Competition and Favoritism in Bank Loan Markets*

Hua Cheng† Yan Dong‡ Xue Li§

Abstract

This paper analyzes costly favoritism related to physical attractiveness and gender in bank loan markets using a market structure-based method. The rationale is that a concentrated market provides more space for loan officers to discriminate against a certain group of borrowers. Using several unique datasets and online maps containing information on market structure and household finance, we find that loan officers prefer good-looking people and males in relatively risky commercial/industrial loan markets. On the other hand, females and especially young good-looking females have an advantage in mortgage loan markets. Although the disadvantage of bearing and raising children cannot be easily disentangled from discrimination in labor markets, it does not pose an issue in mortgage loan markets. We interpret these different patterns of favoritism as a result of differential risk levels associated with the two types of loans.

JEL codes: G21, L13, J70
Keywords: market structure; bank loan; favoritism; discrimination; beauty; gender.

*We are grateful for constant and detailed comments from Jason Abrevaya, Daniel S. Hamermesh, and Philip Dybvig. We also thank for helpful suggestions from Patrick Bolton, Tzu-Kuan Chiu, Shihe Fu, Yuming Fu, Francisco Gallego, Kishore Gawande, Li Gan, Qiang Gong, Michael Geruso, Brendan Kline, Ming Lu, Neale Mahoney, Richard Murphy, Steven Ongena, Shusen Qi, Shunfeng Song, Dragon Tang, Stephen Trejo, Tan Wang, Ji Wu, Tong Yu, Chenhang Zeng, Jie Zheng, and seminar participants in UT-Austin, Southwestern University of Finance and Economics (SWUFE), Nankai University, Nanjing Audit University, Zhongnan University of Economics and Law, 2016 Asia-Pasific Conference on Economics and Finance (Singapore), 2016 Chinese Economist Society Meeting (Shenzhen), 2016 Annual Meeting of the Decision Sciences Institute (Austin) , 2017 China Finance Annual Meeting, and 2018 AEA meeting. We also wish to thank several bank managers and loan officers for beneficial conversations, and China Banking Regulatory Commission (CBRC), Survey and Research Center for China at Southwestern University of Finance and Economics (CHFS) and Sun Yat-Sen University (CLDS) for providing data used in this analysis, and Xia Liu, Zhiguo Xu and Taixin Zhou for their excellent research assistance. Li thanks the financial support from The Ministry of Education of China's Humanities and Social Science Research Western and Border Areas Project (Project 17XJC790006) and Collaborative Innovation Center of Financial Security (Project JRXT201704). All the errors are our own.

†Department of Economics, University of Texas at Austin. E-mail address: harrychenghua@utexas.edu

‡Research Institute of Economics and Management, Southwestern University of Finance and Economics. E-mail address: ydong@swufe.edu.cn

§Corresponding author. Institute of Chinese Financial Studies & Collaborative Innovation Center of Financial Security, Southwestern University of Finance and Economics. 555 Liutai Ave., Wenjiang District, Chengdu, 611130, China. E-mail address: lixue86@swufe.edu.cn

1 Introduction

Access to credit from institutional sources, such as small business loans and mortgage loans, represents an important way to improve welfare of households. Therefore, it is a concern that a growing body of evidence suggests that owners of small businesses from some demographic groups, such as minorities and females, may have less access to institutional financing (Bates 1973, 1991; Cavalluzzo and Cavalluzzo 1998; Cavalluzzo et al., 2002). There are more successful male entrepreneurs than female entrepreneurs, therefore, in small business loan markets loan officers may conceive male entrepreneurs have a better repayment ability and see gender as a signal regarding creditworthiness, but does it really signal quality or is it just a prejudice? Although the literature of labor economics usually find females receive lower wages than males, the disadvantage of bearing and raising children could be associated with real productivity, but such a disadvantage should not pose an issue in small business loan markets. On the other hand, mortgage loans are very safe, it may be not necessary for loan officers consider gender as a signal regarding creditworthiness. Then given most loan officers are males, will females, especially good-looking females, be treated better than males?

Our paper sheds light on particular factors that influence observed differences in the credit market. We do so by using a market structure-based method founded on Becker's (1957) costly discrimination theory. That is, in a concentrated market, banks have large market power, and hence their loan officers can discriminate against certain groups of borrowers without worrying about being driven out of the market. On the other hand, discriminating loan officers are more likely to be driven out of a competitive market. We analyze costly discrimination in China's bank loan markets using several unique datasets and online maps. China provides an excellent case for this kind of research. Although studies about the United States find that Dun & Bradstreet credit scores and FICO scores provide cost effective methods for lenders to evaluate loan applications and monitor borrowers (e.g. Frame et al, 2001; Akhavein et al. 2005; Berger et al. 2005; Berger and Frame, 2007), there is not such information available in China. For small borrowers, this lack of hard information introduces more financial frictions and potentially more discrimination toward certain groups. Small borrowers in most other developing countries face the similar problems, and hence our findings can generalize to them. In addition, since 2000, China's bank industry has experienced large-scale deregulation, with many markets witnessing an explosive growth in the number of different banks and the number of bank branches. Many new loan officers have very limited experience in dealing with borrowers, and hence they probably choose borrowers based on some simple demographic characteristics. Furthermore, China has experienced a housing boom since 2000, and thus home as collateral is very safe. Therefore, it could be easier to detect favoritism in this market.

We examine two types of possible discrimination related to household heads' physical attractiveness (Hamermesh and Biddle,1994) and gender, and the two types of markets under consideration are the commercial/industrial loan (small business loans in the U.S.) markets and the mortgage loan markets. Physical attractiveness or beauty is rated by the student surveyors of the household finance data we use, with rankings between 1 and 10. To follow the usual practice and to accommodate the distribution of beauty ratings, we classify those with a rating of 8-10 as good-looking people, and those with a rating of 1-2 as bad-looking people, although different classifications yield qualitatively identical results. As we will show in summary statistics, the main variable having consistently strong correlation with beauty rating is age. That is, the older an individual, the lower beauty rating. However, an old individual is generally related to a larger amount of wealth which can be used as collateral. This gives us a unique advantage relative to labor markets. In labor markets for manufacturing and some service industries, an old individual may have a lower productivity, which makes it harder to distangle discrimination from productivity. Our prediction is that costly discrimination will tend to decline in a more competitive bank loan market. That is, if less attractive individuals or those of a certain gender have higher default rates and hence are less likely to obtain a loan or are forced to pay higher interest rates, more market competition should not reduce these productive lending practices (in that case they are no longer prejudice). In other words, a certain level of default rates needs to be compensated similarly in markets with different levels of competition.

For commercial/industrial loans, we use a novel identifying technique based on both the community identifier and information collected from online maps. As documented in the literature, commercial/industrial loans for small businesses are usually relationship-based (e.g., Peterson and Rajan, 1994, 2002), and for this reason, we use community-level market concentration. As opposed to borrowers of mortgages, entrepreneurs' collateral is generally much less liquid and has greater volatility in value, and they usually need to borrow from the same bank many times. This means that monitoring is paramount and therefore, the distance between a bank and a small business should be relatively short. Realizing this fact, we find the number of different banks within two kilometers of the community office where a household is located[1]. In China, each community has an official identifier which can be found at the National Bureau of Statistics website[2]. Actually, we also find that market concentration in this circle and that of larger/smaller circles are highly correlated. Gan (2016) notes that this community identifier contains information about whether the community is located in an urban or a rural area, and

[1]A community office is the smallest level government unit in China.

[2]http://www.stats.gov.cn/tjsj/tjbz/tjyqhdmhcxhfdm/2013/index.html

he uses this information to measure China's urbanization. He also remarks that very few papers make use of the information from this community identifier, not to mention the information collected from online maps based on the community identifier. This is not particularly surprising, as the usual publicly available datasets do not contain the community identifier. Even if some administrative datasets do include it, the statistical information regarding economic development is not available at the community level, and for this reason the usual research cannot be improved with the community identifier. However, we find that the community-level market concentration has larger variation than the prefecture-level market concentration, can mitigate the impacts of other prefecture-level confounding factors, and hence can provide larger identification power for our work.

Because households often move out of their original community after they purchase a new home, and because borrowing in each of these instances is a one-time transaction, the prefecture-level market concentration is more appropriate for mortgage loans. A prefecture in China is a level of jurisdiction between the provincial level and the county level, similar in size to a metropolitan statistical area (MSA) in the United States. In the following sections of this paper, community-level market structure refers to the market structure within the 2-kilometer circle of the community office in which a household is located, and prefecture-level market structure relates to market structure in the prefecture where a household is located.

Our principal findings are summarized as follows. First, generally speaking, we find that in a more concentrated commercial/industrial loan market, i.e., those with a higher Herfindahl index (HHI), good-looking people are more likely to obtain loans than average-looking people, and when they do, those loans tend to have lower interest rates, while the converse is true for bad-looking people. For example, with a one-standard-deviation increase in the community-level HHI, the chance that a good-looking male will obtain a loan is 20 percentage points higher compared with an average-looking male. The magnitude is similar for good-looking females compared with average-looking females. Moreover, our results show that males have an advantage over females. Second, in contrast to most findings in labor markets, we detect that females have a strong advantage in a more concentrated mortgage loan market, and this is especially the case for younger, good-looking females. Although the disadvantage of bearing and raising children cannot be easily disentangled from discrimination in labor markets, it does not pose an issue in mortgage loan markets, and hence this explains such findings. Third, both the descriptive statistics and regression estimates evaluated at the mean HHI indicate the existence of an advantage associated with good-looking people in the two types of markets, and an advantage associated with females in mortgage loan markets. We think that this fact is also of some importance. Loan officers can obtain almost the same hard information, such as education, family income, home ownership, retirement status, and household register ("Hukou") as researchers, and it is costly to collect further information from these small borrowers. Therefore, conditioning on these pieces of hard information, the observed premium or penalty probably reflects discrimination related to physical attractiveness and/or gender. Although some regressions do not produce significant results for the variables of major interest, we are encouraged by the fact that only the results in the expected direction are significant. Moreover, it is probably unnecessary for bank loan officers to discriminate against the same person in more than one way. They can reject the application, require a higher interest rate or a larger share of down payment, but not necessarily use all of them together. In summary, the consistent pattern shown in various regressions suggests the existence of costly discrimination in Becker's sense in bank loan markets.

Our findings also shed light on the importance of analyzing different loan markets separately. Commercial/industrial loans are usually riskier than mortgage loans, and hence bank loan officers probably want to take borrowers' physical attractiveness or gender as a sign of creditworthiness, even if the signal is not really associated with better quality. Consistent with this argument, the favoritism related to both beauty and gender are seen in older groups (age$>$35) but not in younger groups (age $\leq$ 35). For example, these older good-looking people or older men might be more willing or able to communicate verbally than older bad-looking people and older women, but this fact is not consistent with an explanation related to visual pleasure. Because there are more successful male entrepreneurs than female entrepreneurs, gender can be seen as a signal in commercial/industrial loan markets. Therefore, both the findings related to physical attractiveness and gender support the interpretation of the role of gender or physical attractiveness as a signal. However, in a more competitive market, it is less likely for loan officers to use this signal. This implies that this signal is not effective in revealing the real credentials of borrowers, and hence is in line with Cavalluzzo et al. (2002) and other papers on U.S. small business loan markets. On the other hand, mortgage loans are pretty safe, and it is thus more likely for loan officers to enjoy visual pleasure. Notice that both of these are consistent with Becker's costly discrimination, but are different from statistical discrimination. Statistical discrimination is toward less creditworthy groups of borrowers, and hence this kind of discrimination will not decline in a more competitive market.

