Why Geographical Information Matters? Evidence From Peer-to-Peer Lending

Abstract

In this paper, we study the role of geography plays in peer-to-peer lending. Evidence shows that the geographical information matters for borrowers' funding probabilities and loan default rate. Moreover, using borrowers' birthplace as an instrumental variable, we find that the underlying reasons of geographical discrimination are different: in cases of negative discrimination, lenders use geographical information as a proxy of unlisted economic variables, while in cases of positive discrimination, lenders' preferences are likely to rely on behavioural factors. Overall, our results provide evidence of lenders' behaviour bias and information cost concern in different scenarios of geographical discriminations in the peer-to-peer lending market.

Keywords: Peer-to-Peer Lending, Geographical Discrimination, Information Cost Theory

1. Introduction

Does geography play a role in lending relationships? This question has attracted some attention in current literature, while leaving the nature of such discrimination in the background. Observed geography-based differences in funding possibility can be due to taste-related factors, profit-related factors, or a combination of both. For instance, given the lower economic development and information diffusion level of certain regions, the information of loan requests from these regions can be less reliable, making access to credit at fair prices more difficult for qualified borrowers. As a result of these adverse selection and moral hazard effects, the average default rate of funded projects from certain regions will increase along with a declination of the lenders' beliefs about the average quality of borrowers. Subsequently, a self-reinforcing Arrowian profit-oriented discrimination naturally rises(Arrow, 1998). On the other hand, preferences and cultural beliefs about geography

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may influence lenders' perceptions of the borrower's risk and their decisions,causing Beckerian taste-oriented discrimination(Becker, 2010).

In the lending market, the taste-oriented and profit-oriented discrimination behave differently. If the discrimination is taste-oriented, differentiated groups have to offer better terms to qualify themselves, such as providing more detailed and complete personal information, offering higher interest rates and reducing uncertainty(Larrimore et al., 2011). The increased interest income and reduced credit risk will make up the animus and meet the demands of business. In this case, the average financial performance is better when the borrower belongs to the discriminated group.

However, if the existing discrimination is mainly profit-based, from the lenders' perspective, the performance of borrowers is highly likely to be correlated with their group membership (Turner, 1999). According to the theory of information cost (Meyer, 1967), lenders are inclined to use group memberships as proxy variables and have preferred choices over disparate groups of people, especially when the acquisition cost of the exact information of borrowers is prohibitive. In this case, the financial performance of the differentiated borrowers should be lower than average.

In the financial sector, one of the main obstacles of identifying the discrimination source is the difficult of quantifying the interaction process between borrowers and lenders. People usually have complicated social interactions which are not perfectly observable by researchers, while endogeneity, in this case, becomes a severe concern(Dell'Ariccia et al., 2012). Turner (1999) raises the information access as one of the most significant challenges of empirical studies on discrimination. In their statement, omitted variables may mislead researchers to conclude a discrimination but actually there is not; and Guryan and Charles (2013) have similar concern of omitted variable issue which would overestimate the discrimination magnitude.

In this vein, Peer-to-Peer (P2P) lending markets provide an opportunity for researchers to cope with these difficulties in identifying sources of discrimination. P2P lending refers to the unsecured loans generated by lenders to borrowers through lending platforms (Funk et al., 1970). It is an online service that directly matches lenders and borrowers and provides the chance for open and transparent micro-credit transactions between individuals, integrating Internet technology with micro-finance. Most of the P2P lending companies operate and provide services entirely online, reducing the loan cost by forgoing the expensive intermediaries(Klafft, 2008). These platforms disclose various types of borrower information, including credit history, as well as various personal statements. Furthermore, they usually earn a profit by charging a fee as the cost of information provision. Compared with traditional financial institutions, the trading pattern is more transparent. More importantly, the lenders can only access borrower profile data via the P2P platforms; therefore, researchers can collect the same information as lenders.

In this paper, we use data from Renrendai, a leading Chinese P2P platform, to answer two related questions: 1) Does geographical discrimination exist in the P2P lending market? 2) If geographical discrimination exists, which type of discrimination should it be attributed to? Since the lenders observe the same information as researchers, we define geographical discrimination as the phenomenon that after controlling all the explicit information shared on the platform, the geographic information of funding applicants is still significantly connected to the success rate of loans.

We chose two representative groups of provinces for comparison of different directions of geographical discrimination. The first group includes three Northeastern provinces[1], which are less developed and more likely to receive negative discrimination in Chinese folk culture. Conversely, the second group contains provinces of the Yangtze River Delta region[2], which have played a leading role in economic development for over 20 years. Section 2 will talk more about the reasons why these two regions are chosen.To identify the reason behind the geographical discrimination, we make use of a regulatory policy change initiated in December 2015, when the Chinese government acted on the supervision and regulation of online loans. The China Banking Regulatory Commission (CBRC) publicly solicits opinions in order to regulate the business activities of online lending information intermediaries. After the Chinese government's action, P2P platforms became responsible for examining and verifying the credit quality of borrowers before putting their loan applications online. Therefore, this regulation could be regarded as an external shock of the credit quality of borrowers.

Based on our analysis, we find strong evidence of the existence of geographical discrimination: other factors being equal, borrowers from the Yangtze River Delta region have a higher success rate than average, while the funding success rate of those from the three Northeastern provinces is significantly lower. Using appropriate instrumental variables, we also reveal different underlying reasons the geographical discrimination: negative geographical discrimination, in which case members living in specific regions are negatively discriminated, is due to economic development; while positive discrimination is likely to be behavioural or taste-based.

