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By *Iftekhar Hasan, Qing He, Haitian Lu*

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Abstract

How does social capital affect trust? Evidence from a Chinese peer-to-peer lending platform shows regional social capital affects the trustee's trustworthiness and the trustor's trust propensity. *Ceteris paribus*, borrowers from higher social capital regions receive larger bid from individual lenders, have higher funding success, larger loan size, and lower default rates, especially for low-quality borrowers. Lenders from higher social capital regions take higher risks and have higher default rates, especially for inexperienced lenders. Cross-regional transactions are most (least) likely to be realized between parties from high (low) social capital regions.

Key words: Social Capital, Trustworthiness, Generalized Trust, Debt Crowdfunding

JEL Classification Code: Z10, G10, O16.

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I. Introduction

Trust, defined as the willingness that a *trustor* voluntarily places resource at the disposal of the *trustee* with expectation of a fair payoff, is fundamental to finance and economic growth. A considerable body of work highlights social capital (SC) stock as an important antecedent of trust (Arrow (1973), Knack and Keefer (1997), Guiso, Sapienza, and Zingales (2004) (2008)). However, the channels through which SC affects trust are unclear. Moreover, the link between society-level SC and micro-level economic transactions has a conceptual gap, which is highlighted when trading partners come from different SC environments.

To examine the impact of SC on trust, we draw from the extant trust literature, which distinguishes *trustworthiness* from *generalized trust* (Colquitt, Scott, and Lepine (2007)). On the one hand, trustworthiness relates to the objective characteristics (e.g., integrity, competence) of a *trustee* (Ang, Cheng, and Wu (2015), Hasan, Hoi, Wu and Zhang (2017a, 2017b)). Generalized trust, on the other hand, refers to the subjective belief of a *trustor* on the likelihood that a potential trading partner will act honestly (Hong, Kubik, and Stein (2005), El-Attar and Poschke (2011)). The level of trust that A (the trustor) places on B (trustee) is a function of B's trustworthiness and A's generalized trust.

We postulate that regional SC simultaneously affects its trustee's trustworthiness and its trustor's generalized trust. SC is the ability of actors to secure benefits by virtue of membership in social networks (Bourdieu (1985)). Social networks are typically associated with norms that promote coordination, cooperation, and reciprocity for the mutual benefit of members (Coleman (1988), Putnam (1995)). A high SC environment helps spread cooperative norms and civic-mindedness (Guiso et al. (2004)), intensifies internal sanctions such as social ostracism (Uhlaner (1989)) and stigmatization (Posner (2000)), and heightens negative moral sentiments associated with opportunistic behaviors (Elster (1989)). Hence, trustors from high SC regions are likely to anticipate cooperative, as opposed to opportunistic, behavior from their counterpart (i.e., trusting), whereas trustees from high SC regions are likely to keep their promises and have low moral hazard (i.e., trustworthy).

We use peer-to-peer lending to test these hypotheses. In the past decade, technological innovations in finance (Fintech) have supported lending between individuals in an online marketplace without the need for financial intermediaries. Owing to the digital and anonymous nature, establishing interpersonal trust is not applicable in online marketplace lending. To

overcome the extreme information asymmetry and adverse selection in this market, lenders seek trust signals to help identify a borrower's "type." Unlike financial institutions, individual lenders use representativeness (Kahneman and Tversky (1972)) or even stereotype (Gilbert and Hixon (1991)) to minimize effortful thought processes. In this context, regional SC provides cursory beliefs and generalizations about others (Bottazzi, Da Rin, and Hellmann (2016)). The impact of SC on trust is instantaneous (Durlauf and Fafchamps (2006)), exogenous to each economic transaction, and could be overweighed in probability judgments (Bordalo, Coffman, Gennaioli, and Shleifer (2016))[1].

We construct a Chinese provincial SC index to capture the SC environment of lenders and borrowers[2]. The SC index is composed of four components: voluntary blood donation, non-governmental organization (NGO) participation, corporate reputation survey, and citizen reputation survey. Drawing from a complete sample of 247,115 unique loans on *Renrendai* (RRD), a leading debt crowdfunding platform in China from 2011 to 2015, we present three sets of evidence.

On the impact of SC on "trustworthiness," we show that all else being equal, borrowers from high SC regions receive larger bid from individual lenders, have higher funding success, larger loan size, and lower default rates. The effect is pronounced among "low-quality" (low-educated, non-repeated, and low-score) borrowers. These results are robust to a variety of robustness checks for endogeneity and alternative explanations.

On the impact of SC on "generalized trust," we find borrowers from high SC regions are more likely to become lenders. Conditional on extending loans, lenders from high SC regions bid larger amount and larger fraction of the loan, but incur high default rates. Further evidence shows that their loans to borrowers from low SC regions contribute to inferior performance. These results focused on inexperienced lenders, that is, those who have not encountered any defaults.

Third, on how regional SC affects cross-regional transactions, we show in a two-by-two matrix that 63% of total investments (accounting for 57% of total transactions) are made by lenders in high SC regions to borrowers in high SC regions. Twenty-one percent of total investments

[1] Zingales (2015) comments: "*Even within the United States, Americans of Swedish origin are more trusting, more in favor of redistribution, and less thrifty than Americans of Italian origin, in the same way that Swedes are more trusting, more in favor of redistribution, and less thrifty than Italians.*"

[2] Section 4.1 presents the construction of the SC index. Our results are robust to city-level SC measures. See Section 5.3.4 for details.

(accounting for 22% of total transactions) are made by lenders in high SC regions to borrowers in low SC regions. Twelve percent of total investments (accounting for 15% of total transactions) are made by lenders in low SC regions to borrowers in high SC regions. Only 4% of total investments (accounting for 5.5% of total transactions) are made by lenders in low SC regions to borrowers in low SC regions. These findings suggest that cross-regional transactions are most (least) likely to be realized between parties from high (low) SC regions, where the aggregate level of trust is highest (lowest).

Our work belongs to the extensive literature on SC and trust. Prior empirical works typically use the word "trust," but they refer to either "trustworthiness" or "generalized trust." For example, to illustrate the impact of SC on *trustworthiness*, Guiso et al. (2004) show that Italian households in high SC regions have easy access to institutional credit. Hasan et al. (2017a) find that US firms headquartered in high SC counties receive favorable bank loan conditions. Ang et al. (2015) find that foreign firms prefer to invest in Chinese regions where local partners and employees are considered trustworthy. Lin and Pursiainen (2018) find that in equity crowdfunding, entrepreneurs from high SC regions have better campaign outcomes. On the impact of SC on *generalized trust*, Hong et al. (2005) and Guiso et al. (2008) find that individuals in high SC environments are more likely to participate in stock markets. Bottazzi et al. (2016) find that societal trust positively predicts European venture capital investments but negatively predicts their successful exits. Unlike previous studies, our highly granular data from peer-to-peer lending allow us to observe separately the impact of SC on trustees' trustworthiness and trustors' generalized trust.

This work adds to the growing number of studies on how non-expert lenders process information in a Fintech environment. As Thakor and Merton (2018) note, technology by itself is not substitute for trust. Prior work finds that non-standard soft information provides trust signals for investors to overcome information friction. Data from Prosper, a US-based peer-to-peer lending platform, reveal that borrowers' trustworthy appearance (Duarte, Siegal, and Young (2012)) and online friendship networks (Lin, Prabhala and Viswanathan (2013)) help improve their funding success through the impression of trustworthiness. Herzenstein, Sonenshein, and Dholakia (2011) and Larrimore, Jiang, Larrimore, Markowitz, and Gorski (2011) find that the use of extended narratives, concrete description, and quantitative words contributes to funding success. Michels (2012) shows that additional unverifiable disclosure is associated with an increase in bidding activity and reduction in the cost of debt. We add to this literature the soft information of

SC. We show that lenders' bidding behavior is affected by the SC of their home and that of the borrower. To our best knowledge, this research is the first work on the impact of regional SC in the world's largest debt crowdfunding market, China.

Finally, we contribute to a strand of literature on the role of trust in cross-border transactions by presenting important empirical evidence from peer-to-peer lending[3]. Guiso et al. (2009) show that trade and investment flows are large between countries that exhibit high mutual trust. Bottazzi et al. (2007) provide evidence that venture capitalists are less likely to fund entrepreneurs in countries whose citizens they trust less, and if they do, the contracts they use are different from the contracts used in countries they trust more. Giannetti and Yafeh (2012) find that culturally distant lead banks offer borrowers small loans at a high interest rate. Ahern, Daminelli, and Fracassi (2015) show that differences in level of trust between acquirer and target countries reduce M&A volume and cumulative abnormal return. Our evidence is consistent with this literature. Our dyadic analysis shows that (1) lenders bid less (more) when their counterpart is from a low (high) SC environment and (2) investments take place most often (least often) between high (low) SC regions.

The remainder of this paper proceeds as follows. Section II reviews the SC and trust literature and develops the hypotheses. Section III introduces the mechanism of online marketplace lending and institutional settings in China. Section IV describes our sample data and variables. Section V and VI present the empirical results. Section VII draws the conclusions.

II. Hypotheses Development

A. Social Capital

The multidimensional concept of SC can be traced to Bourdieu (1985), who defines SC as advantages and opportunities accrued to people through membership in certain communities. In his seminal work, Coleman (1988) claims that three forms of SC can be taken as resources for action: (1) obligations and expectations, (2) information channels, and (3) social norms. Fukuyama (1995) emphasizes on "network-based reciprocal moral obligation" in Japanese society. Yamagishi (1988) describes SC as a system of mutual monitoring. Granovetter (1985) emphasizes the "embeddedness" of social ties in generating trust, establishing expectations, and creating

[3] China is a large and diversified economy. Many countries are small, and their population is comparable to that of Chinese provinces. Boyreau-Debray and Wei (2005) show that the financial market is highly segmented. Capital mobility across regions in China is low, and is closer to the level of international capital movements. Thus, the case of China has implications for studies of international economic activities.

enforcing norms. Putnam (1995) advances the SC concept by injecting the "civicness" aspect. In his influential article "Bowling Alone: America's Declining Social Capital," Putnam presents a strong case that the SC stock in the US is declining, as evidenced by decreasing voting and membership in organizations such as the Parent Teacher Association, the Elks Club, the League of Women Voters, and the Red Cross[4]. Woolcock (1998) proposes a broad definition of SC that includes the information, trust, and norms of reciprocity inherent in a social network.

This article employs the broad definition of SC at society level (also termed as "civic social capital") in the spirit of Putnam (1995), who defines SC as "social organization features, such as networks, norms, and social trust, which facilitate coordination and cooperation for mutual benefit" (p. 67). Collier and Gunning (1999) argue that the economic benefits of a civic society can arise from the building of trust that lessens transaction costs, from the knowledge externalities of social networks, and from an enhanced capacity for collective action. These features, coupled with the appropriate use of sanctions in case of noncompliance, enable groups to overcome collective action problems and deal effectively with multiple social and economic issues (Bloch, Genicot, and Ray (2007)).

B. Social Capital and Trustworthiness

Societal SC can serve as a monitoring system that "rewards" honest dealings and "punishes" opportunistic behaviors (Yamagishi (1988)). In this study, SC serves as a governance institution similar to that played by the formal institution of law. Coleman (1988) argues that dense social networks make the enforcement of group cooperative behavior effective. By aggravating the cost of expropriation and breach, SC provides a mechanism for contract enforcement.

The monitoring aspect of SC can enhance its agent's trustworthiness, diminishes the cost of financial contracting, and facilitates access to external financing. For example, Hasan et al. (2017a) find that firms headquartered in U.S. counties with high SC have low spreads in bank loans and low at-issue spreads in public debt issues. Gupta, Raman, and Shang (2018) show that firms' cost of equity is negatively related to the SC environment surrounding their headquarters. Hasan et al. (2017b) find that firms headquartered in U.S. counties with high SC pay high corporate taxes.

[4] Putnam (1995) identifies the immediate determinants of this phenomenon to the passage from the scene of the civic generation active during the 1920s and 1930s and the succession of an uncivil generation—the baby boomers born and raised after the World War II.

They interpret this result as SC, as a governance institution, constrains self-serving corporate practices that benefit shareholders at the expense of other stakeholders. Huang and Shang (2019) present evidence that firm leverage and short-term debt ratios are negatively associated with SC. They argue that high SC alleviates agency conflicts between managers and shareholders, allowing firms to reduce the amount of debt in their capital structure and the usage of short-term debt in their debt structure. Hoi, Wu, and Zhang (2019) find that SC environment surrounding corporate headquarters is negatively associated with CEO compensation, consistent with SC restraining managerial rent extraction in CEO compensation.

Based on the above findings, we propose:

H1: *Ceteris paribus*, borrowers from high SC societies are more trustworthy than borrowers from low SC societies.

C. Social Capital and Generalized Trust

High SC environment facilitates cooperative norms and civic-mindedness. Consequently, individual trustors who reside in high SC environments are more likely to demonstrate cooperation as opposed to opportunistic behavior from the counterparty. This generalized trust (or "stranger trust") is particularly important in financial contracts characterized by extreme information asymmetry. Empirical evidence supports this claim. Hong et al. (2005) find that social interactions in local geographical areas promote stock market participation and affect trades of money managers residing in the areas. Guiso et al. (2004) exploit SC differences within Italy. They find that in areas with high SC, households more likely use checks and invest less in cash and more in stock. El-Attar and Poschke (2011) find that less-trusting Spanish households invest more in housing and less in financial assets, particularly risky ones.

Based on the above findings, we propose:

H2: *Ceteris paribus*, lenders from high SC societies have higher generalized trust than lenders from low SC societies.

