WVS country data on trust;[15] and (3) we calculate each county's weighted average trust using the percentage of the population from each ancestral country as the weights. We then use *Ancestral Trust* as an instrument for *SK* in assessing the impact of social capital on loan approvals.[16]

As shown in Table 3, the instrumental variable analyses confirm the OLS results from Table 2: Social capital boosts loan approval rates. The first-stage results (column (2)) indicate that the instrument, *Ancestral Trust*, is significantly correlated with social capital: U.S. counties where larger proportions of residents originate from countries with higher societal trust tend to have higher social capital. The second-stage results (column (3)) show that social capital is positively and statistically associated with higher mortgage credit approval. The IV estimates are larger than those from the OLS results. The larger IV results likely reflect strong local average treatment effects (LATE) (Jiang, 2017), i.e., the marginal impact of social capital on mortgage approval might be larger in counties with higher instrumented social capital.

We perform tests of instrument relevance and validity. First, the weak instrument test evaluates the Kleibergen–Paap Wald *F*-test of the excluded exogenous variable in the first-stage regression. The

[15] See worldvaluessurvey.org/wvs.jsp. To reduce sample attrition, we consider the average of trust across the first six waves of the WVS.

[16] Appendix X, Table X.2 Panels A–B show the results are robust to using an alternative instrument. Hoi et al. (2019) use Hofstede's cross-country "power distance" dimension, which measures the extent to which societies accept power inequality among their members. According to Hofstede (2001, 2003), a high power-distance society is one in which national elites hold relatively authoritarian views, subordinate-superior relations are polarized, subordinates are afraid to express disagreement with their superiors (as there is no defense against power abuse by superiors), the social hierarchy constrains communication and information dissemination, and people at various levels are less likely to trust each other. Hoi et al. (2019) contend that U.S. counties with a higher percentage of people from high power-distance countries will exhibit lower levels of social capital.

null hypothesis is that the instrument does not explain variation in social capital. As shown in Table 3, the *F*-test statistic rejects this null hypothesis at the 1% level (*p*-value less than 0.001) in all cases. Second, the underidentification test evaluates the rank condition. The Kleibergen–Paap *rk LM* rejects the null hypothesis at the 1% level (*p*-value less than 0.001) in all cases, as reported in Table 3, indicating that the model is well identified. Thus, the weak identification and underidentification tests suggest that the instrument is relevant and valid. Overall, the IV analyses confirm the OLS findings, reducing endogeneity concerns.

3.4 PSM analysis

We next address concerns that the nonrandom assignment of individuals across U.S. counties could interfere with identifying the impact of social capital on mortgage approvals by using PSM to limit self-section bias (e.g., Caliendo and Kopeining, 2008; Hoi et al., 2019).[17] That is, we construct an artificial control group by matching each treated loan application with a non-treated loan application with similar observable characteristics.

Specifically, we rank counties by *SK* annually from 1998 through 2015 and classify county-years in the top quartile as the *treated* group with high social capital, *High SK* = 1, and those in the bottom quartile as the control group with low social capital, *Low SK* = 1. We use only the top and bottom quartiles in the PSM analyses. We match consumer credit applications from high social capital counties with those from low social capital counties using the nearest propensity scores based on all borrower and county controls in our main specification and the instrument, *Ancestral Trust.* We apply a one-to-one PSM without replacement with a 1% caliper. The one-to-one match without replacement technique ensures we do not have multiple untreated *Low-SK* borrowers assigned to the same *High-SK* treated

[17] PSM has important advantages over IV when addressing endogeneity concerns related to self-selection bias. Lawrence, Minutti-Meza, and Zhang (2011) note that PSM: 1) has the ability to produce samples in which treated and untreated entities are similar, providing a natural framework to estimate the effects of treatment and firm characteristics; 2) provides independence from an explicit functional form; and 3) has the ability to estimate treatment effects more directly and alleviate potential non-linearities related to the treatment effects.

borrowers, which can lead to the control group being smaller than the treated group. The 1% caliper indicates that the acceptable difference in predicted propensity scores between the treatment and the match should be less than or equal to 1%.

We estimate regressions using these matched samples and report the findings in column (3) of Table 3. By comparing otherwise similar individuals in *High*- and *Low-SK* counties, the PSM methodology reduces selection bias and helps identify the impact of social capital on mortgage approval rates. Consistent with the OLS and IV findings, the PSM regression results indicate that social capital significantly increases loan approval rates.

3.5 Potential omitted variable bias

To further address identification concerns, we saturate the OLS, IV, and PSM regression analyses with additional county characteristics to reduce omitted variable concerns and isolate the independent relationship between social capital and mortgage approvals.

First, we control for additional county-level demographic factors, which may simultaneously influence social capital and mortgage approvals. We include *Cnty Education*, the percentage of the county's population with a bachelor's or higher degree; *Cnty Pop Growth*, population growth in a county; *Cnty Pct Minority*, the percentage of minorities in a county; *Cnty Percent Female*, the percentage of resident women in a county; and *Cnty Latitude* and *Cnty Longitude*, the geographic coordinates of the county center. Markets with more educated people, fewer minorities, and fewer women residents may experience more approvals due to higher financial literacy and lower discrimination potential. Additionally, Cortés et al. (2016) find that geographic factors shape approval rates.

Second, we control for additional county-level competition and financial factors. We include *Cnty Bank Competition*, the Herfindahl–Hirschman index (HHI) of local market bank deposit concentration in a county. Markets with higher local bank market concentration may be associated with higher information acquisition, which can facilitate credit availability (e.g., Petersen and Rajan, 1995). We control for *Cnty Bank Branches/Pop*, the ratio of the number of bank branches in a county divided by population, since greater consumer access to banks may result in more credit approvals. We control for *Cnty Inequality (Gini)*, the Gini coefficient of inequality in a county, as markets with less income inequality may have higher approvals due to more financial stability. We control for *Cnty Delinquency 60DPD Rate*, the rate of mortgages 60 days past due in a county (for mortgages that originated at least three years ago); and *Cnty Predicted Delinquency 60DPD Rate*, the predicted rate of mortgages 60 days past due in a county over three years post-origination obtained from the anonymized merged HMDA-McDash database, as anticipated delinquencies may lower approval rates. We report OLS, IV, and PSM analyses that include these additional demographic and financial factors in Table 3, Panel B. Across all specifications, social capital remains statistically significant at the 1% level.[18]

3.6 Falsification tests

Social capital can influence credit approval by enhancing interpersonal connections and trust. To shed empirical light on this mechanism, we conduct several falsification tests. In particular, we test whether the connection between social capital and loan approval weakens among lenders and loans that rely less on interpersonal interactions between loan officers and borrowers.

First, we focus on financial technology (fintech) lenders. Fintech lenders automate many features of the mortgage market and have limited or no personal communications or interactions with borrowers (e.g., Buchak, Matvos, Piskorski, and Seru, 2018; Berger and Black, 2019).[19] Thus, for fintech lenders, social capital is less likely to shape credit approval by enhancing interpersonal connections and trust.

[18] In untabulated results, we further control for three other county traits: the relative strength of the Democratic/Republican party as captured by county election outcomes (e.g., Rubin, 2008); the percentage of a county's population claiming affiliation with an organized religion (e.g., Hilary and Hui, 2009); and the natural logarithm of the median loan officer compensation obtained from the U.S. Department of Labor in the consumer MSA. All our results hold despite significant reductions in sample size.

[19] Fintech lenders may still conduct phone conversations with clients, so the total absence of interaction cannot be ruled out.

We test whether the relationship between social capital and credit approval rates is weaker among fintech lenders than among banks. To do so, we add to our sample two sets of fintech lenders: (1) the fintech lender list provided by Buchak et al. (2018)[20] and (2) the combination of the fintech lender lists by Buchak et al. (2018) and Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021).

Table 4, Panel A reports the results for the effects of social capital on credit approvals while allowing the relationship to differ between banks and fintech lenders. We discover that the effects of social capital on credit approval are weaker for fintech lenders. This is consistent with the idea that social capital shapes credit conditions by facilitating personal communications between borrowers and lenders.

We consider the geographic proximity of the bank to the borrower as a second falsification test. Suppose social capital shapes credit decisions by enhancing interpersonal communications and trust, and geographic proximity influences the extent of such communications. In that case, the geographic distance between borrower and lender should decrease the importance of social capital in credit decisions. To assess whether the relationship between social capital and credit approval rates is stronger for borrowers closer to banks, we examine whether the bank has a branch in the same county as the individual applying for a mortgage using data from the FDIC Summary of Deposits. While not having a branch does not preclude banks from having a mortgage brokerage processing center in the local market, the lack of a deposit branch makes it less likely that the loan officer will meet the borrower directly. The reduced likelihood of these interpersonal interactions again suggests that local social capital will have less impact on credit approval. For these analyses, the sample increases appreciably. In our primary analyses, we exclude applications for which the lender does not have a branch in the property's county. We now include those observations to assess the role of distance. Consistent with

[20] The list was retrieved from Gregor Matvos's website at https://sites.google.com/site/gmatvos/. Note that we use the most recent list of fintech lenders from the website, which is slightly newer than the one in their paper.

the view that social capital influences loan approval by shaping interpersonal interactions and trust, the results in Panel B show a weaker relationship between social capital and credit approvals in this special case.[21]

Our last falsification test considers whether lenders use a mortgage automated underwriting system (AUS) to assist in the credit-granting decision.[22] AUSs do not use soft information based on interpersonal communications with loan officers. Thus, the degree of social capital in the local community will not influence AUSs' credit approval recommendations. However, loan officers, who make the final credit approval decision, use both the data employed by AUSs and soft information obtained from interacting with borrowers and the community. We, therefore, expect that social capital will only shape credit approvals through its effect on loan officer assessments.