Our paper makes contributions to the literature at least in three aspects. First, it adds to the stream of geographical analysis of the P2P lending. For instance, Lin et al. (2013) take Prosper, an online lending platform based in the U.S., as a sample and find that loan applications are more likely to succeed among people within the same region rather than across different regions. Burtch et al. (2014) empirically examine the impacts of cultural differences and geographic distance between borrowers and lenders on lending. Our paper makes a step further by exploring the reason for such geographical discrimination and empirically tests our explanation.

Secondly, to the best of our knowledge, our work is the first to note the asymmetry of geographical discriminations. On the side of negative discrimination, our results are aligned with empirical evidence that the information-cost motivation of lender discrimination is strong due to the data asymmetry. Although P2P platforms have tried to reduce the

[1]Three Northeastern Provinces are three provinces in the northeast of China, including Heilongjiang, Jilin and Liaoning.

[2]Yangtze River Delta region includes three provinces in the East of China: Shanghai, Jiangsu and Zhejiang.

information gap by carrying out qualification examination and data validation (Serrano-Cinca et al., 2015; Weiss et al., 2010), the credit risk is still high on average for P2P loans due to the low investment threshold and borrowing requirements(Pope and Sydnor, 2011). Therefore, lenders tend to use specific hard information, such as borrowers' region, as a proxy variable for unobservable repayment ability of borrowers. On the side of positive discrimination, we find that the underlying reasons are likely to be behavioural. This is aligned with the finding of Guiso et al. (2009), which provide evidence of cultural bias in bilateral trade across nations.

Finally, in view of the unbalanced development among provinces in China, market discrimination is found by many scholars. According to Wang and Zheng (2017), loan success rates with diverse aims in various categories are impacted by the geographical economic development in different degrees. The basic credit and identity information of borrowers in underdeveloped cities gains much more concern than those in developed cities, explaining the disparity between borrowing success rates in less-developed cities compared to more-developed cities. The same economic effect is also found by Jiang and Zhou (2016). Suffering from discrimination, people in high-income regions are inclined to decrease financing cost, while low-income region residents need to increase interest rates to attract lenders. geographical discrimination, however, imposes additional difficulties on borrowers from less-developed regions and prevents some from proper funding opportunities. For the perspective of balancing the levels of geographical development and promoting equal opportunity policy, our paper also has important implications for the regulators.

The remainder of the paper is organized as follows. In section 2, we review related literature and give a brief introduction of geographical discrimination in China. In section 3, we depict the dataset and the settings of variables. In section 4, we examine the existence of geographical discrimination and geographical difference of loan default rates. section 5 utilizes instrumental variables to identify the reason for geographical discrimination, while section 6 concludes.

2. Background

2.1. Geographical Discrimination

Geographical discrimination in a lending relationship, sometimes rephrased as geographical redlining, refers to the phenomenon that lenders are discriminating against borrowers from certain allegedly redlined areas. Current literature on geographical redlining mainly focus on institutional lenders and most of the studies (Benston and Horsky, 1992; Schafer and Ladd, 1981; Munnell et al., 1993) found little evidence between households in redlined areas and those in controlled areas in terms of their ability to secure lending offers. However, this conclusion is restricted to banks and financial institutions in the US, since they are highly regulated by The Community Reinvestment Act, which imposed an affirmation action on lenders. For individual lenders who are not constrained by such regulatory policies, evidence shows that lenders do have some preferences on borrowers' geographical information (Burtch et al., 2014).

In China, Geographical discrimination and its influence on financial decisions has been widely discussed. Historically, internal migration in China was tightly controlled for management reasons, and many barriers to free movement, such as hukou system(Afridi et al., 2015), has not been entirely eliminated today. Under this system, every Chinese citizen was legally bound to register her or his single permanent place of residence, and strict controls were imposed on the mobility of hukou holders. Due to this immobility, regions have strong subculture and develop different lifestyles, which might affect lenders' beliefs and, subsequently, their decisions in a potential lending relationship.

Moreover, from the perspective of macroeconomics, regions across China have unbalanced economic development, regulatory maturity and business environment. therefore, the geographical location of a Chinese citizen might imply the employment opportunities, health and education services and benefit that this person could enjoy. Therefore it is also possible for lenders to make use of geographical information as a proxy variable of some unobservable characteristics of the borrowers.

In 2016, Dr. Keqiang Li, the Premier of China, mentioned a widely circulated saying "*no investment outside Shanhaiguang*" to warn the officials present in a formal government meeting (Zhao and Xu, 2016). Since Shanhaiguan is the dividing line between the Three Northeastern Provinces and other parts of China, this saying thus contains investors' preferences on the geographical information of projects. While in the same year, surveys show that the top ten cities with the most favorable investment environment are located in the Yangtze River Delta region(FDIIntelligence, 2016). Therefore, in this paper, we choose the Three Northeastern Provinces and the Yangzi River Delta as representative regions for negative and positive geographical discrimination respectively.

2.2. Related Literature

Broadly speaking, discrimination refers to the differentiated treatment against a specific group of people. These groups must vary according to some characteristics valued on the market. The reason for discrimination has thus been under debate, and there are two main branches of explanation: taste-oriented and profit-oriented. Becker (2010) states that if people want to exercise discrimination preference, they must put prejudice ahead of profits and must behave as if they are willing to pay something, either directly or by forgoing income, to avoid interaction with the relevant people. Therefore, the discrimination is based on individual taste and results from personal animus towards the group of people. Depending on different situations, taste-oriented discrimination could be competed away by the market (Turner, 1999; Han, 2011) or be sustainable(Pęski and Szentes, 2013).

Phelps (1972) and Arnott (1972) defines discrimination in an alternative way. He emphasizes the role of information asymmetry in the market. In his story, group memberships might act as proxy variables of some important characteristics that are relevant to production and profit, but may not be directly observable or are cost prohibitive for gathering information.

