

Stereotypes in Person-to-Person Lending: Evidence from Debt Crowdfunding

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Abstract

How much do stereotypes affect person-to-person economic exchange? Empirical evidence from a debt-crowdfunding website reveals that individual borrowers from high-social-capital regions enjoy higher funding success, larger loan and bid size, lower interest rates, and more concentrated loan ownership. The effect is more pronounced among borrowers with no credit history or of lower quality. Dyadic data show lenders from regions higher in social capital offer smaller loans at higher interest rates to borrowers from lower-social-capital regions. We consider a range of explanations and find our results most easily explained by investors using region-based stereotypes as a heuristic when making credit decisions.

Key words: Stereotype, Social Capital, Person-to-Person Lending, Debt Contracting.

JEL Classification Code: Z10, G10, O16.

Introduction

Stereotypes, defined as widely held thought or impressions concerning the attributes that characterize a group, are ubiquitous in human interactions. The social psychology literature views stereotypes as a “representativeness” heuristic for human decision making (Kahneman and Tversky 1972; Schneider 2004). Prior economic work has used field experiments to study stereotypes in markets. For example, Bertrand and Mullainathan (2004) sent fictitious resumes to employers using African-American- or White-sounding names to test labor market discrimination. Akerlof and Kranton (2000) claimed that identity – a person’s sense of self relative to others – influences preferences and economic outcomes. Also, one’s lower (higher) self-image may evoke anxiety and discomfort (confidence and comfort) in oneself and may impact economic actions and notions of others e.g., different race, class and regions. In this paper, we study identity and stereotypes in the credit market, the investigation of which has in the past been difficult because of a shortage of observational data on person-to-person credit. Over the past years, however, technological innovations in finance have enabled online credit transactions between anonymous individuals without intermediaries. Moreover, improvements in the underwriting process allow a loan to be crowdfunded by multiple lenders. These unique features allow for the observation not only of “self-image” and the “wisdom of the crowd,” i.e., the market’s *aggregate* assessment of borrowers, but also for dyadic analysis of how individual lenders assess a borrower. This article fills a gap by using data from real transactions on a person-to-person (P2P) lending website in China.

Stereotypes take many forms. In this paper we focus on lender stereotypes regarding the “representative” social capital of a borrower’s home province. Unlike institutions that screen borrowers using algorithms, stereotypical thinking among individuals is “instantaneous” (Durlauf and Fafchamps, 2006), exogenous to each economic transaction (Bottazzi, Da Rin, and Hellmann, 2016), and can be overweighed in probability judgements (Bordalo et al. 2016). As Zingales (2015) pinpoints:

“Even within the United States, immigrants from different locations seem to carry a ‘cultural’ marker, which fades only slowly over time. 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.”

We hypothesize that when individual lenders are uncertain about a borrower's quality, they use region-based identity and stereotypes as a mental shortcut to make investment decisions. Stereotypes affect credit outcomes through a lender's judgment of the probability of opportunistic behavior on the part of borrowers from a certain region. In high-social-capital regions, reciprocity and cooperative norms help to constrain opportunistic behaviors, even in the absence of strong legal and market institutions (Coleman, 1988).¹ This is so because dense social networks intensify internal sanctions such as social ostracism (Uhlener, 1989) and stigmatization (Posner, 2000), and heighten negative moral sentiments associated with perpetuating opportunistic behaviors (Elster, 1989), causing borrowers from such regions to be assigned a higher probability of behaving cooperatively. This leads to the prediction that, all else being equal, borrowers from high-social-capital regions have higher funding success and, conditional upon this success, receive more favorable debt terms than do borrowers from regions of low social capital.

To measure regional social capital we employ a battery of proxies. The objective is to capture the *civic norms* and *social trust* in a province, two elements that both Coleman (1990) and Putman (1993) refer to as manifestation of social capital. We first include (population-weighted) voluntary blood donation without compensation, as well as registered NGO members in a province (Guiso, Sapienza, and Zingales 2004). We also employ two national surveys. One asks respondents to rank “*the top 5 provinces where the enterprises are most trustworthy*” (Zhang and Ke, 2003). The other asks respondents to rate “*how trustworthy are the people in your city*” (Knack and Keefer, 1997). Our fifth proxy, a composite trust index, is based on a principal component analysis (PCA) of the four variables.

We find strong evidence that the social capital of a province positively affects their borrowers' loan outcomes. *Ceteris paribus*, individuals from regions higher in social capital enjoy a higher probability that their loans will be fully funded; they are also able to borrow larger amounts, at lower interest rates. These borrowers also have more concentrated loan ownership, suggesting

¹ Other eco-social conditions, such as the legal environment (Qian and Strahan, 2007), and culture-level religiosity (Cai and Shi, 2014) may have similar effects in constraining opportunistic behavior. However, as Kranton (1996) shows, reciprocal exchange can be a self-enforcing and self-sustaining system. In this study, we control for alternative institutions, but note that our proxies of regional social capital capture non-legal and non-religious social norms that constrain self-serving behaviors.

less risk-sharing demand from loan investors. The economic magnitude of regional social capital is non-trivial: A one-standard-deviation increase in our provincial trust index increases the average loan size by RMB 2,600 (\$400) and reduces the adjusted interest rate by 1.2 percent. Our result is robust to the control of variables at borrower, loan, and region levels, individual-lender fixed effects, the Heckman correction on funding success, and bootstrapping tests.

To the extent that regional social capital can be endogenous, we employ two instruments related to the formation of cooperative norms in a province. The first traces a province's agricultural history of growing rice versus wheat (Talhelm et al. 2014). The second investigates the proportion of the largest ethnic group in the total population of a province (Easterly and Levin 1997). Our instrumental variable analysis strongly supports the baseline result.

If our proposition is correct that lenders use stereotypes as a mental shortcut to ease their decision making, then the theory of adverse selection (Akerlof, 1970) predicts that such stereotyping will benefit borrowers whose credit quality (by hard information) is “below the stereotypical average.” Our findings are in accordance with this prediction: The interaction effect shows that stereotypes are more significant when borrowers are female, have lower income, and shorter work experience. We also find that stereotyping is more frequently used for borrowers with no previous credit history on the website (“first-time” borrower), and when their education level is low.

We carefully test several alternative hypotheses. The first is in-group bias (Yamagishi et al. 1988; Cornell and Welch, 1996; Huff and Kelley, 2003; Guiso, Sapienza, and Zingales, 2009). For example, Fisman, Paravisini, and Vig (2017) find that cultural proximity (shared codes, beliefs, and ethnicity) between borrowers and bank loan officers increases loan size and reduces default. Giannetti and Yafeh (2012) find that banks offer smaller loans at higher interest rates to more culturally distant borrowers. To examine how common traits between lender and borrower affect debt contracting, we take advantage of a large sample of loans where complete personal information of counterparties is available.² Specifically, we assess how observable differences between each lender-borrower pair (e.g., age, gender, credit rating, education, marital status, income, home ownership, work experience, and home environment) affect lending outcomes.

² This is so because some lenders are also borrowers on the same platform, thus must supply personal information.

After controlling for these differences, we find robust results that individual lenders bid less (more) and require higher (lower) interest rates when their borrowers are more downwardly (upwardly) distant in social capital, thereby confirming our baseline findings.

We next investigate the alternative explanation of the investor's "home bias" (Coval and Moskowitz 1999; Grinblatt and Keloharju 2001; Chan, Covrig and Ng 2005). Two pieces of evidence suggest that this phenomenon does not drive our results. First, we show that our finding is robust after excluding loans in which both lenders and borrowers are from the same province. Second, in our dyadic level analysis, by allowing the effect of social capital to depend on whether the home provinces of the counterparties share the same border (Rose 2004), we find the effect of social capital attenuates, but remains significant, when lender and borrower are geographically distant. Finally, we test other sources of stereotypes. Duarte, Siegal, and Young (2012) show that trustworthy appearance in borrower photographs is associated with better loan outcomes. This argument is irrelevant here, however, since the P2P website employed in our study does not allow borrowers to post photos. On the other hand, we see little evidence of stereotypes based on age, gender, or social groups.

Our main conclusion, that region-based stereotypes affect person-to-person economic exchange, has several economic implications. The first is the value of social capital in economics and finance. Knack and Keefer (1997) show that country social capital is associated with measurable economic performance. Guiso, Sapienza, and Zingales (2004) find that regions of high social capital have deeper financial markets. At the firm level, studies find that firms in regions of higher social capital show higher financial reporting quality (Garrett, Hoitash, Prawitt, 2014), less variance in returns (Hilary and Hui 2009), and more innovation (Laursen, Masciarelli, and Prencipe, 2012). A few studies examine the value of social capital in credit. For example, Guiso, Sapienza, and Zingales (2004) show that households in regions of higher social capital in Italy have greater access to institutional credit. Wu, Firth, and Rui (2014) provide evidence that Chinese firms located in higher-trust regions obtain more trade credit from suppliers. Hasan et al. (2015) find that U.S. firms headquartered in high-social-capital counties enjoy favorable loan conditions. However, none of this work addresses lending between individuals and none distinguishes between *local* and *non-local* credit. We fill this gap by focusing on the online environment, where anonymous individuals extend credit to others. To the best of our knowledge,

this paper provides the first empirical evidence on region-based stereotypes in person-to-person lending.

This paper also contributes to emerging work that studies the determinants of funding on P2P platforms. Duarte, Siegal, and Young (2012) show that trustworthy appearance in a borrower's photographs is associated with better loan outcomes. Lin, Prabhala, and Viswanathan (2013) find that the friendship network on the P2P platform increases the likelihood of a loan being funded and reduces interest rates. Their findings are consistent with the role of signaling in reducing information friction. Our test of regional social capital differentiates from theirs in that we point to the impact of social capital as providing environmental pressure constraining opportunistic behaviors. We show that high regional social capital facilitates not only in-group trust, but also out-group perceptions of the quality of borrowers from the region. In this regard, our evidence finds synergy with a stream of country-of-origin (COO) literature that documents the impact of perceptions about a country on an individual's evaluation of that country's products in international business (Li and Wyer, 1994; Lampert and Jaffe, 1996; Newburry Gardberg, and Belkin, 2006; Knight, Holdsworthy, and Mather, 2007). We confirm the COO effect in person-to-person economic exchange using regional evidence from China.

Finally, we contribute to research on the effects of geographical, cultural, and other heterogeneities between trading partners on trust-intensive contracts, such as credit. Fisman, Paravisini, and Vig (2017) find cultural proximity (shared codes, beliefs, and ethnicity) between borrowers and bank loan officers increases loan size and reduces default. Giannetti and Yafeh (2012) find that cultural distance between bank loan officers and borrowers leads to more restrictive loan terms. We extend this line of research by showing that gaps in regional social capital increase distrust. Lenders from high-trust regions are more cautious when lending to borrowers from low-trust regions.