Together, our paper makes three major contributions. First, this is the first paper to relate a beauty premium in credit markets to market structure. Moreover, there are very few papers that discuss a gender premium in bank loan markets. Secondly, we analyze commercial/industrial loan markets and mortgage loan markets separately, and shed lights on the different patterns in loan pricing behavior in different markets. This strongly implies that, in future research, it is important to study different kinds of loan markets separately. Although some researchers have examined costly discrimination in small business loans using the market structure-based method, there only very few studies on mortgage loans such as Berkovec et al. (1998). Using a rich set of FHA-insured loan records and measures of local market concentration to proxy the competitive environment, Berkovec et al. (1998) test for the prediction of better loan performance by minority borrowers relative to white borrowers in more concentrated markets. Thirdly, this is the first study to connect a community identifier and bank branch information collected from online maps. Although this paper studies China in empirical work, our methods can be generalized to the research on other countries with an identifier on small geographical areas available. In other words, we collect new data, analyze them with new methods, deliver bring new findings.

The field of discrimination in bank loan markets is much less developed than it is in labor markets, partly due to limited data availability. Our research aims to elevate the discussions in this field by using new technique and unique datasets. Bank loan terms are usually set by regional offices and probably the headquarters, and hence are usually considered much more standard than labor contracts, especially within the same bank in a certain province. Moreover, the conditions or requirements can usually be found in brochures at bank branches or online and are therefore are quite transparent. However, our findings imply that loan officers still have great freedom in choosing borrowers. Our explanation is that there are severe asymmetries of information in bank loan markets (Stiglitz and Weiss, 1981), and thus it is difficult for banks to set a rigorous standard for their loan officers. Therefore, bank loan officers are granted great autonomy in selecting qualified borrowers and setting corresponding credit terms. Conversations with several bank managers support this possibility. On the other hand, many borrowers might not understand complex financial products very well, and may therefore rely on the explanations provided by bank loan officers. In total, we suggest that carefully designed policies based on our findings may be necessary in alleviating such financial frictions.

The structure of the paper is as follows. Section 2 provides an introduction to Becker's theory on costly discrimination and the institutional background. Section 3 gives a review of the related literature; Section 4 presents the empirical strategy; Section 5 describes the dataset; Section 6 and 7 demonstrate the results and robustness check for the two kinds of bank loan markets; Section 8 is a discussion of our findings. Finally, Section 9 concludes.

2 Theory and Background

2.1 Theory

In his seminal work, *The Economics of Discrimination*, Becker (1957) models discrimination as a personal prejudice against a particular group. In his model, discrimination is costly. Competition should mitigate the presence of this type of discrimination over time. But more concentrated markets do not exert the same pressure for cost minimization. Thus, in the absence of competition, it may be possible to sustain noneconomic discrimination. For example, in labor markets, a discriminating employer foregoes the opportunity to hire cheaper labor and thus achieves a lower profit, which leaves a competitive advantage for nondiscriminating employers. In competitive markets, the nondiscriminating employers drive out discriminating employers and no wage gap will exist if there are enough nondiscriminating employers.

There are actually two types of costly discrimination in Becker's spirit. Consider bank loan markets: loan officers might simply dislike a certain group and be willing to pay to avoid such a group. However, loan officers might be more likely to decline loan applications from a certain group because they think these borrowers are more likely to default, though after controlling for differences in the verifiable credentials, they are not more likely to underperform other groups. In this sense, group attributes serve as a signal or "soft information". In a competitive bank loan market, there is less space for loan officers to discriminate against a certain group of borrowers in either way. In our paper, we document the first type of costly discrimination in commercial/industrial loan markets and the second type in mortgage loan markets. Costly discrimination is different from the statistical discrimination (Phelps, 1972; Arrow, 1973). According to the theory of statistical discrimination, borrowers who are discriminated against are more likely to underperform other groups, and hence this kind of discrimination would not disappear in a competitive market.

Discrimination toward a certain demographic group in the bank loan markets can be carried out in two ways, a lower approval rate, or worse credit terms (e.g., a higher interest rate). A financial institution that would normally loan funds at rate r, could require $r+t$, where t is the discrimination coefficient, or interest premium that must be charged in order to compensate for having to deal with the group toward which the lender has a prejudice. However, because of the presence of asymmetric information in credit markets, the extent to which lenders vary interest rates depending on the attributes of borrowers is unclear. Interest rates may therefore be not always a desirable place to look for evidence of discrimination (Petersen, 1981; Duca and Rosenthal, 1994). If lenders act on their prejudices by turning down certain groups at disproportionate rates, then denial rates would exceed expected levels after controlling for the creditworthiness of these borrowers. Stiglitz and Weiss (1981) show that in equilibrium both credit rationing and limited rate flexibility can occur.

Most of the credit market literature does not consider the relationship between competition and discrimination, and instead estimates some variant of the following econometric model:

$$Y = \alpha + \beta D + X'\gamma + \varepsilon, \tag{1}$$

where Y represents either approval rates or interest rates charged, X is a vector of demographic and risk (and any other relevant) characteristics, and D represents an indicator variable for demographic groups of major interest. Then β captures differences in Y because of all of the characteristics associated with D that are not captured in X. These differences may include statistical and prejudicial discrimination as well as economic differentials not properly accounted for by X. In this paper, we will exploit variation in concentration across bank loan markets and estimate equations in the following form:

$$Y = \alpha + \beta_1 (D * Market) + \beta_2 D + X'\gamma + \varepsilon. \tag{2}$$

Under this specification, β_2 continues to reflect across-group differentials that can arise from a variety of sources that we expect to be invariant with respect to market structure, including statistical discrimination, omitted variables, and possibly prejudicial discrimination. In contrast, β_1 reflects differentials associated with lender market power in households' local area, proxied here by the HHI or other measures of lender market concentration. Wider differentials in less competitive lending markets are consistent with Becker's costly discrimination.

2.2 Background: China's Banking Reform

Prior to 1978, the Chinese financial system followed a mono-bank model (Peoples Bank of China) whereby all the bank branches were part of one administrative hierarchy. In 1978, a banking reform was put on the agenda and various banking functions were devolved from the Peoples Bank of China (PBOC), the central bank of China. Four specialized state-owned banks, the Bank of China (BOC), the Agriculture Bank of China (ABC), the Construction Bank of China (CBC), and the Industrial and Commercial Bank of China (ICBC), the so-called "Big Four", were established. In 1985, additional changes were implemented that were designed to give these institutions greater scope in raising and allocating capital. The four banks are now national commercial banks that compete with each other (Lin and Zhang, 2009).

In the middle and late 1980s, banking reform turned to bank ownership; during this period, the existing banking system structure was held constant. Ownership reform was introduced incrementally. The first Chinese-foreign joint-equity bank, China and South Sea Bank Ltd., was formed in 1984. Two years later the Bank of Communications, the first domestic joint-equity bank, was established. In 1991, Shenzhen Development Bank, also a domestic joint-equity bank, was successfully listed on the Shenzhen Stock Exchange, becoming the first partially public-owned bank in China.

In 1995, the Central Bank Law and the Commercial Bank Law were promulgated. With the implementation of the Commercial Bank Law, urban and rural credit cooperatives started to merge and form city-level commercial banks, which were owned by the state, state-owned enterprises, or private capital. Compared with the "Big Four", joint-equity banks, urban and rural commercial banks and credit unions witnessed a larger expansion over the last two decades. In 2006, the urban commercial banks were allowed to establish branches beyond their home province. Although before then, urban commercial banks were usually very small and focused on their home city, starting then their expansion has been accelerating. Till now some of them have become Fortune 500 companies.

Before 1993, the government allowed foreign banks to establish branches in certain cities to conduct foreign-currency business with foreign firms and citizens only. Starting in 1993, the banking sector started lifting various geographic and client restrictions on foreign bank lending. The government allowed foreign banks in China to conduct both foreign- and local-currency business with foreign firms and citizens, and to conduct foreign-currency business with domestic firms. Under the WTO agreements, restrictions on the operations of foreign financial institutions in the Chinese financial sector were relaxed in stages (Lin, 2011). In the banking sector, foreign banks were scheduled to receive treatment identical to that of national institutions and to provide Rmb (China's currency) business to Chinese firms and individuals by December 2006. From 2001 to 2011, the number of foreign bank branches in China soared from 200 to 800. However, the market share of foreign banks is still much smaller than that of native banks.

Overall, these bank deregulation policies led to more competitiveness in China's bank loan markets, and they can provide plausibly exogenous temporal variation to our study. China's bank deregulation is comparable to that happened in the U.S. from the 1970s to the 1990s, though because of lack of comprehensive bank-level data as the Call reports in the U.S., the former is still underexplored in the literature.

Insert Figure 1 here

Figure 1 plots the mean and standard deviation of prefecture-level HHI by year, using the bank branch data obtained from China Banking Regulatory Commission (CBRC), the bank regulatory agency in this country. As we can see, the average HHI declined from 0.24 in 1995 to 0.13 in 2013, coinciding with the establishment and expansion of various types of banks induced by the bank deregulation. Although the standard deviation of HHI also decreased, the ratio of standard deviation and mean actually increased from 0.5 to 0.7. These facts imply there is large variation in bank market concentration across time and areas. A market of great economic importance is usually more attractive to firms, meaning that market concentration is usually correlated with the economic importance of a market, such as GDP and population size. For this reason, we also plot the mean and standard deviation of prefecture-level logged GDP (those of logged population are very stable across year and hence are not plotted here). Although there is a negative correlation between average HHI and average logged GDP as expected, we notice that the standard deviations seem uncorrelated and hence much variations in HHI is probably not explained by the economic level of a prefecture. In empirical parts, we will also control the measures of economic level, and the results are intact.

2.3 Variation in Market Concentration across Areas

There are three main sources of variation in market concentration across areas, which shows that the observed differences in the treatment of different demographic groups should not result from unobserved variables or reverse causality. First, this variation can be traced to historical differences. During the era of the planned economy (the 1950s to the mid-1990s), financial institutions belonged to the government and channeled funds to local governments and state-owned enterprises, and it is rare for households to obtain credit from banks. The "Big Four" banks, along with many urban commercial banks and credit unions have a history dating back to the planned economy era, and hence the current market structure in a given area is heavily influenced by the historical existence of the branches of these banks. In areas where the central government put on its list of priorities, there would be more bank branches, especially branches belonging to the "Big Four" banks. In addition, joint-equity banks were usually established before the planned economy era, but they were closed in the planned economy era. After the country returned to a market economy, these banks expanded in their original places quickly in their respective regions.