To test this hypothesis, we use the enhanced confidential HMDA data. Specifically, starting in 2018, HMDA enhanced its data collection to include information on credit decisions by AUSs and loan officers, borrower credit scores and age, and the loan-to-value ratios of mortgage applications. In our analyses for the 2018–2019 period, we include all of the previous borrower controls plus the enhanced HMDA-specific controls (credit score, age, and loan-to-value ratios). Because the sample size shrinks significantly, we use the entire enhanced HMDA dataset instead of a 20% random sample. Following Bhutta et al. (2022), *AUS Approved* equals one if the AUS indicates approval and zero otherwise, and *AUS Rejected* equals one if the AUS indicates denial and zero otherwise. Both *AUS Approved* and *AUS Rejected* equal zero if the AUS does not make a straightforward recommendation of either approval or rejection.

Consistent with the view that social capital influences loan decisions by shaping interpersonal

[21] Our effects on the interaction terms hold in all tests in Panels A–B when employing even stricter fixed effects such as *County* × *Year-Month*, except the main *SK* term is superseded by the fixed effects (see Appendix Table X.3).
[22] The three main AUSs used in the U.S. are DU (Desktop Underwriter), LPA (Loan Product Advisor), and TOTAL (credit risk scorecard). However, some lenders use a proprietary system.

communications and trust, we discover that social capital is strongly related to the credit decisions of loan officers but is not significantly related to AUS credit recommendations. Table 4, Panel C, reports loan officer approvals and computer-generated AUS recommendations. Results in column (1) reconfirm that social capital leads to a higher likelihood of credit approval by a loan officer. However, columns (2) and (3) show no statistically significant effects of social capital on AUS approvals or rejections.

3.7 Social capital and screening time

To provide additional information on the view that social capital facilitates lending by reducing informational asymmetries, we examine the time it takes loan officers to screen mortgage applications. The intuition is that social capital facilitates acquiring and processing information about borrowers. That is, greater social capital makes it easier, on average, for loan offers to make loan approval decisions, reducing the time necessary for loan officers to complete their screening of borrowers. To assess this view, we use confidential HMDA data on the number of days loan officers spend screening each mortgage (*Screen Days*). Choi and Kim (2021) note *Screen Days* reflects loan officers' actions at the origination phase, independent of any factors that may occur ex-post, such as changes in economic conditions or borrowers' behavior. Our results in Table 5 confirm that higher social capital is associated with loan officers needing less screening time to make decisions. There might be concerns that faster screening times lead to worse decisions. However, as shown later in Section 5, greater social capital reduces loan delinquency rates, consistent with social capital reducing informational asymmetries and improving the lending market.

4. Social Capital and Mortgage Interest Rates and Maturities

Besides influencing mortgage approval rates, social capital may shape the terms of approved mortgages, such as lending rates and loan maturities. In particular, if social capital reduces informational asymmetries, and thus the problems associated with adverse selection and moral hazard, then higher levels of social capital in a community could improve the terms on mortgages issued to community residents (Nooteboom et al., 1997; Lewicki et al., 1998). Similarly, social capital can increase the social costs to borrowers of defaulting on their debts, allowing private lenders to charge lower interest rates to individuals in high social capital communities than those with lower social capital levels. This section evaluates the relationship between social capital and the interest rates on and maturities of approved mortgages.

We use two datasets to assess the terms of mortgages. First, the anonymized HMDA-McDash has comprehensive information on loan terms, while HMDA used in our main sample does not. However, HMDA-McDash does not identify banks, which prevents us from including bank fixed effects. In evaluating the relationship between social capital and loan terms, we include all other controls and fixed effects from the main specification and control for the following variables in the anonymized HMDA-McDash data: the borrower's FICO score (*Borrower Credit Score*), the loan's *Loan-to-Value Ratio* and whether the borrower is a low documentation borrower, i.e., the borrower did not provide full documentation when applying for the mortgage (*Low Doc Borrower*).

Second, we use the enhanced confidential HMDA data during 2018–2019, including information on interest rates and loan maturities. With these data, we can again condition on *Bank* × *Month-Year* fixed effects, controlling for all lender-specific factors. Similar to our falsification tests in Section 3.6, we use the entire enhanced confidential HMDA dataset over the more limited sample period, 2018–2019, and impose the same selection criteria as in our main analyses. The enhanced confidential HMDA dataset over the 2018–2019 period includes borrower credit score, age, and the loan-to-value ratio, which we use in our analyses in addition to all prior controls and fixed effects.

Table 6 shows that consumers in higher social capital counties obtain mortgages with lower interest rates and longer maturities than similar borrowers in other counties. These results hold when using the anonymized HMDA-McDash data over the entire sample period (columns (1)–(2)) or the enhanced confidential HMDA data over the 2018–2019 period (columns (3)–(4)). These findings are consistent with the view that greater social capital—stronger networks, norms of reciprocity, and trust—not only boosts credit approval rates but also enhances lending terms.

5. Social Capital and Consumer Credit Performance

This section investigates the relationship between social capital and mortgage loan performance. Putnam (2000, p.21) argues that in communities with dense social ties and extensive social interactions, "incentives for opportunism and malfeasance are reduced." In particular, "dense social ties facilitate gossip and other valuable ways of cultivating reputation – an essential foundation for trust in a complex society." From this perspective, social capital will not only affect lenders' credit decisions, but will also shape how borrowers behave after receiving loans, suggesting that borrowers in higher social capital communities will be less likely to default on loans opportunistically and more likely to repay their loans to maintain or bolster their reputations. Social capital can also influence ex-post mortgage performance by influencing ex-ante screening. By reducing informational asymmetries, social capital might enhance the allocation of mortgage credit with positive effects on subsequent loan performance. However, as discussed above, greater social capital could also lead loan officers to make lending decisions based on nepotism and cronyism, with adverse effects on subsequent loan performance. In this section, we assess the impact social capital on mortgage repayments.

We use several measures of loan performance to evaluate this prediction. We focus on *Delinquency 60DPD*, which equals one if the loan was ever 60 days past due during the three years after origination. We discuss the results using other measures of mortgage performance below. We use a 20% random sample from the merged HMDA-McDash dataset over the 1998Q1–2015Q4 period that contains detailed information on mortgage loan performance after origination. As noted above, the merged HMDA-McDash dataset (1) allows us to control for the borrower's credit score, loan-to-value ratio, and whether the borrower is a low documentation borrower, which helps condition on borrower risk, and (2) does not provide the identities of the lenders, so we cannot condition on lender fixed effects.

5.1 Main regression results

We begin by assessing the relationship between *Delinquency 60DPD* and social capital. Table 6 reports regression results using a univariate specification with *State* × *Quarter-Year* fixed effects in column (1). Column (2) adds the full array of borrower and county traits discussed above.

As shown in Table 7, social capital is negatively related to loan delinquency. The results are economically significant. Based on column (2), increasing *SK* from the 10^{th} to the 90^{th} percentile results in a 27% lower probability of delinquency (declining from 10.7% to 7.9%). These results are consistent with the idea that social capital reduces behaviors associated with moral hazard and borrower opportunism, resulting in lower delinquency rates. Unsurprisingly, the regression also indicates that safer borrowers—as measured by higher *Borrower Credit Score*, lower *Loan-to-Value Ratio*, lower *Low Doc Borrower*, lower *Debt-to-Income*, and the presence of a *Co-Applicant*—are less likely to become delinquent. The results also indicate that, conditional on individual and country traits, minorities have higher delinquency rates.[23]

5.2 Additional identification analyses: instrumental variables, PSM, and additional controls

We next address concerns with identifying the impact of social capital on delinquencies. We follow the same empirical strategy used in assessing the impact of social capital on loan approvals.

[23] In untabulated tests, we also check how the effect of social capital on consumer credit performance varies in the cross-section of borrowers. We interact social capital with credit score < 720 (non-prime consumers), loan-to-value ≥ 80%, low documentation (did not provide full documentation at application time), low income (using the median borrower income as a cutoff), female, and minority indicators. Results suggest beneficial effects of social capital on improving credit performance for disadvantaged groups such as low credit score, high loan-to-value, and low documentation, but no additional effects on female consumers and smaller beneficial effects for minorities.

Specifically, we use IV, PSM, and a control function approach that saturates the regression with additional control variables.

As shown in Table 8, Panel A, the IV results confirm the OLS results: There is a strong negative relationship between social capital and borrower credit performance. Instrumented *SK* enters negatively and significantly in the delinquency regression with *Delinquency 60DPD* as the dependent variable. As shown, the Kleibergen–Paap Wald *F*-test of the excluded exogenous variable in the first-stage regression and the Kleibergen–Paap *rk LM* suggest the instrument is relevant and valid. The IV coefficient estimate on *SK* is larger in absolute value terms than the OLS estimates, likely due to local average treatment effects (Jiang, 2017). The IV analyses suggest that social capital exerts a large, positive effect on borrower performance.

The PSM analyses also indicate that social capital reduces mortgage delinquencies. As shown in Table 8, Panel A, column (3), individuals in higher social capital counties (*High SK*) have lower delinquency rates than similar individuals living in lower social capital countries. These results suggest that selection bias is not driving the social capital and loan delinquency results.