III. Institutional Background

A. Social Capital and Credit in China

This paper presents important evidence from the emerging market of China. In this market, laws and courts are ineffective in protecting investors (La Porta, Lopez-de-Silanes, Shleifer, Vishny

(1998)), necessitating reliance on alternative institutions, such as SC. However, heterogeneities in the SC stock are substantial across Chinese regions (see Section 4.1 for details). For instance, using data from the World Values Survey, Ang et al. (2015) show that SC differences among China's 31 provinces are often greater than those among European countries.

China's financial environment is composed of a bank-dominated credit market and a relatively underdeveloped capital market (Allen, Qian, and Qian (2005)). Most credit is extended by state-owned banks to state firms or the listed sector, leaving major obstacles for private small- and medium-sized firms and individuals to secure financing (He, Xue, and Zhu (2017)). "Shadow banks," or financial firms outside the formal banking sector, primarily serve the financial needs of the vast private sector (Elliott, Kroeber, and Yu (2015)). These financial firms take various forms, such as trust companies, inter-corporate loans via financial institutions ("entrusted loans"), microfinance companies, guarantee firms, leasing companies, pawnshops, and unofficial lenders.

In the past decade, the investment and credit demand of Chinese individuals has surged along with the country's rising middle class, and technological development in finance has greatly facilitated person-to-person lending on the Internet. China has over 700 million Internet users, many of whom have developed the habit of making digital payments[5]. Data from *Wangdaizhijia*[6] show that the number of companies operating peer-to-peer marketplaces soared from only 10 in 2010 to 3,984 by March 2016. These firms facilitated a total of 1.745 trillion RMB (USD 268.4 billion) in loans. Although this emerging market is smaller than the country's colossal financial system,[7] by any measure of size, China is the largest peer-to-peer lending market in the world (*The Economist* (2017)).

B. Renrendai Online Marketplace

Much of our data are drawn from RRD, one of the largest peer-to-peer lending platforms in China. Since its official launch in September 2010, RRD has gained over 2.5 million members and has facilitated 13 billion RMB (USD 2 billion) in funded loans as of December 2015. We obtained

[5] Ernst & Young (2017) reveals in a survey of 20 markets that 58% of consumers in China have used Fintech savings and investment services, whereas only 27% of US consumers have done so. The contrast is particularly strong with regard to the adoption of Fintech borrowing services, with 46% of Chinese consumers indicating that they have used these services versus only 13% of US consumers indicating the same.

[6] The leading Chinese peer-to-peer online lending portal. It offers news and data on peer-to-peer lending in China.

[7] For example, the outstanding balance of peer-to-peer credit is roughly 0.8% of China's total bank loans in 2016 (*The Economist* (2017)).

this proprietary dataset from Changsha Aijie Information Technology Co. Ltd. (Aijie), which covers all "manual bidding" transactions on RRD from 2011 to 2015[8].

Two important features for listings on RRD are worth highlighting. First, borrowers on RRD cannot upload their photographs. Duarte et al. (2012) show that on Prosper, trustworthy appearance is associated with better loan outcomes. We can safely dismiss this factor in our setting. Second, borrowers have no choice on interest rate, because RRD adopts a "posted price mechanism," which assigns interest rates and calculates monthly payments on the basis of its proprietary credit rating model[9]. This feature is useful in the institutional setting because the outcome depends directly on lenders' willingness to supply credit at the given interest rate.[10]

To initiate a loan listing on RRD, users first register on renrendai.com by providing the required information, including their ID card (two-sided), bank account, and cellphone number. For verification, borrowers must submit a photo of themselves holding their ID card (not required among lenders). In addition, they need to provide supplementary evidence of their occupation (employment contract), income (bank statement), education, marital status, home ownership, and residential address. As the most important information, residential address holds the most credibility because RRD requires a "proof of address" that includes bank statements, phone bills, and water or electricity bills. We use this variable to identify a borrower's home province.

To make loan requests (called "listing"), borrowers must supply a title, description, loan amount, and maturity. All loans are unsecured personal loans, and their maturity ranges from 1 month to 48 months. In addition, personal information about borrowers, including age, gender, education, income, marital status, house ownership, employment information, and address (city), is verified and disclosed in the platform by RRD.

[8] Individual lenders on RRD can choose one of the two channels to make investments on loan listings. The "automatic bidding" (zidongbiao) channel allows lenders to lock in a sum of money at RRD's wealth management plans for algorithm-based bidding. The "manual bidding" (shoudongbiao) channel requires lenders to manually select and make investment decisions by themselves. The manual bidding channel is peer-to-peer lending in its essence, because it reflects bounded rationality of individual lenders based on the information they have, their cognitive limitations, and the finite amount of time they have to make a decision. These are the data that we use.

[9] The exact credit rating model used by RRD to assign a credit rating is unknown due to its proprietary nature. However, unlike in the US where individuals' FICO scores can be obtained, in China the personal credit score system is non-existent. Each peer-to-peer lending platform claims to have its own credit rating model based on available information. For example, RRD classifies borrower credit ratings into seven categories: AA, A, B, C, D, E, and HR (high risk). A minimum rating is acquired when a borrower inputs the minimum information required by RRD to open an account. If borrowers voluntarily provide more documentary proof, such as bank income statement, house-ownership certificate, then these details are verified by the website, and their credit rating will increase. Moreover, if a borrower has a good repayment history on this platform, then the borrower's credit rating will also increase.

[10] Wei and Lin (2016) note that two mechanisms are popular in online peer-to-peer lending: auctions and posted prices. In auctions, the "crowd" determines the "price" (interest rate) of the transaction through an auction process. In posted prices, the platform determines the interest rate on the basis of its own "grading" of the borrower. RRD adopts the posted price mechanism.

A loan listing can be open for several days. Lenders can bid any amount in multiples of 50 RMB (USD 7.7). The majority of loans are crowdfunded by multiple lenders. A loan that reaches 100% subscription becomes binding; otherwise, the borrower receives zero funding. Once a successful loan is verified by RRD, funds are transferred from the lender(s) to the borrower, minus a platform service fee. Service fee rates vary according to borrowers' credit rating.

Subsequently, borrowers are obligated to repay the principal and interest in monthly installments. Repayments are proportionally distributed to the lenders of a loan. If a repayment is overdue (i.e., funds in the borrower's bank account are insufficient to repay the interest), then RRD makes several attempts to collect, including sending emails and text messages, seeking the borrower's employer, and conducting on-site collections.

IV. Data and Research Design

A. *Measuring Regional Social Capital*

Following the empirical literature, we construct a composite SC index of Chinese provinces. Our SC proxies rely on provincial statistics and national surveys, which incorporate attitudinal and civicness measures of societal trust[11]. The composite SC index has four components: voluntary blood donation (*Blood*), NGO participation (*NGO*), enterprise survey (*Enterprise*), and citizen survey (*Citizen*). Each proxy is illustrated below.

Voluntary Blood Donation

Our first SC proxy, *Blood*, is voluntary blood donation per thousand population in a province. Neither legal nor economic incentives are given to those who donate blood (Guiso et al. (2004)). The act is likely driven by citizens' reciprocity and civic-mindedness. Following Ang et al. (2015), we measure this variable in milliliters of blood donated voluntarily in a province divided by its population in 2000, the only year that province-level data from the Chinese Society of Blood Transfusion were complete[12]. China's blood donation law states that blood can only be collected by the National Blood Center (NBC) and is without compensation. The NBC has operating

[11] Anderson, Mellor, and Milyo (2004) categorize societal SC measures into (1) *attitudinal* measures, where subjects are asked if they agree that "most people can be trusted," "most people try to be fair," "most people try to be helpful," "you cannot trust strangers anymore," and "I am trustworthy;" (2) *behavioral* measures of "trust" suggested by Glaeser et al. (2000), including whether subjects leave their doors purposely unlocked, loan money to friends or strangers, have been a crime victim, or lie to different categories of persons; and (3) "*civicness*" measures, including hours spent volunteering, membership in volunteer groups, attendance in religious services, political volunteering, and voting.

[12] We are grateful to Ang et al. (2015) for sharing these data with us.

branches in all provinces and adopts the same medical procedures across all regions, thereby mitigating the concern that blood donation levels are affected by differences in the quality of healthcare or medical infrastructure among provinces. Panel B (column 2) of Table 1 shows a large variance among Chinese provinces, with an average blood donation of 3.433 mL/1,000 people in Shanghai and only 0.017 mL/1,000 people in Yunnan.

NGO Participation

The second SC proxy, *NGO*, is measured by the number of people registered in NGOs per thousand population in a province. NGOs are typically funded by charities and operated by volunteers. They aim to address poverty reduction, environment protection, and rights of disadvantaged groups. Individual residents in regions with high proportion of NGO participation tend to be civic-minded and cooperative. Data on provincial NGO participation are manually collected from the Chinese Civil Affairs Statistical Yearbook of 2010[13]. Panel B (column 3) shows that Shanghai is the province with the highest NGO participation (4.4 registered NGO members per thousand population) and that Tibet has the lowest NGO participation (only 0.03).

Enterprise Survey

Our third proxy, *Enterprise*, is drawn from a national survey of Chinese enterprises in 2000 (Zhang and Ke (2003))[14]. In this survey, questionnaires were sent to over 15,000 managers of companies in every province of China. Over 5,000 usable responses were received, and respondent managers covered firms from every two-digit industry and ownership type. This variable is elicited from their answers to the question, "*According to your experience, could you list the top five provinces where enterprises are most trustworthy?*" Following Wu, Firth and Rui (2014), we set the SC score of a province as the logarithm of the total score given by the managers. Panel B (column 4) shows that Shanghai (22.7) leads Chinese provinces in enterprise reputation, followed by Beijing (16.6) and Guangdong (10.1). The least trusted province appears to be Hainan (0.1).

Citizen Survey

The fourth proxy, *Citizen*, employs data from the China General Social Survey (CGSS). The CGSS was conducted jointly by the Hong Kong University of Science and Technology Survey Research Center and Renmin University Sociology Department in 2003. A total of 5,894 complete

[13] In the robustness test, we use the average level from 2010 to 2015, and the results are similar across those years.

[14] A similar enterprise survey was used by Burns, Meyers, and Bailey (1993) and by Guiso et al. (2009) in five major European countries.

responses were received. Respondents encompassed Chinese residents in 125 cities from 28 provinces. The *Citizen* variable is elicited from the response to the question "*Do you trust strangers?*" Responses range from 1 ("do not trust greatly") to 5 ("trust greatly"). We average the scores of respondents' choices by the provinces where they are located. Panel B (column 5) shows a considerably small variance among the scores given by the citizens of each province. Shanghai ranks second (2.40) and is surpassed by Jiangxi (2.442). The least trusting provinces appear to be Gansu (2.014) and Guizhou (2.014).

Composite Social Capital Index

Each of the four proxies could be an imperfect measure of SC. For instance, the *Blood* and *NGO* participation proxies capture outcomes more than perceptions. The *Enterprise* and *Citizen* proxies are based on survey data and capture perceptions, yet they suffer from self-esteem and in-group bias. To account for their intrinsic biases, we construct a composite index by applying principal component analysis (PCA). Panel A in Table 1 shows the results of the PCA for our four components. This method shows that only one component has an eigenvalue larger than 1 (2.967). All four components have positive loadings and are closely correlated with the index. Our *SC_index* gives roughly equal weight to *Blood*, *NGO*, and *Enterprise* but low weight to *Citizen*. According to the *SC_index* (Panel B, column 1), Shanghai, Beijing, and Guangdong are the top three SC stock provinces, whereas Gansu, Guizhou, and Yunnan rank in the bottom.

[Insert Table 1 here]

B. Variables of Interest and Controls

Table 2 shows the summary statistics for our main variables. Appendix I includes detailed definitions for each variable. These variables are categorized into (1) listing and loan characteristics, (2) borrower characteristics, and (3) provincial environment.

We first obtain information on the funding success or failure of each loan listing (FUND). For each successful loan, we obtain the loan size (AMOUNT), MATURITY (in months), SPREAD (interest rate relative to benchmarked lending rate of People's Bank of China), number of lenders (OWNERSHIP), stated loan purpose (in descriptive text), number of words used to describe a loan (WORDS), default status (DEFAULT), and BID_TIME for each fully funded loan (in minutes). For each unsuccessful loan, we obtain the proportion of campaign proceeds out of the total amount (FRACTION).

For each borrower, we obtain their unique ID, age, gender, resident province, marital status, income range, education, work experience, home ownership status, and borrowing history on RRD. We also obtain their credit rating assigned by RRD (in seven categories, i.e., AA, A, B, C, D, E, and HR). For provincial variables, other than the four SC proxies, we include GDP per capita (PGDP) to measure their economic environment and the number of law offices per ten thousand residents (LAW_OFFICE) to capture the legal environment. LOAN is the ratio of total bank loans to provincial GDP, which we use to measure the financial development of a province (Rajan and Zingales (1998)). In our regressions, the institutional variables of a province in year *t-1* are matched with loans originating in year *t*.

C. Summary Statistics

Our sample is composed of 247,115 loan listings on RRD from 2011 to 2015. Panel A of Table 2 reports that approximately 24.9% of loan listings are fully funded. Of the 61,577 fully funded loans, the mean of loan size varies significantly from 3,000 RMB (USD 437) to 3 million RMB (USD 461,538). On average, the loan rate is 2.13 times the benchmark lending rate, with significant variation of 0.76–5.38 times the benchmark lending rate. Relative to the stability of China's benchmark lending rate, these large pricing differences reflect, at least in part, the differences in borrower risks. The mean (median) loan maturity is 18.79 (19) months. We construct an additional variable LONGTERM, which is a dummy variable that equals one if the loan maturity is over 12 months and zero otherwise. The variable shows that 80% of borrowers request a long-term loan. Ownership also varies considerably across loans. The average loan has 35.5 lenders in the range of 1–1,370 lenders. The average bid time for each fully funded loan is 69 minutes. Finally, approximately 5.4% of completed loans incur default.