Therefore, this kind of "statistical" discrimination is classified as "profit-oriented"(Guryan and Charles, 2013). This type of discrimination is based on rational optimizing behaviour and imperfect information. Researchers already conduct a few tests of the measurement and identification of discrimination in the context of the labour market (Turner, 1999; Altonji and Pierret, 2001) and police investigation (Knowles et al., 2001).

There are both experimental and empirical evidence of the existence of discrimination. For instance, Fershtman and Gneezy (2001) design games to measure the trust between people from different ethnic groups, Bertrand and Mullainathan (2004) send fictitious CVs to the help-wanted ads, with applicants' names randomly assigned for majority/minority groups and check whether the call-back rate is different for 'applicants' with different name-implied ethnic characteristics. Muravyev et al. (2009); Bellucci et al. (2010); Cheng et al. (2015) use empirical data to analyse the gaps between rejection rate of projects (loan, mortgage etc.) against people in different groups.

Regarding the criterion based on which the discrimination takes place, scholars have surveyed quite a few areas, such as gender, age, culture and race (Schafer and Ladd, 1981; Goering, 1996; Blanchflower et al., 2003; Ravina, 2007; Calomiris et al., 1994). In addition, geographical factors are also discussed in the context of mortgage lending(Ladd, 1998), banking industry (Edie and Riefler, 1931) and property market(Schafer and Ladd, 1981).

Factors affecting P2P investor trading decisions are widely studied in the current literature, generally divided into hard and soft distinctions. Hard information is composed of personal data (Pope and Sydnor, 2011), loan terms (Klafft, 2008) and proposed interest rates (Puro, 2010). Conversely, soft information mainly consists of the information borrowers voluntarily publish on the platform (Iyer, 2009; Han, 2018), such as appearance (Duarte et al., 2012) and linguistic features (Larrimore et al., 2011). Both hard and soft data are important factors to impact lender decisions (Dorfleitner et al., 2016). Based on the data from Prosper, a P2P lending platform in the U.S., Pope and Sydnor (2011) finds that African Americans are less likely to succeed in borrowing than white people with similar credit ratings, while there is no significant evidence that gender affects borrower funding success (Barasinska and Schäfer, 2010).

3. Data and Variables

We obtain the listing and loan data from Renrendai, one of the Chinese largest peer-to-peer lending platforms. The listing includes the amount of funds that a borrower wishes to raise and the interest rate that he or she is willing to pay. Similar to the mechanism of Prosper Inc.(Duarte et al., 2012), the loan soliciting process is as follows: First, borrowers submit his/her funding request online with necessary and voluntary information to invite bids before the platform investigates the credit documents, reviews the quality and places a credit rating for each borrower. Then lenders can decide whether to place bids on the listed loan and how much to invest, on the basis of the available information. If the loan request has been open for seven days but still cannot receive enough funds, the platform will automatically cancel the request.

The data is collected from June 2015 to July 2016. This 14-month period is selected because an external policy shock takes place in the middle. On 28 December 2015, the government published a white paper indicating more tightening regulations on the P2P lending market. At the beginning of 2016, Renrendai officially announced cooperation with China Minsheng Bank on funds depository. The users' account information and the capital flows began to be supervised by the bank. As a result, the 14 months could be divided into two parts: a pre-regulation period that is from June 2015 to December 2015 and a post-regulation period that is from January 2016 to July 2016.

We identified and downloaded all the 265,041 loan applications. After data cleaning process, we validate 162,259 closed loan application records which are listed during the sample period, of which 90373 applications are successfully funded by the lenders. A complete list of all variables derived from Renrendai can be found in Table A.3.

For exposition purpose, We divide variables into four groups. The first group concerns the performance of loan applications, including three variables: a funding indicator which is equal to 1 if the application is successfully funded and 0 otherwise; and a default indicator, which is equal to 1 if the application is funded but the borrower fails to pay the loan and 0 otherwise. We also create a categorical variable named *status* to represent the overall funding status, which has three possible values: if the loan application succeeds, status is "regular" when the loan is paid back on time and is "default" if not. If the loan application does not succeed, status is "rejected".

The second group contains the variables derived from loan characteristics, including the application time, the loan amount, the interest and the loan duration.

The third group is mainly about borrowers' profile, including the age, the gender, the marital status, the revenue level and etc. It also includes a credit rating issued by the Renrendai platform. Although this rating has the same 7 levels as Prosper data used in Duarte et al. (2012), i.e. AA, A, B, C, D, E and HR where HR means "high risk". As shown in table A.1, most of the ratings of applications are polarized.

Insert Table A.1

The third group also contains provincial information of each loan application. Due to reasons such as culture, habit and economic development, the numbers of applications in each province vary a lot, as shown in table A.2. According to the levels of economic development, We pick up two representative groups of provinces for our subsequent analysis, i.e. the region of the Three Northeastern Provinces for negative discrimination and provinces in Yangzi River Delta region for positive discrimination.We also create two dummy variables for those borrowers who reside in these regions.

Insert Table A.2

Among all the 162,259 closed loan applications, 52% of which are rated as "A" and 45% are rated as "HR". Therefore, we create a rating indicator, which is equal to 1 when the borrower obtains a rate equal to or higher than A, and 0 otherwise.

The fourth group is two supplemental variables obtained from the Chinese national bureau of statistics. It includes provincial data of annual GDP and the bad debt rate as they might help to explain geographical impressions later.

Details of the variables are shown in Table A.3. Table A.4 reports the summary statistics before and after the government regulatory policy took place; and table A.5 demonstrates the comparison between the full sample, the Three Northeastern Province and the Yangzi River Delta.