The remainder of this paper proceeds as follows: Section II introduces the mechanism of online marketplace lending and institutional settings in China. Section III describes our sample data and variables. Section IV presents empirical results, and Section V draws conclusions.

1. Institutional Background

This paper presents novel evidence from the emerging market of China. In such markets, formal institutions such as laws are often ineffective in protecting investors (La Porta et al. 1998), necessitating alternative governance, such as that based on social capital. For historical reasons, e.g., ethnicity, regional dialect, culture and geography, social capital in China is unevenly distributed among its 31 provinces. For example, using data from the World Values Survey, Ang, Cheng, and Wu (2015) show that value differences among provinces in China are often greater than those across as many as 13 European countries.

The formal credit market in China is dominated by banks, with five state banks splitting almost half the total loan market. The capital market is relatively underdeveloped, and a majority of listed firms are owned or controlled by the government (Allen, Qian, and Qian, 2005). Not surprisingly, most bank credit is extended by state-owned banks to state-owned enterprises (SOEs) or to large private firms, while private small- and medium-sized firms face substantial obstacles in obtaining external finance from the formal financial sector (He, Xue, and Zhu, 2017).

“Shadow banks,” 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, pawn shops and various unofficial lenders. They perform credit functions similar to those of banks, but are not subject to the same intensive banking regulations.

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 shopping online and making digital payments.³

³ In a survey by Ernst & Young (2017) of 20 markets, in China, 58% of consumers have used Fintech savings and investment services, compared with 27% of US consumers. The contrast is even greater for the adoption of Fintech

Unlike in the U.S., where borrowers are required to have a minimum FICO score to enter the P2P lending market,⁴ in China anyone with an identity card and a bank account can post loan requests on the website.⁵ Data from *Wangdaizhijia* show that the number of operating OML websites soared from only 10 in 2010 to 3,984 by March 2016, and facilitated cumulatively RMB 1.745 trillion (\$ 268.4 billion) in loans. Although this emerging market is relatively small compared with the country's colossal financial system,⁶ by any measure of size, China is the world's leader in online marketplace lending (The Economist, 2017).

2. Sample and Variables

3.1 Measuring Province-level Social Capital

Trust, cooperative norms, and associations within groups each fall within the elastic definitions that scholars have applied to the term social capital (Knack and Keefer, 1997). In online marketplace lending, lenders and borrowers are anonymous strangers. We focus on the provincial social capital of borrowers because lenders choose borrowers (not vice versa) based on an array of borrower information, including a borrower's (ID card-consistent) place of origin.

Following the social capital literature in economics and finance, we measure provincial social capital using the following indicators: voluntary blood donation, NGO participation, enterprise trustworthiness, and citizen trustworthiness. Our first measure is voluntary blood donation per capita in a province. As Guiso, Sapienza, and Zingales (2004) argue, there are neither legal nor economic incentives to donate blood. The activity is likely driven by individuals' civic-mindedness in overcoming collective action problems. Several notes regarding this variable are in order: First, following Ang, Cheng, and Wu (2015), this variable is measured as the milliliters of blood donated voluntarily in a province, divided by its population in 2000, the only

borrowing services, with 46% of Chinese consumers indicating they have used these services, compared with 13% of US consumers. See EY Fintech Adoption Index 2017, available at: [http://www.ey.com/Publication/vwLUAssets/ey-fintech-adoption-index-2017/\\$FILE/ey-fintech-adoption-index-2017.pdf](http://www.ey.com/Publication/vwLUAssets/ey-fintech-adoption-index-2017/$FILE/ey-fintech-adoption-index-2017.pdf)

⁴ For example, In the U.S., online marketplaces such as Prosper require a minimum FICO score of 640, Lending Club requires a minimum of 660 for borrowers to engage in the market.

⁵ Note that, in China, there is no personal credit scoring system such as FICO in the U.S., nor is there a personal bankruptcy law to protect creditors.

⁶ For example, the outstanding balance of P2P credit is roughly 0.8% of China's total bank loans in 2016. (The Economist, 2017).

year that complete province-level data from the Chinese Society of Blood Transfusion is available.⁷ Second, in China, the blood donation law clearly states that blood can only be collected by the National Blood Center (NBC) of China, and is without compensation. The NBC has operating branches in all provinces, and adopts the same medical procedures across all regions, mitigating the concern that the blood donation level is affected by differences in the quality of healthcare or medical infrastructure among provinces. We conjecture that individuals who live in regions with high incidences of blood donation are under higher social pressure and internal norms to behave cooperatively. Table 1 Panel B (Column 2) shows large variance among Chinese provinces, with an average blood donation of 3.43 ml/1000 people in Shanghai to only 0.017 in Yunnan.

Our second indicator is NGO participation, measured by the number of people registered in non-governmental organizations (NGOs) per thousand people in a province. NGOs are typically funded by donations and operated by volunteers, with aims to address social needs such as poverty reduction, environmental protection, and rights of disadvantaged groups. Individuals growing up in regions with higher NGO participation typically are more civic-minded, more caring, and less likely to behave in an opportunistic manner. Our provincial NGO participation data are hand-collected from the Chinese Civil Affairs Statistical Yearbook of 2010.⁸ Panel B (Column 3) shows Shanghai as the province with highest NGO participation (4.4 registered NGO members per thousand population), and the lowest is Tibet, with only 0.03.

Apart from outcome-based proxies of social capital, we measure the perception of Chinese citizens on the “trustworthiness” of non-specific members of another, or their own, province. Our third measure, provincial “enterprise trustworthiness,” draws from a national survey of Chinese enterprises in 2000 (Zhang and Ke, 2003).⁹ 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 cover firms from every two-digit industry and ownership type. Specifically, our “enterprise” variable is elicited from their answers to the question, “*According to your experience, could you list the top five provinces where the enterprises are most*

⁷ We are grateful to Ang, Cheng, and Wu (2015) for sharing these data with us.

⁸ For a robustness test, we use the average of the level from 2010 to 2015, and the results are similar across those years.

⁹ A similar, enterprise trustworthiness survey was used by Burns, Meyers, and Bailey (1993) and Guiso, Sapienza, and Zingales (2009) in five major European Community countries.

trustworthy?” We assign scores to each ranking of provinces and aggregate them to obtain the province’s average score of enterprise trustworthiness.¹⁰ Panel B (Column 4) shows Shanghai (22.7) leads Chinese provinces in enterprise trustworthiness, followed by Beijing (16.6) and Guangdong (10.1). The least enterprise-trustworthy province appears to be Hainan (0.1).

Our fourth measure, “citizen trustworthiness,” follows Wu, Firth, and Rui (2014) and uses data from the China General Social Survey (CGSS). The CGSS was conducted jointly by the Survey Research Center of the Hong Kong University of Science and Technology and the Sociology Department of the Renmin University of China in 2003, and received 5,894 completed responses. Respondents encompass Chinese residents in 125 counties from 28 provinces. Our “citizen” variable is elicited from respondent answers to one question, “*How trustworthy are the people in your city?*” The response ranges from 1 (“highly untrustworthy”) to 5 (“highly trustworthy.”). We calculate province *i*’s level of trustworthiness by aggregating the average score of citizens from that province. One important caveat is that, unlike the third measure, “enterprise,” which is based on respondents’ ranking of *other* provinces, our fourth measure, “citizen,” reflects in-group bias, i.e., people tend to place higher generalized trust in people from their own cities, even if the overall social-capital level of that province may be low. Consistent with this conjecture, Panel B (Column 5) shows much smaller variances among scores given by citizens of each province. Shanghai ranks second (2.40), surpassed by Jiangxi (2.442), and the least trusting provinces appear to be Gansu (2.014) and Guizhou (2.014).

To account for intrinsic biases/limitations of each indicator, we construct a composite, provincial “trust” index by applying principal component analysis (PCA). Table 1 (Panel A) shows the results of the PCA for our proxies of trust. This method shows that only one component has an eigenvalue larger than one (2.967). All four indicators have positive loadings and closely correlate with the index. Our composite index gives roughly equal weighting to blood donation, participation in NGOs and enterprise trustworthiness, but somewhat lower weights to the citizen trustworthiness score. Based on the composite trust index (Panel B, Column 1), Shanghai, Beijing, and Guangdong are the three most trusting provinces, while Gansu, Guizhou, and Yunnan are the least trusting.

¹⁰ To alleviate the home bias, Zhang and Ke (2003) created another score by excluding managers who select their own province as one of the top five. They show the two scores are not significantly different from each other.

[Insert Table 1 here]

3.2 The Renrendai Online Marketplace

Much of our data comes from the Renrendai online marketplace (“RRD”), which contains loan- and investment-level data for all its transactions from September 2010 to December 2015. RRD is one of the largest P2P lending platforms in China, following the model of the Lending Club in the U.S. Since its official launch in 2010, RRD has over 2.5 million members and facilitated 13 billion RMB (USD 2 billion) in funded loans as of Dec 31, 2015. We obtained this proprietary dataset from Changsha Aijie Information Technology Co. Ltd (Aijie).

The lending process on RRD begins with a loan application. Users join renrendai.com by providing a cell phone number, which is verified by the website. To post a loan request on RRD, a prospective borrower must go through additional verification. Borrowers should have a valid national identity card, a valid bank account,¹¹ and provide personal information about themselves including age, gender, education, income, marital status, home ownership, employment information, and address. This information is verified by RRD, which also requires borrowers to provide supporting materials, e.g., a copy of their National ID card, work certification, and diploma. All users are identified by a username that is chosen when registering.

A minimum credit rating grade is obtained once the three items listed above are verified. To make a loan request, called a listing, borrowers must supply a title, description, loan amount, and maturity. All loans are unsecured personal loans, and their maturity ranges from one to 48 months. In addition, each listing shows personal information, such as age, gender, education, income, marital status, home ownership, employment information, and location. RRD normally takes from one to three working days to verify loan information. Loans with incomplete information or are unverified are not allowed for online listing.

Two important features for listings on RRD are worth highlighting: First, unlike other platforms, on RRD, borrowers are *not* allowed to upload their photograph. Duarte, Siegal, and

¹¹ Bundling one’s bank account to one’s RRD user account enables the transfer of money in loan transactions. If the user does not have a bank account, the RRD would automatically create a bank account for the user at Minsheng Bank.