Panel B reports the summary statistics of borrower characteristics. Most borrowers are young, male, married, do not have a bachelor's degree, and have low credit scores. The median income level of borrowers is less than 10,000 RMB (USD 1,538) per month. Only 44% of borrowers own a house, and 15.8% of borrowers report having a home mortgage loan. Panel C reports the summary statistics of (borrower) provincial-level variables. It shows a large variation in economic, legal, and financial development across Chinese provinces. We do not include province-level or

borrower-level fixed effects in most regressions because our *SC_index* is time invariant for all borrowers in the same province[15].

[Insert Table 2 here]

D. Research Design

Our study is motivated by the prevailing role of SC on its home trustee's trustworthiness and its home trustor's generalized trust. Regional SC has major effects on trust-intensive contracts, that is, debt, stock, and venture capital, particularly in cases of severe information asymmetry and limited information exchange. These problems are highlighted in online marketplace lending where lenders are unsophisticated investors.

First, we postulate that a region's SC stock positively affects its home trustee (borrower)'s trustworthiness. If so, then SC should be associated with better both ex ante outcomes of finance, such as funding success and loan size. We also hypothesize that the marginal effects of SC on ex ante outcomes are stronger when borrowers are less educated, borrowing for the first time, and have lower credit score. Apart from "perceived" trustworthiness, we test whether SC affects "actual" trustworthiness by investigating the ex post defaults in fully funded loans.

Next, we examine whether SC affects its home trustor (lender)'s generalized trust. If lenders in high SC environment are inherently more trusting on others, then, controlling for loan and borrower properties, lenders from high SC regions are more likely to bid, and when they do, they bid larger amounts and larger fraction of loan requests. We also expect that the impact of SC on lender's trust propensity is larger on inexperienced lenders, who are more likely to engage in (SC-induced) coarse thinking. Finally, to gain insights into the consequence of high generalized trust, we examine their investment success through ex post default rates.

We employ a battery of robustness tests to tackle the potential endogeneity. Regional SC is clearly not randomly assigned, nor is it a choice. Accordingly, we treat SC of one's home province as historically and econometrically predetermined. We can safely dismiss the possibility of reverse causality because each micro-economic transaction is clearly too small to influence SC among regions. Hence, the main identification challenge is not reverse causality, but whether our SC index

[15] To examine the impact of the interactions between borrowers' characteristics and the SC index on loan terms, we also perform province-level fixed-effect regressions while dropping all provincial-level variables. The results remain robust.

is correlated with other (omitted) factors that simultaneously affect the debt crowdfunding outcomes[16]. Section 5.3 discusses our various empirical strategies.

V. Empirical Results on Social Capital and Trustworthiness

We start by testing how borrowers' SC (B_SC_INDEX) affects their debt crowdfunding outcomes. We infer borrowers' trustworthiness from their funding success (dummy and fraction), loan terms, and default rates. We also consider how the effects of (borrowers') SC vary across heterogeneous borrower characteristics, such as education, credit history, and credit score.

A. Main Results

Table 3 reports the results of borrowers' SC on loan funding success, the number of lenders for a given loan (OWNERSHIP), and loan size (AMOUNT). SUCCESS is a dummy variable that equals 1 if a borrower's loan is fully funded. FRACTION is the proportion of proceeds relative to the loan amount. Columns 1 and 2 use probit models for funding success, and we report the marginal effects for each variable. Columns 3–8 use OLS regressions for FRACTION, OWNERSHIP, and AMOUNT. Our models control a full set of borrower characteristics, loan characteristics, and the institutional environments of their home province.

Columns 1 and 2 of Panel A show that a borrower's SC positively predicts the probability that a listing is fully funded (p=0.006). To illustrate the marginal effect, all else being identical, a borrower from Shanghai has a 5% (or 1.5 percentage points) higher probability of obtaining a loan than a borrower from Gansu does. Columns 3 and 4 on FRACTION show qualitatively similar results: borrowers from provinces with high SC have a high proportion of proceeds relative to the loan amount. The coefficient is statistically significant at the 1% confidence level (p=0.000). Given a fully funded loan, columns 5 and 6 show a negative correlation between our SC index and the number of lenders (p=0.014 and 0.018, respectively). This result indicates low diversification demand from lenders if borrowers are from provinces with high SC. This result is consistent with the findings of Ongena and Smith (2000) and Qian and Strahan (2007), who show that loan ownership is concentrated in countries with strong creditor protections. Columns 7 and 8 show the

[16] A common confounder is economic development. Although we have controlled for provincial GDP per capita, this approach may not be sufficient. See section 5.3.2 on our empirical strategy to distinguish the effect of social capital from that of economic development. Additionally, see Section 5.3.3 on our instrumental variable approach. For a related study, see Chau et al. (2020).

significantly positive correlation between SC and loan size. A one-standard-deviation increase in SC is associated with a 2,000 RMB (USD $300) increase in loan size. The effects are significant at the 1% confidence level.

The signs of control variables are generally consistent with our expectations. Borrowers with high credit ratings, high personal income, high education levels, and long work experience have higher funding success and receive larger loans. Female borrowers have lower funding success than male borrowers do. Loan ownership becomes increasingly diffused when borrowers are old, are female, or own a house. We take note of SPREAD, which is negatively associated with SUCCESS and OWNERSHIP but positively associated with FRACTION[17]. All provincial-level control variables have the expected sign and are statistically significantly different from zero. Provincial GDP per capita and financial development (LOAN) have a positive and statistically significant effect on funding success, loan size, and ownership. One exception is LAW_OFFICE, which has a negative correlation with funding success. This result suggests that individual lenders view a high number of law offices in a province as an indicator of legal costs to enforce their rights.

Panel B shows the result using each of the four SC proxies while keeping the same full set of controlling variables. The probit and OLS regressions show that three of the four SC proxies positively and statistically significantly related to SUCCESS are negatively and significantly related to loan ownership. Moreover, all four SC proxies have a significantly positive relationship with FRACTION and loan amount.

[Insert Table 3 here]

B. Heterogeneity Tests

If our proposition is true that lenders use borrowers' home SC as impression of trust, then theories of adverse selection (Akerlof (1970)) predict that the marginal benefit of SC would be large for low-quality borrowers. To test this proposition, we partition the sample on the basis of quality indicators, such as borrower's education level, credit history on RRD, and credit grade. Table 4 shows the results.

[17] Lenders are attracted to this market due to its promised high return, where the pre-determined interest rates are several times (not simply basis point) higher than the rate that potential lenders could earn in banks. In the beginning, loan lists with high interest rates will mechanically accumulate many more bids than those with low interest. However, high interest rate also signals high moral hazard of borrowers (Stiglitz and Weiss (1981)). If lenders are rational and they can perceive borrowers' quality from offered interest rate, then borrower's lists with high interest are less likely to be fully funded.

Prior works show that an individual's human capital is closely correlated with education (Lusardi and Mitchell (2008), Behrman et al. (2012)) and that borrowers with low human capital tend to have high financial constraints. In Panel A, a borrower is classified highly (low) educated if his or her highest qualification is a bachelor's degree or above (post-tertiary or below). Consistent with adverse selection, SC has little impact on the funding success of highly educated borrowers (columns 2 and 4) but has large and significant impact on undereducated borrowers (columns 1 and 3). As for loan ownership, SC has a negative and statistically significant effect on the number of lenders in both subsamples, and the difference between the undereducated and highly educated groups is statistically insignificant. Finally, the positive effect of SC on loan amount is large and statistically significant among undereducated borrowers, whereas it is insignificantly negative among highly educated borrowers. The difference between them is statistically significant at the 5% level.

Panel B re-runs the regressions by partitioning the sample into repeat and non-repeat borrowers. A borrower is a repeat borrower if he or she appears more than twice on RRD; otherwise, the borrower is a non-repeat borrower. The effects of borrower SC on funding success, fraction, loan ownership, and amount are highly significant in the subsample of non-repeat borrowers but insignificant among repeat borrowers. The differences between the two groups in terms of funding success and loan ownership are statistically significant.

Panel C re-runs the regressions by partitioning the sample into low- versus high-credit-score borrowers. A borrower is classified as high (low) grade if his or her credit score is below 5 (above or equal to 5). The effects of borrower SC on funding success, fraction, and amount are significant in low-grade borrowers but not among high-grade borrowers. The only exception is loan ownership, that is, the impact of borrower SC on the reduction of the number of bidders is significant among high-grade borrowers but not among low-grade borrowers. The difference between the two groups is not statistically significant.

Taken together, the cross-sectional evidence validates our proposition that lenders use borrowers' home SC as impression of trust. Consistent with adverse selection, our proposition benefits borrowers with low education, little credit history, and low credit grade.

[Insert Table 4 here]

C. Robustness Tests

1. Alternative Specifications

Bootstrapping

Hypothesis testing using a large sample like ours can possibly yield a Type I error. To check robustness, we implement a bootstrapping method. Specifically, we draw a subsample that includes half as many observations as the whole sample and repeat our regression analysis for this subsample. We then replicate this procedure 1,000 times and obtain the bootstrap statistics. Panel A (columns 1–4) of Table 5 shows that our results are qualitatively unchanged; that is, (borrowers') SC positively correlates with funding success and loan amounts and negatively correlates with the number of lenders.

Selection Bias

Much of our empirical analysis uses data from fully funded loans, which account for 24.9% of all loan listings. To account for potential bias, we employ the Heckman two-step treatment effects procedure. In the first equation, we estimate the probability that a loan will be fully funded; here, the dependent variable is a dummy of funding success. This equation uses the same specification as in column 1 of Table 3. In the second equation, we use the inverse Mills ratio to correct the selection bias for the performance equations. These equations use the same specifications as (6) and (8) of Table 3. Panel A (columns 5 and 6) of Table 5 presents the results of the Heckman selection model. The effect of SC on loan ownership and amount remains significant.

Familiarity Bias

We are also concerned about familiarity bias in our result. The top group of high SC provinces consists of key provinces, that is, Shanghai and Beijing. By contrast, the bottom group consists of unpopular provinces, that is, Gansu, Qinghai, and Ningxia, where most people in populated coastal areas may never meet someone from these places. To mitigate familiarity bias, we re-run our model specifications that exclude the top group and the bottom group, that is, Shanghai, Beijing, Gansu, Qinghai, and Ningxia. Panel A (columns 7–10) of Table 5 presents the results. The coefficients of SC carry the same signs and remain statistically significant.

2. Social Capital or Economic Development?

Another concern is that our SC index appears to correlate with economic development of the provinces. Our results will be spurious if, for whatever reason, borrowers in economically prosperous regions are more trustworthy. Although we have controlled for economic development (per capita GDP) and other institutional variables in all specifications, ruling out the confounding

impact of economic development is not sufficient. To address this concern, we employ two methods.

First, we re-estimate our basic specifications, splitting the sample between provinces with low economic development (per capita GDP below the median) and provinces with high economic development (per capita GDP above the median). Panel B of Table 5 shows that our results are not driven by either subsample. The negative relationship between SC and loan ownership seems strong among the low economic development regions. This result indicates that the number of lenders for a given loan (OWNERSHIP) responds more to SC in less developed regions.

Next, we perform a difference-in-differences test by investigating how a negative shock to SC (unrelated to economic development) affects peer-to-peer lending. The shock we exploit is the *Guo Meimei* incident[18]. In June 2011, a woman nicknamed "*Guo Meimei* baby," who claimed herself the general manager of the Chinese Red Cross, showed off her wealth on a blog. This incident provides an ideal laboratory for the following reasons. First, it generated a severe trust crisis for the Red Cross Society of China (RCSC), causing donations to suffer[19]. Second, it was an explicit, temporary shock to trust. A police investigation in 2012 showed that *Guo Meimei*'s wealth was actually not from the RCSC, and the RCSC gradually restored its reputation in the following months. Third, the incident isolates the effects of SC from local economic conditions, as the incident was unrelated to local economic conditions. If SC has a real impact on lending, then the shock could temporarily change investors' beliefs about the risk of their assets being stolen, causing them to withdraw or reduce their investments.

Thus, we design a difference-in-differences test surrounding the *Guo Meimei* incident. The incident date is set as month 0, and we focus on six months prior to and six months after the incident[20]. POST is a dummy variable for the months following the *Guo Meimei* incident (i.e., [1, 6]). We divide our sample into two groups according to the borrower SC index. B_SC_INDEX_H is a dummy variable that equals 1 if the SC index in a region is above the median, and zero otherwise. The coefficients on POST*B_SC_INDEX_H allow us to estimate the differences in the changes in lending activities between regions with different SC. Panel C of Table 5 reports the

[18] See incident description on Wikipedia: https://en.wikipedia.org/wiki/Guo_Meimei_(Internet_celebrity)

[19] A survey administered after the incident showed that over 80% of respondents said they would not donate to RCSC anymore, and actual donation to RCSC and other charity organizations also decreased as a result of the *Guo Meimei* incident. (https://finance.qq.com/a/20110805/001991.htm)

[20] Our "manual bidding" transactions on RRD are available from January 2011, as we have only six months of transaction data before the *Guo Meimei* incident.

results. The results in column 5–8 show a consistent negative relation between POST and the probability of funding success and loan size; they also show a positive relation with loan ownership. In addition, funding success exhibits a decline. Given a fully funded loan, loan size becomes smaller and loan ownership becomes increasingly diffused. This finding suggests that in response to the *Guo Meimei* incident, investors perceived an increased risk of theft, and they in turn withdrew or reduced their investments. Of particular interest are the positive coefficients of the interaction terms, POST*B_SC_INDEX_H on SUCCESS, FRACTION, and AMOUNT. The positive values imply that borrowers in regions with high SC experienced fewer reductions in investment after the *Guo Meimei* incident.

[Insert Table 5 here]

3. Instrumental Variable Approach

This section employs an instrumental variable approach to tackle the potential omitted variable bias. A valid instrument should induce changes in our key explanatory variable (regional SC) but should have no independent effect on the dependent variable (debt crowdfunding outcomes), other than through its impact on regional SC.