Finally, the results hold when saturating the regression with additional controls. We use the same additional county-level controls as in the loan approval robustness analyses reported in Table 3. As shown in Table 8, Panel B, the results hold when including additional county-level controls. Furthermore, there is little change in the estimated coefficient on *SK*, suggesting that omitted variables are not biasing the results on *Delinquency 60DPD*.[24]

5.3 Additional credit performance indicators

We confirm the results on social and capital and loan performance using several additional performance

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[24] Robustness tests in Appendix X, Table X.7 Panels A–B, using the additional instrument: *Ancestral Power Distance*, with baseline and extended list of controls, also corroborate our findings in all cases.

measures. Table 9 presents results using two alternative measures of consumer credit performance: *Avg Credit Score*, which equals the borrower's average FICO score during the three years after receiving the mortgage, and *Credit Score Decline* equals one if the individual's FICO score declines below the score at mortgage origination at any time over three years post-origination. The results suggest that social capital is significantly associated with higher consumer credit scores and a lower likelihood of credit score decline after origination, consistent with the view that social capital enhances consumer performance on mortgage loans.[25]

5.4. Using a different dataset to address potential selection bias

Despite including many controls and fixed effects and using instrumental variables and PSM, there might remain concerns that these strategies do not entirely eliminate the possibility that an unobserved trait leads some individuals to be safe borrowers and live in high social capital counties. Such a trait could lead to a spurious, negative relationship between *SK* and *Delinquency 60DPD*. We use an alternative dataset that allows us to include individual fixed effects to address this concern. In this way, we compare the same borrower with two different mortgages.

Specifically, we use the anonymized Federal Reserve Bank of New York's Consumer Credit Panel/Equifax (CCP) data, a quarterly panel dataset that has tracked a 5% U.S. nationally representative sample of consumers since 1999. For our sample, we randomly select 20% of the individuals from the primary CCP sample from 1999 to 2015. To identify each consumer's mortgage(s), we use the CCP's mortgage tradeline data, which track first-lien mortgages quarterly. The unit of observation is a consumer-mortgage-quarter. The data identify the origination date, loan amount, and any payment

[25] In Appendix X, Table X.7, Panel C, we check the sensitivity of our results to using several alternative proxies for consumer credit performance. These are indicators for whether during the three years after mortgage origination (1) the loan was ever in 90 days past due status (*Delinquency 90DPD*), (2) the loan was ever in forbearance or real-estate owned (REO) status (*Foreclosure/REO*), (3) the loan was ever in 30 days past due status (*Delinquency 30DPD*), (4) the loan was ever in forbearance or REO status or the borrower was ever in bankruptcy status (*Foreclosure/REO/Bankruptcy*), and (5) the borrower was ever in bankruptcy status (*Bankruptcy*). We find that social capital is associated with lower delinquency rates as measured by the first four indicators but is not significantly associated with bankruptcy.

delinquencies but do not provide information on approvals or credit terms. Thus, we can use these data to examine loan performance but not credit approvals or mortgage terms. The data also include information on consumers' Equifax Risk Score, age, number of credit inquiries, and county of residence each quarter.[26]

After merging the data, we compare the ex-post performance of mortgage loans originating in counties with high social capital to those with low social capital. We use a regression model similar to that in equation (1). A key difference is that it includes consumer fixed effects to account for unobserved consumer traits, in conjunction with observable consumer and county controls, and time and local market fixed effects. The dependent variable is *Delinquency 60DPD*.

We find a strong, negative relationship between social capital and mortgage delinquencies even when controlling for borrower fixed effects, as shown in Table 10. In addition to borrower fixed effects, the regressions include year-quarter fixed effects. We also include specifications that further condition on local market fixed effects for the state or the census tract of the consumer. Since we include borrower fixed effects, the analyses only include individuals with at least two mortgages in the dataset, which leads to much smaller samples than those in earlier analyses and correspondingly less statistical power. Nevertheless, the results suggest that higher social capital is associated with lower consumer delinquency rates, consistent with the findings above.

6. Conclusions

We discover that the social capital of the community in which a household lives positively influences the likelihood that the household's mortgage application is approved, the terms (e.g., lower interest rates and longer maturities) on approved mortgages, and the household's subsequent performance on

[26] See Lee and van der Klaauw (2010) for a detailed description of the CCP.

those mortgages. The results are robust to conditioning on household and community characteristics and an extensive array of fixed effects, including individual fixed effects, data permitting. Furthermore, the results hold when employing IV and PSM strategies to address identification and selection concerns. The analyses also suggest the mechanisms linking social capital and access to mortgage credit. Consistent with social capital shaping mortgage credit by enhancing interpersonal connections and trust in communities, falsification tests demonstrate that the relationship between social capital and mortgage approvals weakens or disappears when examining lenders that have minimal or no direct interactions with borrowers, namely (i) fintech lender, (ii) lenders that do not have a branch in the property's county, and (iii) automated underwriting systems. The evidence suggests that social capital exerts a strong, independent influence on access to mortgage credit, the terms of that credit, and household performance on those loans by enhancing lender screening and monitoring of borrowers and increasing the social costs to borrowers from defaulting on their debts.

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Figure 1: Social Capital across U.S. Counties in 2014

This figure presents the geographic distribution of social capital (*SK*) across U.S. counties in 2014. *SK* is the original social capital index as reported by the Northeast Regional Center for Rural Development (NRCRD) at the Pennsylvania State University. It was created using principal component analysis of four factors capturing norms and social networks. The figure presents 10 categories based on an equal deciles' methodology, with darker colors representing higher social capital.

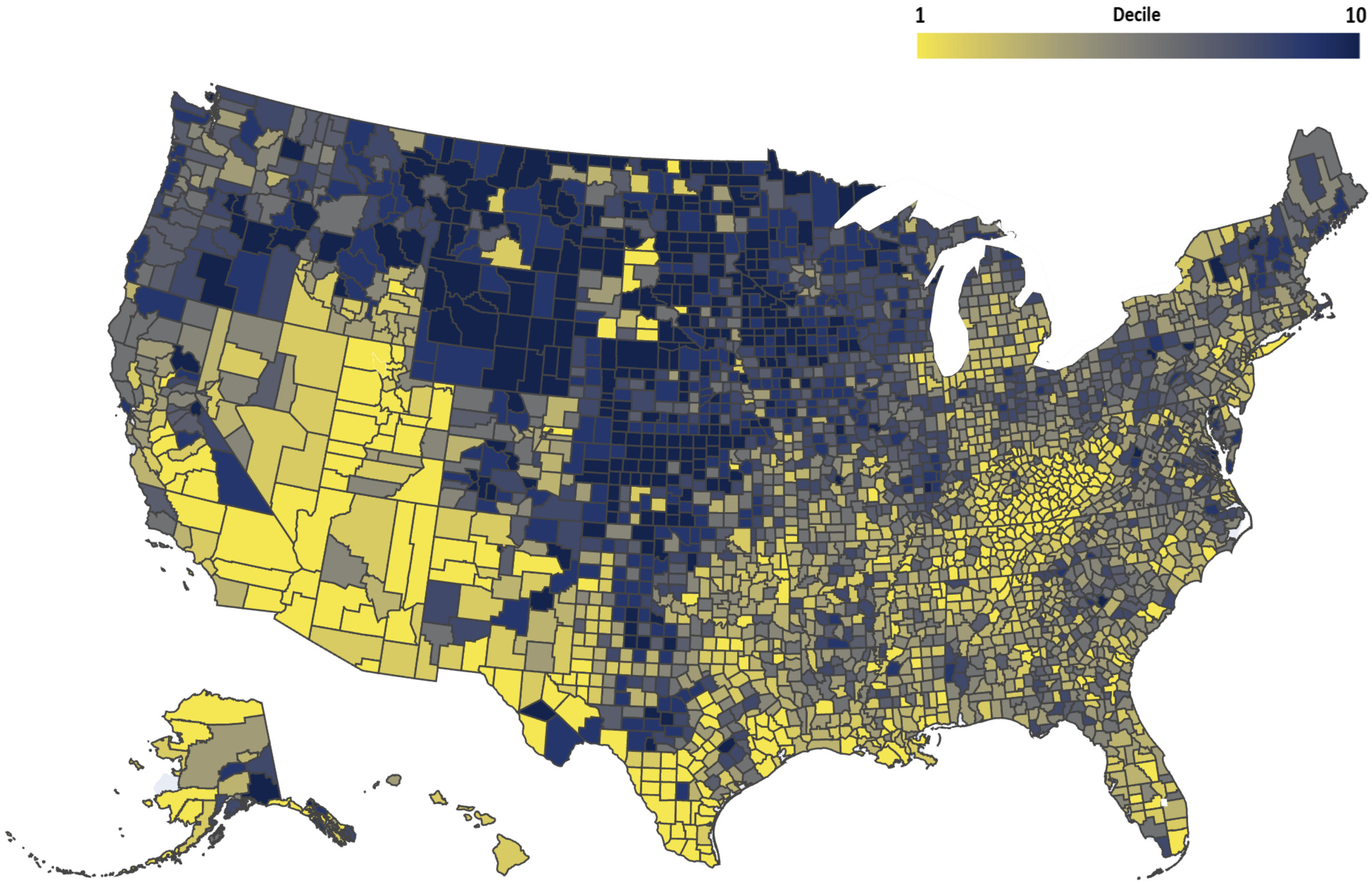

Table 1: Summary Statistics

This table provides summary statistics for the variables used in our main analyses. We use a 20% random sample from the anonymized confidential Home Mortgage Disclosure Act (HMDA) data for analyzing loan approvals, and a 20% random sample from the anonymized Federal Reserve merged HMDA-McDash dataset for analyzing borrower loan performance. Our main samples cover 1998–2015, and they are monthly in confidential HMDA and quarterly in the merged HMDA-McDash. Variable definitions are in Appendix X.