Secondly, the central bank of China has 9 regional bureaus as well as a bureau in every prefecture. According to the 1995 Commercial Bank Law and the 2002 Guidelines for Commercial Banks to Establish New Branches[3], establishing a new bank branch needs to be approved by the

[3] See http://news.xinhuanet.com/zhengfu/2002-02/22/content 285872.htm

corresponding prefecture bureau of the central bank. Therefore, an important source of variation in market concentration across areas comes from the different policy preferences of regulators. We also realize that, in a more concentrated market, dominant players probably have a larger influence on the local regulator's policy, and as a consequence the current market structure tends to persist. Similarly, in a more competitive market, players have limited influence on the local regulator's policy, and the market will still be competitive.

Thirdly, a market of great economic importance is usually more attractive to firms, and hence there should be more applications for establishing new branches. These differences in economic levels can bring differences in approval rates and credit terms across the country. For example, an area with a higher credit risk would be compensated by a lower approval rate and a higher interest rate. However, differences in economic levels should not lead to large differences in approval rates and credit terms among different demographic groups in the same area except via correlation with the market concentration. This is verified by the fact that our results are intact after purging the impact of economic level from market concentration.

Insert Figure 2 here

Figure 2 plots the prefecture-level average HHI during 2009-2013 for the 31 provinces or province-level jurisdictions in mainland China. The darker color stands for a higher market concentration level, whereas the lighter color stands for a lower market concentration level. As can be seen in this graph, the northeastern and western parts, which are relatively poor compared to other parts of the country, have a higher market concentration level on average, whereas the northern and southeastern parts, which are relatively wealthy, have a lower market concentration level on average. However, we can find large variation in a relatively small region, which implies that our measure of market concentration is not very likely to reflect factors specific to a certain region.

3 Related Literature

3.1 Product Market Structure and Discrimination

The relationship between discrimination and product market structure in labor markets has attracted economists' attention for a long time. Milgrom and Oster (1987) propose the invisibility hypothesis that job skills of disadvantaged workers are not easily discovered by potential new employers, but that promotion enhances visibility and alleviates this problem. Then, in a competitive labor market equilibrium, firms profit by hiding talented disadvantaged workers in low-level jobs. As a result of the inefficient and discriminatory wage and promotion policies, disadvantaged workers experience lower returns to investments in human capital than other workers. Ashenfelter and Hannan (1986) examine the relationship between product market competition and employment by linking data on female employment with measures of market concentration in the banking industry. Their results provide strong support for a negative relationship between market concentration and the relative employment of women. This relationship is primarily due to differences across markets rather than individual firms. A more recent and influential paper about discrimination and market structure in labor markets, Black and Strahan (2001), documents that male bank employees' wages fell much more than women's after deregulation. This suggests that rents in a more concentrated market were shared mainly with men, while women's share of employment in managerial positions also increased following deregulation. Our results do not present a consistent disadvantage of females in bank loan markets, and we find that females actually have an advantage in mortgage loan markets. The banking industry is an ideal place to test discrimination using a market structure-based method. Many industries, such as wholesale and retail industries, are contestable markets with few entry costs, and for this reason the market concentration level may not reflect real market power. On the other hand, for utilities and other "natural monopoly" markets, there is no variation in market concentration. The banking industry is regulated by the government and has large variation in market concentration, which makes it easier to test discrimination based on market structure.

Berkovec et al. (1998) explore the differences in local competitive environment to study the costly discrimination toward minorities in mortgage loan markets. They results suggest the existence of noneconomic discrimination. They argue that this approach substantially reduces the potential for omitted-variable bias that has cast a shadow on previous studies of lending discrimination. Cavalluzzo et al. (2002) examine the small business loan markets and find substantial differences in denial rates between firms owned by African Americans and white males using the 1993 Survey of Small Business Finances. Consistent with Becker's (1957) theory, they also find increases in competition in the firms local banking market reduces these differences. They also find female borrowers are less likely to obtain a loan in a more concentrated market. Similar to them, we find a male premium in a more concentrated commercial/industrial loan markets; however, we find that women are treated better in a more concentrated mortgage loan market. Moreover, Mitchell and Pearce (2009) also test the discrimination toward minorities using the market structure method and find similar evidence. Other research also discuss the impacts of market structure on small business loans using the Surveys of Small Business Finances, such as Berger et al. (1998) and Cavalluzzo and Cavalluzzo (1998).

Overall, in contrast to the large volume of empirical literature on labor markets, the discussions on discrimination in loan markets especially bank loan markets are still very scarce. This is perhaps not surprising. Although the Federal Reserve's Survey of Consumer Finances contains abundant information on household asset and income, it does not have enough geographic identifiers (MSA or county) to link with market structure data, not to mention measures on beauty and many other individual characteristics. In addition, the most recent Small Business Survey is the 2003 version, and we do not realize a paper testing discrimination in mortgage loan markets and small business loan markets related to market structure together. Our paper will provide a test of Becker (1957)'s theory in a case study of bank loan markets. Because we obtain prefecture and community identifiers for our sampled households, we can link the prefecture-level and community-level bank concentration information with households' borrowing history. Our results therefore provides a stronger identification than using province-level data.

3.2 Physical Attractiveness

Our interest in physical attractiveness is inspired by the influential work by Hamermesh and Biddle (1994). They develop a theory of sorting across occupations based on looks and derive its implications for testing for the source of earnings differentials related to looks. Holding constant demographic and labor-market characteristics, they find that plain people earn less than people of average looks, who earn less than the good-looking, and the effects are slightly larger for men than for women. Later papers, such as Hamermesh and Abrevaya (2013), find that such a beauty premium exists in many western countries and is related to better life satisfaction. They also discuss the measurement error issue in beauty resulting from different practices in recording individuals' beauty. Hamermesh (2011) reviews the literature on beauty economics. However, the surveys on such a beauty premium in developing countries such as China are still very limited. Compared to the western countries, anti-discrimination laws are non-existent or weakly enforced in these countries. Moreover, China is much more racially homogeneous than most western countries, with the ethnic Han group taking up a share of 91.5% (2010 Population census) in the national population, and most other ethnic groups are physically indistinguishable from the ethnic Han group. This implies that the beauty ratings given by different raters are more likely to be inherently consistent and hence better for us to examine the beauty premium.

Three papers discuss discrimination related to beauty in peer-to-peer lending markets, using data from Prosper.com. Duarte et al. (2012) find that borrowers who appear more trustworthy have higher probabilities of having their loans funded, while borrowers who appear more trustworthy indeed have better credit scores and default less often. Overall, their findings suggest that impressions of trustworthiness matter in financial transactions as they predict investors' as well as borrowers' behavior. On the other hand, a further examination by Ravina (2012) confirms the existence of beauty premium but finds that beautiful borrowers turn out to be as likely to default as average-looking borrowers with similar credentials, who are on average less likely to obtain funds and are charged higher rates. Her finding is consistent with the experiment-based results by Mobius and Rosenblatt (2006), Andreoni and Petrie (2008), Olivola and Todorov (2010) and others, who find that the beautiful are treated better, are perceived as more productive and are more confident, but that their actual productivity is not higher than that less attractive individuals. Finally, Pope and Sydnor (2011) find evidence of significant racial disparities in this market. Although interesting, peer-to-peer lending markets are much smaller and less important than bank loan markets. Moreover, the borrowers on Prosper.com post their pictures voluntarily, which makes the selection issue hard to tackle. Therefore, Hamermesh (2011) comments on the area:

This discussion of credit markets illustrates yet another area where a person's beauty modifies an economic exchange. Research in this area is just beginning, and the evidence is very far from conclusive. It does seem, though, that lenders are willing to exchange more generous terms on loans for the pleasure of dealing with good-looking borrowers. They do this not because good looks predict that the loan will perform better, but because they are prejudiced against bad-looking applicants.

Compared with these papers, our market structure based method also makes it more straightforward to distinguish discrimination from unobservable credentials that impact loan offers' decisions. For example, since we find that on average good-looking people are treated better, we may conjecture that this is partly because good-looking people have some unobservable creditworthy attributes. However, the market will compensate for this difference in profit resulting from the difference in these attributes, either when the market is more concentrated or more competitive. That is, with a changing degree of market concentration, the differences in profit resulting from the difference in these attributes are pretty much the same, and hence should have few impacts on the estimate for the interaction term.

4 Empirical Strategy

4.1 Regression Specification

We will estimate the role of market competition in mitigating discrimination in bank loan markets. Based on data availability, we will analyze bank loan approval (whether the loan application was approved or rejected if a household once submitted a loan application) and the annualized interest rate of the loan of the largest amount. We study the them separately for commercial/industrial loan markets and mortgage loan markets because of the quite different characteristics of the two markets.

For bank loan approval, either in commercial/industrial loan markets or mortgage loan markets, we include the households who once applied a loan, and estimate the following regression equation:

$$Approve_{isp} = \beta_1 + \beta_2 Feature_{isp} Market_{isp} + \beta_3 Feature_{isp} + \beta_4 Market_{isp} + \beta_5 X_{isp} + \lambda_s + \varepsilon_{isp}, \tag{3}$$

where i, s, p represents household i in community or prefecture p of province s. $Approve$ is a dummy variable indicating whether the households loan application was accepted or rejected. $Feature$ can be dummy variables for good-looking people, bad-looking people, or gender (male equal to 1). $Market$ represents measures of market concentration such as HHI, C5, or C3. For commercial/industrial loan markets, we use community-level measures of market concentration, and the residual from a regression of market concentration on the community type (rural area, small town, small city, median city and big city). On the other hand, because a household probably moves out of its original community after buying a new house, we use prefecture-level measures of market concentration for mortgage loan markets, and the residual from a regression of market concentration on logged GDP and population size. We use a linear probability model, because we include mutiple interaction terms in the regressions. As explained in Ai and Norton (2003), the marginal effect of interacted variables is not the same as the coefficient of the interaction term, and they may have opposite signs. With multiple interaction terms, there is not an effective way to get the correct marginal effect using nonlinear models such as logit or probit model.

The variables of major interest are the interaction terms $Feature_{isp} Market_{isp}$. Taking $Goodlooks * HHI$ as an example, we expect a positive sign for the estimated coefficient in the regressions with the possibility that the loan application was approved as the dependent variable. X are a set of controls including an indicator for agricultural Hukou, rural status, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, and their interaction terms with market concentration. λ_s are province fixed effects. We do not use prefecture fixed effects to avoid having too many parameters for a relatively small sample size of commercial/industrial loans (the much larger R-squared than the adjusted R-squared implies possible overfitting). Another subtle issue is that the equilibrium combination of loan approval and interest rate has less within-prefecture variation for arbitrage reasons, especially for mortgage loans. However, we notice that the results are qualitatively identical and usually still significant with prefecture fixed effects. Besides the major results, we also report the marginal effect of *Feature* at the mean value of market concentration, i.e. $\beta_2 * meanMarket_{isp} + \beta_3$, which shows the beauty or gender premium at the average level of market concentration.

For commercial/industrial loan markets, we will also control for home ownership to further account for the impact of family wealth, though we do not try to control for family income because it is probably impacted by the credit support from banks. For mortgage loan markets, we will also control for logged family income and retirement status. We also include the interaction terms of these variables with market concentration. Since the majority of borrowers in this dataset report being granted a loan between 2009 and 2013, we use the measures of community-level market concentration in 2011 for commercial/industrial loans (to save labor cost) and the average measures of prefecture-level market concentration across these five years for mortgage loans. Using alternative average measures[4] does not change our results because market concentration is highly persistent in the same market across time.