Young (2012) show that on *Prosper*, a trustworthy appearance in the borrower's photographs is associated with better loan outcomes. Therefore, this factor can be safely dismissed in our setting. Second, borrowers have no choice in their interest rate: RRD assigns an interest rate and calculates monthly repayment based on its proprietary credit-rating model and the self-reported information of the borrower.¹² This is a useful feature of the institutional setting, since given the pre-set interest rate, the equilibrium outcome of whether the loan is provided depends directly on the willingness of lenders to supply credit at the given interest rate.

Individual lenders on RRD can choose one of two channels to make an investment on loan listings. The “automatic bidding” (*zidongbiao*) channel allows lenders to lock in a sum of money on RRD with pre-set criteria for bidding and authorizes RRD to make investments for them once the eligible loan listings are available. The other channel, “manual bidding” (*sanbiao*), requires lenders to manually select and make investment decisions themselves. In this study we use the manual bidding channel data, since this method is P2P lending in its essence, for 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.

For manual bidding, a listing is typically open for several days. Figure 1 shows the entry page for lenders, where all active listings are shown with borrower's user ID, loan title, borrowing amount, asking rate, credit rating, percentage completed, and time remaining. Lenders can search, filter, and sort these listings. By clicking on a specific listing, lenders can observe additional information about the listing, such as loan description, borrower's age, gender, place of origin, education, income, home ownership, and authentication status, but no photograph of the borrower is allowed (Figure 2).

To bid on a listing, a lender must submit the bid amount. The minimum bid amount is RMB 50 (USD 7.7) and RRD does not encourage one lender to bid for the whole loan. A listing that

¹² The exact credit rating model used by RRD to assign a credit rating is unknown due to its proprietary nature. However, unlike in the U.S. where an individual's FICO scores can be obtained, in China the personal credit score system is non-existent. Each P2P 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 the borrower supplies the minimum information required by RRD to open an account. If borrowers voluntarily provide more documentary proof, such as a bank income statement or home-ownership certificate, and these details are verified by the website, their credit rating will increase. Moreover, if the borrower has a good repayment history on this platform, the credit rating will also increase.

reaches 100 percent funding status becomes a successful loan, otherwise the borrower receives zero funding. As a result, a successful loan typically has multiple lenders. Once a successful loan is verified by RRD, funds are transferred from lender(s) to borrower, minus a platform service fee. The service fee varies depending on the borrower's credit rating.

Subsequently, borrowers are obligated to repay the principal and interest in monthly installments. The repayments are proportionally distributed to the lenders of the loan. If a repayment is overdue (i.e., there is insufficient fund in the borrower's bank account to repay the interest), RRD makes several attempts to recover the loan, including email, text messages, and calling the borrower. However, as a platform, RRD does not bear the credit risk of the borrower.

3.3 Variables of Interest and Controls

Appendix A includes detailed definitions for each variable and Table 2 contains summary statistics on the variables. We categorize our variables of interest into: (1) listing and loan, (2) borrower, (3) provincial environment, and (4) lender characteristics. Each is introduced in order.

We obtain information on the funding success or failure of each loan listing. For each funded loan, we obtain the size (in RMB), maturity (in months), interest rate (in basis point spread over benchmarked lending rate of PBOC), number of lenders involved, stated purpose of the loan (in descriptive text), number of words used to describe a loan, and its default status.

For each borrower, we obtain the user ID, age, gender, place of origin (province), marital status, income range, education, work experience, home ownership status, and borrowing history on RRD. We also obtain the credit rating assigned to each borrower by RRD (in seven categories: AA, A, B, C, D, E, and HR).

For provincial institutional variables, other than the five trust measures described above, we first include GDP per capita to measure the economic environment. To capture the legal environment of a province we include the number of law offices per ten thousand residents. The density of law offices captures the demand for legal services in a province and is positively associated with the rule of law (Ray, Shleifer, and Vishny, 1996). We proxy the financial environment of a province as follows: *Loan* is the ratio of total bank loans to provincial GDP,

which measures the size of the financial market (Rajan and Zingales, 1998). In our regressions, institutional variables of a province in the year $t-1$ are matched with loans originating in year t .

3.4 Summary Statistics

Our sample comprises 247,565 loan listings on RRD with complete information on each variable from September 2010 to December 2015. Panel A of Table 2 reports that about 24.9 percent of loan listings are fully funded. Of the 61,641 fully funded loans, the mean of loan size varies significantly from RMB 48.1 thousand (USD 7,400) to 3 million (USD 461,538). On average, the loan rate is 2.13 times the bench market lending rate, with significant variation from 0.59 to 5.38 times the bench market lending rate. Compared with the stability of China's benchmark lending rate, these large pricing differences, at least in part, reflect differences in borrower risks. The mean and median loan maturity is 18.78 and 18 months, respectively. We construct an additional variable *longterm*, which is a dummy variable that equals one if the loan maturity is more than 12 months, and zero otherwise. It shows that 80 percent of borrowers request a long-term loan. Loan ownership also varies considerably across borrowers. The average loan has 35.48 lenders, ranging from 1 to 1370 lenders. Finally, about five percent of funded loans incur default.

Panel B reports the summary statistics of demographics, income, and educational information for each borrower. The statistics suggest that most borrowers are young, male, married, less educated, have low credit scores and a credit history on RRD. In addition, the median income level of borrowers is less than ten thousand RMB (USD 1,538) per month, and only 44 percent of borrowers own a home.

Panel C of Table 1 also reports the summary statistics for provincial-level variables. It shows that there is a large variation in the development of the economy and financial markets across China's provinces.

[Insert Table 2 here]

It is worth mentioning that we do not include either province-level and borrower-level fixed effects in most of our regressions, because our trust index is time-invariant for all borrowers in

the same province. In addition, most borrowers have only one loan in our sample period. However, to examine the impact of the interactions between borrowers' characteristics and the trust index on loan items (Table 5), we perform province-level fixed-effect regressions, while dropping all provincial-level variables.

3. Social Capital and Credit: Loan-level Empirical Results

In our regression model, we begin by testing how social trust affects loan characteristics and the probability of a listing being fully funded. We next consider how investors' reliance on social trust varies across characteristics of heterogeneous borrowers, such as their credit history and education. In a robustness check, we implement a two-stage, least squares instrument regression.

4.1 Funding Success

Table 3 reports the logit regression result of a listing being fully funded. Specification 1 includes our trust index with all available information on the borrower's characteristics and regional environmental variables. Consistent with our expectation, it shows that social trust in the borrower's home province increases the probability that a listing will be fully funded. The coefficient is statistically significant at the one-percent confidence level. As the reported coefficients are the effect of a marginal change in the regressors on the probability of obtaining a loan, we can estimate the economic size of this trust effect. All else being equal, the probability of obtaining a loan for borrowers in the highest-trust province (Shanghai) is 1.5 percentage points (or 5 percent) higher probability of obtaining a loan than in the lowest-trust province (Gansu).

The signs of control variables are consistent with our expectation. For example, borrowers with higher credit rating, personal income, and education level, and with longer work experience have a greater probability of receiving fully funded loans. On the other hand, we find that borrowers with home ownership and those with larger numbers of prior loans have a lower probability of receiving fully funded loans. This finding is consistent with investors' being more hesitant to fund borrowers with other concurrent liabilities (e.g., a mortgage on their home or

other outstanding loans on RRD). Finally, we find female borrowers are less likely to have their loans fully funded than are male borrowers.

All provincial-level control variables have the expected sign and most of them are statistically significantly different from zero. The level of per capita GDP and measure of financial development (*loan*) of a province have a positive and statistically significant effect on funding probability. In contrast, in areas with a relatively stronger legal environment, a borrower's loan listing is less likely to be funded.¹³

In specifications 2-5, we check the robustness of findings by using four proxies of trustworthiness, while keeping the same set of controlling variables. These checks show that three out of our four trustworthiness proxies (with the exception of "citizen") are positively and statistically significantly related to funding probability.

[Insert Table 3 here]

4.2 Loan Ownership, Size and Pricing

Table 4 uses the same specifications to estimate the effect of trust on the number of lenders for a given loan (*Ownership*), loan size (*Amount*) and pricing (*Interest rate*), using all fully funded loans. In addition, we also controlled for whether the loan is long term (maturity over 12 months) or short term (maturity below 12 months). Panel A of Table 4 reports the estimated effects of our trust index on these variables. We find first that a borrower's credit profile, income, and education produce expected results, i.e., a better rated, educated, and high-income borrower with longer work experience can borrow larger amounts at lower interest rates. Loan ownership becomes more diffuse when borrowers are old, female, married, and have higher credit scores, higher income levels, and own a home. Many of these results are consistent with the findings of the small business lending literature (e.g., Petersen and Rajan, 1994). As expected, a long-term loan is also associated with a larger loan amount, higher interest rate, and diffused ownership.

Turning to our trust index, we find that social trust in a borrower's home province has a *negative* and statistically significant effect on the number of lenders for a given loan (Columns (1) and (2)). It indicates that there is more risk-sharing demand by investors when borrowers are

¹³ One possible explanation is that the efficiency of the legal system reduces the reliance on peer-to-peer lending for external finance.

perceived as less trustworthy. This result is consistent with Ongena and Smith (2000) and Qian and Strahan (2007), who show that the credit rights in a country are positively associated with concentration of loan ownership. In addition, the level of per capita GDP has a positive effect on the number of lenders for a given loan.

We find a positive and statistically significant association between the trust index and loan amount in both specifications (Columns (3) and (4)). The economic effect of trust is also large: A one-standard-deviation increase in social trust is associated with a 2-thousand RMB increase in loan amount. Thus, impressions regarding a borrowers' trustworthiness have a positive effect on loan size.

Finally, results in Columns 5 and 6 show that our trust index is negatively related to loan interest rates, and that the coefficients are both statistically and economically significant. A one-standard-deviation increase in a borrower's trust index leads to about a 0.7% decline in interest rate. Taking an extreme case, a loan to a borrower in Gansu (where the trust index is -1.887) would charge an interest rate around 3.1 percent higher than a loan to a borrower in Shanghai (where the trust index is 5.768). Thus, borrowers from higher-trust regions are more likely to obtain credit at a lower interest rate. Table 4 also shows that borrowers pay a lower interest rate in provinces where their home legal environment is stronger, consistent with the finding of Qian and Strahan (2007). Finally, greater economic and financial development is associated with higher interest rates (Column (4)).

Panel B of Table 4 repeats the tests in Panel A, using our four proxies of borrower social trust, controlling for borrower characteristics, regional environment, and loan maturity. It shows that most proxies of social trust are negatively (and significantly) related to loan ownership, positively (and significantly) related to loan size, and negatively (and significantly) related to interest rate, thereby validating our baseline results.