Panel A: Anonymized HMDA (20% Random Sample)

Variable	**Mean**	**Standard deviation**	**25th percentile**	**Median**	**75th percentile**	**N**
Key Dependent Variables						
Approved	0.816	0.388	1.000	1.000	1.000	2,859,250
Originated	0.795	0.403	1.000	1.000	1.000	2,574,130
Social Capital Variable						
SK	-0.627	0.953	-1.265	-0.634	-0.025	2,859,250
Borrower Controls						
Debt-to-Income	2.236	4.635	1.176	2.083	2.971	2,578,020
Ln(Borrower Income)	4.294	0.783	3.761	4.248	4.762	2,578,020
Minority	0.186	0.389	0.000	0.000	0.000	2,578,020
Female	0.279	0.449	0.000	0.000	1.000	2,578,020
Co-Applicant	0.506	0.500	0.000	1.000	1.000	2,578,020
Metro	0.889	0.314	1.000	1.000	1.000	2,578,020
Ln(Loan Amount)	4.816	1.053	4.174	4.875	5.521	2,578,020
Ln(Loan Amount) Sq	24.298	9.887	17.426	23.768	30.487	2,578,020
County Controls						
Ln (Cnty Income)	16.053	1.659	14.920	16.227	17.292	2,578,020
Cnty Unemployment Rate	5.309	2.100	3.900	5.000	6.300	2,578,020
Δ Cnty HPI (3 Month Lag)	0.004	0.010	-0.000	0.005	0.010	2,578,020
Population Density	2.196	6.925	0.221	0.650	1.765	2,578,020
Cnty Credit Score	694.406	23.295	679.607	696.074	711.353	2,578,020
Cnty Age	47.905	2.566	46.202	47.488	49.293	2,578,020
Cnty Age Sq	2301.448	251.138	2134.625	2255.141	2429.801	2,578,020

Panel B: Anonymized HMDA-McDash Merge (20% Random Sample)

Variable	**Mean**	**Standard deviation**	**25th percentile**	**Median**	**75th percentile**	**N**
Key Dependent Variables						
Delinquent 60DPD	0.094	0.291	0.000	0.000	0.000	1,979,528
Delinquent_90DPD	0.077	0.267	0.000	0.000	0.000	1,979,528
Forbearance/REO	0.047	0.211	0.000	0.000	0.000	1,979,528
Delinquent_30DPD	0.171	0.376	0.000	0.000	0.000	1,979,528
Forbearance/REO/Bankruptcy	0.047	0.213	0.000	0.000	0.000	1,979,528
Bankruptcy	0.001	0.032	0.000	0.000	0.000	1,979,528
Social Capital Variable						
SK	-0.646	0.917	-1.238	-0.653	-0.063	1,979,408
Borrower Controls						
Borrower Credit Score	725.792	61.419	687.000	738.000	776.000	1,453,076
Loan-to-Value Ratio	0.725	0.223	0.697	0.795	0.844	1,453,076
Low Doc Borrower	0.222	0.416	0.000	0.000	0.000	1,453,076
Debt-to-Income	2.444	1.183	1.642	2.390	3.196	1,453,076
Ln(Borrower Income)	4.433	0.685	3.970	4.394	4.836	1,453,076
Minority	0.167	0.373	0.000	0.000	0.000	1,453,076
Female	0.296	0.457	0.000	0.000	1.000	1,453,076
Co-Applicant	0.473	0.499	0.000	0.000	1.000	1,453,076
Metro	0.933	0.249	1.000	1.000	1.000	1,453,076
Ln(Loan Amount)	5.165	0.839	4.700	5.204	5.717	1,453,076
Ln(Loan Amount) Sq	27.378	8.451	22.095	27.082	32.684	1,453,076

Ln (Cnty Income)	16.272	1.513	15.343	16.450	17.341	1,453,076
County Controls						
Cnty Unemployment Rate	5.520	2.026	4.167	5.133	6.433	1,453,076
Δ Cnty HPI	0.015	0.025	0.002	0.014	0.029	1,453,076
Population Density	2.051	6.098	0.290	0.757	1.788	1,453,076
Cnty Credit Score	698.377	23.004	682.806	699.545	715.788	1,453,076
Cnty Age	48.140	2.376	46.583	47.838	49.464	1,453,076
Cnty Age Sq	2323.146	232.909	2169.950	2288.446	2446.664	1,453,076

Table 2: Effects of Social Capital on Credit Approval – Baseline Results

This table reports loan-level regression estimates from a linear probability model that explains the relation between social capital and mortgage approval decisions. Column (1) presents a model without any controls, column (2) presents a model that includes borrower and county controls. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved by the lender (action_type = 1 or 2), and 0 if it was denied (action_type = 3). The key explanatory variable is *SK*, the county-level social capital index developed by using the principal component analysis (PCA) of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measure and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)
Dependent Variable	Approved	Approved
Independent Variables		
SK	0.029***	0.014***
	(14.836)	(6.732)
Borrower Controls		
Debt-to-Income		-0.001***
		(-4.348)
Ln(Borrower Income)		0.082***
		(63.016)
Minority		-0.057***
		(-13.911)
Female		0.006***
		(6.177)
Co-Applicant		0.009***
		(6.623)
Metro		0.034***
		(11.491)
Ln(Loan Amount)		0.079***
		(13.320)
Ln(Loan Amount) Sq		-0.009***
		(-12.727)
County Controls		
Ln (Cnty Income)		0.004***
		(3.386)
Cnty Unemployment Rate		-0.000
		(-0.597)
Δ Cnty HPI		0.067
		(1.180)
Population Density		-0.000
		(-1.180)
Cnty Credit Score		0.001***
		(6.490)
Cnty Age		-0.010
		(-1.332)
Cnty Age Sq		0.000
		(0.919)
State × Month-Year FE	✓	✓
Bank × Month-Year FE	✓	✓
Cluster by County	✓	✓
Observations	2,859,250	2,578,020
Adjusted R-squared	0.089	0.122

Table 3: Effects of Social Capital on Credit Approval – Additional Identification Analyses

This table reports loan-level regression estimates from a linear probability model that explains the relation between social capital and mortgage origination decisions when conducting endogeneity and other sensitivity tests. In Panel A, columns (1)–(2), we report estimates from an instrumental variable analysis. We use *Ancestral Trust* as the instrument, the county-level weighted average of World Values Survey's societal trust, where the weights are the percentages of people with first ancestry country information as reported in the U.S. Census Bureau's ancestry data. Column (3) shows regression results from a matched sample analysis, where counties with a high social capital value (top 25%) were matched (1:1 matching without replacement and a 1% caliper) to counties with a low social capital value (bottom 25%), based on similar characteristics, including the instrument *Ancestral Trust*. Panels B1–B2 control for additional county characteristics that could impact the results. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved by the lender (action_type = 1 or 2), and 0 if it was denied (action_type = 3). The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measure and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: IV and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS *(repeated for convenience)*	IV 1st stage	IV 2nd stage	PSM
Dependent Variable		SK	Approved	Approved
Independent Variables				
SK	0.014***		0.078***	
	(6.732)		(3.311)	
High_SK				0.034***
				(7.792)
Instrument:				
Ancestral Trust		0.045***		
		(3.527)		
Borrower, County Controls	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	2,578,020	2,578,020	2,578,020	316,067
Adjusted R-squared	0.122	0.755	0.046	0.128
K–P Weak Identification			12.44***	
K–P Underidentification			11.67***	

Panel B: Additional Controls: OLS, IV, and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS	IV 1st stage	IV 2nd stage	PSM
Dependent Variable	Approved	SK	Approved	Approved
Independent Variables				
SK	0.011***		0.092***	
	(5.168)		(2.729)	
High_SK				0.034***
				(5.295)
Instrument:				
Ancestral Trust		0.037***		
		(3.167)		
Additional Controls				
Cnty Education	0.022	4.056***	-0.299**	-0.029
	(0.982)	(10.813)	(-2.001)	(-0.741)
Cnty Pop Growth	0.098**	-4.128***	0.449**	0.351***
	(1.992)	(-3.161)	(2.370)	(2.766)
Cnty Pct Minority	0.023**	-1.347***	0.143**	0.051***
	(2.088)	(-4.115)	(2.186)	(2.843)
Cnty Pct Female	0.214***	3.149*	-0.048	0.399**
	(2.686)	(1.896)	(-0.262)	(2.153)
Cnty Latitude	0.004***	0.032**	0.002	0.003*
	(4.448)	(2.009)	(0.906)	(1.655)
Cnty Longitude	0.002*	0.036***	-0.002	0.002
	(1.749)	(2.845)	(-1.100)	(1.310)
Cnty Bank Competition	0.018*	0.530***	-0.025	0.006
	(1.788)	(3.201)	(-0.937)	(0.263)
Cnty Bank Branches/Pop	0.154***	0.878***	0.067	0.210***
	(4.452)	(2.766)	(1.256)	(2.746)
Cnty Inequality (Gini)	-0.087**	3.419***	-0.354**	-0.026
	(-2.200)	(3.622)	(-2.190)	(-0.385)
Cnty Delinquency 60DPD Rate	-0.034***	0.130*	-0.041***	-0.011
	(-5.828)	(1.696)	(-4.313)	(-0.658)
Cnty Predicted Delinquency 60DPD Rate	-0.006	-2.446***	0.196**	-0.031
	(-0.545)	(-10.418)	(2.111)	(-0.890)
Borrower, County Controls	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	2,363,024	2,363,024	2,363,024	177,987
Adjusted R-squared	0.118	0.848	0.046	0.125
K-P Weak Identification			10.03***	
K-P Underidentification			10.22***	

Table 4: Effects of Social Capital on Credit Approval – Falsification Tests

This table reports loan-level regression estimates from a linear probability model explaining the relationship between social capital and mortgage origination decisions when investigating channels and other analyses. Panel A shows differential effects for fintech lenders versus banks using definitions of fintech from Buchak, Matvos, Piskorski, and Seru (2018) and Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021). Panel B shows differential effects for applications from lenders without deposit branches in the borrower county. Panel C uses 2018–2019 enhanced confidential HMDA (full sample) and investigates regular loan officer approvals for mortgages versus automated underwriting system (AUS) decisions (approvals and rejections). The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved, and 0 if it was denied. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Fintech vs. Banks