An older borrower probably possesses better working skills, has accumulated more wealth and hence can provide more collateral. Notice that we find a very strong negative correlation between beauty rating and age, which implies that the beauty premium is not likely a reflection of better economic conditions. Education increases income potential, and loan officers might also see better-educated people as having greater creditworthiness. A married couple would lose more if they defaulted, while health can enhance productivity and bring confidence (Ravina, 2012). Indicators for Hukou, rural status, party member status, home ownership, family income, and retirement status can further serve as proxies for the repayment willingness and ability. Our household finance dataset does not contain a direct variable for total family income, and hence we define family income as the sum of wage income, agricultural income and business income. We do not include government subsidies here because they cannot signal borrowers' repayment ability in the same way as other income sources, though the results with government subsidies included are almost the same.

Furthermore, we include the households whose loan application was approved, and estimate the effect on interest rate in both markets using the following regression equations:

[4]For example, we consider using the average measures of 2007-2011 or 2008-2012 for households whose loan application were rejected. We do not think measures with very different periods should be used for the accepted and rejected groups. Market competition becomes much fiercer over time, and hence a rejected household can probably reapply a loan several years later.

$$Interest_{ispt} = \beta_1 + \beta_2 Feature_{ispt} Market_{ispt} + \beta_3 Feature_{ispt} + \beta_4 Market_{ispt} + \beta_5 X_{ispt} + \lambda_s + \lambda_t + \varepsilon_{ispt}, \tag{4}$$

where $Interest$ refers to the Interest rate of the loan of the largest amount a household borrowed, winsorized at 20 percent. Although we may also be interested in the amount of the loan, current data available do not allow us to distinguish between the demand and supply sides. For example, if we observe that a beautiful borrower received a smaller loan amount than a less attractive borrower, we cannot say whether the good-looking borrower requested a smaller amount or the lender only guaranteed part of the requested loan. For this reason, we do not analyze the amount of the loan.

Taking $Goodlooks * HHI$ as an example, we expect a negative sign for the estimated coefficient in the regressions with interest rate as the dependent variable. Besides the variables mentioned above, for the regressions of the interest rate of commercial/industrial loans, we also control for an indicator variable for a loan with collateral, an indicator variable for whether the interest rate is adjustable (an adjustable loan affords the bank more flexibility to adjust the loan interest rate, such as in times of a high deposit interest rate), and their interaction terms with market concentration. For mortgage loans, we also control for an indicator variable for public housing fund loans (gongjijin loans)[5] and its interaction term with market concentration. Here $Market$ represents measures of market concentration such as HHI, C5, or C3 in the year the loan was granted (rather than the average measures in the regressions of loan approval), and λ_t are loan granted year fixed effects.

We understand some other variables may be also related to interest rates, such as maturity. However, for the following reasons we do not include them in the main analysis. First, since we already control a rich set of covariates, which should already capture the impact of other variables, especially economic conditions. Secondly, a large share of individuals do not report these variables, and hence leads to reduced statistical power and selection problem. Thirdly, maturity is an endogeneous variable, i.e. a loan officer can require a higher interest rate and shorter maturity to reduce credit risks. Fourthly, most of the strongest results happen in approval decisions, rather than interest rates, and thus our main conclusion is identical regardles of the additional covariates in the regression for interest rates. Overall, our results are similar when we control more covariates and hence use smaller samples.

[5] gongjijin is a type of compulsory savings for employed workers. When these workers buy homes, they can apply loans backed by the compulsory savings collected from him/her and other employed workers, up to a certain limit.

4.2 Measures of Market Concentration

We construct HHI, C5 (the market share of the largest five banks), and C3 (the market share of the largest three banks), the regular measures of market concentration. Following Dong (2016)'s and Chong, Lu and Ongena (2013)'s practice, we calculate these measures based on bank branch presence. That is, we calculate the number of the branches belonging to a certain bank and divide it by the total number of branches in a community or prefecture, and use this as the market share of this bank. Then we calculate HHI as usual. We keep all the commercial banks and credit unions in China. For household borrowers, credit unions are quite similar to other banks and are very important in small towns and rural areas, though excluding them does not change our results.

Unlike FDIC's Summary of Deposits, our dataset does not contain prefecture-level total deposits for a bank, and hence we cannot construct measures of market concentration based on deposits. Although many studies on the U.S. construct HHI based on deposits following the practice of U.S. Department of Justice, bank regulators consider branch presence as a very important measure of market power, as the intrastate and interstate branching restrictions show; indeed, the Summary of Deposits reports state-level and MSA-level total deposit and the number of branches together. As widely documented in the literature (i.e. Rose and Hudgins), the existence of a bank branch boosts deposits' confidence, and hence more branches can attract more depositors. In addition, it is easier for borrowers to find or visit a bank with more branches, and as a consequence after considering search cost or transportation cost, a bank with more branches should have larger market power. A big bank with many branches and hence large market power can also press small banks to follow its agenda. As to China, we usually see different banks are more likely to have a similar number of branches in eastern provinces than in western provinces, where we usually see several big banks staying with many small banks with only one branch, and banks usually consider the former markets as more competitive.

Furthermore, we consider the following checks. First, using the 2013 annual reports for the publicly traded banks in China, we find that the correlation between the number of branches and the amount of deposits (or loans) is 0.7 and significant under the1 percent level. Secondly, using the 2013 China City Statistical Yearbooks, we find that the correlation between the number of branches and the amount of deposits (or loans) for prefectures is 0.8 and significant under the1 percent level. This would not happen if banks with a larger number of branches had much smaller deposits (or loans) per branch in a prefecture, or if banks with a larger number of branches had much larger deposits (or loans) per branch in a prefecture. Thirdly, using FDIC's 2013 Summary of Deposits, we find that the correlation between state-level (or MSA-level) total deposits and the number of branches for a bank is 0.7 and significant under the 1 percent level. Therefore, the HHI constructed based on the number of branches should be similar to the HHI based on total deposits or total loans.

We will always report the results using HHI. Although not reported in the main analysis for brevity, regressions using C5 and C3 always give qualitatively identical results. This is because the three measures are highly positively correlated. We use prefecture-level market concentration for mortgage loans. Although households can probably move out of their original community after buying a new house, it is not very likely that they move out of their original prefecture. It is not uncommon for an individual living in a certain county to work in another county in the same prefecture, and therefore is reasonable for him/her to borrow from a bank branch along this route.

4.3 Community-level Market Concentration from Online Maps

In this paper, community-level market structure refers to market structure within the 2-kilometer circle around the community office where a household is located. Commercial/industrial loans for small businesses are usually relationship-based as the literature of relationship banking documents (e.g., Peterson and Rajan, 1994, 2002), and for this reason we use community-level market concentration for this market. As opposed to borrowers of mortgages, entrepreneurs' collateral is less liquid and has greater volatility in value, and they usually need to borrow from the same bank many times. This means that monitoring is very important (Diamond, 1991; Berger and Udell, 1995) and the distance between a bank branch and a small business cannot be long. Peterson and Rajan (2002) find that a usual borrower is less than 5 miles from its lenders in the U.S. using the Survey of Small Business Finances. Brevoort and Hannan (2006) suggest that distance could have an increasing importance in US commercial lending (lender's decisions). Therefore, since the key advantage of our dataset is that we can obtain the community identifier, for commercial/industrial loans, we will find the number of different banks within 2 kilometers around the community office where a household was located. Not surprisingly, community-level market concentration has larger variation than prefecture-level market concentration, can mitigate the impacts of other prefecture-level confounding factors, and hence can provide large identifying power for us.

The choice of 2 kilometers is due to the labor intensive hand-collecting work of bank branches to a large extent, and we think it is reasonable for China. Compared with the U.S., China's population and thus bank branches are more concentrated (for many urban areas the number of branches is beyond 100 and they belong to more than 20 banks). Moreover, cars were not very common for almost all the possible borrowing years in our sample. The 2-kilometer circle has an area of 12.6 square kilometers, about one half of the East district (25 square kilometers with 0.92 million people) or the West district (32 square kilometers with 1.24 million people), two central county-level districts in Beijing, and therefore is large and contains a substantial number of bank branches for many urban areas. When we search the bank branches using the Baidu Maps, we find that a bank with more branches in a smaller circle is almost always has more branches in the 2-kilometer circle. We also search bank branches beyond the 2-kilometer circle for randomly chosen communities and find that a bank with more branches in the 2-kilometer circle always has more branches in a larger circle. Indeed, the level of market concentration in a smaller circle is highly correlated with that of a larger circle.

Importantly, a community is small enough so that it can measure the approximate location of a sampled household accurately for our purpose. For example, we find that the East district and West district of Beijing include 187 communities and 255 communities respectively, which means that the community size is about 0.13 square kilometers in these districts, around one percent of a 2-kilometer circle (12.6 square kilometers). Overall, the community size is approximately comparable across the country.

Specifically, we use the Baidu Maps (http://map.baidu.com/), an online map search engine like Google Maps but having a higher precision for China's locations, for this purpose. The procedure for constructing the community-level market concentration is the following: we enter the address of a community office on Baidu Maps, then search "Yinhang (bank in Chinese)" in the "Locations Nearby" and can find the names of bank branches within 2 kilometers around the community office as shown on the left-hand side of Figure 3. Although the search results also include ATMs, we do not keep them because they cannot grant a loan.

Insert Figure 3 here

A tricky part is that the bank branches found online are those existing currently, rather than those existing in the loan granted years. Some of the current bank branches might not exist several years ago, and some branches existing years ago might have already closed. We can solve this issue by matching the branches sought online with the branch file obtained from the China Banking Regulatory Commission (CBRC), which contains the establishment year and closing year of a branch. Noticing that the name sought from the online maps does not always coincide with the name in the branch file perfectly, it is necessary to make sure the match is correct using the address information from the branch file in these cases.

4.4 Measure of Physical Attractiveness

The beauty ratings are given by student surveyors of CHFS, ranging from 1 to 10, with a lower rating representing a a worse-looking individual. To accommodate the distributions of beauty ratings in our samples as shown in Figure 4 and to follow the practice in this literature, we classify a rating of 1-2 as bad-looking, since there is a natural cutoff between a rating of 2 and above. To balance the concerns about sample size and the danger of classifying plain-looking people as good-looking ones, we classify a rating of 8 to 10 as good-looking. Classifying a rating of 9-10 as good-looking increases the magnitude of the impact of the interaction term of good-looking indicator and HHI and the impact of good-looking at the mean HHI generally, whereas classifying a rating of 7-10 as good looking reduces the magnitude of these impacts. These findings suggest that the ratings are indeed statistically effective. Moreover, using the 2012 China Labor-force Dynamics Survey carried out by Sun Yat-Sen University, which also contains beauty ratings given by college student surveyors ranging from 1-10 like our dataset, we find that each additional centimeter of height is associated with a 0.05 higher beauty rating for females and a 0.06 higher rating for males, and the beauty rating is also significantly negatively correlated with weight for females but not for males. This is consistent with the importance of slimness in judging women's beauty rather than men's in this country. Actually, using a matched sample based on individual characteristics, we observe such patterns as well[6]. Especially, as we will show in summary statistics, the main variable having consistently strong correlation with beauty rating is age. That is, the older an individual, the lower beauty rating. However, an old individual is generally related to a larger amount of wealth which can be used as collateral. This gives us a unique advantage relative to labor markets. In labor markets for manufacturing and some service industries, an old individual may have a lower productivity, which makes it harder to disentangle discrimination from productivity.