We employ two instrumental variables. The first instrument traces back a province's agricultural specialization of growing rice versus wheat. Subsistence style theory argues that some forms of subsistence require more functional interdependence than other forms, and ecology narrows the types of subsistence that are possible. Talhelm et al. (2014) find that Chinese regions with a history of farming rice have a more cooperative norm than those with a history of growing wheat. This is because paddy rice requires irrigation and high labor demand, causing farmers in rice-growing regions to form cooperative labor exchanges. By contrast, wheat does not need to be irrigated, and wheat farmers can rely on rainfall, which does not require coordination with their neighbors. On the one hand, societies that need to cooperate intensively develop more interdependent culture and accumulate higher SC stock over time[21]. On the other hand, a region's environmental suitability for rice, which relies on soil, climate, and topographic factors, should not have a direct impact on today's urban consumer credit, except for its impact on the formation

[21] As Talhelm et al. (2014) wrote, for southerners growing rice, "strict self-reliance might have meant starvation" (p. 604). For related studies, see Ahern et al. (2015) and Mourouzidou-Damtsa et al. (2019).

of regional cooperative culture and SC[22]. Specifically, we calculate the logarithm of the "rice suitability" index of Chinese provinces (RICE_SUIT). The index is a z-score of the environmental suitability of each province for growing wetland rice according to the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database.

Our second instrument exploits the ethnic diversity in Chinese provinces. The ethnic diversity in China provides an exogenous driving force behind the regional variation in SC[23]. Prior cross-country studies show that diversity of ethnic groups in a country increases communication costs, social fragmentation, and probability of civil conflict (Easterly and Levine (1997)), reduces social trust (Guiso et al. (2009)), and leads to poor quality of institutions (Alesina, Devleeschauwer, Easterly, Kurlat, and Wacziarg (2003)). A total of 56 ethnic groups are unequally distributed across China's 31 provinces, and each group has its own language, core values, and customs. Ang et al. (2015) find that ethnic and linguistic diversities in each Chinese province are negatively related to local trustworthiness. Following this literature, we extract data from the China Statistical Yearbook in 2009 to construct a variable ETHNIC that refers to the fractionalization of the largest ethnic group in a province, which should be positively correlated with regional SC stock. However, conceiving a direct impact of regional ethnic diversity on outcomes of nation-wide debt crowdfunding is difficult, other than through its impact on the local SC stock.

Using the full sample, Table 6 reports the results from the instrument variables RICE_SUIT and ETHNIC. Columns 1 and 2 run the regression of the probit and linear models for funding success, and column 3–5 run the linear regression models for fraction, loan ownership, and amount, respectively. We control for loan and borrower variables, regional variables, and year fixed effects, but omit their coefficients for brevity. Consistent with expectation, the first-stage results in Panel B show that RICE_SUIT and ETHNIC variables are positive and significantly correlated with the SC index. The second-stage results in Panel A validate our baseline results that regional SC is an important determinant of funding success, loan ownership, and loan amount. In addition, we conduct an over-identification test because the number of instrument variables is greater than the

[22] One way to think about the indirect impact of rice specialization on credit would be to consider the credit needs of rice-growing households, who need to limit their exposure to shocks that can be handled with available credit and insurance (Morduch (1995)). A complete specialization on rice requires highly seasonal labor demand, which often cannot be procured locally and expose farmers to high risk against production failure or decreasing prices (Klasen, Priebe, and Rudolf (2013), Di Falco and Chavas (2008)). In the long run, regions with high rice specialization might develop deeper agricultural credit and insurance market. This effect, however, is indirect, and pertinent to agricultural finance as opposed to urban consumer credit.

[23] Ethnic diversity, which requires long duration of uninterrupted human settlements (Ahlerup and Olsson (2007)) is typically treated as an exogenous explanatory factor in economics. For a good review of this literature, see Alesina and La Ferrara (2005).

number of endogenous variables. The reported p-value of Hansen-J statistics is larger than 0.05, we conclude that the over-identification restriction is valid.

A valid instrument should satisfy the relevance condition and exclusion restriction condition. The *p*-value for the *F* statistics for the joint significance of the instrument variables is 0.000, which is sufficient to alleviate the relevance concern. We implement tests from Stock and Yogo (2005) for weak instruments. Panel B gives critical values for 2SLS at the 10% level[24]. The reported minimum eigenvalue statistic greatly exceeds the critical value of 19.93 and is large enough to reject the null hypothesis of weak instruments. Another concern is that the instruments (rice production suitability and ethnic diversity) are likely correlated with the local economy and thus do not satisfy the exclusion restriction. With regard to the exclusion-restriction condition (i.e., the instrumental variable does not affect lending through channels other than SC), we implement an additional test. If the instrumental variable influences lending only through the SC channel, then the instrumental variable should have statistically insignificant effects on lending conditional on SC.

We implement two additional tests on the exclusion restrictions. First, if the instrumental variable influences lending through other channels, then the residuals of the second-stage regression should be correlated with the instrumental variable. Panel C reports the regression results of the residuals of the second-stage regression on both instrument variables. The coefficients in both instruments are statistically and economically insignificant. Second, if the instrument variables influence lending activities only through SC, then the instrumental variable should have statistically insignificant effects on lending conditional on SC. In panel D, we include both instrument variables in the benchmark regressions. For simplicity, we include but do not report borrowers' personal characteristics, regional economic variables, and financial variables. The SC index yields consistent results, but all the estimated coefficients of the instrumental variables are statistically insignificant.

[Insert Table 6 here]

4. City-level Evidence

[24] We also use the LIML estimator at 10% level and obtain similar results.

Our SC measure at province-level may be too coarse[25]. China is a large country, and each of its provinces is comparable to a European country by population[26]. People would certainly not consider that all Italians, French, and British are alike in trustworthiness. Fortunately, one of our SC proxies, *Citizen*, employs data from the CGSS for 125 cities in 28 provinces. The number of cities in CGSS varies from 1 city in Hainan Province to 7 cities in Guangdong Province[27]. City-level analysis provides more variation and testing power than provincial-level analysis. Columns 1–4 of Table 7 present the results, which are qualitatively unchanged. City-level citizen proxy, *Citizen_city*, positively correlates with funding success and loan amounts, and negatively correlates with the number of lenders.

To further exploit the SC variations within a common region, we turn to a smaller sample of 11 cities in three neighboring provinces of Yunan (3), Guizhou (2), and Sichuan (6)[28]. The "Yun–Gui–Chuan" region (collectively termed as the "southwest region") is one of the seven geographical divisions in China[29], and were historically often jointly governed[30]. People in this region interact with one other intensively and share similar culture and dialects[31]. Standard errors tend to increase because we have only 11 cities in the sample, and we cluster the standard errors at city level. Columns 5–8 present the results, which remain robust in the smaller sample. For robustness check, we also use a sample of another 11 cities in two adjacent provinces of Guangdong and Guangxi, and obtain similar results[32].

5. Time-series Evidence

[25] We thank an anonymous referee for raising this issue.

[26] For example, eight Chinese provinces have population that is comparable to Italy (60.5 million), France (65 million), and UK (68 million). These provinces are: Guangdong (104 million), Shandong (100 million), Henan (94 million), Sichuan (81 million), Jiangsu (79 million), Hebei (72 million), Hunan (66 million), and Anhui (60 million).

[27] One limitation of city-level analysis is that borrowers are located in 200 cities of China, but the data of city-level SC are available only for 87 cities.

[28] The analysis based on one single province will produce inaccurate estimation due to a small sample of cities.

[29] Southwest China, in a narrow sense, covers only three provinces of Sichuan, Guizhou, and Yunnan. In a broad sense, it also covers Chongqing municipality and Tibet autonomous region.

[30] The region covering the three provinces was historically jointly governed by the state of Shu Han during the Eastern Han Dynasty (220–280). In the 13th century, the Mongolian army conquered the Southern Song Dynasty and created Sichuan, Yunnan, and Guizhou administrative region (Fei (2017)). Since then, the region was administratively governed by Mongols in the Yuan Dynasty (1271–1368), by Hans in the Ming Dynasty (1368–1644), and by the Manchu in the Qing Dynasty (1636–1912).

[31] Southwestern Mandarin is spoken by 260 million people in most of Central and Southwestern China. See https://en.wikipedia.org/wiki/Southwestern_Mandarin

[32] Results are saved for brevity and are available upon request.

One criticism on our results is that our proxy for SC is cross-sectional in nature. Indeed, the common proposition is that a society's SC, which accumulates over a long time, is highly persistent (Putnam, Leonardi, and Nanetti (1994)). However, certain shocks may cause societal SC to change quickly (Algan and Cuhuc (2014), Guriev and Melnikov (2016)), which will bias our result. Fortunately, one of our provincial-level measures of SC, *NGO*, is time-varying. We thus include borrower-level fixed effects to control for time-invariant unobservable heterogeneity. Columns 9–12 of Table 7 show the results. It shows that NGO participation in year $t-1$, NGO_t-1, is significantly positively related with funding success and loan size, and it is negatively related with the number of lenders (ownership).

[Insert Table 7 here]

D. Social Capital and Default Rates

In this section, we use the ex post measure of default rates to test whether borrowers from high SC regions are indeed trustworthy. To test this proposition, we run probit models in which the dependent variable is DEFAULT, which takes the value 1 if borrowers do not make a repayment on time and the value of 0 otherwise.

Column 1 in Table 8 shows a negative relation between SC and default. The coefficients of marginal effects are statistically and economically significant. A one-standard-deviation increase in borrowers' SC index leads to a decline in default rate of approximately 0.4 percentage points or 8% of the sample mean. In an extreme case, a loan made to a borrower in Gansu (SC index of −1.887) has a probability of default that is approximately 1.7 percentage points higher than that for a loan made to a borrower in Shanghai (SC index of 5.768); this value is approximately one-third of the sample mean. Column 2, which is based on OLS regression, presents a similar result. As shown in Columns 3–4, we separately investigate the impact of SC on default rates for low- and high-educated borrowers. Among high-educated borrowers, SC does not significantly predict default. By contrast, in the sample of low-educated borrowers, SC is negatively related to default. This result suggests that SC constrains the opportunistic behavior of low-educated borrowers more than it does on high-educated borrowers. As shown in Columns 5, 6, and 7, we employ the Heckman selection model, bootstrapping method, and instrument variable regression[33] in our probit model of default. We find a significantly negative relationship between SC and default rates, which validates our baseline results.

[33] Column 7 of Table 9 reports the results from the instrument variables RICE_SUIT and ETHNIC.

[Insert Table 8 here]

E. Lender Fixed Effect

Thus far, the results using each loan as a unit of observation show the collective wisdom that borrowers from high SC regions are more trustworthy. To see whether the same is true among individual lenders, we use each lender's bid as a unit of observation. In debt crowdfunding, a borrower can obtain funding from multiple lenders. Each lender also bids on different borrowers. Our 61,577 fully funded loans are composed of 2,172,520 bids made by 114,119 unique ID lenders. Although RRD assigns each lender a unique user ID, it does not require lenders to provide personal information required from borrowers. Thus, we control for lenders' fixed effects to examine how borrowers' SC affects lenders' bids. The regression model is:

(1) $bid_amount_{ij,t}(default_{ij,t}) = \beta_0 + \beta_1 B_SC_index_j + \beta_2 control_{j,t} + \delta_i + \delta_t + e_{ij}$,

where $bid_amount_{ij,t}$ $(default_{ij,t})$ represents the bid amount (DEFAULT) of lender i in borrower j in time t. $B_SC_index_j$ is the home SC of borrower j, and $control_{j,t}$ represents the loan and borrowers' characteristics and regional variables. δ_i , δ_t represent the lender fixed effects and time fixed effects, respectively. $e_{ij,t}$ is the standard error.

The results presented in Table 9 confirm our baseline finding. That is, Columns 1–3 show that individual lenders make larger investments to borrowers from higher SC regions. A one-standard-deviation increase in a borrower's home SC increases a lender's bid size by 86.1 RMB (USD 13), an increase of almost a fifth in the median amount of a lender's investment. The effects are significant at the 1% confidence level. We also construct a variable BID_RATIO, which is the fraction of lender i's bid relative to the loan amount requested by borrower j (bid_ratio_{ij}). Columns 4–6 show that higher SC is associated with a larger BID_RATIO. Finally, the results in Columns 7–9 confirm that a borrower's SC significantly reduces default probabilities.

[Insert Table 9 here]

VI. Empirical Results on Social Capital and Generalized Trust

A. Dyadic Analysis

Although the results suggest that lenders use information about potential borrowers' SC when making lending decisions, little is known about the influence of SC on lenders' generalized trust.

One unique advantage of our study is that we can extract crucial details in a subsample of lending in which borrower and lender information is available. In other words, we can identify a specific lending relationship (i.e., who is borrowing and from whom) and examine how lenders' and borrower's SC affects lending decisions. We proceed in two steps. First, we identify lender characteristics from borrowers' information set and construct lender–borrower pairs. We then study how SC affects lender bids and the consequences of loans in terms of observable outcomes (i.e., the probability of default).

B. The Lender-borrower

We match a lender's user ID with a borrower's ID, yielding a nontrivial group of borrowers who bid on the same platform. The data show 1,743 unique lenders (bidding-borrowers) with investments in 21,727 loans, accounting for more than one-third of total fully funded loans. We first identify the factors that affect the likelihood of borrowers becoming bidders in the platform. The dependent variable equals 1 if borrowers bid in the RRD online lending market, and zero otherwise. The main variable of interest is the level of SC. The control variables are (1) listing and loan characteristics, (2) borrower characteristics, and (3) provincial environment.