[Insert Table 4 here]

4.3 When Does Social Capital Matter More?

If our proposition is correct that investors assess borrower quality based on the social capital of their origins, then we expect that the marginal benefit of social capital to differ between low- and high-quality borrowers. The hypothesis is that lower-quality borrowers would benefit more from the high social capital of their region, given the adverse selection (Akerlof 1970).

To test this hypothesis, we first study whether the effect of social capital on credit varies across borrower gender, income, and work experience. Table 5 reports provincial-level, fixed-effect regressions relating to funding success and our ownership, loan size, and pricing variables to the control variables and the interactions of trust and various borrower characteristics. Each cell shows the estimates for the interactions between trust and specific borrower characteristics, e.g., age, gender, marital status, income, and work experience. The direct effect of trust is not identified in models of the province fixed-effect regressions, as the fixed effects absorb any cross-province variations. Since many loans are made in each province but there is no variation in our within-province trust index, we cluster errors across all borrowers in the same province.

We first find that the impact of our trust index on loan ownership varies significantly with borrower gender, income, and work experience. Given the overall negative effect of trust on the number of lenders (Table 4), the positive coefficients for the interactions of borrower income and trust and work experience and trust suggest that social trust affects loan ownership more significantly when a borrower has lower income and shorter work experience. The interaction between trust and gender is negative, suggesting that trust affects loan ownership most when the borrower is female. We also find that marital status, borrower income and work experience complement the effects of trust on loan size. Married borrowers, with a higher level of income and longer work experience, who live in trust-intensive provinces, obtain the largest loan amounts (Columns 5 and 6). Regarding the interest rate of a loan, we find that the interaction between work experience and trust is positive. Thus, given that the overall relation between trust and interest rate is significantly negative (Table 4), the impact of trust on lowering interest rates is stronger for borrowers with shorter work experience.

[Insert Table 5 here]

4.3.1 *Less-educated Borrowers*

We separately investigate the impact of social capital on borrowers with low and high levels of education, because prior research has shown that an individual's human capital is closely correlated with education (Lusardi and Mitchell 2008; Behrman et al., 2012), and that borrowers with lower levels of education are often discriminated against for credit by formal financial institutions. Thus, if regional social capital benefits lower-quality borrowers, we expect its effect on credit to be stronger for lower than for higher educated borrowers. To test this hypothesis, we re-estimate our benchmark specifications, splitting the sample between borrowers with higher and lower education levels. A borrower is classified as high (low) education if his or her highest qualification is a bachelor's degree or above (post-tertiary or below).

Table 6 Panel A presents the results. The first two columns report the logit estimates of the effect of social trust on the likelihood of funding success. Social trust has no significant impact on the funding success of highly educated borrowers. In contrast, however, in the sample with less-educated borrowers, the effect is twice as large and is statistically significant at the one-percent confidence level.

Columns (3) and (4) show that our trust index has a negative and statistically significant effect on the number of lenders in both subsamples. It seems that the number of lenders is more sensitive to social capital among highly educated people, but the difference between the less- and the highly educated groups is not statistically significant.

Columns (5) and (6) show that the effect of social capital on loan size is both large and statistically significant among less-educated borrowers but is insignificantly negative among highly educated borrowers. The difference between them is statistically significant at the five-percent level.

Columns (7) and (8) report the estimated impact of social capital on interest rates. Surprisingly, the loan interest rate is more sensitive to social capital among highly educated people. This difference is also statistically significant at the five-percent level. In conjunction with the impact of social trust on loan size, our results suggest that lenders are more willing to fund larger loans to under-educated borrowers from regions of high social capital but are less willing to charge lower interest rates.

4.3.2 First-time Borrowers

On the RRD platform, a significant proportion of borrowers engage in more than one credit transaction. Rajan (1992) argues that such repeated interaction provides lenders with soft information about a borrower's credit quality. If social capital reduces information friction in person-to-person lending, then we expect its effect to be larger in severe information asymmetries, i.e., for "first-time" borrowers with no credit history on the platform. Panel B of Table 6 separately reports the regressions of social trust on our variables of interest on the subsample of "first-time" and "repeat" borrowers. The results in Columns (1)-(8) confirm this conjecture. With the exception of loan amount, the coefficients for the trust index on funding success, loan ownership, and interest rate are all statistically and economically stronger for first-time than for repeat borrowers.

[Insert Table 6 here]

4.4 Robustness Tests on Sample and Selection

Our results so far have shown significant and pervasive correlations between regional social capital and loan outcomes for borrowers. To gain more confidence in the causal relationship, we perform the following robustness tests.

First, we are concerned that a large sample such as ours can make insignificant results to become statistically significant, i.e., yield type 1 errors. To check the robustness of our results, we implement a bootstrap method. More specifically, we draw a subsample that contains half as many observations as the whole sample and repeat our regression analysis for this subsample. We then replicate this procedure 1000 times and obtain the resulting bootstrap statistics. Columns (1)-(4) of Table 7 presents the bootstrap results, and shows that we obtain similar results.

Next, we address the issue of selection bias. Data on loan contract terms allow us to investigate how social capital affects loan size, pricing, and ownership. However, this data set is conditional on loans being fully funded. Loans not receiving 100 percent funding are not included in our sample. To correct for this possible problem, we employ the Heckman two-step treatment effects procedure. In the first equation, we estimate the probability that a loan will be

fully funded, where the dependent variable is a dummy for the approval of loan lists. 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 (1), (3) and (5) of Table 4. Columns (5)-(7) of Table 7 present the results of a Heckman selection model, and we find that the effect of social capital on loan ownership, size, and pricing remains significant.

[Insert Table 7 here]

4.5 Unobserved Heterogeneity and Instrumental Variable Analysis

Region-based social capital is clearly not randomly assigned. Nor, however, is it a choice variable. Accordingly, we treat regional social capital as both historically and econometrically predetermined. The main identification challenge, hence, is not self-selection but is systematic differences between high- and low-social-capital regions. In our regressions, we control for observable differences such as economic, legal, and financial environments to ensure that they do not drive any differences in borrower loan outcomes, which results in unobserved heterogeneity.

Short of random assignment, the presence of unobserved heterogeneity in observational data is inevitable; however, it is important to note what it does and does not affect in our setting. Unobserved heterogeneity does not affect the validity of the fact that borrowers from high-social-capital regions have better loan outcomes, regardless of any systematic unobservable dimensions of difference between high- and low-trust regions. It may, however, affect our *interpretation* of this fact. In other words, do our trust index and proxies truly capture social trust, or do they merely reflect unobservables?¹⁴ To tackle this potential problem, we employ an instrumental variable approach.

We employ two instruments related to the cooperative norms in a province. The first is the province's agricultural history. Talhelm et al. (2014) find Chinese regions that have a history of farming rice have a more cooperative culture than those with a history of growing wheat. Farmers in rice-growing regions are more likely to form cooperative labor exchanges, especially

¹⁴ For example, regional social capital can be highly correlated with government intervention.

when transplanting and harvesting, which are activities that must be completed within a short window of time. In economic terms, paddy rice makes cooperation more valuable, encouraging rice farmers to form tight relationships based on reciprocity and to avoid behaviors that create conflict. In comparison, wheat is easier to grow. Wheat does not need to be irrigated, and wheat farmers can rely on rainfall, which they do not coordinate with their neighbors. Consequently, we calculate the logarithm of “rice suitability” index of Chinese regions (*Rice_suit*). The index is a z score of the environmental suitability of each province for growing wetland rice, based on the United Nations Food and Agriculture Organization’s Global Agro-ecological Zones database.

Our second instrumental variable is the proportion of the largest ethnic group in a province’s total population (*Ethic*). Prior studies have shown that ethnic diversity is associated with increases in social conflict (Easterly and Levin 1997) and reduces the trust environment in an area (Guiso, Sapienza, and Zingales, 2009). There are 56 ethnic groups unequally distributed across China’s 31 provinces, each with its own language, core values, and customary beliefs. The diversity of ethnic groups in a region increases communication costs and, thus, should be inversely related to cooperative behaviors (Ang, Cheng, and Wu, 2015).

To argue the exclusion restriction, it is conceivable that regional rice suitability and number of different ethnic inhabitants, developed over many generations, cannot directly affect any traits of today’s Internet lending, other than through their impact on the norms and behaviors of borrowers from a specific region. This argument is consistent with an eco-social approach in cross-cultural psychology (Berry et al. 1992; Georgas, van de Vijver, and Berry 2004), which argues that biological and cultural adaptations are implanted in the human capital of a social system, as well as in the psychological characteristics of that population.

Table 8 reports the results from the instrument variable regression of both probit and linear models for funding success, and linear regression models for loan ownership, amount, and interest rate, respectively. We also control for loan and borrower variables, regional environmental variables, and year fixed effects, but their coefficients are not reported for brevity. The first-stage results in Panel B show that both variables are positively and statistically significantly correlated with the trust index. The partial F-statistics in the first stage total more than 10,000, which is sufficiently large to alleviate concerns regarding weak instrumental

variables. The rice-suitable index and the population percentage of major ethnic groups are strong predictors of the level of trust. The second-stage results presented in Panel A of Table 8 clearly show that the trust index is still a strong determinant of funding success, loan ownership, amount, and interest rate.

[Insert Table 8 here]

4. Dyadic-level Analysis

One important feature of debt crowd funding is that each loan is sliced into smaller investments by multiple lenders. On the RRD platform, lenders are encouraged to diversify their risk by bidding in small amounts to different borrowers. This procedure allows us to conduct more informative, dyadic-level analysis by observing the size of the stake that an individual lender is willing to invest for a specific borrower, and at what interest rate.

In our dyadic-level analysis, each unit of observation is a lender-borrower pair. We first examine the robustness of our baseline results by controlling for lender fixed effects. We then isolate a subsample of lender-borrower dyads for which we can collect individual characteristics at both ends of the loan. This enables the investigation of how lender-borrower dissimilarities affect credit outcomes.

5.1 Lender fixed effects

In our fully funded loans, we identify a sample of 2,173,006 investment observations, in which 114,123 lenders invest in 61,641 loan listings. Each observation represents a lender-borrower pair. A borrower who obtains funding from multiple lenders will generate multiple observations. We conduct a multivariate ordinary least squares (OLS) regression analysis in lenders' bid amount and interest rate, modeled as a function of borrowers' characteristics:

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

where $bid_amount_{ij,t}(interest_{ij,t})$ represents the bid amount (interest rate) of lender i in borrower j in time t . $trust_j$ is the social capital of borrower j , $control_{j,t}$ represents loan and borrowers' characteristics and regional economic and financial variables. δ_i, δ_t represent the lender fixed effect and year fixed effect, respectively. $e_{i,t}$ are standard errors.