Dependent Variable	(1) Approved	(2) Approved
Independent Variables		
SK	0.016***	0.016***
	(8.322)	(8.424)
SK × Fintech (Buchak et al.)	-0.028***	
	(-5.813)	
SK × Fintech (Buchak et al. & Jagtiani et al.)		-0.028***
		(-6.169)
Borrower, County Controls	✓	✓
State × Month-Year FE	✓	✓
Lender × Month-Year FE	✓	✓
Cluster by County	✓	✓
Observations	2,811,339	2,849,273
Adjusted R-squared	0.168	0.169

Panel B: Zero Deposit Branches

Dependent Variable:	(1) Approved
Independent Variables:	
SK	0.010***
	(6.553)
SK × Zero Deposit Branches	-0.004***
	(-3.088)
Zero Deposit Branches	-0.028***
	(-25.803)
Borrower, County Controls	✓
State × Month-Year FE	✓
Bank × Month-Year FE	✓
Cluster by County	✓
Observations	7,907,462
Adjusted R-squared	0.145

Panel C: Loan Officer Approvals vs. AUS Decisions (Approvals and Rejections)
Using 2018–2019 Enhanced HMDA Data

	(1)	(2)	(3)
Dependent Variable:	Approved	AUS Approved	AUS Rejected
Independent Variables:			
SK	0.012***	-0.001	0.001
	(4.209)	(-0.908)	(1.087)
Borrower Credit Score	0.001***	0.001***	-0.001***
	(59.627)	(36.482)	(-42.197)
Borrower Age	-0.007***	-0.003***	0.001***
	(-25.890)	(-13.851)	(9.350)
Borrower Age Sq	0.000***	0.000***	-0.000***
	(18.735)	(10.589)	(-7.658)
Loan-to-Value Ratio	-0.045***	-0.021***	0.035***
	(-8.660)	(-5.046)	(11.327)
Debt-to-Income	-0.001*	-0.000*	0.000
	(-1.902)	(-1.669)	(0.848)
Ln(Borrower Income)	0.088***	0.014***	-0.029***
	(38.522)	(12.085)	(-31.251)
Minority	-0.024***	-0.007***	0.003*
	(-6.846)	(-2.727)	(1.719)
Female	0.013***	0.002**	0.001
	(11.062)	(2.251)	(1.141)
Co-Applicant	-0.003*	-0.001	-0.003***
	(-1.912)	(-1.108)	(-4.365)
Metro	0.022***	-0.003	-0.003*
	(4.995)	(-1.437)	(-1.779)
Ln(Loan Amount)	-0.056***	0.062***	-0.015***
	(-6.027)	(8.650)	(-4.273)
Ln(Loan Amount) Sq	0.006***	-0.009***	0.003***
	(6.492)	(-10.658)	(6.981)
County Controls	✓	✓	✓
State × Month-Year FE	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓
Cluster by County	✓	✓	✓
Observations	759,490	759,490	759,490
Adjusted R-squared	0.198	0.765	0.163

Table 5: Effects of Social Capital on Screening Time

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and loan screening time in days between the date the application is received and the date the application receives a decision. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Screen Days*, the number of days between the date the application was received and the date the loan officer took a decision on it. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)
Dependent Variable	Screen Days
Independent Variables	
SK	-1.797***
	(-4.318)
Borrower, County Controls	✓
State × Month-Year FE	✓
Bank × Month-Year FE	✓
Cluster by County	✓
Observations	2,578,020
Adjusted R-squared	0.087

Table 6: Other Contractual Loan Terms at Origination (Approved Loans)

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and borrower performance when looking at other contractual terms for approved loans. Columns (1)–(2) use a 20% random sample from the anonymized Federal Reserve–merged HMDA-McDash dataset, covering the period 1998:Q1–2015:Q4. Columns (3)–(4) show a robustness check using the 2018–2019 enhanced confidential HMDA (full sample). In the table, the dependent variables are two contractual terms for originated loans, *Interest Rate*, the mortgage interest rate at origination, and *Maturity*, the loan maturity in years at origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Borrower Credit Score, Loan-to-Value Ratio, Low Doc Borrower (col 1-2 only), Borrower Age and Borrower Age Sq (col. 3-4 only), Debt-to-Income, Joint Account, Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions appear in Appendix X. Regressions also include State × Quarter FE in columns (1)–(2) and State × Month-Year FE and Bank × Month-Year FE in columns (3)–(4). Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Anonymized HMDA-McDash (main sample)		*Robustness using 2018–2019 Enhanced HMDA*	
	(1)	(2)	(3)	(4)
Dependent Variable	Interest Rate	Maturity	Interest Rate	Maturity
Independent Variables				
SK	-0.053***	0.044*	-0.019***	0.056*
	(-7.334)	(1.732)	(-3.137)	(1.731)
Borrower, County Controls	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓		
State × Month-Year FE			✓	✓
Bank × Month-Year FE			✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,452,672	1,452,976	637,605	617,571
Adjusted R-squared	0.684	0.280	0.474	0.371

Table 7: Effects of Social Capital on Loan Performance – Baseline Results

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and borrower performance. The table uses a 20% random sample from the anonymized Federal Reserve–merged HMDA-McDash dataset, covering Q1 of 1998 through Q4 of 2015. The dependent variable is *Delinquency 60DPD*, an indicator for whether the loan was ever in 60 days past due status of delinquency over the three years after origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. Column (1) presents a model without any controls, and column (2) presents a model that includes borrower and county controls. *Borrower Controls* at the time of the application: *Borrower Credit Score, Loan-to-Value Ratio, Low Doc Borrower, Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Quarter-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Dependent Variable	(1) Delinquent 60DPD	(2) Delinquent 60DPD
Independent Variables		
SK	-0.027***	-0.013***
	(-11.863)	(-7.370)
Borrower Controls		
Borrower Credit Score		-0.001***
		(-79.552)
Loan-to-Value Ratio		0.026***
		(9.041)
Low Doc Borrower		0.040***
		(17.119)
Debt-to-Income		0.002**
		(2.116)
Ln(Borrower Income)		0.002
		(1.044)
Minority		0.029***
		(8.254)
Female		0.001
		(1.255)
Co-Applicant		-0.039***
		(-27.125)
Metro		-0.000
		(-0.152)
Ln(Loan Amount)		0.078***
		(3.250)
Ln(Loan Amount) Sq		-0.003***
		(-3.297)
County Controls		
Ln (Cnty Income)		0.001
		(0.452)
Cnty Unemployment Rate		-0.001
		(-1.376)
Δ Cnty HPI		-0.116
		(-1.447)
Population Density		-0.000
		(-1.082)
Cnty Credit Score		-0.000***
		(-2.871)
Cnty Age		0.007
		(0.830)
Cnty Age Sq		-0.000
		(-0.636)
State × Quarter-Year FE	✓	✓
Cluster by County	✓	✓
Observations	1,979,408	1,452,984
Adjusted R-squared	0.128	0.233

Table 8: Effects of Social Capital on Loan Performance – Additional Identification Analyses

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and borrower performance using endogeneity tests and other sensitivity analyses. In Panel A, columns (1)–(2), we report estimates from an instrumental variable analysis. We use *Ancestral Trust* as the instrument, the county-level weighted average of World Values Survey's societal trust, where the weights are the percentages of people with first ancestry country information as reported in the U.S. Census Bureau's ancestry data. Column (3) shows regression results from a matched sample analysis where counties with a high social capital value (top 25%) were matched (1:1 matching without replacement and a 1% caliper) to counties with low social capital value (bottom 25%) based on similar characteristics including the instrument *Ancestral Trust*. Panels B1–B2 control for additional county characteristics that could impact the results. The table uses a 20% random sample from the anonymized Federal Reserve–merged HMDA-McDash dataset, covering the period 1998:Q1–2015:Q4. The dependent variable is *Delinquency 60DPD*, an indicator for whether the loan was ever in 60 days past due status of delinquency over the three years after origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Borrower Credit Score, Loan-to-Value Ratio, Low Doc Borrower, Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Quarter-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: IV and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS *(repeated for convenience)*	IV 1st stage	IV 2nd stage	PSM
Dependent Variable	Delinquent 60DPD	SK	Delinquent 60DPD	Delinquent 60DPD
Independent Variables				
SK	-0.013***		-0.120***	
	(-7.370)		(-2.858)	
High_SK				-0.019***
				(-3.865)
Instrument:				
Ancestral Trust		0.039***		
		(3.242)		
Borrower, County Controls	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,452,984	1,452,984	1,452,984	216,218
Adjusted R-squared	0.233	0.713	0.075	0.250
K–P Weak Identification			10.51***	
K–P Underidentification			10.17***	