Insert Figure 4 here

Indeed, although there is some concern about the subjective nature of measures on physical attractiveness, it is easy to adjust statistically for biases in drawing conclusions about the relationship between differences in beauty and any outcome. In our study, we control a rich set of individual characteristics and economic conditions and their interaction terms with market concentration, and thus the remaining variation in beauty rating is not likely to be only a reflection of other individual characteristics and economic conditions. The real question is whether

[6]Specifically, we combine the two surveys, and run a regression with an indicator for one survey as the dependent variable and individual characteristics as independent variables and obtain a matched sample.

people agree on the beauty of a particular individual, and the extent of that agreement, if any. Although in our study and most other papers, the beauty of an individual was rated by a single surveyor, Hamermesh (2011, pages 24-28) provides rich evidence for the high correlation between ratings given by different people. Hamermesh and Biddle (1998) find a Cronbach's alpha of 0.75, while Andreoni and Petrie (2008) find an alpha of 0.86 and an intra-class correlation coefficient of 0.76. Ravina (2012) find 0.77 and 0.76 for these two commonly used measures of reliability[7]. Moreover, when classifying people into three beauty groups, which is the usual practice, the misclassification error should be small.

Insert Figure 5 here

The peak of the distribution at ratings 5-7 is similar as findings in many surveys conducted in Western countries. However, a special phenomenon in our data is the right skewness of the distribution, which deserves an explanation. One possible reason is that Western countries usually have many means-tested welfare programs and hence inequality is relatively low in these countries; however, there are very few such programs in China. The 2011 CHFS has been shown to have a income distribution that is similar to that of other well-known surveys in China (Zhang et al., 2014). Comparing the distributions of family income in the 2011 Current Population Survey March supplement and the 2011 CHFS and adjusting the sampling weights, we find that only 5 percent of the population has family income lower than 10 thousand U.S. dollars and the density declines to 0 as the family income nears 0, as shown in Figure 5. On the other hand, we find a much larger share of households with family income close to 0 in CHFS (government subsidies are included here to make this measure comparable to CPS family income[8]). We remind the readers that the two samples are not perfectly comparable because of differences in sampling methods; however, the differences in the distributions are intriguing and should not be fully driven by the sampling methods. Not surprisingly, the distribution of physical attractiveness partly reflects the long-term accumulation of these kinds of inequality, though we can control for economic factors in regressions to obtain a direct effect of beauty. Moreover, we also notice that our sample is nationwide, with most households either living in underdeveloped provinces, small towns and rural areas, or being migrants in developed areas. When just looking at the local citizens in developed areas, we find a less skewed distribution of beauty ratings.

[7] There has not been a study documenting a weak or no correlation between the beauty ratings given by different people till now, which is probably not due to the "significance bias" in usual studies. It should be interesting to document such a deviation in beauty ratings as well.

[8] Not including government subsidies give an almost identical distribution.

4.5 Online Borrowing

Finally, there is probably a concern about online borrowing. A long distance between a small business and its lenders is rare even in the U.S., as widely documented by the literature on relationship banking (Peterson and Rajan, 2002; Brevoort and Hannan, 2006). Online bank loans are even less prevalent in China than in the United States. Conversations with several bank loan officers suggest that online borrowing is not likely to confound our results for the following reason. In this country, banks cannot track the credit history of potential borrowers such as the Dun & Bradstreet credit scores or FICO scores effectively as in the United States, because a large-scale network sharing consumers' credit history among banks, utility companies, landlords and others has not been established till our sample period. A limited number of banks grant loans to their customers online but with very stringent conditions. Taking the Industrial and Commercial Bank of China (the largest bank in China) as an example, it requires fixed deposits as collateral and the maturity of an online loan is at most 1 year. On the other hand, the maturity of a mortgage loan is generally longer than 10 years, and most commercial/industrial loans do not have fixed deposits as collateral.

5 Data and Descriptive Statistics

We construct the measures of market concentration, using an administrative dataset obtained from the China Banking Regulatory Commission (CBRC) and online maps (for community-level market concentration). The CBRC dataset provides information about the address, establishment year and closing year of each bank branch in this country, which allows us to construct measures of market concentration in each prefecture/circle for each year, based on the number of branches a bank has in that prefecture/circle and that year[9].

The information about households' bank loans is obtained from the confidential 2013 China Household Finance Survey (CHFS) dataset, conducted by the Southwestern University of Finance and Economics in China. This survey employs a stratified three-stage random sample design based on probability proportional to size, interviewing 28,228 households across 29 provinces, 262 counties, and 1,048 communities[10]. This survey is the only nationally representative survey in China that has detailed information about household finance and assets, including housing, business assets, financial assets, and other household assets. In this paper,

[9]Each bank branch has a branch code given by the central bank, which contains the code of the prefecture where this branch is located. Therefore, branch codes can be used to construct the prefecture-level measures. For the 2-kilometer circles, we use the online maps as discussed in the previous section.

[10]We use the version updated in February 2015. The newer version updated in April 2016 loses much information.

we focus on two types of bank loans: commercial/industrial loans, and mortgage loans for the first home. Although this dataset also contains information about agricultural and educational loans, the government intervenes heavily in these two types of loan markets, and for this reason they are not analyzed here. Mortgage loans for a second home have also been highly regulated by the government since 2007, as part of the policies that are in place to curb the housing bubble. This survey was also conducted in 2011 and contains 8438 households. However, we do not use it because it does not contain community or prefecture identifiers, nor does it distinguish agricultural loans from commercial/industrial loans.

For our purposes, we use the household heads in the CHFS, and the gender and most other individual characteristics hence refer to those household heads. For beauty, the choice of household heads is not important, because a good-looking male tends to marry a good-looking female, as suggested by the assortative mating theory (e.g. Pencavel, 1998). The choice of household heads is probably important for our discussions on gender because most households contain both males and females. Although the survey asks the interviewees to name the head directly, we use a more delicate algorithm to determine the household heads for the main analysis. First, we retain an interviewee and his/her spouse, because the interviewee probably knows much better about the household's financial position if the household head is his/her spouse rather than his/her parents or children. Second, we sort educational attainment within a household and consider the individual with the higher level of education to be the household head. This is because the individual with more education should have a higher ability to understand loan conditions and search for better loan terms. Third, if the educational attainment is the same for both family members, we choose the one with a higher wage level as the head. This is because the individual with more income should be more likely to influence the borrowing decision and to repay the loan. Finally, if they have the same wage level, we keep the one named by the interviewee as the head. Alternatively, we also consider the case in which we simply keep the individual named by the interviewee as the head, and the results are very similar. This is not surprising, because the named head has 0.8 years extra educational attainment (about 10 percent of the mean educational attainment) and 2000 yuan extra wage income (about 25 percent of the mean wage income) on average, and these differences are highly significant. Actually, CHFS tends to select the one more familiar with household financial position if there were more than one family members present, and hence the interviewee is more likely to be the named head.

It should be noted that, in China, females' labor force participation is as high as that of males on average, and hence the gender of a household head is usually determined by the employment status or income of individuals in this household. Indeed, the marriage rate for female-headed families is close to that for male-headed families, and we do not find an obvious disadvantage in socioeconomic status for the former.

In addition, to complement prefecture-level variables such as log GDP and population size, we obtain relevant data from the 1995-2013 China City Statistical Yearbooks.

Insert Table 1 here

In columns (1) to (4) of Table 1, we compare the chance that a loan application was approved (or rejected) and annualized interest rate in commercial/industrial loan markets, for different beauty groups and gender groups. We ignore average-looking males and females in this comparison for clarity, and in this way we can obtain a “sharper” comparison. On average, the chance of good-looking males’ applications being approved is almost the same as their bad-looking counterparts, while there is a statistically significant gap of 13 percentage points for good-looking and bad-looking females. The gaps in interest rates are 3 and 3.3 percentage points respectively and are highly significant. These gaps are large since the one-year benchmark loan interest rate set by China’s central bank was 6 percent in 2013. These facts imply the possible existence of favoritism toward good-looking borrowers and discrimination against bad-looking ones. Moreover, we notice that good-looking females are less likely to have collateral and that the interest rate is more likely to be adjustable for them.

Switching to individual characteristics, good-looking men and women are, on average, 3 and 4 years younger than bad-looking men and women respectively, which confirms the validity of our beauty measure. A younger individual perhaps has a lower ability to repay a loan, especially for commercial/industrial loans. We do not find statistically significant or economically large differences in most other attributes, implying that our measure of physical attractiveness is not very likely to reflect the confounding impacts of these attributes. Good-looking people have one extra year of educational attainment and are less likely to live in rural areas, which could be associated with a higher repayment ability. Moreover, good-looking men are more likely to be married and own a home, and are less likely to have an agricultural Hukou than bad-looking men, while the converse is true for women. Overall, good-looking people are highly significantly older than bad-looking people, but the differences in other characteristics are generally very small.

Columns (5) and (6) focus on the comparison between the two genders. Males and females have similar approval rates and interest rates, and the differences in collateral and interest rate adjustability are also trivial. Furthermore, males are older, more likely to be married or be party members, and own a home, but are also more likely to live in rural areas and have an agricultural Hukou. Overall, it is hard to say which gender group is more creditworthy based on these characteristics.

Insert Table 2 here

Columns (1) to (4) of Table 2 report the major variables used in analyzing mortgage loan markets for different sets of groups. The chances of good-looking males and females' applications being approved are 6 and 7 percentage points significantly higher than their bad-looking counterparts respectively, while the gaps in a interest rates are 1.3 and 0.2 percentage points respectively, and the gaps in down payment ratio are trivial. Moreover, the chance that a loan application was approved is much larger than that for commercial/industrial loan markets, reflecting the safety of mortgage loans, since a house or apartment as collateral has a pretty stable value.

Again, good-looking men and women are 3 and 5 years younger than bad-looking men and women, which confirms the validity of our beauty measure. Good-looking people are better educated and more healthy, are more likely to be communist party members, have a higher family income, are less likely to live in rural areas, and are less likely to have an agricultural Hukou, which are probably related to better credentials. However, good-looking people are younger and are less likely to be married, which are probably related to worse credentials. Again, Overall, good-looking people are highly significantly older than bad-looking people, but the differences in other characteristics are generally limited.

Columns (5) and (6) show the differences between the two gender groups. We notice that males are less likely to be granted a loan and face a higher interest rate than females. Furthermore, males are older, more likely to be married or be party members, and are less likely to be retired, but are less educated, have a lower family income, are more likely to live in rural areas and have an agricultural Hukou. Overall, it is hard to determine which gender group is more creditworthy based on these characteristics.