Table 10 shows the results of probit and logistic regressions, and we report the marginal effects for each variable. Clearly, high SC increases the chance of a borrower bidding in the lending market. This result suggests that compared with borrowers who never bid in the market, individuals in regions with high SC are more likely to extend loans. In addition, bidding borrowers are more likely to be male, married, younger, and highly educated. Bidding borrowers are also likely to have more working experience and are more likely to own properties. However, in contrast to borrowers who never bid in the market, bidding borrowers tend to have lower credit ratings and personal income. Bidding borrowers are also more likely to come from less developed regions and regions with higher ratio of total bank loan to GDP. We interpret this surprising result as follows: lower credit rating and income borrowers from less developed regions typically have less access to finance and investment opportunities. Once they are familiar with the platform and become aware of investment opportunities available to them, they are more likely to become bidders. By contrast, in regions with high ratio of private debt to GDP, borrowers have easy access to credit and can afford to be profligate. As a result, they are more likely to bid in pursuit of higher return.

[Insert Table 10 Here]

C. Lenders' Social Capital and Investment

Next, we focus on bids made by these borrowers, whose information is available. As a result, we have borrower and lenders characteristics, which yield 49,759 lender–borrower bid pairs in 21,727 fully funded loan projects.

Panel A of Table 11 reports the summary statistics for the main variables of lenders and borrowers. Consistently, individuals from high SC regions are likely to be lenders. The difference in the SC of the two groups is economically large and statistically significant. Compared with lenders, borrowers are more likely to be female, married, older, and undereducated. Borrowers are also likely to have a shorter work experience and are less likely to own properties. Interestingly, borrowers tend to have higher credit ratings and income, indicating the importance of repayment ability.[34] In addition, lenders are more likely to come from rich regions with better legal and financial development. Panel B shows the bid information for this sample. The mean and median size of lender investment are 1,000 RMB and 300 RMB, respectively. Most loans are long term and charge an average of 2.22 times the benchmark lending interest rates[35]. Moreover, we calculate the geographical distance between lenders and borrowers. Their mean and median distances are 969.73 and 970.03 km, respectively, which suggest that most lending takes place across provinces.

We first examine how lenders' SC affects their bid behaviors. We use this sample to estimate how lenders' SC affects their bid amount, while controlling for borrower fixed effects. Our regression specifications mimic that in Column (3) of Table 9, except that all control variables are on the side of *lenders.* Our working hypothesis is that lenders from higher SC regions have higher level of generalized trust, which positively predicts investment. Panel A of Table 12 reports results that are consistent with our hypothesis. Columns 1–3 show that lenders' SC index is positively related to bid amount[36]. These results suggest that for the same borrower, lenders from regions with higher SC are more trusting; in turn, they bid larger. This finding is consistent with that of

[34] Borrowers need their repayment ability assessed by the platform to be allowed to borrow. However, lenders have no eligibility requirement to be a bidder.

[35] One natural concern is that borrower-lenders can differ from non-borrower lenders in systematic ways. Assuming that is true, then we should find systematic differences in loan properties between our average and paired-loan sample. However, as Panel B shows, no differences in loan terms are statistically significant, as reported in Table 2.

[36] The results remain qualitatively unchanged when we use the ratio of bid amount over loan size.

Bottazzi et al. (2016), who find a positive relationship between generalized trust and investment in the context of venture capital.

The results so far reflect how lenders' SC affects the magnitude of loans conditional on observing lenders' SC. The potential problem is that pairs with lending relationships are only observable when borrowers bid in the same platform. For example, the results in Table 10 show that borrowers in regions with high SC are more likely to bid. However, important differences in SC may exist in lender–borrower pairs for which we do not observe lenders' SC.

We address this issue by implementing a Heckman selection model, which considers the selection bias arising from considering only lender–borrower pairs with observable information. Columns 4–6 report the results of the second-stage Heckman estimation. The first stage of Heckman is a probit model, mimicking Table 10, in which the dependent variable equals 1 if a borrower bids in the lending market (the lender's information is available) and zero otherwise. The explanatory variables are the same as those in column 2 of Table 10. The second stage is an OLS regression that includes controls variables from the lender side and the inverse Mills ratio to correct the selection bias. The results show that the positive effect of lender SC in bid size remains qualitatively unchanged. The significant coefficients on the Mills ratio indicate the importance of correcting selection bias.

Next, we ask whether and how the *differences* in regional SC between borrower and lender affect lending transactions. To isolate the effects of SC and eliminate alternative explanations, we control for the distance between lender and borrower provinces, as well as other observable differences between lenders and borrowers that affect investments.

(2) $bid_amount_{ij,t} = \beta_0 + \beta_1 D_SC_index_j + \beta_2 d_control_{ij,t} + \beta_3 lndistance_{ij} + \delta_t + \delta_i + \delta_j + e_{ij,t}$,

where $bid_amount_{ij,t}$ is lender i's bid size for borrower j at time t, and $D_SC_index_j$ is the effects of the difference in lenders' and borrowers' SC index ($L_SC_index_i - B_SC_index_j$). The SC difference allows us estimate directly if loans flow from an individual in a low SC region to an individual in a high SC region, or vice versa. A negative coefficient implies that lenders bid less when lenders have higher SC than a borrower. $d_control_{ij}$ represents the difference in the other explanatory variables between lender i and borrower j (in absolute value). These variables capture

the "distance" between each lender–borrower pair in terms of gender, education, income, grade, marriage, house ownership, and so on. We also include the natural logarithm of physical distance between lender i and borrower j ($distance_{i,j}$). δ_t represents the time fixed effect. In addition, equation (2) allows us to control for lender and borrowers' fixed effects (δ_i and δ_j).

Columns 1–3 of Panel B report the results for lender bid amounts for a given loan with different specification[37]. A direct way to capture how borrower and lender SC affects investment is to consider a simple regression of $B_SC_index_j$ and $L_SC_index_i$ on bid amount[38]. Consistent with our expectation, column 1 shows that B_SC_index and L_SC_index are positively correlated with BID_AMOUNT. This result suggests that on average, lenders from regions with higher SC tend to make larger investments, whereas borrowers from regions with higher SC receive larger bids. These effects are statistically and economically significant. Column 2 presents the effects of the difference in lender and borrower SC indexes (*D_SC_index*, lender minus borrower) on BID_AMOUNT after controlling for the difference in other explanatory variables. The negative coefficient suggests that lenders bid less (more) when borrowers are from provinces with lower (higher) SC. Thus, an investment is more likely to push through if a borrower is from a region with high SC. This result is important and intuitive. Together with the results in Table 10, this finding suggests that individuals with high SC are more likely to bid but bid less when borrowers are from provinces with low SC. To the extent that trust is a relative concept, our results show that trustors from high-trust environments are more cautious when dealing with trustees from low-trust environments[39].

Of interest is the finding that the coefficients of *lndistance* are statistically significant in columns 1–2, suggesting that lenders tend to bid more for distant borrowers. Prior work shows that investors tend to trust counterparties that are close to home more than they do those in remote regions (Coval and Moskowitz (1999), Grinblatt and Keloharju (2001), Petersen and Rajan (2002), and Chan, Covrig, and Ng (2005)). To disentangle the effect of home bias from that of SC on investment, we employ the following strategy. First, we exclude investments in which lenders and borrowers come from the same province. Second, we include an indicator variable that equals 1 if

[37] We also examine how borrowers' and lenders' social capital affects bid ratio and obtain similar results. For brevity, we do not report the results.

[38] We do not control for lender and borrowers' fixed effects when we include B_SC_INDEX and *L_SC_index* separately in our regression, as the fixed effects are captured by their corresponding social capital.

[39] This evidence is consistent with the findings of Giannetti and Yafeh (2012), who find that culturally distant lead banks offer borrowers small loans at a high interest rate.

the two provinces share the same border (BORDER); it equals zero otherwise. We then repeat the similar regressions in column 2 of Panel B and include *Border* and the interaction term between BORDER and the SC index. The results in column 3 show that both coefficients on BORDER and B_SC_INDEX are statistically insignificant. In sum, we find no evidence that home bias eliminates the effect of SC on investment.

We also implement a Heckman selection model to address selection bias. Columns 4–6 report the results of the second-stage Heckman estimation. The first stage is a probit model, which is the same as Panel A. The second stage is an OLS regression that includes control variables capturing the difference in the other explanatory variables between lender and borrower, and the inverse Mills ratio. The results show that the OLS regression is robust to this correction for selection. In sum, lenders bid less (more) for borrowers from lower (higher) SC provinces.

[Insert Table 12 here]

D. Lenders' Social Capital and Investment Performance

After exploring the direction and magnitude of loans, we focus on understanding how lenders' SC affects investment performance. We first examine if lender SC predicts default while controlling for borrower fixed effects. Our regression specifications mimic Panel A of Table 12, except that the dependent variable is DEFAULT, which equals 1 if borrowers do not pay on time; it equals 0 otherwise. Probit models have difficulty dealing with lender fixed effects. Thus, we run linear probability models controlling for characteristics from the lender side and borrower fixed effects[40].

Our working hypothesis is that lenders from regions with higher SC are more trusting on others. On the one hand, lender SC could positively predict investment; on the other hand, it may induce investment in high-risk projects, leading to high default rates. We report the results in Panel A of Table 13. Columns 1–3 show a marginally higher default probability for bids made by lenders from regions with high SC than those made by lenders from regions with low SC.

We also implement a Heckprobit model to address selection bias (probit model with sample selection). Columns 4–6 report the results of the second-stage Heckprobit estimation. The first stage is a probit model, which is the same as Panel A of Table 10. The results from the second stage are consistent, suggesting that a lender's SC is positively related to the probability of loan

[40] We also implement a Heckprobit model (probit model with sample selection) to check the robustness of our results.

default. The coefficient of athrho is statistically significant, indicating the importance of addressing selection bias.

Next, we focus on lender–borrower pairs and explore how the difference of regional SC between borrowers and lenders affects the probability of default. We adopt the same estimation method as equation (2), except that the dependent variable is default. Columns 1–3 of Panel B report the results for the probability of default in a given loan with different specifications. We first consider a simple regression of B_SC_index and L_SC_INDEX on default. Column 1 reports that the coefficients of borrowers' SC (B_SC_INDEX) are negative and statistically significant at the 1% level. By contrast, the coefficients of lenders' SC (L_SC_INDEX) are positively related to default rates. Consistent with our previous findings, borrowers from regions with high SC are more trustworthy, whereas lenders from regions with high SC have higher generalized trust, which leads to higher default rates.

Of particular interest is the positive coefficient of *D_SC_index* in column 2 after controlling for borrower and lender fixed effects. It indicates that the higher default rates incurred by lenders from high SC regions are likely explained by their investment to borrowers from lower SC regions, the latter are more likely to default. In column 3, we repeat the regressions in column 2 of Panel B and include the dummy variable BORDER and the interaction term between BORDER and the SC index. Both coefficients on BORDER and B_SC_INDEX are statistically insignificant. Columns 4–6 of Panel B show the same specifications on default rates by correcting the selection bias. We find similar results for SC's effect on the probability of loan default. In addition, the results in column 6 show that being in neighboring provinces reduces the probability of loan default, but interaction term BORDER*B_SC_INDEX is statistically insignificant. In sum, we find no evidence that investors' home bias eliminates the effect of SC on default.

[Insert Table 13 here]

E. Does Bad Experience Affect Generalized Trust?

The results above suggest that lenders from high SC provinces are more likely to bid, and when they do, they bid more, but incur more defaults. It indicates that SC affects its trustors' generalized trust. However, we expect that trustors' propensity to trust others would be affected by past experience, especially when a trustor had bad experience in trusting others.

To test this hypothesis, we partition lenders into those who had experienced default (experienced), and those who had not (inexperienced). We re-estimate the lender–borrower pair

regressions, mimicking Table 12 and Table 13. The results are reported in Table 14[41]. In each group, we first examine if lender SC affects their bid behaviors and predicts default while controlling for borrower fixed effects. We then turn to examine the effect of the differences in regional SC while controlling for both lender and borrower fixed effects. Columns 1–6 show the results of inexperienced lenders, and columns 7–12 report that of experienced. Consistent with expectation, the impact of lender SC on default is positive and significant on inexperienced lenders, but not significant on experienced lenders. Moreover, experienced lenders reduce their investment amount to borrowers from lower SC environment. Taken together, our evidence suggests that lenders learn from their experience on the platform, and the instantaneous impact of SC on generalized trust concentrates on inexperienced trustors.

[Insert Table 14 here]

F. Social Capital and Regional Capital Flows

To observe clearly how regional SC affects cross-border investment flows, we prepare a two-by-two matrix. First, we classify Chinese provinces into high and low SC regions on the basis of the sample medium in our SC index. Next, we divide lenders and borrowers into those from high and low SC regions. We then calculate the (1) number of bids, (2) mean/medium size of bids, and (3) total amount of investment for each pair.

Table 15 reports the findings. Approximately 63% of total investments (28,148 bids with a total size of 32.3 million RMB (USD 4.97 million)) flow from high SC regions to high SC regions. The mean and medians of bid size are 1,150 and 300 RMB, respectively. By contrast, only approximately 4.2% of total investments (2,708 bids with a total size of 2.14 million RMB (USD 0.33 million)) flow from low SC regions to low SC regions. In addition, approximately 21% of investment flows from lenders in high SC regions to borrowers in low SC regions, and 11.7% of investment flows from lenders in low SC regions to borrowers in high SC regions. The difference between the medium of each two groups (high–low) is statistically significant at the 1% level.

The results in Table 15 suggest how cross-regional investment flows are affected by the aggregate level of trust among trading partners. The aggregate level of trust is strongest when counterparties come from high SC regions and is weakest when counterparties are from low SC

[41] We obtain similar results when we exclude lenders who bid only one time.

regions. If the trust level is too low, then trade opportunities are unlikely to be realized. This evidence is consistent with the findings of Guiso et al. (2009) who show that trade and investment flows are larger between countries and exhibit higher mutual trust.