Insert Table A.3, A.4 and A.5

4. Empirical Analysis

The empirical study is conducted in three steps: first, we study whether the geographical discrimination exists; secondly, we make use of the external policy shock and conduct a difference-in-difference analysis on the geographical difference of loan default rate; thirdly, we use an instrumental variable to identify whether there is a signal mechanism behind the geographical discrimination.

4.1. The existence of geographical discrimination

We start our analysis by relating the probability of a listing being funded of funded loans to our geographical dummies. As we can see from table A.3, the mean of funding success rate is one after the new regulatory policy was carried out[3]. Therefore, we only use the data BEFORE the regulation became effective to exam the existence of geographical discrimination on application success rate.

Insert Table A.6

The results are shown in Table A.6. Specifications 1-4 are related to the region of Three Northeastern Provinces and specification 5-8 are related to the Yangzi River Delta region. Obviously, all the coefficients of the NorthEast region dummies are negative where the significance level is 0.01 when borrowers' profile are controlled and 0.05 when only loan characteristics are taking into account. Correspondingly, all the coefficients of the Yangzi River Delta region dummies are positive, at the same level of significance with the Three Northeastern Provinces indicator. These results confirm that there is indeed geographical discrimination against borrowers from Chinese northeast provinces. Even after

[3] Actually, only 19 of 69871 applications failed after 31/12/2015.

controlling the credit rating issued by the website and borrowers' profile, the significance level of provincial indicator's coefficient becomes even higher.

The indicators of verification status and credit rating level represent the platform's effort to mitigate the information asymmetry between lenders and borrowers. It is not surprising that these two variables have a positive association with the probability of successful loan applications, which implies these steps taken by the platform are informative and they do have some substantial impact to make up the information gap between lenders and borrowers. However, the significance of geographical indicators implies that geographical discrimination still exists.

Besides the main results, most coefficients of other variables also fit with our expectations and current literature. For instance, In terms of loan characteristics, a borrowing with a larger amount, a higher interest rate and a shorter period is less likely to be funded because lenders need to bear a higher risk for higher returns(Iyer, 2009; Dorfleitner et al., 2016).

4.2. Geographical Differences of Loan Default Rate

Although the last subsection shows evidence on the probabilistic difference of success rate of loan applications initiated by borrowers from different regions, it is unclear whether this difference is driven by higher default risk or just people's beliefs. If it is due to higher default risk, the discrimination would be profit-oriented and taste-oriented otherwise.

Insert Table A.7

Table A.7 reports the corresponding results, and there are two remarks that we could make:

Remark 1. *Region indicator is significantly associated with default rates of P2P loans before 2016.*

Even after controlling credit ratings and verification status, borrowers from the Three Northeastern Provinces still have a higher default rate and those from the Yangzi River Delta region have a lower default rate. This might attribute to some region-specific unobservable heterogeneity of different borrowers. In the next subsection, we will further look into possible reasons.

Remark 2. *The new regulatory policy introduced at the end of 2015 has a substantial impact on the geographical difference of default rate.*

We take the logit regression as an example for explanatory purpose. The coefficient of Northeastern indicator is_TNP is 0.842, while the coefficient of the cross term of $is\_TNP \times Post2015$ is -1.332. The relatively large size and the negative sign of the cross term imply that the default rate of borrowers from this region sharply declined or even reversed after the policy became effective. For comparison, the coefficient of is_YRD is -0.452, while the coefficient of the cross term $is\_YRD \times Post2015$ is 0.178 but not significant. This result implies that this quality shock has substantial impact on mitigating negative geographical discrimination but limited effects on the positive side.

Naturally, only successful loan applications have the possibility to be in default. One potential concern for only using data of successful loan applications is that we might underestimate the association between geographical information and default rate, since many applicants before 2016 failed to raise fund and hence have no chance to default subsequently. Therefore, for a robustness check, we use the categorical variable "Status"to conduct a multinomial regression using the full sample. As usual, we have borrowers' profile and loan characteristics controlled and use "rejected" as the reference level. Multinomial regression results are reported in table A.8.

Insert Table A.8

As table A.8 demonstrates, other things equal, an average borrower from the Three Northeastern Province has lower possibility to be "regular" while has a higher possibility to default; on the other hand, one from Yangzi River Delta region has a higher possibility to be "regular" and a lower possibility to default. Most of the coefficients are significant at 0.01 level.

Now we have two empirical facts showing that geographical information is associated with both the application success rate and the default rate. However, it is still too early to claim a causal relationship between these two variables. In the next subsection, we will explore the reasons behind these geographical differences.

4.3. What The Geographical Discrimination Stands For?

To directly establish a causal relationship between geographical information and the success rate is difficult due to the endogeneity problem, i.e. it is not entirely clear what the geographical information means to the lenders. We introduce two possible factors that might affect lenders' decision: the provincial GDP and bad debt rate to represent the level of economic development and provincial financial risks respectively. Adding these two variables into the regression model of table A.6, we report the updated results in table A.9.

Insert Table A.9

Clearly, adding GDP and Bad Debt Rate into the regression models leads to a decrease in the size of geographical discrimination, represented by the coefficients of geographical dummies. We take the logit model as an example: compared with table A.6, the coefficient declines from -0.224 to -0.176 for is_TNP, and from 0.153 to 0.115 for is_YRD. Moreover, the coefficients of GDP are consistently positive and significant at 0.01 level.