Panel B: Additional Controls: OLS, IV, and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS	IV 1st stage	IV 2nd stage	PSM
Dependent Variable	Delinquent 60DPD	SK	Delinquent 60DPD	Delinquent 60DPD
Independent Variables				
SK	-0.008***		-0.108***	
	(-3.523)		(-3.248)	
High_SK				-0.011**
				(-2.334)
Instrument:				
Ancestral Trust		0.039***		
		(4.053)		
Additional Controls				
Cnty Education	-0.037	3.689***	0.317**	-0.067**
	(-1.591)	(10.744)	(2.475)	(-2.084)
Cnty Pop Growth	0.163**	-5.751***	-0.422*	0.464***
	(1.997)	(-3.570)	(-1.664)	(3.337)
Cnty Pct Minority	0.056***	-0.805***	-0.040	0.043***
	(2.612)	(-3.091)	(-0.815)	(2.603)
Cnty Pct Female	0.133	3.775***	0.520***	0.047
	(1.592)	(3.171)	(2.669)	(0.344)
Cnty Latitude	0.001	0.036**	0.004**	0.003*
	(0.841)	(2.246)	(2.205)	(1.788)
Cnty Longitude	-0.002**	0.034***	0.002	-0.000
	(-2.525)	(2.808)	(1.245)	(-0.320)
Cnty Bank Competition	0.008	0.483***	0.058**	0.010
	(0.702)	(3.638)	(2.455)	(0.734)
Cnty Bank Branches/Pop	0.031***	1.465***	0.181***	0.047***
	(3.307)	(7.657)	(3.249)	(2.948)
Cnty Inequality (Gini)	-0.082**	2.295***	0.145	0.010
	(-2.150)	(2.862)	(1.065)	(0.200)
Cnty Approval Rate	-0.234***	1.633***	-0.067	-0.188***
	(-10.358)	(7.522)	(-1.112)	(-7.084)
Borrower, County Controls	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,452,563	1,452,563	1,452,563	216,146
Adjusted R-squared	0.234	0.812	0.092	0.250
K–P Weak Identification			16.42***	
K–P Underidentification			17.09***	

Table 9: Other Performance Indicators

This table reports loan-level regression estimates from a model explaining the relation between social capital and borrower performance when looking at additional performance indicators. The table uses a 20% random sample from the anonymized Federal Reserve–merged HMDA-McDash dataset, covering the period 1998:Q1–2015:Q4. The dependent variables are *Avg. Credit Score*, average of borrower FICO score over three years since origination, and *Credit Score Decline*, an indicator for whether the borrower experienced a FICO score less than the origination FICO over the three years since origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Borrower Credit Score, Loan-to-Value Ratio, Low Doc Borrower, Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. All regressions include State × Quarter-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)
Dependent Variable	Avg. Credit Score	Credit Score Decline
Independent Variables		
SK	2.610***	-0.008***
	(7.614)	(-4.310)
Borrower, County Controls	✓	✓
State × Quarter-Year FE	✓	✓
Cluster by County	✓	✓
Observations	968,058	968,057
Adjusted R-squared	0.656	0.062

Table 10: Additional Analysis Using a Different Dataset to Address Potential Selection Bias

This table reports additional tests to address potential selection bias and covers regression estimates for models explaining the relations between social capital and borrower performance using a different dataset. We use a 20% random sample from the anonymized FRBNY Consumer Credit Panel/Equifax (CCP) data, covering the period 1998:Q1–2015:Q4. The dependent variable is *Delinquency 60DPD*, an indicator for whether the loan was ever in 60 days past due status of delinquency over the three years after origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. Models include borrower and county controls. *CCP Borrower Controls* at the loan origination time are: *Borrower Equifax Riskscore*, *Joint Account*, *Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq* as well as *Ln(No Borrower Credit Inquiries previous 24 months)*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X. Regressions include Consumer FE and other Fes in various specifications, Quarter-Year FE, State FE, Census Tract FE, or State × Quarter-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Performance over 3 Years since Origination			
	(1)	(2)	(3)	(4)
Dependent Variable	Delinquent 60DPD	Delinquent 60DPD	Delinquent 60DPD	Delinquent 60DPD
<u>Independent Variables</u>				
SK	-0.006***	-0.004*	-0.006**	-0.008***
	(-2.757)	(-1.694)	(-2.340)	(-2.896)
CPP Borrower, County Controls	✓	✓	✓	✓
Consumer FE	✓	✓	✓	✓
Year-Quarter FE	✓		✓	✓
State × Quarter-Year FE		✓		
State FE			✓	
Census Tract FE				✓
Cluster by County	✓	✓	✓	✓
Observations	229,188	229,125	229,188	226,849
Adjusted R-squared	0.282	0.293	0.282	0.305

Appendix X: Additional Robustness and Other Analyses

Table X.1: Variable Definitions

This table provides definitions and data sources for variables used in our analyses.

Variable	Definition	Sources
Dependent Variables		
Approved	Indicator that equals 1 if a loan application was approved (both originated or not), and 0 if it was denied.	HMDA
Originated	Indicator that equals 1 if a loan application was approved (originated), and 0 if it was denied.	HMDA
Delinquent_60DPD	Indicator that equals 1 for mortgages that are ever in 60 days past due delinquency status over three years after origination.	HMDA-McDash
Delinquent_90DPD	Indicator that equals 1 for mortgages that are ever in 90 days past due delinquency status over three years after origination.	HMDA-McDash
Forbearance/REO	Indicator that equals 1 for mortgages that are ever in forbearance or real-estate owned (REO) delinquency status over three years after origination.	HMDA-McDash
Delinquent_30DPD	Indicator that equals 1 for mortgages that are ever in 30 days past due delinquency status over three years after origination.	HMDA-McDash
Forbearance/REO/Bankruptcy	Indicator that equals 1 for mortgages that are ever in forbearance or REO or borrower is in bankruptcy status over three years after origination.	HMDA-McDash
Bankruptcy	Indicator that equals 1 for borrowers that are ever in bankruptcy status over three years after origination.	HMDA-McDash
Social Capital Variables		
SK	County-level social capital index developed by using the PCA of four factors capturing the joint effect of social networks and cooperative norms in U.S. counties. It is based on NRCRD component data and adjusted following prior literature to resolve reporting inconsistencies across certain years.	NRCRD
Instruments		
Ancestral Trust	County-level weighted average of ancestral trust, where weights are the percentages of people with first ancestry country information as per U.S. Census Bureau's ancestry data. Trust is derived from the country-level World Values Survey question "Generally speaking, would you say that most people can be trusted or that you need to be very careful in dealing with people?". The WVS only allows for two answers: 1: "Most people can be trusted", and 0: "Can't be too careful."	US Census, World Values Surveys
Ancestral Power Distance	County-level weighted average of Hofstede's cultural score for power distance (the extent to which the less powerful expect and accept that power is distributed unequally or social inequality, are afraid to express disagreement with the more powerful), where weights are the percentages of people with first ancestry country information as per U.S. Census Bureau's ancestry data.	US Census, Hofstede (2001)
Borrower Controls		
Debt-to-Income	Ratio of debt to income.	HMDA
Ln(Borrower Income)	Natural log of borrower income.	HMDA
Minority	Indicator for minority borrower.	HMDA
Female	Indicator for female borrower.	HMDA
Co-Applicant	Indicator for presence of co-applicant on the loan application.	HMDA
Metro	Indicator for metro areas (MSA).	HMDA
Ln(Loan Amount)	Natural log of loan amount.	HMDA
Ln(Loan Amount) Sq	Natural log of loan amount squared.	HMDA
Borrower Credit Score	Borrower FICO credit score. We use the terms credit score and FICO to refer to consumer FICO scores interchangeably.	HMDA-McDash
Loan-to-Value Ratio	Ratio of loan to value.	HMDA-McDash
Low Doc Borrower	Indicator for borrower providing less than full documentation at application time.	HMDA-McDash
County Controls		
Ln (Cnty Income)	Natural log of county-level yearly income.	IRS
Cnty Unemployment Rate	County unemployment rate.	BLS/Haver Analytics
Δ Cnty HPI	Change in county HPI.	Corelogic Solutions
Population Density	County population density (population/square miles).	US Census Bureau
Cnty Credit Score	County average consumer Equifax Risk Score.	CCP
Cnty Age	County average consumer age.	CCP
Cnty Age Sq	County average consumer age.	CCP

Table X.2: Credit Approval: Additional Identification and Other Robustness Tests

This table reports loan-level regression estimates from a linear probability model that explains the relation between social capital and mortgage origination decisions when conducting endogeneity and other sensitivity tests. In Panel A, column (1) we repeat the estimates from the OLS analysis for convenience to facilitate comparison with other models, while in columns (2)–(3), we report estimates from an instrumental variable analysis. We use *Ancestral Power Distance* as the instrument, which is the county-level weighted average of Hofstede's cultural score for power distance, where the weights are the percentages of people with first ancestry information as reported in the U.S. Census Bureau's ancestry data. Finally, column (4) shows regression results from a matched sample analysis, where counties with a high social capital value (top 25%) were matched (1:1 matching without replacement and a 1% caliper) to counties with a low social capital value (bottom 25%), based on similar characteristics, including the instrument *Ancestral Power Distance*. Panel B follows the same structure and methodology as Panel A, but reports OLS, IV, PSM estimates, when additionally controlling for even more county characteristics that could impact the results. Panels C–E report OLS estimates from other sensitivity tests. Thus, Panel C reports results using an alternative dependent variable, *Originated*, an indicator that equals 1 if a loan application was approved by the lender (action_type = 1), and 0 if it was denied (action_type = 3). Panel D shows results using alternative social capital methods and alternative sampling methods. Panel D excludes observations in M12 (December).