6 Results: Commercial/industrial loans

6.1 Main Results

As a reminder, our prediction is that costly discrimination resulting from loan officers' prejudice will tend to decline in a more competitive bank loan market. Indeed, if the group of less attractive people or a certain gender has a higher default rate on average and hence is less likely to obtain a loan or faces a higher interest rate, more market competition would probably not reduce these productive lending practices (in that case they are no longer prejudice). This is in the same spirit as the studies on labor markets, such as Ashenfelter and Hannan (1986) and Black and Strahan (2001). The prejudice might be related to visual pleasure, but it can also be related to the willingness to extract a signal or "soft information." For example, in labor markets an employer may see a certain racial group as being less productive and hence pays these workers a lower wage than others. If this group of workers actually has a similar productivity to other groups', the employer's decision leads to costly discrimination. Therefore, we consider these kinds of signals or "soft information" to be results of prejudice. This is in line with Cavalluzzo et al. (2002) and Ravina (2012).

For commercial/industrial loans, we report results using the community-level HHI or the HHI residual from a regression of HHI on the community type (rural area, small town, small city, median city and big city). In columns (1) to (4) of Table 3, we find that there probably exists favoritism toward good-looking people in loan approval decisions. Specifically, in a more concentrated market, i.e., those with a higher HHI, good-looking people are significantly more likely to obtain a loan. For example, with a one-standard-deviation increase in community-level HHI (about 0.3), the chance that a good-looking male will obtain a loan is 20 percentage points higher compared with an average-looking male. The magnitude of this difference is very similar among females.

Columns (5) and (6) show that males are more likely to obtain a loan in a more concentrated market. One possible explanation is that women are probably considered to have weaker business skills than males, perhaps because there are many more successful male entrepreneurs. Now we consider the beauty or gender premium at the average level of market concentration. When setting HHI equal to its mean value of 0.4, we find that good-looking females are significantly more likely to obtain a loan, though neither the differences between good-looking males, bad-looking males, and average-looking males, nor the difference between the two gender groups is significant.

Insert Table 3 here

The upper part of Table 4 shows that bad-looking females pay a significantly higher interest rate in a more concentrated market. For example, with a one-standard-deviation increase in HHI, the interest rate faced by a bad-looking woman is 5 percentage points higher than that faced by an average-looking woman. The differences between other groups are relatively small and insignificant. This suggests that favoritism or discrimination in commercial/industrial loans is mainly through approval/reject decisions and, to a lesser extent, the interest rate. This fact is consistent with Cavalluzzo et al. (2002), who find that African Americans and women are less likely to obtain a loan but are not charged a significantly higher interest rate in a more concentrated commercial/industrial loan market. They notice that Stiglitz and Weisss adverse selection hypothesis can explain this. That is, in relatively risky commercial/industrial loan markets, the approval decision is probably a better screening mechanism. A high interest rate may encourage risk-taking behavior, and hence is not always in lenders' interests. Moreover, our conversations with loan officers suggest the following practice: interest rates are usually set by the provincial offices and probably the headquarters, which makes it relatively harder to adjust the interest rate than to make approval/rejection decisions.

Again, we consider the beauty or gender premium at the average level of market concentration. Setting HHI equal to its mean, we find that bad-looking males and females pay 3 and 4 percentage points lower interest rates respectively, compared to average-looking males and females, and these differences are highly significant. Males also pay a lower interest rate than females, though this difference is not significant.

Overall, using the HHI or HHI residual as the measure of market concentration gives very similar results. This is perhaps not surprising. Indeed, a market of great economic importance is usually more attractive to firms, and hence there should be more applications for establishing new branches. These differences in economic levels can result in the differences in approval rates and credit terms across the country. For example, an area with a higher credit risk would be compensated by a lower approval rate and a higher interest rate. However, differences in economic levels should not lead to large differences in approval rates and credit terms among different demographic groups in the same area, except via the correlation with market concentration.

Insert Table 4 here

6.2 Interpretation and Subsample Analysis

Here we provide further interpretations of our findings through two sets of subsample analysis. Both of them support the interpretation based on a signal of quality.

The literature on beauty usually discusses three channels unrelated to real productivity: visual pleasure, the confidence channel, and verbal communication channels (Mobius and Rosenblat, 2006; Gallego, 2015). That is, not only can good-looking people bring visual pleasure, but they can also be more confident, and be more willing or able to communicate verbally. In other words, bank loan officers probably see confidence or communication skills as a signal of better quality, though these features are not necessarily related to higher productivity. In this sense, we can say the beauty premium or gender premium is a kind of prejudice. As opposed to borrowers of mortgages, entrepreneurs' collateral is usually much less liquid and has greater volatility in value. Therefore, it is necessary for bank loan officers to learn more about the borrowers.

Although the 2013 CHFS does not contain questions directly related to confidence or oral communication, we can elicit the possible channels in an indirect way. We divide samples based on age 35, which is a typical cutoff for visual pleasure, though using 40 as the cutoff age gives similar results. If we document that bias toward good-looking people is concentrated among the age group younger than 35, this beauty premium probably mainly results from visual pleasure, and from confidence to a lesser extent. However, if bias is concentrated among the age group older than 35, it is probably more likely to result from enhanced willingness or skills in verbal communication. We run the subsample regressions with the approval decision as the dependent variable, because the sample size for interest rate is smaller.

Insert Table 5 here

Table 5 presents the results. We find that significant favoritism toward good-looking males is concentrated among the age group older than 35. The situation is similar for good-looking females, though this is insignificant partly due to a smaller sample size. Our explanation is that commercial/industrial loans are risky, and hence loan officers give less weight to visual pleasure, but more weight to the perceived higher quality based on better verbal communication. Of course, we acknowledge the limitation of this judgment. This result is in stark contrast to that for mortgage loans, as we will discuss later.

Similarly, we also find that the favoritism toward males relative to females is concentrated in the age group older than 35. This is also consistent with the explanation of a signal regarding borrowers' quality. There are many more successful older male entrepreneurs than older female entrepreneurs, and therefore it is possible for loan officers to see older male entrepreneurs as being more reliable. On the other hand, it is rare to see either successful young male entrepreneurs or young female entrepreneurs, and hence a young male entrepreneur is not more trustable than young female entrepreneurs.

In the lower part of Table 4, we further separate the samples based on whether or not collateral was required. As we find in the websites of several banks, the types of collateral are various and can be any valuable assets, such as machines and inventories. These assets usually are not very liquid, and they are also more volatile in value than homes. It is possible that more favoritism or discrimination exists for loans without collateral because, in these cases, it is harder to verify the credentials of borrowers. We find that this is, indeed, true. For example, for loans without collateral, good-looking males pay a significantly lower interest rate compared to average-looking males in a more concentrated market, whereas for loans with collateral, we do not observe such a differential. Indeed, in the case without collateral, a loan officer may try to obtain a signal on borrowers' credentials. Because the size of the female subsample is small, we do not conduct this exercise for it.

Therefore, both the findings regarding physical attractiveness and gender support the interpretation of a signal. However, in a more competitive market, it is less likely for loan officers to use this signal. This implies that the signal is not effective in revealing the real credentials of borrowers. This is consistent with Becker's costly discrimination. It should be noted that this is different from statistical discrimination. Statistical discrimination is toward less creditworthy groups of borrowers, and hence will not decline in a more competitive market.

Starting in 2000, China's bank industry has experienced large-scale deregulation, with many markets witnessing an explosive growth in the number of different banks and the number of bank branches. Many new loan officers have very limited experience in dealing with borrowers, and they do not have Dun & Bradstreet credit scores or FICO scores to check. Therefore, they probably choose borrowers based on some simple demographic characteristics. Although our dataset does not contain information on the characteristics of loan officers, future studies with suitable data can test whether experienced loan officers perform differently from new loan officers.

7 Results: Mortgage loans

7.1 Main Results

In mortgage loan markets, home as the collateral is very safe, it should be less likely for loan officers to see physical attractiveness and gender as a signal for quality, whereas visual pleasure should be more likely to affect lenders' decisions. If this is the case, we should observe the favoritism is concentrated in younger groups, such as the age group younger than 35. As we talk with bank managers, being a loan officer needs much overtime work and business trips, which makes men are much more likely to be loan officers. Given that most loan officers are male, we probably observe that females, especially young good-looking females, are preferred in a more concentrated market. Our empirical findings confirm this prediction.

Insert Table 6 here

As shown in Table 6 and 7, we cannot find favoritism toward good-looking males. This is reasonable, since to male loan officers, a good-looking male borrower should not bring more visual pleasure than a plain male borrower. Although we do not find a beauty premium for the whole female sample, this is not surprising because the female sample contains both old and young females, and hence the results for the whole sample mask the pattern for the younger sample. A subsample analysis in Table 8 shows that young good-looking females are significantly more likely to obtain a loan in more concentrated markets, and young bad-looking females are less likely to obtain a loan and pay a much higher interest rate in more concentrated markets compared to average-looking females. This suggests the importance of visual pleasure in these markets as we expect.

The most striking findings involve gender discrimination. In stark contrast to most findings in labor markets, we find that women are much more likely to obtain a loan and pay a significantly lower interest rate in a more concentrated market. For example, as shown in Table 6 and 7, with a one-standard-deviation increase in HHI (0.04), females are 0.5 percentage points more likely to obtain a loan, and pay 0.3 percentage points lower interest rate. These gaps are large since the mean differences between males and females are 3 and 0.4 percentage points respectively.

Insert Table 7 here

Furthermore, we set HHI to its mean (0.12 for loan approval and 0.14 for the interest rate and down payment ratio). We find that good-looking males and females are 4 and 0.2 percentage points more likely to obtain a loan respectively, while men are 1.4 percentage points less likely to obtain a loan compared to women. Moreover, bad-looking males face a significantly higher interest rate, and males pay a higher interest rate at the mean HHI.

To explain these findings, we note that there is no inherent disadvantage for female borrowers in mortgage loan markets. Given the relative majority of male bank loan officers, the preference for females is not that surprising. By contrast, one major concern for employers considering a female job-seeker is that women usually spend plenty of time in bearing and raising children, which might reduce their productivity. This does not pose a problem in bank loan markets. In commercial/industrial loan markets, women are probably considered to have weaker business skills than males, perhaps because there are many more successful male entrepreneurs. However, this is not a problem in mortgage loan markets as well.

This fact is also inconsistent with Cavalluzzo et al.'s (2002) finding on the female disadvantage using the Survey of Small Business finances in the United States. Because the studies on costly discrimination based on market structure usually use the Surveys of Small Business finances, and for this reason they analyze only commercial/industrial loans, our findings on a female premium in mortgage loan markets provide a whole picture on this topic.

7.2 Interpretation and Subsample Analysis

Similar to the previous section, we also divide the samples based on the cutoff of age 35 in Table 8. Interestingly the results are in stark contrast to those for commercial/industrial loans. Young good-looking females are significantly more likely to obtain a loan in more concentrated markets, and young bad-looking females are less likely to obtain a loan and face a much higher interest rate in more concentrated markets compared to average-looking females. This suggests that visual pleasure could explain the favoritism toward good-looking females. On the other hand, visual pleasure does not seem to be important for loan officers when dealing with either old or young male applicants. This result is also reasonable because most loan officers are male.

In columns (5) and (6), we find that the discrimination against males is concentrated in the age group younger than 35. This also suggests that young females are more likely to induce visual pleasure experience than young males.