That the size of the effect shrinks does not imply that any coefficient of geographical dummies is not significant. Actually, they are still significant at 0.01 level, which has two possible explanations: 1) the discrimination is triggered by non-economic factors; 2) in the decision process, the region represents some "omitted variables" that are not in our variable list. Particularly, it is worth pointing out that the second explanation consistent with the information cost theory proposed by Meyer (1967). It states that the discrimination is motivated by a reduction of information-searching cost to avoid the potential losses. Lenders thus rely on both the application document and their established notions derived from their private knowledge, such as provincial GDP and bad debt rate, and show more/less inclination to invest on Northeastern/Delta borrowers.

In summary, we find that the power of GDP and bad rate can partially explain the existence of geographical discrimination. This is aligned with the explanation of Peng et al. (2016); Jiang and Zhou (2016), which states that when making loan granting decisions, lenders perhaps subliminally link economic factors with the geographic information although they do not explicitly appear in the application document.

We employ the method of instrumental variable(s) to cope with the endogeneity problem due to omitted variables. Fortunately, we have the first three digits of the borrowers' ID card in the application document, the first two of which represents the information of their birthplace. As shown in the correlation matrix of all these relevant variables in figure A.1, there exists a very strong correlation between the place where the borrower resides[4] and the place where the borrower is born.

Insert Figure A.1

On the other hand, the borrower's ID number is simply regarded as a proof of ID verification. Rarely the lender will take it as an informative piece of borrowers' profile. Moreover, the birthplace is hardly to be manipulable, it is hence exogenous in our analysis. Therefore, the borrower's birthplace is a valid instrumental variable for us to figure out what the discrimination stands for. If it is "taste-oriented" and the discrimination is really about the region where the borrower resides, the IV regression would show the significance of the fitted value of region indicator.

Since the dependent variable is binary, the standard method of IV regression is likely to lead inefficient estimators. We thus use two variations of IV technologies: a Two-Stage Least Square (2SLS) estimation for binary variables developed by Newey (1987) and a Two-Stage Residual Inclusion (2SRI) estimation developed by Terza et al. (2008). The first method is very close to the standard IV regression, the only change is to replace the second-stage OLS with a probit regression. Taking is_TNP as an example, the two stages are:

[4] It is also the address shown in the application document.

$$
\begin{aligned}
OLS: is\_TNP &= birth\_TNP + bad\_debt + GDP + v \\
Probit: is\_success &= \widehat{is\_TNP} + bad\_debt + GDP + LoanSpecControls \\
&\quad + BorrowerProfileControls + \epsilon
\end{aligned}
$$

The second method is mainly for non-linear regressions. It performs the same OLS regression in the first stage, but take the residual as a new variable in the second stage, conduct a probit regression together with the endogenous explanatory variable itself:

$$
\begin{aligned}
OLS: is\_TNP &= birth\_TNP + bad\_debt + GDP + v \\
Probit: is\_success &= \widehat{v} + is\_TNP + bad\_debt + GDP + \epsilon \\
&\quad + LoanSpecControls + BorrowerProfileControls
\end{aligned}
$$

All the relevant results are reported in table A.10.

Insert Table A.10

Remark 3. *Lenders' preferences are asymmetric on less/more developed regions.*

The coefficients of geographical indicators in table A.10 reveals an intriguing result: after using Birthplace as the instrumental variable, is_YRD is significant but is_TNP is not. Besides, GDP has a higher-level significance (1%) for Northeastern provinces than for Yangtze River Delta (10%). The results show that GDP, i.e. the development level of geographical economics, has considerable explanatory power with respect to the discrimination against borrowers from certain regions[5].

For applications that are negatively discriminated, The main concern of lenders seem to be on the economic side, represented by the "GDP" variable, and there is no evidence that lenders hold an "intrinsic" negative view on stereotypes of borrowers. However, for regions that are positive discriminated [6], lender's preference cannot be fully explained by the economic development (GDP). It implies that the reason of lenders' favour in those regions is likely to be behavioural. For example, according to Lin et al. (2013), funding is

[5]The Three Northeastern provinces in our study

[6]Yangtze River Delta region in our study.

more likely to succeed among people within the same region rather than across different regions. According to an industry report published by a Chinese consulting firm, Yingcan Consulting, 19.79% of the lenders come from the Yangtze River Delta. the 'hometown-fellow complex' may thus help explaining where the behavioural bias comes from. However, We are unable to conduct a further exploration since we cannot identify the personal profile of lenders from the Renrendai website.

5. Conclusion

This research focuses on the geographical discrimination problem in Chinese P2P lending and the reason it stands for. Based on the dataset from one of the largest and well-developed P2P platforms in China, we find that the geographical discrimination exists and can be partially explained by the economic development level. Evidence shows that the geographical discrimination is a mix of "taste-oriented" and "profit-oriented" motivations. We also find the part of "taste-oriented" discrimination of lenders is asymmetric in the sense that lenders only have truly geographical preference on highly developed regions, while for less developed regions, lenders use the region indicator as a proxy variable to infer more information of borrowers.

We acknowledge some limitations of our research. First, due to the lack of lenders' geographical information in data selected, the difference between lenders' region and borrowers' region cannot be controlled, which may act as a determinant of funding success likelihood. Secondly, the soft information in the description of loans is not extracted to be added into the explanatory variables, which may impose another impact on the success of the loan application too. Finally, GDP and bad debt rate are introduced as additional control variables, we, nevertheless, leave the discussion of culture-related variables open for future research.