Results presented in Table 9 confirm the baseline finding: A borrower’s social capital has a positive impact on a lender’s bid amount, and a negative impact on interest rate. These effects are all statistically significant at the one-percent level. A one-standard deviation increase in the borrower’s social capital increases the lender’s investment by 86.1 RMB, an increase of almost a fifth in the median amount of a lender’s investment (500RMB).

[Insert Table 9 here]

5.2 Lender-Borrower Pairs

One caveat to note with our data is that, although RRD assigns each lender a unique user ID, it does not require lenders to provide their personal information. Fortunately, a group of lenders is also borrowing on the same platform and, thus, is required to provide personal information. This generates a sizable paired sample, in which both borrowers’ and lenders’ information is available.

We use the lender’s user ID to match the ID of borrowers, which provides us 1,745 unique lenders who invest in 22,084 loan projects, generating 51,796 lender-borrower pairs with complete information. Since we know the location of both lenders and borrowers, we can measure the physical distance between them (the distance of provincial capitals between a lender and a borrower).

Panel A of Table 10 reports summary statistics for the main variables of both lenders and borrowers. Individuals from high-social-capital regions are more likely to be lenders. The difference in social trust between the two groups is economically large and statistically significant. Borrowers are more likely to be female, married, older, less-educated, with shorter work experience, and are less likely to own property. Interestingly, borrowers tend to have higher credit ratings and income, indicating the importance of repayment ability. In addition, lenders are more likely to come from rich regions with better legal and financial development.

Panel B of Table 10 shows the investment information for our subsample. The mean and median size of lender investment are 1,000 RMB and 300 RMB, respectively. Most loans are long term and charge 2.22 times¹⁵ the benchmark lending interest rates¹⁵. The mean and median

¹⁵ One natural concern is that borrower-lenders can differ from non-borrower lenders in systematic ways. For example, one can expect borrower-lenders to be less risk-averse than ordinary lenders. Assuming that is true, then we should find systematic

distances between lender and borrower are 968.07 KM and 969.31 KM, respectively, suggesting that most lending take place across provinces.

Panel C reports results from the following multivariate OLS regression analysis in lenders' bid amounts ($bid_amount_{ij,t}$) and interest rates ($interest_{ij,t}$)

$$bid_amount_{ij,t}(interest_{ij,t}) = \beta_0 + \beta_1 d_trust + \beta_2 d_control_t + distance_{i,j} + \delta_t + e_{ij,t} \quad (2)$$

where d_trust represents the difference per social-capital region between lender i and borrower j . The negative (positive) value implies that borrowers come from higher (lower) social-capital regions than do lenders. Thus, results from applying this formula allow us to estimate directly whether loans flow from individuals in low-social-capital regions to individuals in high-social-capital regions, or whether the interest rate is lower when individuals in low-social-capital regions extend loans to individuals in high-social-capital regions. $d_control_t$ represents the difference for control variables between lender i and borrower j . We also include the physical distance between lender i and borrower j ($distance_{i,j}$). Since the distance between lender i and borrower j is time invariant, $distance_{i,j}$ also captures the lender-borrower pair fixed effect in our regression.

The first three columns in Panel C report results for lenders' bid amount in a given loan with different specifications. In line with previous findings, the negative coefficient of the difference in trust (d_trust) confirms that individuals in low-social-capital regions lend more to those from high-social-capital regions. We also find that the bid amount increases when the borrower is female, married, and has longer work experience (the coefficients of these variables are negative). Finally, the positive coefficients in the variables of age, education, law_office and pgdp means that bid amount increases as the lenders are older, more highly educated, and from regions with better legal and economic development than are borrowers. The distance between lender and borrower seems to have a limited impact on bidders' investment.

Columns (4) to (6) report the results on the interest rate with different specifications. The coefficient of the difference in social capital (d_trust) is positive and statistically significant at the one-percent level, indicating that interest rate decreases as the borrower has higher social

differences in loan properties between our average and paired-loan sample. However, as Panel B shows, there are no statistically significant differences in loan terms, as reported in Table 2. This result mitigates concerns about selection bias.

capital than the lender. The positive coefficients on the differences in control variables, i.e., age, gender, education, and marital status confirm that interest rates decrease as the borrowers are older, female, married, and more highly educated in rich regions. We also find that interest rates decline as the lenders have lower credit scores than the borrowers. Finally, the positive coefficient in *Indistance* means that interest rates rise with an increase in the distance between lender and borrower.

Taken together with results of Table 9, these results suggest that lenders from high-social-capital regions offer smaller loans at higher interest rates to borrowers from low-social-capital regions.

[Insert Table 10 here]

5.3 Social Capital or Home Bias?

It is conceivable, however, that the effect of regional social capital on credit merely reflects the “home bias” of the investor. Prior work has shown that investors tend to trust counterparties in their home more than those in remote regions (Grinblatt and Keloharju, 2001), for distance is associated with higher cost of information (Petersen and Rajan, 2002). For example, Coval and Moskowitz (1999) find US investment managers exhibit a strong preference for locally headquartered firms. Chan, Covrig, and Ng (2005) show that mutual fund managers allocate a disproportionately larger proportion of their investments to domestic stocks. Therefore, our results might be spurious if they are driven by lenders’ overweighting borrowers in a few high-social-capital provinces.

To disentangle the effect of home bias from that of social capital on credit, we perform the following tests. We first exclude investments in which both lenders and borrowers are from the same province. We then include an indicator variable, which equals one if the two provinces share the same border (*border*), and zero otherwise. We repeat the regression in Panel C of Table 10, and include both the dummy variable *border* and the interaction term *border*d_trust*.

Results in the first two columns show a slightly larger impact of the difference in social capital between lender and borrower (*d_trust*) on the loan offering, relative to that estimated in Table 10.

Thus, the effect of social capital persists after including only cross-border investments. The coefficient of *border* is negative and statistically significant at the 10-percent level, indicating that lenders tend to offer smaller loans to borrowers in adjacent provinces. Furthermore, the interaction term *border*d_trust* is significantly positive, which is the opposite sign as the effect of *d_trust*, indicating that social capital affects loan size more when lenders' and borrowers' provinces are not adjacent.

Columns (3) and (4) of Table 11 shows that the impact of the difference in social capital between lender and borrower (*d_trust*) on the interest rate is similar to those in Table 10. Lenders from high-social-capital regions require higher interest rates from borrowers from low-social-capital regions. This result still holds when we exclude investments in which both lenders and borrowers are from the same province. In addition, the interaction term *border*d_trust* is significantly negative in Column (4), which is opposite in sign to the effect of *d_trust*. This result suggests that social capital has a stronger effect on interest rates when lenders' and borrowers' provinces are not adjacent.

Taken together, these results suggest that our results are not driven by the home bias of investors. Moreover, social capital has a more pronounced impact on loan contracts when lenders offer loans to remote borrowers.

[Insert Table 11 here]

5. Conclusion

How much do region-based stereotypes affect person-to-person economic exchange? We answer this question using highly granular data from a debt-crowdfunding website. Drawn on the real credit that individual lenders extend to a stranger, we find that borrowers from high-social-capital regions have higher funding success, larger loan and bid size, lower interest rates, and more concentrated loan ownership. Our evidence is consistent with the theory that the collective reputation of a region, which develops generation by generation, has positive externalities on their agents' access to finance, especially from "outside" and "outgroup" investors. To the best

of our knowledge, this is the first paper to investigate the role of regional social capital in direct rather than institutional lending.

We also find that borrowers of inferior credit quality benefit the most from the social capital of their home province. This is consistent with adverse selection, but also sheds light on the financial inclusion theory: low-income, low-education borrowers and those without credit history are likely to be rejected by formal financial institutions, such as banks. Our result shows these disadvantaged people can leverage on their home region's social capital to access finance through the Internet.

Finally, our evidence shows that the informative role of regional social capital becomes weaker when counterparties share geographical or other similarities. To the extent that regional social capital provides environmental pressure against opportunistic behavior, our results show a possible supplementary relationship between heterogeneous networks in person-to-person economic exchange.

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Table 1 Social Trust Proxies

Panel A represents the results of applying principal component analysis to four proxies of social trust: Namely, blood donation, NGO participation, enterprise trustworthiness and citizen trustworthiness. Proportion explained, eigenvalue and factor loading for the first factor are presented. The social trust index (Trust) is constructed by applying loadings (coefficient) to standardized four proxies of social trust. Panel B reports the values of trust index and four proxies across regions. The definitions and data sources of all variables are presented in Appendix A.

Panel A Principal component analysis

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

Panel B Measures of trustworthiness across regions

Province	Trust	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 trustworthiness measures, economic and financial variables. The definitions and data sources of all variables are presented in Appendix A.

Variable	mean	sd	min	p50	max	N
Panel A: Listing and Loan characteristics						
fund	0.249	0.432	0	0	1	247565
words	114.560	70.317	0	94	244	247565
amount	4.81	7.01	0.3	3.78	300	61641
maturity	18.78	10.16	1	18	48	61641
longterm	0.80	0.40	0	1	1	61641
interest rate	2.13	0.31	0.588	2.146	5.379	61641
ownership	35.48	48.96	1	22	1370	61637
default	0.05	0.23	0	0	1	61641
bid_time	4417.94	29838.70	0	37	603037	61637
Panel B: Borrower's characteristics						
age	32.679	7.456	17	31	73	247563
gender	0.136	0.343	0	0	1	247565
grade	5.976	1.939	1	7	7	247565
edu	1.933	0.780	1	2	4	247201
marriage	0.556	0.497	0	1	1	247525
income	3.131	1.221	1	3	6	246811
house	0.428	0.495	0	0	1	247565
work_exp	2.351	1.019	1	2	4	246557
past_num	4.152	5.654	1	3	148	247565
Panel C: Provincial variables						
Trust_index	0.000	1.722	-1.887	-0.340	5.768	28
Trust1: blood	0.966	0.802	0.017	0.783	3.433	28
Trust2: Ngo	1.745	0.944	0.034	1.599	4.380	31
Trust3: enterprise trust	2.730	5.161	0.100	0.700	22.700	30
Trust4: citizen trust	2.200	0.120	2.014	2.191	2.442	28
pgdp	1.116	0.387	0.554	1.026	2.515	186
loan	0.567	1.098	0.095	0.288	7.790	186
law_office	0.163	0.143	0.060	0.123	0.894	186