[Insert Table 15 here]

VII. Conclusion

This paper presents the first empirical evidence on the impact of regional SC in a non-institutional lending setting. Using highly granular data from a Chinese peer-to-peer lending website, we show regional SC affects lending decision and outcome through its impact on borrowers' trustworthiness and lenders' generalized trust. *Ceteris paribus*, borrowers from high SC regions have high funding success, large loan size, concentrated loan ownership, and low default rates. The effect is particularly strong among low-quality borrowers, and robust to endogeneity concerns. By contrast, lenders from higher SC regions make larger investments but have lower success. Regional heterogeneities in SC also affect investment flows. Cross-regional transactions are most (least) easily to be realized when counterparties are from high (low) SC regions. Our results suggest that Fintech users use non-standard soft information such as regional SC to facilitate their decision making, and SC is an important antecedent of cross-border transactions.

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Table 1 Social Capital Proxies

Panel A represents the results of applying principal component analysis to the four proxies of social capital, namely, blood donation, NGO participation, enterprise survey, and citizen survey. Proportion explained, eigenvalue, and factor loading for the first factor are presented. The social capital index (SC_index) is constructed by applying loadings (coefficient) to the standardized four proxies of social capital. Panel B reports the value of SC_index and four proxies across provinces. For variable definitions and details of their construction, see Appendix I.

Panel A Principal Component Analysis

	Blood	NGO	Enterprise	Citizen
Loadings	0.5201	0.5380	0.5423	0.3822
Proportion explained		0.742		
Eigenvalue		2.967		

Panel B Measures of Social Capital Across Regions

Province	SC_index	Blood	NGO	Enterprise	Citizen
Shanghai	5.768	3.433	4.380	22.7	2.402
Beijing	4.035	3.314	3.594	16.6	2.225
Guangdong	2.193	1.331	3.145	10.1	2.344
Zhejiang	1.530	1.259	3.361	3.5	2.321
Shandong	1.389	1.454	2.088	6.4	2.382
Jiangsu	1.135	1.179	2.846	5.7	2.239
Fujian	0.269	1.086	1.599	0.9	2.374
Tianjing	0.224	0.828	2.326	1.7	2.251
Jiangxi	−0.068	0.115	1.849	0.2	2.442
Hainan	−0.207	0.654	1.893	0.1	2.283
Hebei	−0.225	1.315	1.328	1.4	2.207
Shanxi	−0.308	1.428	1.642	0.6	2.125
Liaoning	−0.314	1.383	1.881	1.9	2.046
Hubei	−0.316	0.760	2.104	0.5	2.175
Chongqing	−0.365	0.554	2.380	0.5	2.150
Shaanxi	−0.373	0.807	1.935	0.7	2.173
Heilongjiang	−0.628	1.050	1.056	0.7	2.208
Hunan	−0.703	0.540	1.316	0.4	2.249
Henan	−0.810	1.174	1.151	0.6	2.111
Sichuan	−0.938	0.309	1.780	0.9	2.119
Guangxi	−1.014	0.272	1.182	0.6	2.225
Anhui	−1.015	0.489	1.501	0.4	2.127
Xinjiang	−1.044	0.494	1.068	1.1	2.175
Inner	−1.178	0.703	1.086	0.7	2.100
Jilin	−1.637	0.495	0.897	0.7	2.033
Yunnan	−1.649	0.017	1.056	1.4	2.075
Guizhou	−1.864	0.383	0.826	0.2	2.014
Gansu	−1.887	0.230	0.938	0.3	2.014
Ningxia	.	.	1.118	0.2	.
Qinghai	.	.	0.741	0.2	.
Tibet	.	.	0.034	.	.

Table 2 Summary Statistics

Panel A reports the summary statistics of listing and loan characteristics. Panel B reports the summary statistics of demographic, income, and education information of borrowers. Panel C reports the summary statistics of social capital measures and those of the economic and financial variables. For variable definitions and details of their construction, see Appendix I.

Variable	Mean	Std. Dev.	Min	P50	Max	N
Panel A Listing and Loan Characteristics						
FUND	0.249	0.433	0	0	1	247115
FRACTION	0.272	0.444	0	0	1	247103
WORDS	114.504	70.328	0	94	244	247115
AMOUNT	4.819	7.016	0.3	3.78	300	61577
MATURITY	18.791	10.156	1	18	48	61577
LONG TERM	0.798	0.401	0	1	1	61577
SPREAD	2.132	0.303	0.762	2.146	5.379	61577
OWNERSHIP	35.504	48.976	1	22	1370	61573
DEFAULT	0.054	0.227	0	0	1	61577
BID_TIME	69.136	461.297	1	1	10051	61573
Panel B Borrowers' Characteristics						
AGE	32.679	7.458	17	31	71	247113
GENDER	0.136	0.343	0	0	1	247115
GRADE	5.975	1.940	1	7	7	247115
EDU	1.933	0.780	1	2	4	246751
MARRIAGE	0.557	0.497	0	1	1	247075
INCOME	3.133	1.221	1	3	6	246361
HOUSE	0.428	0.495	0	0	1	247115
HOUSE_LOAN	0.158	0.365	0	0	1	247115
WORK_EXP	2.352	1.019	1	2	4	246109
PAST_NUM	4.153	5.659	1	3	148	247115
Panel C Provincial Variables						
SC_INDEX	0.000	1.722	-1.887	-0.340	5.768	28
SC1: BLOOD	0.966	0.802	0.017	0.783	3.433	28
SC2: NGO	1.745	0.944	0.034	1.599	4.380	31
SC3: ENTERPRISE	2.730	5.161	0.100	0.700	22.700	30
SC4: CITIZEN	2.200	0.120	2.014	2.191	2.442	28
PGDP	4.042	2.047	1.097	3.483	10.523	186
LOAN	1.116	0.387	0.554	1.026	2.515	186
LAW_OFFICE	0.163	0.143	0.060	0.123	0.894	186

Table 3 Funding Success, Loan Size, and Ownership

This table presents the results from the regressions of the SUCCESS indicator, FRACTION, loan size, and ownership onto borrowers' home borrower social capital (B_SC_INDEX*)*, as well as a set of control variables. Year dummies are also included. Panel A reports the results for the social capital index. Columns 1–2 use probit models. Columns 3–8 use OLS regressions. Panel B reports the results for the four proxies of social capital. Borrowers' personal characteristics and regional economic and financial variables are included but not reported. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

Panel A Social Capital Index

	SUCCESS		FRACTION		OWNERSHIP		AMOUNT	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
B_SC_INDEX	0.001***	0.002***	0.002***	0.003***	−0.008***	−0.010**	0.125***	0.108***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.004)	(0.032)	(0.042)
AGE	0.002***	0.001***	0.002***	0.001***	0.012***	0.010***	0.056***	0.045***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.004)	(0.004)
GENDER	−0.003**	−0.008***	−0.008***	−0.012***	0.108***	0.085***	0.737***	0.609***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.010)	(0.009)	(0.087)	(0.085)
GRADE	−0.082***	−0.077***	−0.179***	−0.175***	−0.120***	−0.088***	−0.795***	−0.727***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.003)	(0.032)	(0.027)
EDU	0.005***	0.005***	0.005***	0.006***	−0.000	0.015***	0.110**	0.205***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.005)	(0.047)	(0.048)
MARRIAGE	0.008***	0.007***	0.007***	0.008***	0.064***	0.065***	0.171***	0.210***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)	(0.044)	(0.045)
INCOME	0.005***	0.004***	0.006***	0.005***	0.159***	0.149***	1.042***	1.002***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.003)	(0.003)	(0.024)	(0.021)
HOUSE	−0.008***	−0.005***	−0.004***	−0.001	0.080***	0.160***	1.338***	1.732***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.011)	(0.011)	(0.134)	(0.155)
HOUSE_LOAN	0.007***	0.004***	0.009***	0.007***	0.055***	0.032**	−0.352***	−0.525***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.013)	(0.012)	(0.113)	(0.115)
WORK_EXP	0.005***	0.007***	0.008***	0.010***	−0.073***	−0.058***	−0.001	0.080*
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)	(0.042)	(0.044)
SPREAD		−0.032***		0.014***		−0.179***		−0.256
		(0.001)		(0.001)		(0.014)		(0.185)
WORDS		0.000***		0.000***		0.001***		0.004***
		(0.000)		(0.000)		(0.000)		(0.000)
PAST_NUM		−0.002***		−0.003***		−0.014***		−0.090***
		(0.000)		(0.000)		(0.001)		(0.005)
LAW_OFFICE		−0.046***		−0.062***		−0.088		−0.072
		(0.007)		(0.008)		(0.059)		(0.564)
LOAN		0.010***		0.015***		0.033**		0.114
		(0.002)		(0.002)		(0.016)		(0.095)
PGDP		0.002***		0.002***		0.010***		0.037*
		(0.000)		(0.000)		(0.003)		(0.020)
Constant			1.530***	1.447***	2.013***	2.121***	−0.737***	−0.779
			(0.006)	(0.007)	(0.037)	(0.059)	(0.179)	(0.517)
Observations	243,042	243,042	243,030	243,030	60,966	60,966	60,970	60,970
R^2/Pseudo R^2	0.597	0.604	0.650	0.652	0.165	0.186	0.129	0.142

Panel B Four Proxies of Social Capital

	SUCCESS				FRACTION			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blood	0.002*				0.003*			
	(0.001)				(0.001)			
NGO		0.004***				0.005***		
		(0.001)				(0.001)		
Enterprise			0.001***				0.001***	
			(0.000)				(0.000)	
Citizen				−0.008				0.012**
				(0.005)				(0.006)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes
Constant					1.442***	1.441***	1.444***	1.406***
					(0.007)	(0.007)	(0.007)	(0.014)
Observations	243,042	244,640	244,515	243,042	243,030	244,628	244,503	243,030
R^2/Pseudo R^2	0.604	0.604	0.604	0.604	0.652	0.652	0.652	0.651

	OWNERSHIP				AMOUNT			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Blood	0.015				0.197*			
	(0.009)				(0.101)			
NGO		−0.012*				0.319***		
		(0.007)				(0.052)		
Enterprise			−0.003***				0.038***	
			(0.001)				(0.014)	
Citizen				−0.153***				0.610***
				(0.039)				(0.217)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes
Constant	2.037***	2.057***	2.049***	2.377***	1.941***	1.781***	2.057***	0.697
	(0.060)	(0.059)	(0.059)	(0.103)	(0.496)	(0.496)	(0.523)	(0.643)
Observations	60,966	61,089	61,081	60,966	60,970	61,093	61,085	60,970
R^2/Pseudo R^2	0.194	0.195	0.195	0.194	0.096	0.097	0.097	0.096

Table 4: Heterogeneity Tests

Panel A reruns regressions by partitioning the sample into undereducated versus highly educated borrowers. A borrower is classified as highly educated if his or her highest qualification is a bachelor's degree or above (post-tertiary or below). Panel B reruns regressions by partitioning the sample into repeat borrowers, or those who appear more than twice on the RRD platform (Rep), and non-repeat borrowers (Non-rep). Panel C reruns regressions by partitioning the sample into low- versus high-grade borrowers. A borrower is classified as high (low) grade if his or her credit score is below 5 (above or equal to 5). Borrowers' characteristics and regional variables are included. Dif represents the difference of the coefficient of B_SC_INDEX between two groups. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction see, Appendix I.

Panel A Under- versus Highly-educated Borrowers

	SUCCESS		FRACTION		OWNERSHIP		AMOUNT	
	Low	High	Low	High	Low	High	Low	High
B_SC_INDEX	0.002***	0.001	0.003***	0.001	−0.009*	−0.021***	0.138**	-0.007
	(0.001)	(0.001)	(0.001)	(0.001)	(0.005)	(0.008)	(0.054)	(0.082)
Loan and borrower variables	yes	Yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	Yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	Yes	yes	yes	yes	yes	yes	yes
R^2/Pseudo R^2	0.625	0.531	0.670	0.602	0.187	0.204	0.156	0.127
Observations	184,134	58,908	184,128	58,973	45,484	15,512	45,487	15,513
Dif	0.001		0.002**		0.012		0.145**	

Panel B Non-repeat versus Repeat Borrowers

	SUCCESS		FRACTION		OWNERSHIP		AMOUNT	
	Non	Rep	Non	Rep	Non	Rep	Non	Rep
B_SC_INDEX	0.002***	0.0002	0.002**	0.002	−0.010**	0.0001	0.108**	0.249
	(0.001)	(0.002)	(0.001)	(0.002)	(0.004)	(0.012)	(0.054)	(0.160)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
R^2/Pseudo R^2	0.657	0.328	0.704	0.374	0.155	0.230	0.135	0.179
Observations	166,846	76,196	166,836	76,196	53,802	7,164	53,806	7,164
Dif	0.001**		0		−0.01**		−0.141	

Panel C Low- versus High-grade Borrowers

	SUCCESS		FRACTION		OWNERSHIP		AMOUNT	
	Low	High	Low	High	Low	High	Low	High
B_SC_INDEX	0.003***	−0.002	0.004***	−0.001	0.009	−0.015***	0.056**	0.113
	(0.001)	(0.002)	(0.002)	(0.004)	(0.009)	(0.005)	(0.054)	(0.072)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
R^2/Pseudo R^2	0.102	0.275	0.131	0.107	0.265	0.099	0.299	0.082
Observations	196,054	46,988	196,050	46,980	16,091	44,875	16,091	44,877
Dif	0.005**		0.005**		−0.024		−0.057	