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Appendix A. Figures and Tables

Table A.1: Credit Ratings

Credit Rating	Number	Percentage
A	84226	52.00%
AA	40	0.00%
B	65	0.00%
C	210	0.00%
D	2290	0.01%
E	2946	0.02%
HR	72482	45.00%

Table A.2: Applications Per Province

Variables	Province	Number	Percentage(%)
The Three Northeastern Provinces	Heilongjiang	3627	
	Jilin	3707	8.33
	Liaoning	6997	
The Yangzi River Delta	Shanghai	4957	
	Jiangsu	13541	16.42
	Zhejiang	8160	
	Anhui	3960	
	Beijing	5462	75.25
	Chongqing	5817	
	Fujian	12058	
	Gansu	2068	
	Guangdong	21632	
	Guangxi	2521	
	Guizhou	4761	
	Gainan	1418	
	Gebei	5503	
	Henan	7389	
	Hubei	7328	
	Hunan	6464	
	Inner_mongolia	1338	
	Jiangxi	2135	
	Ningxia	376	
	Qinghai	151	
	Shaanxi	4718	
	Shandong	10557	
	Shanxi	2318	
	Sichuan	6396	
	Tianjin	2172	
	Tibet	116	
	Xinjiang	1003	
	Yunnan	3609	

Table A.3: Variables Constructed from Renrendai Data

	Variable Name	Variable Definition
Performance Indicator:	*is_ successful*	An indicator that equals one if an application is fully funded and becomes a loan and is zero otherwise.
	in_ default	An indicator that equals one if a funded project fails to pay back the loans and is zero otherwise.
	status	A categorical variable, which has three possible values: if the loan application succeeds, status is "regular" when the loan is paid back on time and is "default" if not. If the loan application does not succeed, status is "rejected".
Loan Characteristics:	*amount*	The requested loan amount in 1000 CNY.
	interest	The rate the borrower pays on the loan.
	duration	In how many months the loan matures.
	post-2015	Whether the loan application is listed after the new regulatory policy being effective.
Borrower's Profile:	*age*	Borrower's age, range from 21 to 62.
	gender	Borrower's gender, 1 if the borrower is male, 0 otherwise.
	education	Borrower's education level, 1-5 represents high school or lower, junior college, undergraduate and postgraduate or higher respectively.
	is_ TNP	Whether the borrower resides in any of the Three Northeastern Provinces.
	is_ YRD	Whether the borrower resides in the region of Yangzi River Delta.
	is_ married	1 if the borrower is married, 0 otherwise.
	is_ divorced	1 if the borrower is divorced, 0 otherwise.
	has_ house	1 if the borrower is a house owner, 0 otherwise.
	has_ car	1 if the borrower is a car owner, 0 otherwise.
	rating	Borrower's credit rating issued by the website. 1 for AA and A, 0 otherwise.
	is_ verified	1 if the borrower has uploaded a valid document and verified by the website, 0 otherwise.
	middle_ income	1 if the borrower's monthly revenue is between 5000 and 10000, 0 otherwise.
	high_ income	1 if the borrower's monthly revenue is above 10000, 0 otherwise.
	birth_ TNP	1 if the borrower was born in the region of the Three Northeastern Provinces, 0 otherwise.
	birth_ YRD	1 if the borrower was born in the region of Yangzi River Delta, 0 otherwise.
Supplemental Variables:	*bad_ rate*	The provincial non-performing loan ratio.
	gdp	The annual provincial GDP.

Table A.4: Summary Statistics: Pre- and Post-Regulation

Variables	Total			Pre-Regulation			Post-Regulation		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Default	162306	0.01	0.08	126080	0.01	0.08	36226	0.01	0.09
Regular	162306	0.55	0.50	126080	0.42	0.49	36226	0.99	0.09
Rejected	162306	0.44	0.50	126080	0.57	0.50	36226	0.00	0.02
Amount	162306	64.34	64.60	126080	60.48	68.11	36226	77.78	48.16
Interest	162306	11.52	1.14	126080	11.87	1.03	36226	10.33	0.58
Duration	162306	24.00	10.50	126080	21.49	9.95	36226	32.72	7.21
Age	162306	33.73	8.02	126080	33.17	7.79	36226	35.69	8.49
Gender	162306	0.78	0.42	126080	0.80	0.40	36226	0.70	0.46
Education	162306	2.03	0.77	126080	1.97	0.77	36226	2.24	0.71
Is_married	162306	0.60	0.49	126080	0.58	0.49	36226	0.68	0.47
Is_Divorced	162306	0.08	0.27	126080	0.07	0.25	36226	0.11	0.32
Has_House	162306	0.50	0.50	126080	0.48	0.50	36226	0.55	0.50
Has_Car	162306	0.23	0.42	126080	0.26	0.44	36226	0.13	0.34
Rating	162306	0.67	0.47	126080	0.57	0.49	36226	0.99	0.12
Is_verified	162306	0.74	0.44	126080	0.66	0.47	36226	1.00	0.00
Middle_income	162306	0.35	0.48	126080	0.37	0.48	36226	0.27	0.44
High_income	162306	0.35	0.48	126080	0.35	0.48	36226	0.35	0.48
Bad_debt	162306	1.74	0.55	126080	1.76	0.57	36226	1.70	0.51
GDP	162306	40.27	24.67	126080	40.32	24.70	36226	40.12	24.54

Table A.5: Summary Statistics: Full Sample, Three Northeastern Provinces, Yangzi River Delta