Table 3 Funding Success

This Table presents results from logit regressions of the *Fund* indicator onto measures of trustworthiness, trust index (Column 1) and four proxies of trustworthiness (Column 2-5), as well as sets of control variables. We report the estimated marginal effects, and the Pseudo R2. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	(1)	(2)	(3)	(4)	(5)
Trust_index	0.002*** (0.001)				
blood		0.002* (0.001)			
Ngo			0.004*** (0.001)		
enterprise				0.001*** (0.000)	
citizen					-0.008 (0.005)
age	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
gender	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)	-0.007*** (0.002)
grade	-0.072*** (0.000)	-0.072*** (0.000)	-0.072*** (0.000)	-0.072*** (0.000)	-0.072*** (0.000)
edu	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)	0.006*** (0.001)
marriage	0.008*** (0.001)	0.008*** (0.001)	0.009*** (0.001)	0.008*** (0.001)	0.009*** (0.001)
income	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)	0.004*** (0.000)
house	-0.004*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)	-0.005*** (0.001)
work_exp	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
words	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
past_num	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
law_office	-0.051*** (0.007)	-0.052*** (0.008)	-0.044*** (0.006)	-0.060*** (0.008)	-0.045*** (0.006)
loan	0.010*** (0.002)	0.010*** (0.002)	0.008*** (0.002)	0.012*** (0.002)	0.009*** (0.002)
pgdp	0.002*** (0.000)	0.003*** (0.000)	0.002*** (0.000)	0.002*** (0.000)	0.004*** (0.000)
Observations	243,489	243,489	245,087	244,962	243,489
Pseudo R-squared	0.599	0.599	0.598	0.598	0.599

Table 4 Loan ownership, size and pricing

This table presents the regression results of ownership, amount and interest rate for a given loan onto measures of trustworthiness as well as different set of control variables. Panel A reports the results for trust index. Panel B reports the results for four proxies of trustworthiness index respectively. Borrowers' personal characteristics and regional economic and financial variables are included, but not reported for simplicity. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

Panel A: Social Trust index

	Ownership		Amount		Interest rate	
	(1)	(2)	(3)	(4)	(5)	(6)
Trust_index	-0.009** (0.004)	-0.009** (0.004)	0.115*** (0.043)	0.116*** (0.043)	-0.004*** (0.001)	-0.004*** (0.001)
age	0.010*** (0.001)	0.010*** (0.001)	0.048*** (0.004)	0.047*** (0.004)	-0.000*** (0.000)	-0.001*** (0.000)
gender	0.087*** (0.009)	0.081*** (0.009)	0.597*** (0.084)	0.587*** (0.086)	-0.005*** (0.002)	-0.009*** (0.002)
grade	-0.096*** (0.003)	-0.078*** (0.003)	-0.722*** (0.031)	-0.695*** (0.041)	0.042*** (0.001)	0.051*** (0.001)
edu	0.017*** (0.005)	0.020*** (0.005)	0.201*** (0.048)	0.205*** (0.048)	-0.012*** (0.001)	-0.011*** (0.001)
marriage	0.069*** (0.009)	0.071*** (0.009)	0.215*** (0.044)	0.219*** (0.044)	-0.018*** (0.002)	-0.016*** (0.002)
income	0.151*** (0.003)	0.154*** (0.003)	1.005*** (0.023)	1.010*** (0.022)	-0.013*** (0.001)	-0.011*** (0.001)
house	0.164*** (0.008)	0.167*** (0.008)	1.450*** (0.096)	1.454*** (0.094)	0.061*** (0.003)	0.063*** (0.003)
work_exp	-0.059*** (0.004)	-0.049*** (0.004)	0.093** (0.046)	0.108*** (0.041)	-0.003** (0.001)	0.002 (0.001)
words	-0.014*** (0.001)	-0.011*** (0.000)	-0.088*** (0.004)	-0.084*** (0.006)	-0.002*** (0.000)	-0.000 (0.000)
past_num	0.001*** (0.000)	0.001*** (0.000)	0.005*** (0.001)	0.004*** (0.001)	-0.000*** (0.000)	-0.000*** (0.000)
longterm		0.273*** (0.011)		0.410** (0.181)		0.148*** (0.005)
law_office	-0.056 (0.059)	-0.040 (0.058)	-0.121 (0.564)	-0.096 (0.562)	-0.166*** (0.022)	-0.157*** (0.021)
Loan	0.022 (0.016)	0.024 (0.016)	0.116 (0.095)	0.120 (0.095)	0.056*** (0.005)	0.058*** (0.005)
Pgdp	0.010*** (0.003)	0.007** (0.003)	0.035* (0.021)	0.031 (0.020)	0.006*** (0.001)	0.005*** (0.001)
Constant	1.688*** (0.087)	1.529*** (0.084)	-3.266*** (0.408)	-3.505*** (0.403)	2.745*** (0.111)	2.659*** (0.113)
Observations	61,027	61,027	61,031	61,031	61,031	61,031
R-squared	0.184	0.191	0.141	0.142	0.239	0.262

Panel B Four proxies of Social Trust

	Ownership				Amount				Interest			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
blood	0.010 (0.010)				0.197** (0.100)				-0.011*** (0.002)			
Ngo		-0.015** (0.007)				0.327*** (0.054)				-0.018*** (0.002)		
enterprise			-0.003*** (0.001)				0.039*** (0.014)				-0.002*** (0.000)	
citizen				-0.193*** (0.040)				0.622*** (0.217)				-0.022** (0.011)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Regional variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	1.372*** (0.176)	1.094*** (0.196)	1.159*** (0.175)	1.328*** (0.167)	-0.930*** (0.333)	-1.026*** (0.334)	-0.769** (0.335)	-2.192*** (0.582)	1.954*** (0.135)	1.821*** (0.134)	1.999*** (0.135)	1.976*** (0.135)
Observations	61,027	61,150	61,142	61,027	61,031	61,154	61,146	61,031	61,031	61,154	61,146	61,031
R-squared	0.191	0.191	0.191	0.191	0.096	0.097	0.097	0.096	0.248	0.248	0.248	0.248

Table 5 Province fixed-effect regressions

This table reports how the interactions of trust and borrower's characteristics affect the funding probability and loan ownership, size and pricing. Each entry reports the estimates for the interactions of trust and specific borrower's characteristics, namely age, gender, marriage, income and working experience, respectively. Loan, borrowers' personal characteristics and regional economic and financial variables are included, but not reported. Year, and regional fixed effects are included. Robust standard errors clustered at province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	Fund		Ownership		Amount		Interest rate	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
age*Trust_index	-0.0000 (0.0001)	-0.0000 (0.0001)	0.0003 (0.0005)	0.0003 (0.0005)	0.0068 (0.0043)	0.0061 (0.0040)	0.0003* (0.0001)	0.0002 (0.0001)
gender*Trust_index	-0.0013 (0.0012)	-0.0012 (0.0011)	-0.0184** (0.0068)	-0.0182** (0.0067)	0.1111 (0.1265)	0.1388 (0.1353)	-0.0019 (0.0029)	-0.0019 (0.0027)
marriage*Trust_index	0.0002 (0.0010)	0.0002 (0.0010)	0.0092 (0.0070)	0.0090 (0.0066)	0.1946*** (0.0462)	0.1802*** (0.0486)	-0.0007 (0.0020)	-0.0013 (0.0019)
income*Trust_index	0.0005 (0.0008)	0.0005 (0.0008)	0.0088* (0.0049)	0.0087* (0.0051)	0.2240*** (0.0595)	0.2209*** (0.0517)	-0.0008 (0.0017)	-0.0007 (0.0017)
work_exp*Trust_index	-0.0006 (0.0005)	-0.0006 (0.0005)	0.0185*** (0.0066)	0.0190** (0.0069)	0.2854*** (0.0464)	0.2706*** (0.0463)	0.0033* (0.0017)	0.0032* (0.0017)
Loan and borrower variables	yes	yes	yes	yes	yes	yes	yes	Yes
Regional variables	no	yes	no	yes	no	yes	no	Yes
Year fixed effect	yes	yes	yes	yes	yes	yes	yes	Yes
Province fixed effect	yes	yes	yes	yes	yes	yes	yes	Yes
Observations	243,489	243,489	61,027	61,027	61,031	61,031	61,031	61,031

Table 6: Sub sample analysis

Panel A re-runs regressions in a subsample, splitting the sample on the basis of the level of education of the borrower. A borrower is defined as low educated if his or her highest qualification is below bachelor's degree. Consequently, a borrower is defined as highly educated if his or her highest qualification is a bachelor's degree or above. Panel B re-runs regressions in a subsample, splitting our sample into those of first borrowing, which take place when a borrower appears for the first time on the RRD platform (First) and the rest (Non). Borrowers' personal characteristics and regional economic and financial variables are included. The difference is the coefficient of trust index in low education (first time) group minus the coefficient of trust index in high education (non-first time) group. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

Panel A Low- and high-educated borrowers

	Fund		Ownership		Amount		Interest rate	
	Low	High	Low	High	Low	High	Low	High
Trust_index	0.002*** (0.001)	0.001 (0.001)	-0.009* (0.005)	-0.021*** (0.008)	0.138** (0.054)	-0.007 (0.082)	-0.004*** (0.001)	-0.010*** (0.002)
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-squared			0.187	0.204	0.156	0.127	0.287	0.193
Pseudo R2	0.625	0.531						
Observations	184447	59042	45484	15543	45487	15544	45487	15544
Dif	0.001		0.012		0.145**		0.006**	

Panel B First- and non-first time Borrowers

	Fund		Ownership		Amount		Interest rate	
	First	Non	First	Non	First	Non	First	Non
Trust_index	0.0025*** (0.0007)	0.0017** (0.0008)	-0.0081* (0.0043)	-0.0044 (0.0095)	0.0787* (0.0413)	0.4839*** (0.1728)	-0.0034*** (0.0008)	0.0080 (0.0052)
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-squared			0.1387	0.1952	0.1352	0.1063	0.2939	0.1060
Pseudo R2	0.69	0.2441						
Observations	121,095	122,394	49,841	11,186	49,844	11,187	49,844	11,187
Dif	0.0008*		-0.0037		-0.4052**		-0.0114***	

Table 7 Alternative specifications

This Table presents results from a series of regressions of the funding indicator, loan ownership, size and pricing onto our trust index, and sets of control variables. In Column (1)-(4), we implement a bootstrap method, which draws a subsample that has half as many observations as the whole sample, and repeat our regression analysis for this subsample. In Column (5)-(7), we employ the Heckman two-step treatment effects procedure to correct the selection bias. Loan, borrowers' personal characteristics and regional economic and financial variables are included, but not reported. Year and regional fixed effects are included. Robust standard errors clustered at province level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	Bootstrap				Selection		
	Fund (1)	Ownership (2)	Amount (3)	Interest rate (4)	Ownership (5)	Amount (6)	Interest rate (7)
Trust Index	0.002** (0.001)	-0.010* (0.006)	0.115* (0.061)	-0.004*** (0.001)	-0.010** (0.004)	0.117* (0.027)	-0.004*** (0.001)
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
IML					-0.498*** (0.033)	4.676*** (0.228)	-0.225*** (0.009)
R-squared		0.1838	0.1414	0.2386			
Pseudo R2	0.599						
Wald chi2					9996.47	6293.54	7055.58
Observations	243,489	61,027	61,031	61,031	244,960	244,964	244,964