Compared with commercial/industrial loan markets, in a period with soaring housing prices, home as collateral is very safe. Therefore, loan officers might give less weight to verbal communication or other attributes serving as a signal and enjoy more from visual pleasure.

Insert Table 8 here

To this point, we notice that women usually spend more time on searching, so a natural question is whether the observed advantage of women in mortgage loans should be attributed to more intensive search. We argue that this is not possible in this study. Search intensity is related to its opportunity costs, which is controlled when including education, income and other hard qualities. Moreover, although it is possible that women derive additional utility from shopping clothes, it is hard to believe that they also enjoy spending more time in a bank. The explanation of opportunity costs is also not compatible with the advantage of men in commercial/industrial loans.

8 Discussion

Bank loan terms are usually set by provincial offices and probably the headquarters, and hence are usually considered much more standard than labor contracts, especially within the same bank in a certain province. Moreover, the conditions or requirements can usually be found in the brochures at bank branches or online and are therefore quite transparent. However, our findings imply that bank loan officers still have great freedom in choosing borrowers.

Our explanation is that there are severe asymmetries of information in bank loan markets (Stiglitz and Weiss, 1981), and thus it is difficult for banks to set a rigorous standard for their loan officers. Therefore, loan officers are granted great autonomy in selecting qualified borrowers and setting corresponding credit terms. By dealing with preferred but not more creditworthy groups, loan officers can probably receive private benefits while impose a higher cost on their banks. On the other hand, many borrowers might not understand complex financial products very well, and may therefore rely on the explanations provided by bank loan officers.

Our findings also suggest the importance to analyze different loan markets separately. Commercial/industrial loans are usually riskier than mortgage loans, and hence bank loan officers probably want to extract a signal regarding borrowers' credentials from their physical attractiveness or gender, even if the signal is not really associated with better quality. On the other hand, mortgage loans are pretty safe, and hence it is more likely for loan officers to enjoy visual pleasure.

Our paper is designed to elevate the understanding of costly discrimination in bank loan markets, an underexplored field. Therefore, our new empirical methods, unique data, regression results, and explanations generally achieve this purpose.

9 Conclusion

This paper analyzes costly discrimination related to physical attractiveness and gender in bank loan markets using a market structure-based method. The rationale is that high market concentration increases the degree of favoritism or discrimination, which is confirmed by empirical evidence based on several unique datasets and online maps containing information about market structure and household borrowing. We document evidence that in a more concentrated commercial/industrial loan market, compared with average-looking people, good-looking people are more likely to obtain loans, and face lower interest rates, while the converse is true for bad-looking people. Moreover, our results show that males have an advantage over females.. On the other hand, in contrast to most findings in labor markets, we find that females have a strong advantage in a more concentrated mortgage loan market. Although the disadvantage of bearing and raising children cannot be easily disentangled from discrimination in labor markets, it does not pose an issue in mortgage loan markets and hence explains such findings. The consistent pattern shown in various regressions suggests the existence of taste-based discrimination in bank loan markets.

Discrimination in bank loan markets is not widely discussed by economists, perhaps due to limited data access. Compared to Western countries, anti-discrimination laws are either nonexistent or weakly enforced in many developing countries including China. Our paper therefore contributes to the understanding of discrimination in bank loan markets, and can potentially lead to better policies in combating such discrimination.

References

[1] Ai, Chunrong, and Edward Norton (2003). "Interaction Terms in logit and probit models," *Economics Letters*, 80(1): 123-129.

[2] Akhavein, Jalal, Scott Frame and Lawrence White (2005). "The Diffusion of Financial Innovations: An Examination of the Adoption of Small Business Credit Scoring by Large Banking Organizations ," *Journal of Business*, 78(2): 577-596.

[3] Andreoni, James, and Ragan Petrie (2008). "Beauty, Gender and Stereotypes: Evidence from Laboratory Experiments," *Journal of Economic Psychology*, 29(1): 73-93.

[4] Ashenfelter, Orley, and Timothy Hannan (1986). "Sex Discrimination and Product Market Competition: The Case of the Banking Industry," *Quarterly Journal of Economics*, 101(1): 149-174.

[5] Arrow, Kenneth (1973). "The Theory of Discrimination," in O. Ashenfelter and A. Rees, ed: *Discrimination in Labor Markets*, Princeton University Press.

[6] Bates, Timothy (1971). "Black Capitalism: A Quantitative Analysis," New York: Praeger.

[7] Bates, Timothy (1971). "Commercial Bank Financing of White and Black-owned Small Business Startups," *Quarterly Review of Economics and Business*, 31: 64-80.

[8] Becker, Gary (1957). "The Economics of Discrimination," University of Chicago Press.

[9] Berger, Allen, Anthony Saundersc, Joseph Scalised, and Gregory Udell (1998). "The Effects of Bank Mergers and Acquisitions on Small Business Lending," *Journal of Financial Economics*, 50(2): 187-229.

[10] Berger, Allen, and Scott Frame (2006). "Small Business Credit Scoring and Credit Availability," *Journal of Small Business Management*, 45(1): 5-22.

[11] Berger, Allen, Scott Frame, and Nathan Miller (2005). "Credit Scoring and the Availability, Price, and Risk of Small Business Credit," *Journal of Money, Credit and Banking*, 37(2): 191-222.

[12] Berger, Allen, and Gregory Udell (1995). "Relationship Lending and Lines of Credit in Small Firm Finance ," *Journal of Business*, 68(3): 351-381.

[13] Berkovec, James, Glenn Canner, Stuart Gabriel, and Timothy Hannan (1998). "Discrimination, Competition, and Loan Performance in FHA Mortgage Lending," *Review of Economics and Statistics*, 80(2): 241-250.

[14] Black, Sandra, and Philip Strahan (2001). "The Division of Spoils: Rent-Sharing and Discrimination in a Regulated Industry," *American Economic Review*, 91(4): 814-831.

[15] Brevoort, Kenneth and Timothy Hannan (2006). "Commercial Lending and Distance: Evidence from Community Reinvestment Act Data," *Journal of Money, Credit and Banking*, 38(8): 1991-2012.

[16] Cavalluzzo, Ken, Linda Cavalluzzo(1998). "Market Structure and Discrimination: The Case of Small Businesses," *Journal of Money, Credit and Banking*, 30(4): 771-792.

[17] Cavalluzzo, Ken and Linda Cavalluzzo, and John Wolken (2002). "Competition, Small Business Financing, and Discrimination: Evidence from a New Survey," *Journal of Business*, 75(4): 641-679.

[18] Chong, Terence, Liping Lu, and Steven Ongena (2013). "Does Banking Competition Alleviate or Worsen Credit Constraints Faced by Small- and Medium-sized Enterprises? Evidence from China," *Journal of Banking & Finance*, 37(9): 34123424.

[19] Diamond, Douglas (1991). " Monitoring and Reputation: The Choice between Bank Loans and Directly Placed Debt ," *Journal of Political Economy*, 99(4): 689-721.

[20] Dong, Yan (2016). "Bank Development and Industry Structure," working paper.

[21] Duarte, Jefferson, Stephan Siegel and Lance Young (2012). "Trust and Credit: The Role of Appearance in Peer-to-peer Lending," *Review of Financial Studies*, 25(8): 2455-2484.

[22] Duca, John, and Stuart Rosenthal (1994). "Do Mortgage Rates Vary Based on Household Default Characteristics? Evidence on Rate Sorting and Credit Rationing," *Journal of Real Estate Finance and Economics*, 8(2): 99-113.

[23] Frame, Scott , Aruna Srinivasan, and Lynn Woosley (2001). " The Effect of Credit Scoring on Small-Business Lending ," *Journal of Money, Credit and Banking*, 33(3): 813-825.

[24] Freixas, Xavier and Jean-Charles Rochet (2008). "Microeconomics of Banking," 2nd Edition, MIT press.

[25] Gallego, Francisco (2015). "What's Behind Her Smile? Looks, Self-Esteem, and Labor Market Outcomes," working paper.

[26] Gan, Li (2016). "Migration and Urbanization in China," presented at the 2016 China meeting of Econometric Society.

[27] Gan, Li, Zhichao Yin, Nan Jia, Shu Xu and Shuang Ma (2013). "Data You Need to Know about China," Springer.

[28] Goldberg, Matthew (1982). "Discrimination, Nepotism, and Long-Run Wage Differentials," *Quarterly Journal of Economics*, 97(2): 307-319.

[29] Guiso, Luigi, and Paolo Sodini (2013). "Household Finance: An Emerging Field," in *Handbook of the Economics of Finance*, Vol.2: 1397-1532.

[30] Hamermesh, Daniel (2011). "Beauty Pays," Princeton University Press.

[31] Hamermesh, Daniel, and Jason Abrevaya (2013). "Beauty is the Promise of Happiness?" *European Economic Review*, 64: 351-368.

[32] Hamermesh, Daniel, and Jeff Biddle (1998). "Beauty, Productivity and Discrimination: Lawyers' Looks and Lucre," *Journal of Labor Economics*, 16(1): 172-201.

[33] Hamermesh, Daniel, and Jeff Biddle (1994). "Beauty and The Labor Market," *American Economic Review*, 84 (5): 1174-1194.

[34] Lin, Huidan (2011). "Foreign Bank Entry and Firms Access to Bank Credit: Evidence from China," *Journal of Banking & Finance*,35: 1000-1010.

[35] Lin, Xiaochi and Yi Zhang (2009). "Bank Ownership Reform and Bank Performance in China," *Journal of Banking & Finance*,33(1): 20-29.

[36] Milgrom, Paul, and Sharon Oster (1987). "Job Discrimination, Market Forces and the Invisibility Hypothesis," *Quarterly Journal of Economics*, 102(3): 453476.

[37] Mitchell, Karlyn, and Douglas Pearce (2009). "Lending Technologies, Lending Specialization, and Minority Access to Small-business Loans," *Small Business Economics*, 37: 277-304.

[38] Mobius, Mark, and Tanya Rosenblat (2006). "Why Beauty Matters," *American Economic Review*, 96(1): 222-235.

[39] Olivola, Christopher Y., and Alexander Todorov (2010). "Fooled by First Impressions? Reexamining the Diagnostic Value of Appereance Based Inferences," *Journal of Experimental Social Psychology*, 46 (2): 315-324.

[40] Pencavel, John (1998). " Assortative Mating by Schooling and the Work Behavior of Wives and Husbands," *American Economic Review Papers and Proceedings*, 88(2): 326-329.

[41] Petersen, Richard (1981). "An Investigation of Sex Discrimination in Commercial Banks' Direct Consumer Lending," *Bell Journal of Economics*, 12(2): 547-561.

[42] Petersen, Mitchell and Raghuram Rajan (1994). "The Benefits of Lending Relationship: Evidence from Small Business Data," *Journal of Finance*, 49(1): 3-37.

[43] Petersen, Mitchell and Raghuram Rajan (2002). "Does Distance Still Matter? The Information Revolution in Small Business Lending," *Journal of Finance*, 57(6): 2533-2570.

[44] Pope, Devin and Justin Sydnor (2011). "What's in a Picture? Evidence of Discrimination from Prosper.com," *Journal of Human Resources*, 46(1): 53-92.

[45] Phelps, Edmund (1972). "The Statistical Theory of Racism and Sexism," *American Economic Review*, 62 (4): 659-661.