Variables	Total			Three Northeastern Provinces			Yangzi River Delta		
	N	Mean	SD	N	Mean	SD	N	Mean	SD
Default	162306	0.01	0.08	14331	0.01	0.08	26658	0.01	0.07
Regular	162306	0.55	0.50	14331	0.69	0.46	26658	0.55	0.50
Rejected	162306	0.44	0.50	14331	0.30	0.46	26658	0.45	0.50
Amount	162306	64.34	64.60	14331	67.70	56.01	26658	65.11	66.71
Interest Rate	162306	11.52	1.14	14331	11.48	1.06	26658	11.51	1.15
Duration	162306	24.00	10.50	14331	28.15	9.94	26658	23.88	10.36
Age	162306	33.73	8.02	14331	36.37	8.54	26658	33.05	7.76
Gender	162306	0.78	0.42	14331	0.70	0.46	26658	0.81	0.39
Education	162306	2.03	0.77	14331	2.09	0.72	26658	2.08	0.79
Is_married	162306	0.60	0.49	14331	0.59	0.49	26658	0.61	0.49
Is_Divorced	162306	0.08	0.27	14331	0.14	0.35	26658	0.06	0.25
Has_house	162306	0.50	0.50	14331	0.67	0.47	26658	0.46	0.50
Has_car	162306	0.23	0.42	14331	0.19	0.39	26658	0.24	0.43
Rating	162306	0.67	0.47	14331	0.77	0.42	26658	0.66	0.47
Is_verified	162306	0.74	0.44	14331	0.81	0.39	26658	0.74	0.44
Middle_income	162306	0.35	0.48	14331	0.39	0.49	26658	0.31	0.46
High_income	162306	0.35	0.48	14331	0.37	0.48	26658	0.36	0.48
Bad_debt	162306	1.74	0.55	14331	1.62	0.09	26658	1.74	0.54
GDP	162306	40.27	24.67	14331	18.58	35.90	26658	59.01	28.18

Table A.6: geographical discrimination

	Dependent variable:							
	Is_success							
	OLS		*Logit*		*OLS*		*Logit*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Is_TNP	-0.005^{***}	0.006^{**}	-0.224^{***}	-0.135^{**}				
	(0.002)	(0.003)	(0.076)	(0.054)				
Is_YRD					0.004^{***}	0.005^{**}	0.153^{***}	0.062^{*}
					(0.001)	(0.002)	(0.048)	(0.035)
Rating	0.414^{***}		3.854^{***}		0.413^{***}		3.852^{***}	
	(0.003)		(0.112)		(0.003)		(0.112)	
Is_Verified	0.093^{***}		2.663^{***}		0.093^{***}		2.665^{***}	
	(0.001)		(0.049)		(0.001)		(0.049)	
Constant	0.481^{***}	3.683^{***}	10.763^{***}	37.418^{***}	0.481^{***}	3.684^{***}	10.722^{***}	37.374^{***}
	(0.014)	(0.013)	(0.594)	(0.271)	(0.014)	(0.013)	(0.594)	(0.270)
Borrowers' Profile	Yes	No	Yes	No	Yes	No	Yes	No
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,080	126,080	126,080	126,080	126,080	126,080	126,080	126,080
R^2	0.887	0.693			0.887	0.693		
Adjusted R^2	0.886	0.693			0.886	0.693		
McFadden's Pseudo R^2			0.860	0.748			0.860	0.748
Note:								*p<0.1; **p<0.05; ***p<0.01

Table A.7: Default Rate of Borrowers from Different Regions

	Dependent variable:							
	In_default							
	OLS		*Logit*		*OLS*		*Logit*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post2015		0.016***		0.394***		0.015***		0.300***
		(0.001)		(0.098)		(0.001)		(0.101)
Is_TNP	0.002*	0.005***	0.554***	0.842***				
	(0.001)	(0.001)	(0.147)	(0.165)				
Is_TNP× post2015		−0.007***		−1.332***				
		(0.002)		(0.399)				
Is_YRD					−0.003***	−0.006***	−0.405***	−0.452***
					(0.001)	(0.001)	(0.103)	(0.120)
Is_YRD× post2015						0.006***		0.178
						(0.002)		(0.234)
Rating	−0.202***	−0.194***	−10.427***	−10.458***	−0.202***	−0.194***	−10.397***	−10.438***
	(0.002)	(0.002)	(1.037)	(1.038)	(0.002)	(0.002)	(1.037)	(1.039)
Is_verified	−0.017***	−0.024***	0.256	0.127	−0.017***	−0.024***	0.210	0.086
	(0.003)	(0.003)	(0.166)	(0.170)	(0.003)	(0.003)	(0.166)	(0.170)
Constant	0.115***	0.035***	−7.756***	−8.013***	0.116***	0.036***	−7.470***	−7.661***
	(0.010)	(0.011)	(1.322)	(1.325)	(0.010)	(0.011)	(1.324)	(1.325)
Borrowers' Profile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	90,369	90,369	90,369	90,369	90,369	90,369	90,369	90,369
R^2	0.175	0.177			0.175	0.177		
Adjusted R^2	0.175	0.177			0.175	0.177		
McFadden's Pseudo R^2			0.564	0.566			0.564	0.565

Note: *p<0.1; **p<0.05; ***p<0.01

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Table A.8: Multinomial Regression on Funding Status