The table uses a 20% random sample from the anonymized confidential Home Mortgage Disclosure Act (HMDA) Loan Application Registry, covering the period 1998:M1–2015:M12. Unless specified otherwise, the dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved (action_type = 1 or 2), and 0 if it was denied (action_type = 3). The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Table X.1. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Alternative IV and PSM Analyses

Model	(1) OLS *(repeated for convenience)*	(2) IV 1^{st} stage	(3) IV 2^{nd} stage	(4) PSM
Dependent Variable		SK	Approved	Approved
Independent Variables				
SK	0.014***		0.024***	
	(6.732)		(3.303)	
High_SK				0.035***
				(7.093)
Instrument:				
Ancestral Power Distance		-0.046***		
		(-6.108)		
Borrower, County Controls	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	2,578,020	2,578,020	2,578,020	201,834
Adjusted R-squared	0.122	0.775	0.039	0.138
K–P Weak Identification			37.31***	
K–P Underidentification			28.11***	

Panel B: Additional Controls: OLS, Alternative IV, and PSM Analyses

Model	(1) OLS	(2) IV 1^{st} stage	(3) IV 2^{nd} stage	(4) PSM
Dependent Variable	Approved	SK	Approved	Approved
Independent Variables				
SK	0.011***		0.035***	
	(5.168)		(5.372)	
High_SK				0.040***
				(5.701)
Instrument:				
Ancestral Power Distance		-0.053***		

		(-11.126)		
Additional Controls				
Cnty Education	0.022	2.936***	-0.072**	0.040
	(0.982)	(8.196)	(-2.083)	(0.709)
Cnty Pop Growth	0.098**	-3.523***	0.200***	0.615***
	(1.992)	(-3.088)	(2.876)	(4.934)
Cnty Pct Minority	0.023**	0.229	0.058***	-0.003
	(2.088)	(0.857)	(3.809)	(-0.116)
Cnty Pct Female	0.214***	2.148	0.137	0.226
	(2.686)	(1.336)	(1.420)	(1.163)
Cnty Latitude	0.004***	0.029**	0.003***	0.003
	(4.448)	(1.965)	(3.565)	(1.489)
Cnty Longitude	0.002*	0.043***	0.001	-0.001
	(1.749)	(3.723)	(0.525)	(-0.506)
Cnty Bank Competition	0.018*	0.428***	0.005	0.016
	(1.788)	(2.722)	(0.489)	(0.714)
Cnty Bank Branches/Pop	0.154***	0.992***	0.129***	0.215**
	(4.452)	(3.296)	(3.639)	(2.493)
Cnty Inequality (Gini)	-0.087**	3.351***	-0.165***	-0.044
	(-2.200)	(3.912)	(-3.354)	(-0.515)
Cnty Delinquency 60DPD Rate	-0.034***	0.124*	-0.036***	-0.014
	(-5.828)	(1.662)	(-6.017)	(-0.742)
Cnty Predicted Delinquency 60DPD Rate	-0.006	-2.100***	0.053***	-0.021
	(-0.545)	(-9.835)	(2.900)	(-0.561)
Borrower, County Controls	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	2,363,024	2,363,024	2,363,024	177,987
Adjusted R-squared	0.118	0.860	0.039	0.134
K–P Weak Identification			123.80***	
K–P Underidentification			103.30***	

Panel C: Alternative Dependent Variable

	(1)
Dependent Variable	Originated
Independent Variables	
SK	0.017***
	(7.084)
Borrower, County Controls	✓
State × Month-Year FE	✓
Bank × Month-Year FE	✓
Cluster by County	✓
Observations	2,323,039
Adjusted R-squared	0.144

Panel D: Alternative Social Capital Variables and Sampling Methods

	NRCRD years only	SK linearly interpolated	CCES turnout
	(1)	(2)	(3)
Dependent Variable	Approved	Approved	Approved
Independent Variables			
SK	0.017***		
	(6.557)		
Interpol SK		0.010***	
		(5.482)	
CCES Self-Reported Voter Turnout			0.017***
			(3.615)
Borrower, County Controls	✓	✓	✓
State × Month-Year FE	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓
Cluster by County	✓	✓	✓
Observations	393,744	2,562,810	2,539,582
Adjusted R-squared	0.112	0.122	0.121

Panel E: Exclude Month 12 (December)

	(1)
Dependent Variable	Approved
Independent Variables	
SK	0.015***
	(6.451)
Borrower, County Controls	✓
State × Month-Year FE	✓
Bank × Month-Year FE	✓
Cluster by County	✓
Observations	2,017,866
Adjusted R-squared	0.109

Table X.3: Effects of Social Capital on Credit Approval – Falsification Tests (Using Alternative Specification)

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and mortgage origination decisions when investigating channels and other analyses and using alternative fixed effects. Panel A shows differential effects for fintech lenders versus banks using definitions of fintech from Buchak, Matvos, Piskorski, and Seru (2018) and Jagtiani, Lambie-Hanson, and Lambie-Hanson (2021). Panel B shows differential effects from lenders without deposit branches in the borrower county. Panel C uses 2018–2019 enhanced confidential HMDA (full sample) and investigates regular loan officer approvals for mortgages versus automated underwriting system (AUS) decisions (approvals and rejections). The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved, and 0 if it was denied. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Appendix X.1. All regressions include County × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: Fintech vs. Banks

	(1)	(2)
Dependent Variable	Approved	Approved
Independent Variables		
SK × Fintech (Buchak et al.)	-0.044***	
	(-6.162)	
SK × Fintech (Buchak et al. & Jagtiani et al.)		-0.045***
		(-6.513)
Borrower, County Controls	✓	✓
County × Month-Year FE	✓	✓
Lender × Month-Year FE	✓	✓
Cluster by County	✓	✓
Observations	2,695,036	2,733,009
Adjusted R-squared	0.178	0.179

Panel B: Sold and Zero Deposit Branches

	(1)
Dependent Variable:	Approved
Independent Variables:	
SK × Zero Deposit Branches	-0.005***
	(-3.876)
Zero Deposit Branches	-0.028***
	(-23.181)
Borrower, County Controls	✓
County × Month-Year FE	✓
Bank × Month-Year FE	✓
Cluster by County	✓
Observations	7,791,494
Adjusted R-squared	0.155

Table X.4: Credit Approval: Social Capital Components and Trust

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and mortgage origination decisions when looking at social capital individual components and trust. In column (1), we repeat the main results from Table 2, while in column (2), we decompose the social capital measure by its individual components, *PVOTE, RESPN, NCCS,* and *ASSN*. Column (3) shows results using social trust as a key independent variable based on the General Social Surveys (GSS) data at University of Chicago. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved (action_type = 1 or 2), and 0 if it was denied (action_type = 3). The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data or its components, *PVOTE, RESPN, NCCS*, and *ASSN*. Details on the social capital measures and construction are in Appendix Y. *TRUST* is an indicator for whether people in a county believe most other people can be trusted or not based on the GSS data. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Table X.1. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	(1)	(2)	(3)
Dependent Variable	Approved	Approved	Approved
Independent Variables			
SK	0.014***		
	(6.732)		
PVOTE		0.011***	
		(4.686)	
RESPN		0.005**	
		(2.301)	
NCCS		0.004*	
		(1.877)	
ASSN		0.011***	
		(4.100)	
TRUST			0.007**
			(2.160)
Borrower, County Controls	✓	✓	✓
State × Month-Year FE	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓
Cluster by County	✓	✓	✓
Observations	2,578,020	2,578,020	1,202,215
Adjusted R-squared	0.122	0.122	0.115

Table X.5: Credit Approval: Segmentation using County Characteristics

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and mortgage origination decisions when conducting cross-sectional tests by county characteristics: unemployment rate, house price index (HPI) change, average consumer Equifax Risk Score for a county, and local market concentration for deposits and mortgages. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved, and 0 if it was denied. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Table X.1. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: County Risk (Unemployment Rate (UR), HPI Change, and Average Consumer Equifax Risk Score)

	High County UR	Low County UR	High County HPI Change	Low County HPI Change	Low County Equifax Risk Score	High County Equifax Risk Score
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Approved	Approved	Approved	Approved	Approved	Approved
Independent Variables						
SK	0.017***	0.014***	0.013***	0.014***	0.020***	0.014***
	(5.984)	(6.811)	(5.547)	(7.765)	(5.981)	(6.055)
Borrower, County Controls	✓	✓	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓	✓	✓
Observations	1,312,791	1,230,630	1,277,684	1,263,476	1,272,960	1,276,936
Adjusted R-squared	0.123	0.117	0.116	0.130	0.127	0.109
Difference groups (*t*-stat)	0.832		-0.354		1.664*	

Panel B: County Competition (HHI Deposits, HHI Mortgages)

	Low County HHI Deposits	High County HHI Deposits	Low County HHI Mortgages	High County HHI Mortgages
	(1)	(2)	(3)	(4)
Dependent Variable	Approved	Approved	Approved	Approved
Independent Variables				
SK	0.014***	0.013***	0.018***	0.012***
	(5.052)	(5.293)	(5.472)	(5.361)
Borrower, County Controls	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,282,731	1,257,855	1,277,323	1,255,033
Adjusted R-squared	0.119	0.128	0.119	0.130
Difference groups (*t*-stat)	0.277		1.664*	

Table X.6: Credit Approval: Segmentation using Bank Characteristics

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and mortgage origination decisions when conducting cross-sectional tests by bank characteristics sourced from the Call Reports and HMDA, respectively: size, capitalization, and local market concentration for mortgages. The table uses a 20% random sample from the anonymized confidential HMDA Loan Application Registry, covering the period 1998:M1–2015:M12. The dependent variable is *Approved*, an indicator that equals 1 if a loan application was approved, and 0 if it was denied. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Table X.1. All regressions include State × Month-Year FE and Bank × Month-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

	Large Bank	Small Bank	High Capital Adequacy	Low Capital Adequacy	Low Bank HHI Mortgages	High Bank HHI Mortgages
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Approved	Approved	Approved	Approved	Approved	Approved
Independent Variables						
SK	0.015***	0.009***	0.018***	0.011***	0.017***	0.010***
	(6.068)	(5.313)	(7.307)	(3.796)	(7.752)	(4.745)
Borrower, County Controls	✓	✓	✓	✓	✓	✓
State × Month-Year FE	✓	✓	✓	✓	✓	✓
Bank × Month-Year FE	✓	✓	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓	✓	✓
Observations	1,952,954	624,876	1,139,848	954,400	1,211,291	1,341,845
Adjusted R-squared	0.120	0.170	0.116	0.137	0.132	0.132
Difference groups (*t*-stat)	2.121**		1.941*		2.475***	