Table 8 Instrumental Variable Analysis

This table reports the first and second stage result of our instrumental variable analysis. Our first instrument *rice_suit*, is suitability of each province for growing wetland rice based on the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database. The second instrument is *Ethnic*, is the fraction of the largest ethnic group in a province. Borrowers' personal characteristics and regional economic and financial 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% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	(1)	(2)	(3)	(4)	(5)
	Fund	Fund	Ownership	Amount	Interest rate
Panel A: Second stage					
Trust_index	0.018** (0.008)	0.002** (0.001)	-0.021*** (0.007)	0.203*** (0.050)	-0.007*** (0.002)
Constant		1.124*** (0.016)	1.673*** (0.087)	-2.078*** (0.373)	2.728*** (0.112)
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	241,370	241,370	60,882	60,886	60,886
R-squared		0.681	0.183	0.108	0.236
Panel B: First Stage					
rice_suit	0.479*** (0.002)	0.479*** (0.002)	0.461*** (0.004)	0.462*** (0.004)	0.462*** (0.004)
ethnic	2.396*** (0.011)	2.396*** (0.011)	2.727*** (0.029)	2.747*** (0.029)	2.747*** (0.029)
Loan and borrower variable	yes	yes	yes	yes	yes
Regional variable	yes	yes	yes	yes	yes
Year fixed effect	yes	yes	yes	yes	yes
R-squared		0.820	0.805	0.805	0.805
Loglikelihood	-322825.63				
Partially F-statistics for the joint significance of the instruments		57778.9	13319.4	13476.9	13476.9
Over-identification(P value J stat)		0.065	0.061	0.163	0.417

Table 9 Lender fixed effect

This table estimates the basic regressions by controlling lender fixed effect. RRD platform assigned a unique id to its customers. A lender can bid for many loan lists. This enables us to control the lender fixed effect. The regression results of bid_amount and interest rate of a given investment onto differences of measure of trustworthiness index as well as control variables. Borrowers' personal characteristics and regional economic and financial 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% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	bid amount		Interest rate	
	(1)	(2)	(3)	(4)
Trust_index	0.004*** (0.000)	0.005*** (0.000)	-0.003*** (0.000)	-0.003*** (0.000)
age	-0.000 (0.000)	0.000 (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
gender	0.002*** (0.001)	0.003*** (0.001)	-0.005*** (0.000)	-0.006*** (0.000)
grade	-0.009*** (0.001)	-0.011*** (0.001)	0.041*** (0.000)	0.047*** (0.000)
edu	0.001** (0.000)	0.001 (0.000)	-0.002*** (0.000)	-0.001*** (0.000)
marriage	0.000 (0.001)	0.000 (0.001)	-0.012*** (0.000)	-0.011*** (0.000)
income	0.010*** (0.001)	0.010*** (0.001)	-0.007*** (0.000)	-0.007*** (0.000)
house	0.006*** (0.001)	0.006*** (0.001)	0.054*** (0.000)	0.055*** (0.000)
work_exp	0.022*** (0.001)	0.021*** (0.001)	0.006*** (0.000)	0.011*** (0.000)
words	0.000*** (0.000)	0.000*** (0.000)	-0.000*** (0.000)	-0.000*** (0.000)
past_num	-0.000 (0.000)	-0.000*** (0.000)	-0.002*** (0.000)	-0.000*** (0.000)
longterm		-0.043*** (0.004)		0.168*** (0.002)
law_office	0.011** (0.005)	0.004 (0.005)	-0.146*** (0.003)	-0.120*** (0.002)
loan	-0.002 (0.001)	-0.001 (0.001)	0.042*** (0.001)	0.039*** (0.001)
pgdp	-0.000 (0.000)	0.000 (0.000)	0.005*** (0.000)	0.004*** (0.000)
Constant	-0.049 (0.031)	-0.021 (0.031)	2.378*** (0.032)	2.271*** (0.034)
Observations	2,173,006	2,173,006	2,173,006	2,173,006
R-squared	0.009	0.010	0.278	0.325
Number of Investors	114,123	114,123	114,123	114,123

Table 10 Lender-borrower pairs

Panel A reports the summary statistics for both lenders and borrowers. We conduct t-value tests for the mean difference and Wilcoxon signed-ranks tests for the median difference, respectively. Panel B reports the summary statistics of the lender's investment. Panel C estimates the basic regressions using lender-borrower pairs. All variables, including controls are in the value of difference between that of lenders and borrowers. $d_$ represents the variable of lenders minus the corresponding variables of borrowers. Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

Panel A Characteristics for lenders and borrower

variable	Lender		Borrower		Dif	
	mean	median	mean	median	mean	median
Trust_index	1.944	1.530	0.870	0.269	1.075***	1.261***
age	35.404	33	38.708	37	-3.304***	-4.000***
gender	0.034	0	0.153	0	-0.119***	0.000***
grade	5.124	6	3.422	2	1.702***	4.000***
edu	2.681	3	1.989	2	0.692***	1.000***
marriage	0.742	1	0.786	1	-0.044***	0.000***
income	3.159	3	3.998	4	-0.839***	-1.000***
house	0.700	1	0.472	0	0.228***	1.000***
work_exp	2.724	3	2.560	2	0.164***	1.000***
past_num	7.062	2	4.770	1	2.293***	1.000***
law_office	0.323	0.160	0.193	0.149	0.130***	0.010***
loan	1.398	1.113	1.130	1.002	0.268***	0.111***
pgdp	5.759	5.925	5.194	5.171	0.564***	0.754***

Panel B Characteristics for investment

variable	mean	sd	min	p50	max
bid_amount	0.10	0.40	0.00	0.03	30.00
Interest rate	2.22	0.39	0.59	2.15	5.38
maturity	15.25	9.63	1.00	12.00	48.00
longterm	0.69	0.46	0.00	1.00	1.00
distance	968.07	561.87	0.00	969.31	3463.17

Panel C Regression Analysis using Differences between Lenders and Borrowers

	bid amount			interest rate		
	(1)	(2)	(3)	(4)	(5)	(6)
d_Trust_index	-0.009*** (0.001)	-0.009*** (0.001)	-0.009*** (0.001)	0.007*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
d_age	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
d_gender	-0.022*** (0.006)	-0.022*** (0.006)	-0.022*** (0.006)	0.043*** (0.003)	0.039*** (0.003)	0.039*** (0.003)
d_grade	-0.000 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.044*** (0.001)	-0.042*** (0.001)	-0.042*** (0.001)
d_edu	0.003* (0.002)	0.003* (0.002)	0.003* (0.002)	0.007*** (0.001)	0.008*** (0.001)	0.008*** (0.001)
d_marriage	-0.013*** (0.003)	-0.012*** (0.003)	-0.012*** (0.003)	0.032*** (0.003)	0.030*** (0.003)	0.030*** (0.003)
d_income	0.001 (0.001)	0.001 (0.001)	0.001 (0.001)	-0.002** (0.001)	-0.001 (0.001)	-0.001 (0.001)
d_house	0.004* (0.003)	0.004 (0.003)	0.004 (0.003)	-0.019*** (0.003)	-0.011*** (0.003)	-0.010*** (0.003)
d_work_exp	-0.003** (0.001)	-0.003** (0.001)	-0.003** (0.001)	-0.033*** (0.001)	-0.030*** (0.001)	-0.030*** (0.001)
longterm		-0.023*** (0.006)	-0.022*** (0.006)		0.005 (0.005)	0.005 (0.005)
words		0.000*** (0.000)	0.000*** (0.000)		-0.001*** (0.000)	-0.001*** (0.000)
d_law_office	0.100*** (0.015)	0.100*** (0.015)	0.101*** (0.015)	-0.082*** (0.013)	-0.081*** (0.013)	-0.082*** (0.013)
d_loan	-0.009* (0.004)	-0.010** (0.004)	-0.010** (0.004)	-0.024*** (0.005)	-0.021*** (0.005)	-0.021*** (0.005)
d_pgdp	0.005*** (0.001)	0.005*** (0.001)	0.005*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
Indistance			-0.001 (0.001)			0.002* (0.001)
Constant	0.033*** (0.006)	0.020*** (0.007)	0.024*** (0.009)	2.699*** (0.056)	2.776*** (0.056)	2.767*** (0.056)
Observations	48,677	48,677	48,677	48,677	48,677	48,677
R-squared	0.006	0.006	0.006	0.243	0.248	0.249

Table 11 Trust and Border

This table estimates the basic regressions using lender-borrower pairs. All variables, including controls are in the value of difference between that of lenders and borrowers. d_* represents the variables of lenders minus the corresponding variables of borrowers. Interaction term, $d_Trust_index*border$, and Year dummies are also included. Robust standard errors are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% level, respectively. The definitions and data sources of all variables are presented in Appendix A.