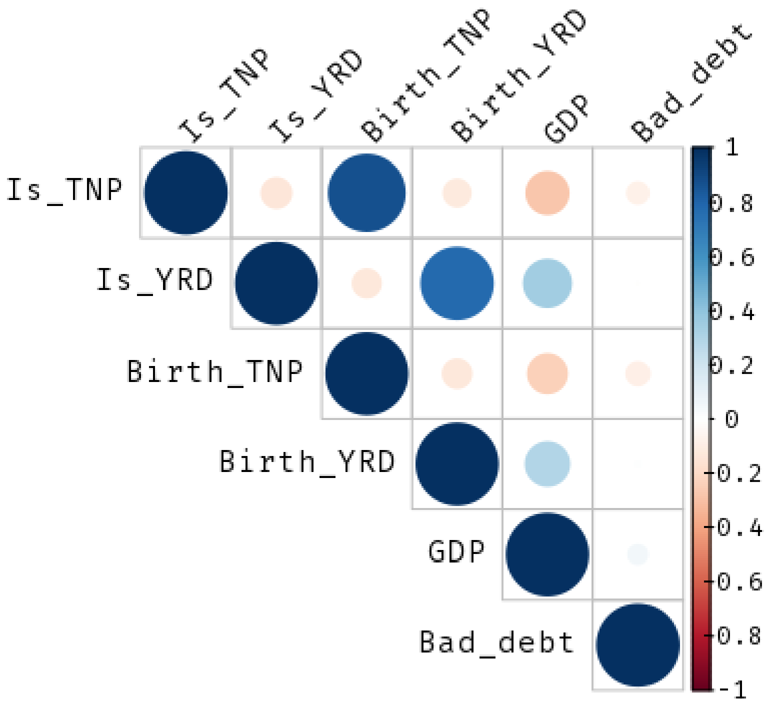
	Multinomial Regressions							
	(1)		(2)		(3)		(4)	
	default	regular	default	regular	default	regular	default	regular
Is_TNP	0.143	-0.367^{***}	0.411^{***}	-0.341^{***}				
	(0.127)	(0.073)	(0.140)	(0.081)				
Is_YRD					-0.265^{***}	0.171^{***}	-0.266^{**}	0.236^{***}
					(0.097)	(0.045)	(0.114)	(0.049)
Ratings	-5.761^{***}	3.738^{***}	-5.295^{***}	4.164^{***}	-5.740^{***}	3.727^{***}	-5.148^{***}	4.148^{***}
	(1.075)	(0.105)	(0.919)	(0.113)	(1.072)	(0.105)	(0.846)	(0.113)
Post2015			6.637^{***}	6.071^{***}			6.677^{***}	6.198^{***}
			(0.244)	(0.231)			(0.266)	(0.254)
Is_TNP$\times$ post2015			7.280^{***}	8.541^{***}				
			(0.196)	(0.196)				
Is_YRD$\times$ post2015							-0.224	-0.397
							(0.633)	(0.603)
Constant	6.602^{***}	14.188^{***}	3.404^{***}	10.577^{***}	6.704^{***}	14.211^{***}	3.576^{***}	10.508^{***}
	(1.221)	(0.531)	(1.258)	(0.603)	(1.222)	(0.532)	(1.255)	(0.603)
Borrowers' Profile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Akaike Inf. Crit.	34,552.430	34,552.430	29,736.320	29,736.320	34,556.650	34,556.650	29,740.850	29,740.850

Note: *p<0.1; **p<0.05; ***p<0.01

Table A.9: Effects of Provincial GDP and Bad Debt Ratio

	Dependent variable:			
	Is_success			
	OLS	*Logit*	*OLS*	*Logit*
	(1)	(2)	(3)	(4)
Is_TNP	-0.004^{**}	-0.176^{**}		
	(0.002)	(0.078)		
Is_YRD			0.003^{**}	0.115^{**}
			(0.001)	(0.050)
Rating	0.413^{***}	3.865^{***}	0.413^{***}	3.863^{***}
	(0.003)	(0.112)	(0.003)	(0.112)
Is_verified	0.093^{***}	2.666^{***}	0.093^{***}	2.668^{***}
	(0.001)	(0.049)	(0.001)	(0.049)
GDP	0.001	0.072^{***}	0.001	0.068^{**}
	(0.001)	(0.027)	(0.001)	(0.027)
Bad_debt	0.0004	0.040	0.001	0.041
	(0.001)	(0.031)	(0.001)	(0.031)
Constant	0.469^{***}	9.920^{***}	0.471^{***}	9.934^{***}
	(0.016)	(0.665)	(0.016)	(0.665)
Borrowers' Profile	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes
Observations	126,067	126,067	126,067	126,067
R^2	0.887		0.887	
Adjusted R^2	0.887		0.887	
McFadden's Pseudo R^2		0.861		0.861
Note:		$^{*}p<0.1; ^{**}p<0.05; ^{***}p<0.01$		

Figure A.1: Correlation Matrix



As shown in the legend on the right of the figure, deeper colours implies stronger correlations.

Table A.10: IV Regressions

	Dependent variable:							
	Is_success							
	2SLS	2SRI	2SLS	2SRI	2SLS	2SRI	2SLS	2SRI
Is_TNP		−0.039		0.0003				
		(0.039)		(0.040)				
$\widehat{Is\_TNP}$	−0.018		0.022					
	(0.038)		(0.040)					
Is_YRD						0.100^{***}		0.082^{**}
						(0.030)		(0.033)
$\widehat{Is\_YRD}$					0.097^{***}		0.081^{**}	
					(0.030)		(0.033)	
GDP			0.041^{***}	0.042^{***}			0.025^{*}	0.026^{*}
			(0.013)	(0.013)			(0.014)	(0.014)
Bad_debt			0.024	0.024			0.022	0.021
			(0.015)	(0.015)			(0.015)	(0.015)
Constant	5.502^{***}	5.506^{***}	5.020^{***}	5.009^{***}	5.480^{***}	5.458^{***}	5.162^{***}	5.138^{***}
	(0.284)	(0.284)	(0.319)	(0.319)	(0.284)	(0.284)	(0.321)	(0.321)
Residual as Regressors	No	Yes	No	Yes	No	Yes	No	Yes
Credit Rating	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Verification Status	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Borrowers' Profile	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Loan Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	126,067	126,067	126,067	126,067	126,067	126,067	126,067	126,067
Log Likelihood	−12,191.100	−12,183.420	−12,185.300	−12,177.240	−12,186.240	−12,182.730	−12,182.490	−12,179.840
McFadden's Pseudo R^2	0.858	0.859	0.859	0.859	0.859	0.859	0.859	0.859
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$