Table X.7: Loan Performance: Additional Identification and Other Robustness Tests

This table reports loan-level regression estimates from a linear probability model explaining the relation between social capital and borrower performance using additional robustness and sensitivity analyses. It reports loan-level regression estimates from a linear probability model that explains the relation between social capital and mortgage origination decisions when conducting endogeneity and other sensitivity tests. In Panel A, column (1) we repeat the estimates from the OLS analysis for convenience to facilitate comparison with other models, while in columns (2)–(3), we report estimates from an instrumental variable analysis. We use *Ancestral Power Distance* as the instrument, which is the county-level weighted average of Hofstede's cultural score for power distance, where the weights are the percentages of people with first ancestry country information as reported in the U.S. Census Bureau's ancestry data. Finally, column (4) shows regression results from a matched sample analysis, where counties with a high social capital value (top 25%) were matched (1:1 matching without replacement and a 1% caliper) to counties with a low social capital value (bottom 25%), based on similar characteristics, including the instrument *Ancestral Power Distance*. Panel B follows the same structure and methodology as Panel A, but reports OLS, IV, PSM estimates, when additionally controlling for even more county characteristics that could impact the results. Panels C–D report OLS estimates from other sensitivity tests. Thus, Panel C reports results using alternative dependent variables, *Delinquency 90DPD, Foreclosure/REO, Delinquency 30DPD*, *Foreclosure/REO/Bankruptcy*, and *Bankruptcy*, indicators for whether the loan was ever in 90 days past due, foreclosure or REO status, 30 days past due, foreclosure, REO or bankruptcy status, or bankruptcy status over the three years after origination. Panel D shows results using alternative social capital methods and alternative sampling methods.

The table uses a 20% random sample from the anonymized Federal Reserve–merged HMDA-McDash dataset, covering the period 1998:Q1–2015:Q4. Unless specified otherwise, the dependent variable is *Delinquency 60DPD*, an indicator for whether the loan was ever in 60 days past due status of delinquency over the three years after origination. The key explanatory variable is *SK*, the county-level social capital index developed by using the PCA of four factors that capture social networks and cooperative norms in U.S. counties based on NRCRD component data. Details on the social capital measures and construction are in Appendix Y. *Borrower Controls* at the time of the application: *Borrower Credit Score, Loan-to-Value Ratio, Low Doc Borrower, Debt-to-Income*, *Joint Account*, *Ln (Borrower Income), Minority, Female, Co-Applicant, Metro, Ln(Loan Amount),* and *Ln(Loan Amount) Sq*. *County Controls* include characteristics of the borrower's county: county income, unemployment rate, change in HPI, population density, average credit score, average consumer age, and average consumer age squared. Variable definitions are in Table X.1. All regressions include State × Quarter-Year FE. Heteroskedasticity-robust *t*-statistics clustered at the county level are reported in parentheses below the coefficient estimates. Significance at the 10%, 5%, and 1% levels is indicated by *, **, and ***, respectively.

Panel A: IV and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS *(repeated for convenience)*	IV 1st stage	IV 2nd stage	PSM
Dependent Variable	Delinquent 60DPD	SK	Delinquent 60DPD	Delinquent 60DPD
Independent Variables				
SK	-0.013***		-0.046***	
	(-7.370)		(-2.891)	
High_SK				-0.029***
				(-4.629)
Instrument:				
Ancestral Power Distance		-0.036***		
		(-5.620)		
Borrower, County Controls	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,452,984	1,452,984	1,452,984	143,172
Adjusted R-squared	0.233	0.729	0.109	0.232
K–P Weak Identification			31.58***	
K–P Underidentification			26.37***	

Panel B: Additional Controls: OLS, IV, and PSM Analyses

	(1)	(2)	(3)	(4)
Model	OLS	IV 1st stage	IV 2nd stage	PSM
Dependent Variable	Delinquent 60DPD	SK	Delinquent 60DPD	Delinquent 60DPD
Independent Variables				
SK	-0.008***		-0.021***	
	(-3.523)		(-3.601)	
High_SK				-0.020***
				(-3.376)
Instrument:		-0.053***		

Ancestral Power Distance				
		(-12.000)		
Additional Controls				
Cnty Education	-0.037	2.555***	0.009	-0.069*
	(-1.591)	(7.941)	(0.329)	(-1.924)
Cnty Pop Growth	0.163**	-5.038***	0.086	0.198
	(1.997)	(-3.560)	(1.111)	(1.060)
Cnty Pct Minority	0.056***	0.824***	0.043**	0.050**
	(2.612)	(3.430)	(1.991)	(2.508)
Cnty Pct Female	0.133	3.097***	0.184**	0.152
	(1.592)	(2.737)	(2.101)	(1.014)
Cnty Latitude	0.001	0.032**	0.001	-0.002
	(0.841)	(2.208)	(1.355)	(-1.087)
Cnty Longitude	-0.002**	0.043***	-0.001*	-0.001
	(-2.525)	(4.133)	(-1.678)	(-0.993)
Cnty Bank Competition	0.008	0.438***	0.015	0.006
	(0.702)	(3.330)	(1.294)	(0.401)
Cnty Bank Branches/Pop	0.031***	1.612***	0.051***	0.017
	(3.307)	(9.188)	(4.078)	(1.178)
Cnty Inequality (Gini)	-0.082**	2.201***	-0.052	-0.017
	(-2.150)	(2.949)	(-1.158)	(-0.300)
Cnty Approval Rate	-0.234***	1.418***	-0.212***	-0.148***
	(-10.358)	(7.094)	(-8.639)	(-4.787)
All Previous Borrower, County Controls	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓
Observations	1,452,563	1,452,563	1,452,563	143,092
Adjusted R-squared	0.234	0.827	0.114	0.233
K–P Weak Identification			144.00***	
K–P Underidentification			106.00***	

Panel C: Alternative Dependent Variables

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Delinq. 90DPD	Foreclos. /REO	Delinq. 30DPD	Foreclos. /REO/ Bankruptcy	Bankruptcy
Independent Variables					
SK	-0.012***	-0.008***	-0.014***	-0.008***	0.000
	(-6.922)	(-6.406)	(-7.427)	(-6.410)	(1.060)
Borrower, County Controls	✓	✓	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓	✓	✓
Cluster by County	✓	✓	✓	✓	✓
Observations	1,452,984	1,452,984	1,452,984	1,452,984	1,452,982
Adjusted R-squared	0.222	0.150	0.218	0.149	0.003

Panel D: Alternative Social Capital Variables

	NRCRD years only	SK linearly interpolated	CCES turnout
	(1)	(2)	(3)
Dependent Variable	Delinquent 60DPD	Delinquent 60DPD	Delinquent 60DPD
Independent Variables			
SK	-0.010***		
	(-5.032)		
Interpol SK		-0.012***	
		(-7.158)	
CCES Self-Reported Voter Turnout			-0.018**
			(-2.296)
Borrower, County Controls	✓	✓	✓
State × Quarter-Year FE	✓	✓	✓
Cluster by County	✓	✓	✓
Observations	319,724	1,449,753	1,430,993
Adjusted R-squared	0.190	0.233	0.233

Appendix Y: Social Capital Measures

SK = The social capital index, created using principal component analysis of four factors capturing social networks and norms in U.S. counties, using data reported by NRCRD. The four factors are standardized to have a mean of 0 and a standard deviation of 1, and the first principal component is considered the index of social capital. The social capital components are available in 1997, 2005, 2009, and 2014. Data for missing years are backfilled using estimates from the preceding year for which data are available. Thus, we fill in missing data from 1998 to 2004 using available data in 1997, and data from 2006 to 2014 using data in 2005. For 2015, we use data from 2014.

The four factors included in the social capital index are:

1) *PVOTE*: Voter turnout or percentage of voters who voted in the presidential election;
2) *RESPN*: Response rate to the Census Bureau's decennial census;
3) *ASSN*: Aggregate for types of social associations (religious, civic and social, business, political, professional, labor, bowling centers, fitness and recreational sports, public golf courses and country clubs, sports teams and clubs) in the local market divided by population per 1,000;
4) *NCCS*: Number of tax-exempt non-profit organizations divided by population per 10,000.
   Data and more details on components are at https://aese.psu.edu/nercrd/community/social-capital-resources.

We address two reporting inconsistencies across years following prior research. First, the data in 1997 contain additional information for organizations such as memberships in sports and recreation that are no longer available in later years. To resolve this, the index is based only on information from 10 types of social associations consistently reported in all years and thus excludes membership organizations related to sports and recreation (*MEMSPT*) and membership organizations not elsewhere classified (*MEMNEC*). Second, data for Alaska and Hawaii only became available in 2014. For consistency, these two states are not included in the analysis.

Given that there exist no legal or direct material incentives to vote or participate in census surveys (e.g., Knack, 1992; Guiso, Sapienza, and Zingales, 2004), *PVOTE* and *RESPN* likely reflect individual behaviors that are expressions of civic responsibilities. Hence, they are in tune with the social capital theory. Conversely, *ASSN* and *NCCS* reflect a large range of parallel social interactions across many social networks, including non-profit and other social organizations, clubs, and avenues. Coleman (1988) and Putnam (1993) contend it is precisely these types of network ties in the social environment that foster cooperation and bolster the civic norms of the networks. Consequently, we employ these four measures to build the social capital construct in our analysis.

CCES Self-Reported Voter Turnout = The percentage of votes cast in the presidential election based on Cooperative Congressional Election Survey (CCES) data (https://cces.gov.harvard.edu/). This is also a component of the social capital index from NRCRD but is often used as a standalone measure of social capital.