Table 5 Robustness Tests

Panel A reports the robustness tests on the impact of social capital on trustworthiness. Columns 1–4 implement a bootstrapping method, which draws a subsample with half as many observations as the whole sample, and repeat our regression analysis for this subsample. Columns 5–6 employ the Heckman two-step treatment effect procedure to correct the selection bias. Columns 7–10 report the estimates that exclude Shanghai, Beijing, Gansu, Qinghai, and Ningxia. Panel B reruns regressions by partitioning the sample into low- versus high-economic development regions. Dif represents the difference of the coefficient of B_SC_INDEX between two groups. Panel C reports the difference-in-differences results using the *Guo Meimei* incident as shock to social capital. POST is a dummy variable for the months following the Guo Meimei incident (i.e., [1, 6]). B_SC_INDEX_H is dummy variable that equals 1 if the borrower social capital index in a region is above the median, and zero otherwise. Borrowers' characteristics, regional variables, and year dummies are included. Robust standard errors clustered at province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

Panel A Alternative Methods

	Bootstrap				Selection		Excluding Sample			
	SUCCESS	FRACTION	AMOUNT	OWNERSHIP	AMOUNT	OWNERSHIP	SUCCESS	FRACTION	AMOUNT	OWNERSHIP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
B_SC_INDEX	0.002**	0.003***	−0.010*	0.108*	−0.0094**	0.1065***	0.002***	0.003***	−0.0102**	0.0547**
	(0.001)	(0.001)	(0.005)	(0.057)	(0.004)	(0.028)	(0.001)	(0.001)	(0.005)	(0.024)
Loan and borrower variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Regional variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
IML					−0.564***	4.522***				
R^2/Pseudo R^2	0.604	0.653	0.186	0.142			0.604	0.6503	0.1695	0.2267
Wald chi^2					7126.7	6382.2				
Observations	243,042	243,030	60,966	60,970	244,517	244,517	224,442	224,431	55,555	55,558

Panel B Low- versus High-economic Development

	SUCCESS		FRACTION		OWNERSHIP		AMOUNT	
	Low	High	Low	High	Low	High	Low	High
B_SC_INDEX	0.002*	0.002***	0.005**	0.003***	−0.028**	−0.01**	0.139***	0.146**
	(0.001)	(0.001)	(0.002)	(0.001)	(0.013)	(0.005)	(0.054)	(0.062)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes
R^2/Pseudo R^2	0.6265	0.5839	0.6522	0.6527	0.2005	0.1827	0.2974	0.1234
Observations	119,618	123,424	119,610	123,420	30,863	30,103	30,865	30,105
Dif	0.000		0.002		−0.018**		−0.007	

Panel C Guo Meimei Incident

	SUCCESS	FRACTION	OWNERSHIP	AMOUNT
	(1)	(2)	(3)	(4)
Post	−0.047***	0.008	0.157*	−1.026***
	(0.011)	(0.014)	(0.095)	(0.259)
B_SC_INDEX_H	−0.020	−0.019	−0.143	-0.012
	(0.023)	(0.016)	(0.110)	(0.229)
POST*B_SC_INDEX_H	0.042**	0.053***	0.108	0.609**
	(0.018)	(0.017)	(0.114)	(0.283)
Constant		0.553***	1.342***	−2.821***
		(0.044)	(0.283)	(0.999)
Loan and borrower variables	yes	yes	yes	yes
Regional variables	yes	yes	Yes	yes
Year fixed effect	yes	yes	Yes	yes
Observations	12,097	12,097	1,348	1,348
R^2/Pseudo R^2	0.271	0.297	0.106	0.201

Table 6 Instrument Variable Regressions

Panels A and B report the second and first stage results of our instrumental variable analysis, respectively. Our first instrument, RICE_SUIT, refers to the suitability of each province for growing wetland rice according to the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database. The second instrument is ETHNIC, which denotes the fraction of the largest ethnic group in a province. Panel C reports the regression results of the residuals of the second-stage regression on both instrument variables. Panel D reports the estimates of including both instrument variables in the benchmark regressions. Borrowers' characteristics, regional variables, and year dummies are included. Robust standard errors clustered at province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

	SUCCESS (1)	SUCCESS (2)	FRACTION (3)	OWNERSHIP (4)	AMOUNT (5)
Panel A: Second Stage					
B_SC_INDEX	0.016**	0.002**	0.003***	−0.021***	0.200***
	(0.008)	(0.001)	(0.001)	(0.007)	(0.050)
Constant		1.256***	1.455***	2.109***	1.244***
		(0.006)	(0.007)	(0.059)	(0.538)
Loan and borrower variable	yes	Yes	yes	Yes	yes
Regional variable	yes	Yes	yes	Yes	yes
Year fixed effect	yes	Yes	yes	yes	yes
Observations	240,923	240,923	240,911	60,821	60,825
Panel B: First Stage					
RICE_SUIT	0.479***	0.479***	0.479***	0.460***	0.461***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
ETHNIC	2.396***	2.396***	2.396***	2.725***	2.745***
	(0.011)	(0.011)	(0.011)	(0.025)	(0.025)
R^2		0.820	0.820	0.805	0.805
Loglikelihood	−321695				
F statistics (P-value)		0.000	0.000	0.000	0.000
Minimum eigenvalue statistics		65777	65777	14116	14285
Critical value: 10%		19.93	19.93	19.93	19.93
Over-identification (P-value)		0.073	0.494	0.051	0.173
Panel C: Residual Regression on Instruments					
RICE_SUIT		0.0006	−0.0003	−0.0049	0.0211
		(0.0005)	(0.0006)	(0.0040)	(0.0285)
ETHNIC		0.0052	0.0022	0.0478	−0.2044
		(0.0040)	(0.0040)	(0.0315)	(0.2260)
R^2		0	0	0.0001	0
Panel D: Tests for Exclusion Restriction					
B_SC_INDEX	0.002**	0.002***	0.002***	−0.021***	0.214***
	(0.001)	(0.001)	(0.001)	(0.005)	(0.046)
RICE_SUIT	−0.000	−0.001	0.000	−0.001	0.015
	(0.001)	(0.001)	(0.001)	(0.005)	(0.022)
ETHNIC	0.004	0.006	0.005	0.048	−0.294
	(0.004)	(0.004)	(0.005)	(0.038)	(0.213)
R^2	0.605	0.683	0.653	0.131	0.108

Table 7 City-level Analysis and Time Series Evidence

This table presents the results from the regressions of the success indicator, fraction, loan size, and ownership onto citizen survey at the city level (citizen_city) and NGO Participation in year $t-1$ (NGO_$t-1$), as well as a set of control variables. Columns 1–4 present the results of city level analysis for all cities. Columns 5–8 present the results of city-level analysis for a smaller sample of 11 cities in three neighboring provinces of Yunan, Guizhou, and Sichuan. Columns 9–12 present the results of NGO participation by controlling for borrower fixed effects. Borrowers' characteristics, regional variables, and year dummies are included. Robust standard errors clustered at province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

	City-full sample				City-small sample				Time-varying			
	SUCCESS	FRACTION	OWNERSHIP	AMOUNT	SUCCESS	FRACTION	OWNERSHIP	AMOUNT	SUCCESS	FRACTION	OWNERSHIP	Amount
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Citizen_city	0.009**	0.016***	−0.154***	0.842**	0.052**	0.067*	−0.672*	0.893*				
	(0.005)	(0.005)	(0.035)	(0.394)	(0.025)	(0.031)	(0.324)	(0.460)				
NGO_$t-1$									0.190*	0.197*	−3.129*	3.602*
									(0.115)	(0.117)	(1.727)	(2.026)
Constant		1.455***	2.294***	−1.808**		1.124*	7.180**	5.813	0.708	0.237	3.524	20.366
		(0.014)	(0.098)	(0.889)		(0.508)	(2.534)	(11.605)	(0.775)	(422.823)	(3.965)	(22.098)
Loan and borrower variable	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Regional variable	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Observations	104,812	104,804	31,913	31,916	10,601	10,600	2,323	2,323	244,711	241,720	61,094	61,093
R^2/Pseudo R^2	0.662	0.709	0.167	0.112	0.602	0.635	0.23	0.4	0.003	0.008	0.001	0.021

Table 8 (Borrower) Social Capital and Default Rates

This table presents the regression results of default rates for a given loan onto B_SC_INDEX, as well as different sets of control variables. Columns 1 and 2 implement probit and OLS regressions, respectively. Columns 3-4 rerun the regression by using subsamples of undereducated versus highly educated borrowers. Columns 5, 6, and 7 employ the Heckman selection model, bootstrapping method, and instrument variable regressions, respectively. The first stage results are not reported here for brevity. Loan, borrowers' personal characteristics, and regional economic and financial variables are included, but they are also not reported. Year fixed effects are included. Robust standard errors clustered at the province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

			Education				
	Probit	OLS	Low	High	Selection	Bootstrap	Instrument
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
B_SC_INDEX	−0.002**	−0.002***	−0.003***	−0.000	−0.002**	−0.002*	−0.048**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.024)
Constant		−0.118***			−0.018		−7.526***
		(0.013)			(0.011)		(0.890)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes
Observations	60,984	60,984	45,471	15,513	244,517	60,984	60,825
Wald chi^2					1310.7		928.1
R^2/Pseudo R^2	0.475	0.212	0.496	0.39		0.475	

Table 9 Lender Fixed Effects

This table estimates the basic regressions by controlling for lender fixed effects. The RRD platform assigns a unique ID to each customer. A lender can bid for many loan lists. Our approach enables us to control for the lender fixed effects. The BID_AMOUNT, BID_RATIO, and *default rate* of a given investment are regressed onto borrowers' social capital index and sets of control variables. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

	BID_AMOUNT			BID_RATIO			DEFAULT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
B_SC_INDEX	0.0054***	0.0049***	0.0043***	0.0003***	0.0002***	0.0003***	−0.0011***	−0.0012***	−0.0003**
	(0.0004)	(0.0004)	(0.0004)	(0.0000)	(0.0000)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Constant	0.2078***	0.1869***	0.1938***	0.0613***	0.0678***	0.0701***	−0.0740***	−0.0768***	−0.0664***
	(0.0105)	(0.0120)	(0.0123)	(0.0021)	(0.0030)	(0.0030)	(0.0028)	(0.0038)	(0.0038)
Loan and borrower variables	Yes	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	No	no	yes	no	no	yes	no	no	yes
Year fixed effect	No	yes	yes	no	yes	yes	no	yes	yes
Observations	2,172,520	2,172,520	2,172,520	2,172,520	2,172,520	2,172,520	2,172,520	2,172,520	2,172,520
R^2/Pseudo R^2	0.0044	0.0082	0.0083	0.0302	0.0376	0.0378	0.2284	0.2320	0.2325
Number of investors	114,119	114,119	114,119	114,119	114,119	114,119	114,119	114,119	114,119

Table 10 Determinants of Borrowers Bidding in the Platform

This table reports results of probit and logistic regressions for determinants of borrowers who also bid on the platform. We report the marginal effects for each variable. Columns 1 and 2 use probit models. Columns 3 and 4 use logistic regressions. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

	Probit		Logistic	
	(1)	(2)	(3)	(4)
B_SC_INDEX	0.0020***	0.0062***	0.0021***	0.0066***
	(0.0002)	(0.0004)	(0.0002)	(0.0005)
AGE	−0.0003***	−0.0003***	−0.0003***	−0.0003***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GENDER	−0.0128***	−0.0120***	−0.0140***	−0.0130***
	(0.0013)	(0.0013)	(0.0015)	(0.0015)
GRADE	0.0017***	0.0018***	0.0014***	0.0016***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
EDU	0.0075***	0.0075***	0.0077***	0.0077***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
MARRIAGE	0.0037***	0.0040***	0.0039***	0.0041***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)
INCOME	−0.0012***	−0.0008***	−0.0012***	−0.0008***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
HOUSE	0.0058***	0.0061***	0.0062***	0.0066***
	(0.0009)	(0.0008)	(0.0009)	(0.0009)
HOUSE_LOAN	0.0056***	0.0061***	0.0053***	0.0057***
	(0.0009)	(0.0009)	(0.0009)	(0.0009)
WORK_EXP	0.0041***	0.0039***	0.0041***	0.0039***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
PAST_NUM	0.0026***	0.0026***	0.0024***	0.0024***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
LAW_OFFICE		0.0072		0.0107**
		(0.0046)		(0.0049)
LOAN		0.0061***		0.0057***
		(0.0012)		(0.0013)
PGDP		−0.0063***		−0.0070***
		(0.0005)		(0.0006)
Observations	120,454	120,454	120,454	120,454
Pseudo R^2	0.1159	0.1357	0.1133	0.1339

Table 11 Lender–borrower Pairs

Panel A reports the summary statistics for lenders and borrowers. We conduct t-value tests for the mean difference and Wilcoxon signed-ranks tests for the median difference. Panel B reports the summary statistics of lenders' bids. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

Panel A Characteristics of Lenders and Borrowers

	Lender		Borrower		Dif	
Variable	Mean	Median	Mean	Median	Mean	Median
SC_index	1.889	1.530	0.857	0.269	1.032***	1.261***
AGE	35.226	33	38.736	37	−3.510***	−4.000***
GENDER	0.035	0	0.153	0	−0.118***	0.000***
GRADE	5.262	7	3.432	2	1.830***	5.000***
EDU	2.653	3	1.984	2	0.669***	1.000***
MARRIAGE	0.748	1	0.789	1	−0.041***	0.000***
INCOME	3.113	3	4.007	4	−0.894***	−1.000***
HOUSE	0.704	1	0.474	0	0.230***	1.000***
HOUSE_LOAN	0.325	0	0.176	0	0.149***	0.000***
WORK_EXP	2.750	3	2.564	2	0.186***	1.000***
PAST_NUM	7.145	2	4.785	1	2.360***	1.000***
LAW_OFFICE	0.313	0.160	0.191	0.149	0.122***	0.010***
LOAN	1.381	1.105	1.126	1.002	0.254***	0.104***
PGDP	5.738	5.883	5.190	5.171	0.549***	0.712***

Panel B Characteristics of Bids

variable	Mean	Std. Dev.	Min	P50	Max
BID_AMOUNT	0.10	0.39	0.00	0.03	30
INTEREST RATE	2.22	0.39	0.76	2.15	5.38
MATURITY	15.22	9.62	1	12	48
LONG-TERM	0.68	0.46	0	1	1
DEFAULT	0.04	0.19	0	0	1
DISTANCE	968.97	561.16	0	970.03	3,463.17