	<u>Bid amount</u>		<u>Interest rate</u>	
	(1)	(2)	(3)	(4)
d_Trust_index	-0.010*** (0.001)	-0.010*** (0.001)	0.007*** (0.001)	0.007*** (0.001)
d_age	0.001*** (0.000)	0.001*** (0.000)	0.002*** (0.000)	0.001*** (0.000)
d_gender	-0.021*** (0.006)	-0.021*** (0.006)	0.043*** (0.003)	0.039*** (0.003)
d_grade	-0.001 (0.001)	-0.001 (0.001)	-0.043*** (0.001)	-0.041*** (0.001)
d_edu	0.003 (0.002)	0.003 (0.002)	0.007*** (0.001)	0.008*** (0.001)
d_marriage	-0.014*** (0.004)	-0.013*** (0.004)	0.035*** (0.003)	0.032*** (0.003)
d_income	0.001 (0.001)	0.001 (0.001)	-0.003*** (0.001)	-0.002* (0.001)
d_house	0.005* (0.003)	0.004 (0.003)	-0.019*** (0.003)	-0.011*** (0.003)
d_work_exp	-0.003** (0.001)	-0.003** (0.001)	-0.033*** (0.001)	-0.030*** (0.001)
longterm		-0.021*** (0.006)		0.011** (0.005)
words		0.000*** (0.000)		-0.001*** (0.000)
d_law_office	0.101*** (0.015)	0.101*** (0.015)	-0.078*** (0.013)	-0.077*** (0.013)
d_loan	-0.009** (0.004)	-0.010** (0.005)	-0.025*** (0.005)	-0.022*** (0.005)
d_pgdp	0.005*** (0.001)	0.005*** (0.001)	0.003*** (0.001)	0.003*** (0.001)
d_Trust_index*border	0.005*** (0.002)	0.005*** (0.002)	-0.002 (0.002)	-0.003* (0.002)
border	-0.007* (0.004)	-0.007* (0.004)	0.006 (0.005)	0.006 (0.005)
Constant	0.031*** (0.007)	0.016* (0.009)	2.823*** (0.069)	2.899*** (0.068)
Observations	45,691	45,691	45,691	45,691
R-squared	0.006	0.007	0.245	0.250

Appendix A: Variable definition and data resource

	Definitions	source
Borrowers' characteristics		
grade	Credit score of the borrowers when the listing is created, ranging from 1 (high) to 7 (low)	RRD
age	The age of borrower	RRD
gender	A dummy variable that equals 1 if the borrower is female and zero otherwise	RRD
education	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 years and five years, 4 means more than five years.	RRD
income	monthly income provided by the borrower during registration. Possible values are between 1 and 6 where 1 indicate less than one thousand RMB, 2 means between one and five thousand, 3 means between five thousand and ten thousand, 4 means between ten thousand and twenty thousand, 5 means between twenty thousand and fifty thousand, 6 means more than fifty thousand	RRD
marriage	A dummy variable that equals 1 if the borrower is married, and zero otherwise	RRD
house	A dummy variable that equals 1 if the borrower has housing, and zero otherwise	RRD
ownership	The number of bids placed on a listing when the listing is fully funded	RRD
past_num	The number of past borrowing	RRD
nonperform	The number of past overdue loans	RRD
Loan information		
interest rate	The interest rate that borrower pays on the loan. The rate is adjusted by the benchmark rate of PBOC	RRD
amount	The requested loan amount in ten thousands of RMB	RRD
bid amount	The amount that lenders bid on the loan in ten thousands of RMB	RRD
maturity	The loan maturity in months	RRD
fund	An indicator equals one if a listing is fully funded and zero otherwise	RRD
ownership	Number of lenders in a given loan	RRD
listing date	The date when the listing is created	RRD
bid time	The time (in seconds) between the time the listing is created and the time the listing is fully funded	RRD
title	The loan title provided by the borrower	RRD
content words	The state provided by the borrower in the loan application number of words used by the borrower in the listing text.	RRD
default	An indicator that equals one if the loan status is "repayment by platform", or "overdue" and is zero otherwise.	RRD

Trust variable		
Trust_index	constructed by applying loadings (coefficient) to standardized four proxies of social trust	Authors' estimation
blood	The milliliters of blood donated voluntarily in a province, divided by its population in 2000	The Chinese Society of Blood Transfusion in 2000
Ngo	The participation of NGO is measured as registered members of non-governmental organizations (NGO) 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 the enterprises are most trustworthy?"	Zhang and Ke (2003)
citizen	The response to the following question: "How trustworthy are the people in your city?" The response ranges 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 thousands of RMB divided by population in the province	China Statistical Yearbook, various years
law_office	Number of law office units per ten thousands population in a province	Provincial reports of qualification examinations for attorneys and certified accountants, Various year
loan	Ratio of total bank loans to GDP in a province	China Statistical Yearbook, various years
rice_suit	The logarithm of "rice suitability", which is a z score of the environmental suitability of each province for growing wetland rice based on the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database (27).	the United Nations Food and Agriculture Organization's Global Agro-ecological Zones database
ethic	The population percentage of major ethnic groups in a province.	China Statistical Yearbook

Figure 1 Entry page

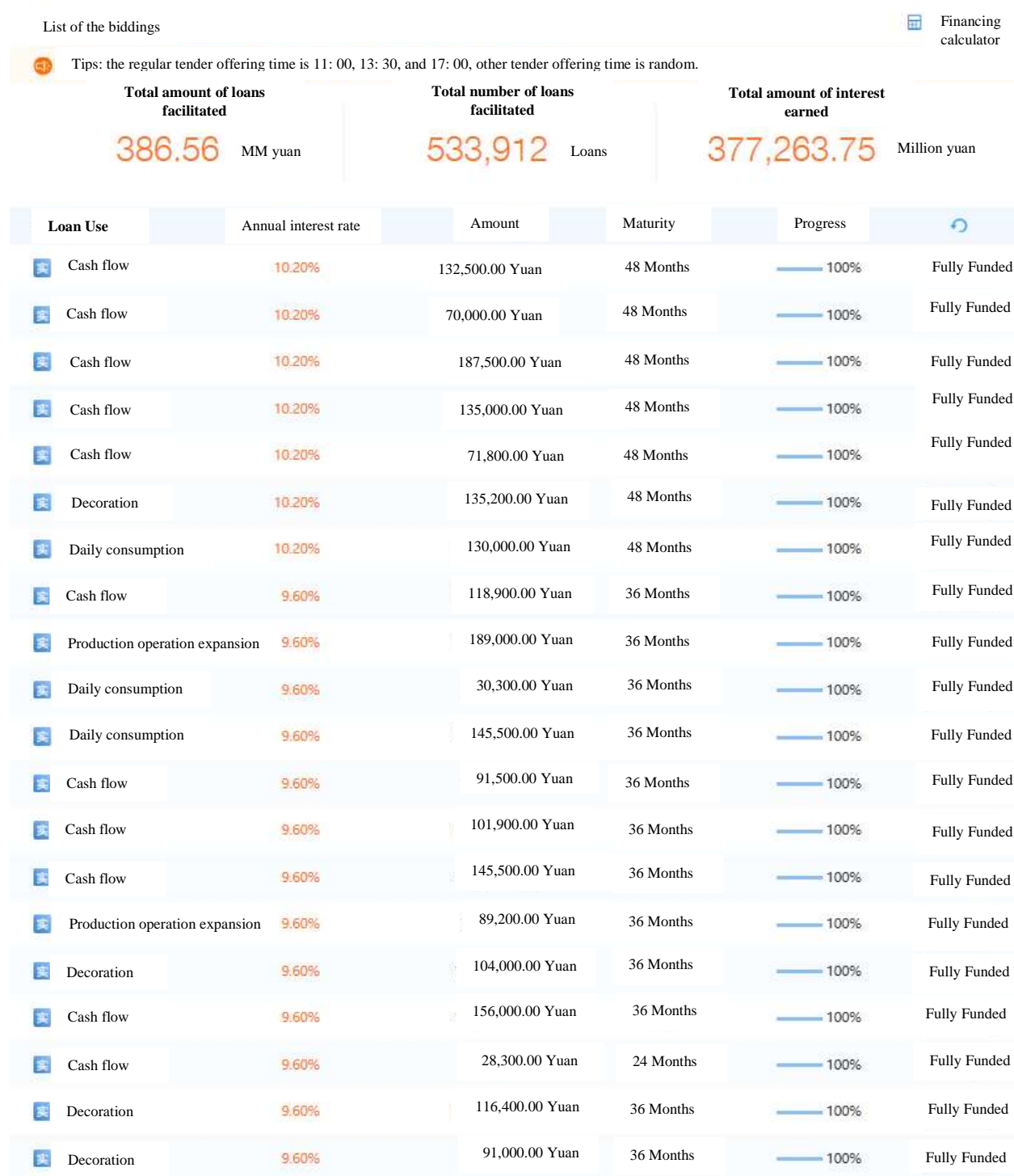


Figure 2 Loan Listing

数字投资 债权转让

Cash flow Loan Agreement (Template)

104,800 Yuan

The total amount of the subject

10.80%

Annual interest rate

48 个月

Maturity

42 月

Remaining period


Safeguarding User interest protection

Repayment Monthly repayment/equal

Prepayment rate **0.00%**

2017-10-27

Next payment date



Details of the loan Bidding records Repayment performance Claims information Transfer record

工作信息

Company industry	Commonweal organizations	Company size	Less than 10 people	Position	Regular employee
City	Chengdu, Sichuan	Years of service	More than 5 years		

Reviewing status

Project	Status	Pass date
Credit report	 Completed	2017-03-27
Identity authentication	 Completed	2017-03-27
Working authentication (working class)	 Completed	2017-03-27
Income authentication	 Completed	2017-03-27
Field authentication	 Completed	--

1. Renrendai undertakes to always uphold objectivity and impartiality principles, strictly control the risk, and exercise due diligence in authenticating the borrower's information, but does not guarantee that the authenticated information is 100% correct.

2. If the borrower is long-term overdue, his/her personal information will be publicized.

3. The Renrendai platform is only an information publishing platform. It does not provide any guarantee or promise to protect the borrower in any express or implied manner. The lender should make independent judgment and make decisions based on its investment preferences and risk tolerance, and bear the risk of their own funds and responsibilities. Market risk, the investment need to be cautious.

Use of funds

Status: Minsheng Bank has accepted

Narrative

Company staff, now living in Chengdu, Sichuan Province, engaged in public management, social organizations and international organizations industry, job income is stable, loans for cash flow. The above information has been field certification Fang Youzhong letter company inspection certification. At the same time, the auditors of the information provided by the borrower is true and effective, in line with the loan approval criteria.

Details of scatter		Tender records	Repayment performance	Claims information	Transfer record
			Number of people	178	Amount 104,800 Yuan
Rank	Bidder	Amount	Time		
1	W***5	500.00 Yuan	2017-03-27 20:11		
2	W***7	500.00 Yuan	2017-03-27 20:11		
3	v***n	500.00 Yuan	2017-03-27 20:11		
4	W***3	500.00 Yuan	2017-03-27 20:11		
5	W***3	500.00 Yuan	2017-03-27 20:11		
6	l***4	350.00 Yuan	2017-03-27 20:11		
7	布***家	500.00 Yuan	2017-03-27 20:11		
8	q***4	500.00 Yuan	2017-03-27 20:11		
9	w***0	500.00 Yuan	2017-03-27 20:11		
10	b***n	500.00 Yuan	2017-03-27 20:11		

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Registration date 2017-3-23

Investment statistics

Personam 0
U project 0
Xin project 0

Loan statistics

Loan application 1 Overdue 0
Loan 1 Overdue amount 0.00 Yuan
Loans under repayment 1 Overdue 0 Times

List of the biddings

Title of loan	Annual interest rate	Amount	Time limit	Overdue	Borrowing date	
Decoration	10.80%	104,800.00 Yuan	48 Months	Never	2017-03-27	Fully Funded