Table 12 (Lender) Social Capital and Investment in Lender–borrower Pairs

Panel A estimates the impact of a lender's social capital on bid amount controlling for borrower fixed effects. Lenders' personal characteristics, regional economic and financial variables are included but are not reported. Panel B presents OLS and Heckman selection model regressions for the impact of lenders' and borrowers' social capital, as well as their difference (L_SC_INDEX minus B_SC_INDEX), on bid amount. The differences in the other explanatory variables between lender and borrower are included but are not reported. OLS regressions include observations in which lenders' information is available. Heckman regressions include all borrowers in regressions. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

Panel A Borrower's Fixed Effects

	OLS			Heckman		
	(1)	(2)	(3)	(4)	(5)	(6)
L_SC_INDEX	0.0089***	0.0089***	0.0090***	0.0079***	0.0078***	0.0078***
	(0.0012)	(0.0012)	(0.0012)	(0.0008)	(0.0008)	(0.0008)
Constant	0.0859***	0.0859***	0.4170***	0.1231***	0.1213***	0.0972***
	(0.0023)	(0.0023)	(0.0015)	(0.0037)	(0.0070)	(0.0098)
Loan and lender variables	yes	yes	yes	no	yes	yes
Regional variables (lender)	no	no	yes	no	no	yes
Year fixed effect	no	yes	yes	no	yes	yes
Mills' Ratio				−0.0406***	−0.0398***	−0.0379***
Observations	48,742	48,742	48,145	271,151	271,151	271,151
R^2/Pseudo R^2	0.0136	0.0136	0.0135			
Number of borrowers	18,090	18,090	18,017	18,090	18,090	18,017

Panel B OLS and Heckman Selection Model Regressions for Investments in Lender–borrower Pairs

	OLS			Heckman		
	(1)	(2)	(3)	(4)	(5)	(6)
B_SC_INDEX	0.0074***			0.0068***		
	(0.0016)			(0.0011)		
L_SC_INDEX	0.0050***			0.0049***		
	(0.0011)			(0.0010)		
D_SC_INDEX		−0.0991***	−0.0962***		−0.0090***	−0.0123***
		(0.0157)	(0.0169)		(0.0011)	(0.0012)
lndistance	0.0023*	0.0037*		0.0023**	0.0047***	
	(0.0013)	(0.0020)		(0.0012)	(0.0012)	
BORDER			−0.0063			−0.0088
			(0.0048)			(0.0054)
D_SC_INDEX*BORDER			0.0011			0.0028
			(0.0022)			(0.0019)
Constant	0.1161***	0.1759*	0.2174**	0.1397***	0.2259***	0.2605***
	(0.0195)	(0.0974)	(0.0977)	(0.0186)	(0.0264)	(0.0261)
Loan and lender variables (difference)	yes	yes	yes	yes	yes	yes
Regional variables (difference)	no	yes	yes	no	yes	yes
Year fixed effect	no	yes	yes	no	yes	yes
Lender and borrower fixed effect	no	yes	yes	no	yes	yes
Mills' Ratio				−0.0595*	−0.0595*	−0.0857***
Observations	47,067	47,067	44,229	270,288	270,228	267,390
R^2/Pseudo R^2	0.0082	0.1180	0.1218			

Table 13 (Lender) Social Capital and Default in Lender–borrower Pairs

Panel A estimates the impact of a lender's social capital on the probability of loan default controlling for borrower fixed effects. Lenders' personal characteristics, regional economic and financial variables are included but are not reported. Panel B presents OLS and Heckprobit regressions for the impact of borrower's and lender's social capital on the probability of loan default. The difference in the other explanatory variables between lender and borrower are included but are not reported. OLS regressions include observations in which lenders' information is available. Heckman regressions include all borrowers in regressions. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction, see Appendix I.

Panel A Borrower's fixed effects

	OLS			Heckprobit		
	(1)	(2)	(3)	(4)	(5)	(6)
L_SC_index	0.0003*	0.0003*	0.0003	0.0004**	0.0003*	0.0003*
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)
Constant	0.1034	0.1034	0.0481			
	(0.0672)	(0.0672)	(0.0849)			
Loan and lender variables	yes	yes	yes	no	yes	yes
Regional variables (lender)	no	no	Yes	no	no	yes
Year fixed effect	no	yes	Yes	no	yes	yes
athrho				0.8123***	0.5833***	0.5830***
				(0.0268)	(0.0245)	(0.0245)
Observations	47,378	47,378	46,796	270,325	269,893	269,893
R^2/Pseudo R^2	0.0216	0.0216	0.0224			
Number of borrowers	17,872	17,872	17,799			

Panel B OLS and Heckprobit regressions for defaults in lender–borrower pairs

	OLS			Heckprobit		
	(1)	(2)	(3)	(4)	(5)	(6)
B_SC_INDEX	−0.0014***			−0.0007***		
	(0.0004)			(0.0001)		
L_SC_INDEX	0.0007*			0.0002*		
	(0.0004)			(0.0001)		
D_SC_INDEX		0.0822*	0.0845*		0.0004***	0.0004***
		(0.0447)	(0.0469)		(0.0001)	(0.0001)
Lndistance	−0.0001	−0.0004		−0.0001	0.0001	
	(0.0005)	(0.0004)		(0.0001)	(0.0001)	
BORDER			0.0000			−0.0012*
			(0.0017)			(0.0007)
D_SC_INDEX*BORDER			−0.0004			0.0001
			(0.0005)			(0.0002)
Athrho				0.9586***	1.0389***	1.0370***
				(0.0147)	(0.0189)	(0.0200)
Constant		0.1843***	0.1718***			
		(0.0650)	(0.0637)			
Loan and lender variables (difference)	yes	yes	yes	yes	yes	yes
Regional variables (difference)	no	yes	yes	no	yes	yes
Year fixed effect	no	yes	yes	no	yes	yes
Lender and borrower fixed effect	no	yes	yes	no	no	no
	48,002	47,067	44,229	47,936	47,067	44,229
R^2/Pseudo R^2	0.0339	0.0920	0.0984			

Table 14 Inexperienced versus Experienced Investors

This table re-estimates lender–borrower pair regressions by partitioning lenders into those who had experienced default (experienced) and those who had not (inexperienced). Columns 1, 4, 7, and 10 control only for borrower fixed effects, whereas the rest of the columns control for borrower and lender fixed effects, Borrowers' characteristics and regional variables are included. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. For variable definitions and details of their construction see Appendix I.

	Inexperienced Lenders						Experienced Lenders					
	AMOUNT			DEFAULT			AMOUNT			DEFAULT		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
L_SC_INDEX	0.0103***			0.0005*			0.0099***			0.0001		
	(0.0021)			(0.0003)			(0.0015)			(0.0003)		
D_SC_INDEX		−0.8713*	−0.9673***		0.0012**	0.0010**		−0.1247*	−0.1122***		−0.0001	0.0001
		(0.5070)	(0.3263)		(0.0005)	(0.0005)		(0.0722)	(0.0220)		(0.0003)	(0.0004)
lndistance		0.0055			−0.0004			0.0042*			−0.0003	
		(0.0050)			(0.0007)			(0.0025)			(0.0004)	
BORDER			0.0019			0.0008			−0.0096*			0.0013
			(0.0114)			(0.0019)			(0.0053)			(0.0023)
D_SC_INDEX*BORDER			0.0065			0.0008			0.0000			−0.0009
			(0.0059)			(0.0010)			(0.0025)			(0.0006)
Loan and lender variables	yes	no	no	yes	no	no	yes	no	no	yes	no	no
Regional variables (lender)	yes	no	no	yes	no	no	yes	no	no	yes	no	no
Loan and lender variables (difference)	no	yes	yes	no	yes	yes	no	yes	yes	no	yes	yes
Regional variables (difference)	no	yes	yes	no	yes	yes	no	yes	yes	no	yes	yes
Year fixed effect												
Constant	−0.1926	−0.7308	−0.6980**	0.0215	0.1252***	0.1225***	0.5614***	0.1082	0.1890	0.0822	0.0984***	0.0967***
	(0.1778)	(0.5500)	(0.2774)	(0.1342)	(0.0149)	(0.0145)	(0.0703)	(0.1817)	(0.1465)	(0.0567)	(0.0244)	(0.0254)
Observations	19,293	19,322	18,115	19,293	19,322	19,322	27,503	27,745	26,114	27,503	27,745	26,114
R^2	0.0073	0.7039	0.2367	0.0121	0.2845	0.2845	0.0253	0.4135	0.0956	0.0303	0.0337	0.0360

Table 15 Social Capital and Regional Capital Flows

This two-by-two matrix shows how investment flows from lenders in high/low social capital regions to borrowers in high/low social capital regions. A province is classified as a high (low) social capital region if it is above/below the sample medium. *N* is the number of bids, *Mean/medium* is the mean/medium size of the bid, and *Total* is the total amount of investment. We conduct *t*-value tests for the mean difference and Wilcoxon signed-rank tests for the median difference. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Borrower / Lender	High			Low			High - Low		
	N	Mean /median	Total	N	Mean /median	Total	N	Mean /median	Total
High	28148	0.115	3230.8	11118	0.098	1085.7	17030	0.017***	2145.1
		0.030			0.030			0.000***	
Low	7459	0.081	600.5	2708	0.079	214.4	4751	0.002	386.1
		0.025			0.020			0.005***	
High - Low	20689	0.034***	2630.3	8410	0.018**	871.2			
		0.005***			0.010***				

Appendix I: Variable Definition and Data Source

	Definition	Source
Borrowers' Characteristics		
GRADE	Credit score of borrowers when a listing is created, ranging from 1 (high) to 7 (low)	RRD
AGE	Age of borrower	RRD
GENDER	A dummy variable that equals 1 if the borrower is female and equals 0 otherwise	RRD
EDU	Equals 4 if the borrower's highest qualification is a master's degree or above, 3 if the borrower's highest qualification is a bachelor's degree, 2 if the borrower's highest qualification is post-tertiary, and 1 if the borrower's highest qualification is secondary or below.	RRD
WORK_EXP	Employment length in years. Possible values are between 1 and 4, where 1 means less than one year, 2 means between one and three years, 3 means between three and five years, and 4 means more than five years.	RRD
INCOME	Monthly income provided by a borrower during registration. Possible values are between 1 and 6, where 1 indicates less than 1,000 RMB, 2 means between 1,000 and 5,000 RMB, 3 means between 5,000 and 10,000 RMB, 4 means between 10,000 and 20,000 RMB, 5 means 20,000 RMB to 50,000 RMB, and 6 means more than 50,000 RMB.	RRD
MARRIAGE	A dummy variable that equals 1 if the borrower is married and equals 0 otherwise	RRD
HOUSE	A dummy variable that equals 1 if the borrower has a house and equals 0 otherwise	RRD
HOUSE_LOAN	A dummy variable that equals 1 if the borrower has a house mortgage loan and equals 0 otherwise	
OWNERSHIP	Number of bids placed on a listing when the listing is fully funded	RRD
PAST_NUM	Number of loans made in the past	RRD
Loan information		
INTEREST RATE	Interest rate that the borrower pays on the loan (rate is adjusted by the benchmark rate of People's Bank of China)	RRD
AMOUNT	Requested loan amount in ten thousands RMB	RRD
BID AMOUNT	Amount that lenders bid on a loan in ten thousand RMB	RRD
BID_RATIO	Ratio of bid size divided by the loan amount requested	RRD
MATURITY	Loan maturity in months	RRD
FUND	An indicator that equals 1 if a listing is fully funded and equals zero otherwise	RRD

FRACTION	Proportion of campaign proceeds out of the total loan amount	RRD
OWNERSHIP	Number of lenders in a given loan	
LISTING DATE	Date when the listing is created	RRD
BID TIME	Time (in minutes) between the time the listing is created and the time the listing is fully funded	RRD
CONTENT	State provided by the borrower in the loan application	RRD
WORDS	Number of words used by the borrower in the listing text	RRD
DEFAULT	An indicator that equals 1 if the loan status is "repayment by platform" or "overdue" and equals zero otherwise.	RRD
Social Capital variable		
SC_INDEX	Constructed by applying loadings (coefficient) to the standardized four proxies of social capital	Authors' estimation
BLOOD	Amount of blood, in milliliters, donated voluntarily in a province divided by its population in 2000	Chinese Society of Blood Transfusion in 2000
NGO	Participation of NGO is measured as the number of registered NGO members per thousand population in a province	China Statistical Yearbook, various years
ENTERPRISE	Enterprise Survey System (Trust 3: enterprise trust). In this survey, managers answer the following question: "*According to your experience, could you list the top five provinces where enterprises are most trustworthy?*"	Zhang and Ke (2003)
CITIZEN	The response to the question: "*How trustworthy are the people in your city?*" The responses range from 1 ("highly untrustworthy") to 5 ("highly trustworthy"). We capture a region's level of trustworthiness by its cities' average score in a province.	China General Social Survey (CGSS)
Provincial variable		
PGDP	GDP in the province in ten thousand RMB divided by the population in the province	China Statistical Yearbook, various years
LAW_OFFICE	Number of law office units per ten thousand population in a province	Provincial reports of qualification examinations for attorneys and certified accountants, various years
LOAN	Ratio of total bank loans to GDP in a province	China Statistical Yearbook, various years
RICE_SUIT	Logarithm of "rice suitability," which is a z-score of the environmental suitability of each province for growing wetland rice according to the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database.	United Nations Food and Agriculture Organization's Global Agro-ecological Zones database

ETHIC	Population percentage of major ethnic groups in a province	China Statistical Yearbook
DISTANCE	Physical distance between provincial capital cities of lenders and borrowers	Authors' estimation

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