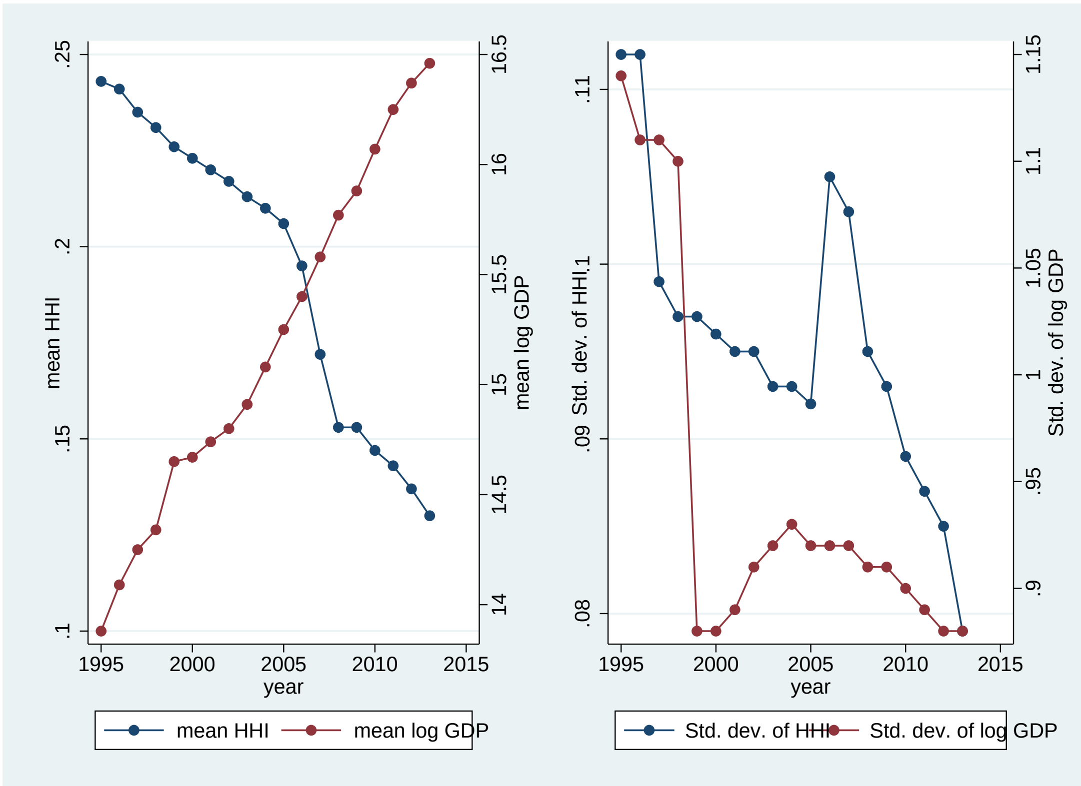
[46] Ravina, Enrichetta (2012). "Love & Loans: The Effect of Beauty and Personal Characteristics in Credit Markets," working paper.

[47] Rose, Peter, and Sylvia Hudgins (2012). "Bank Management & Financial Services," 9ed, McGraw-Hill Education.

[48] Stiglitz, Joseph, and Andrew Weiss (1981). "Credit Rationing in Markets with Imperfect Information," *American Economic Review*, 71(3): 393-410.

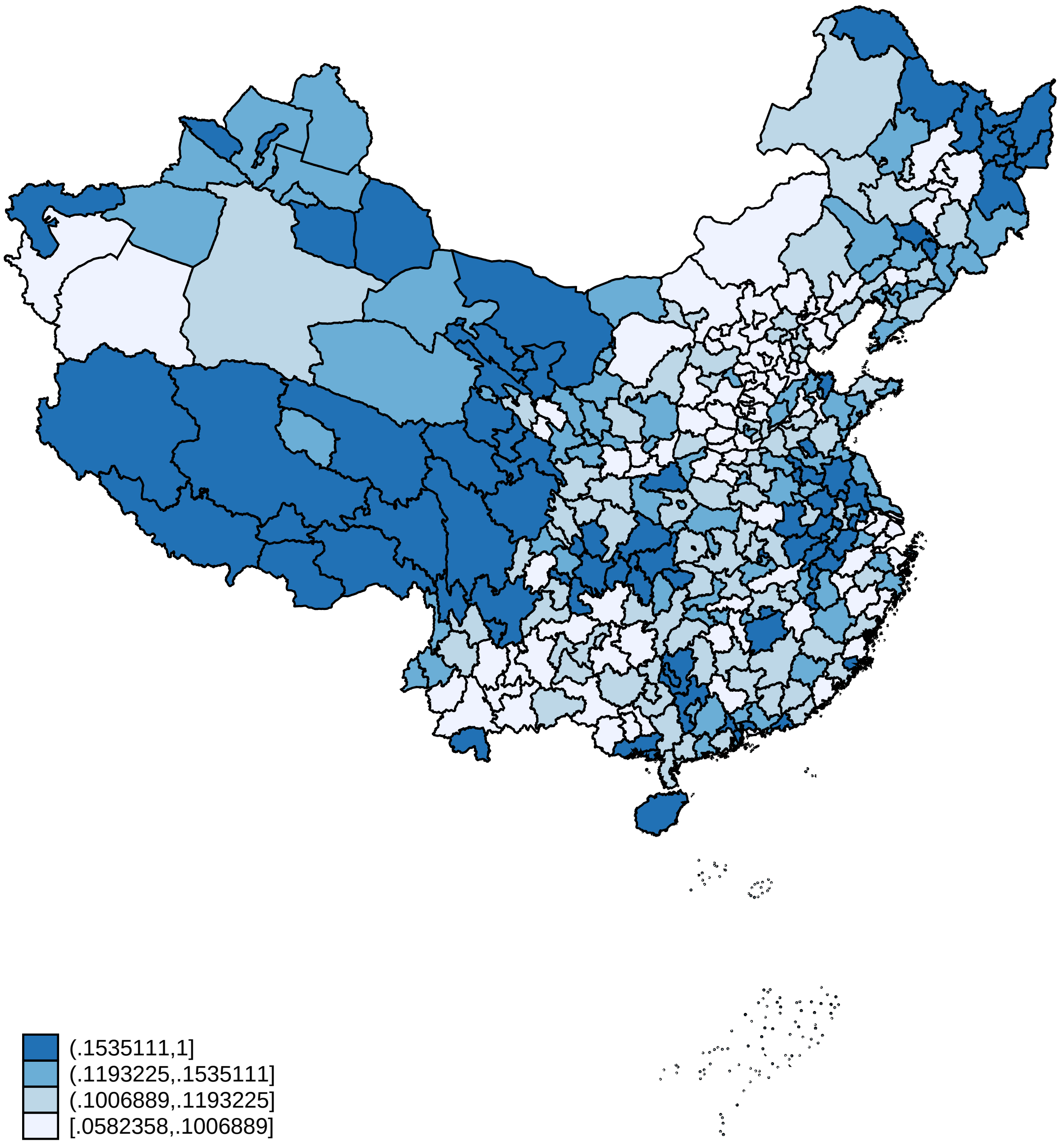
[49] Zhang, Chunni, Qi Xu, Xiang Zhou, Xiaobo Zhang, and Yu Xie (2014). "Are Poverty Rates Underestimated in China? New evidence from Four Recent Surveys," *China Economic Review*, 31: 410-425.

Figure 1: Mean and standard deviation of prefecture-level Herfindahl index (HHI) and logged GDP by year



Note: the left graph plots the mean of prefecture-level HHI and logged GDP by year, and the right graph plots the standard deviation of prefecture-level HHI and logged GDP by year. When calculating HHI, we use the number of branches belonging to a bank dividing by the total number of branches in this area as the market share of this bank, and obtain the sum of the squared shares of these banks. Data source: China Banking Regulatory Commission (CBRC) and China City Statistical Yearbooks.

Figure 2: Prefecture-level average HHI during 2009-2013 in mainland China

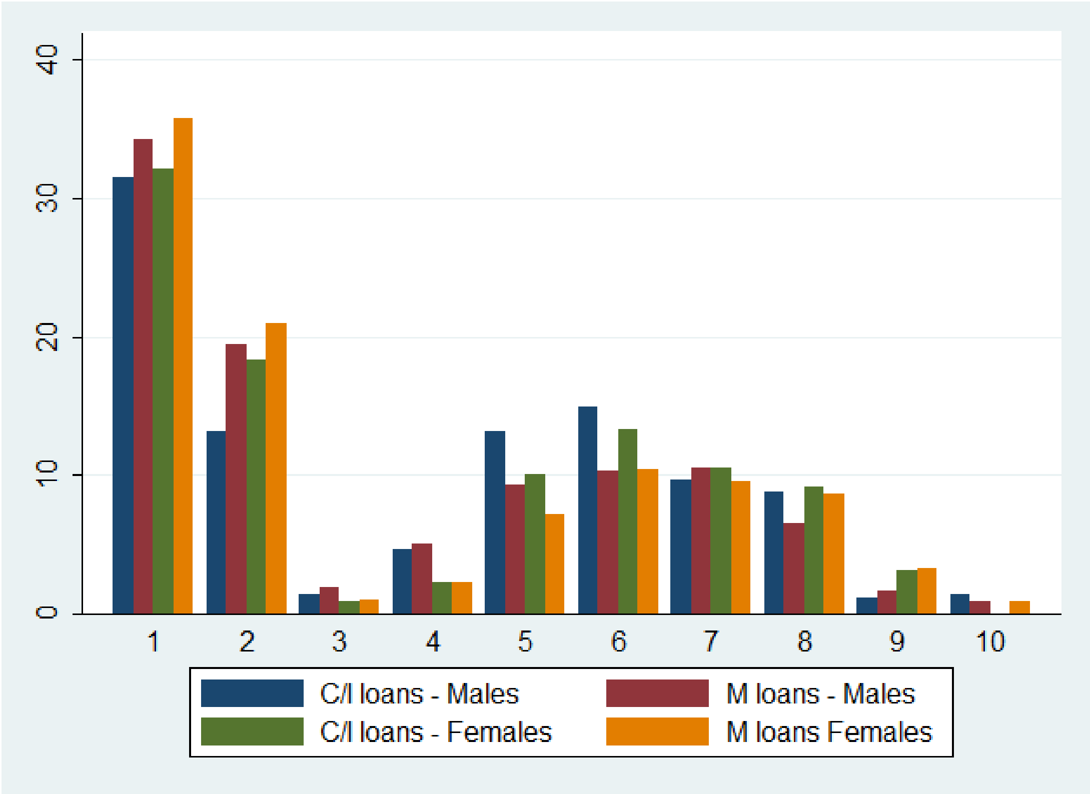


Note: the northeastern and western parts have a higher market concentration level on average, whereas the northern and southeastern parts have a lower market concentration level on average. However, we can find large variation in a relatively small region. When calculating HHI, we use the number of branches belonging to a bank dividing by the total number of branches in this area as the market share of this bank, and obtain the sum of the squared shares of these banks. Data source: China Banking Regulatory Commission (CBRC).

Figure 3: Example: the map of Xinyuan community, Beijing and bank branches nearby

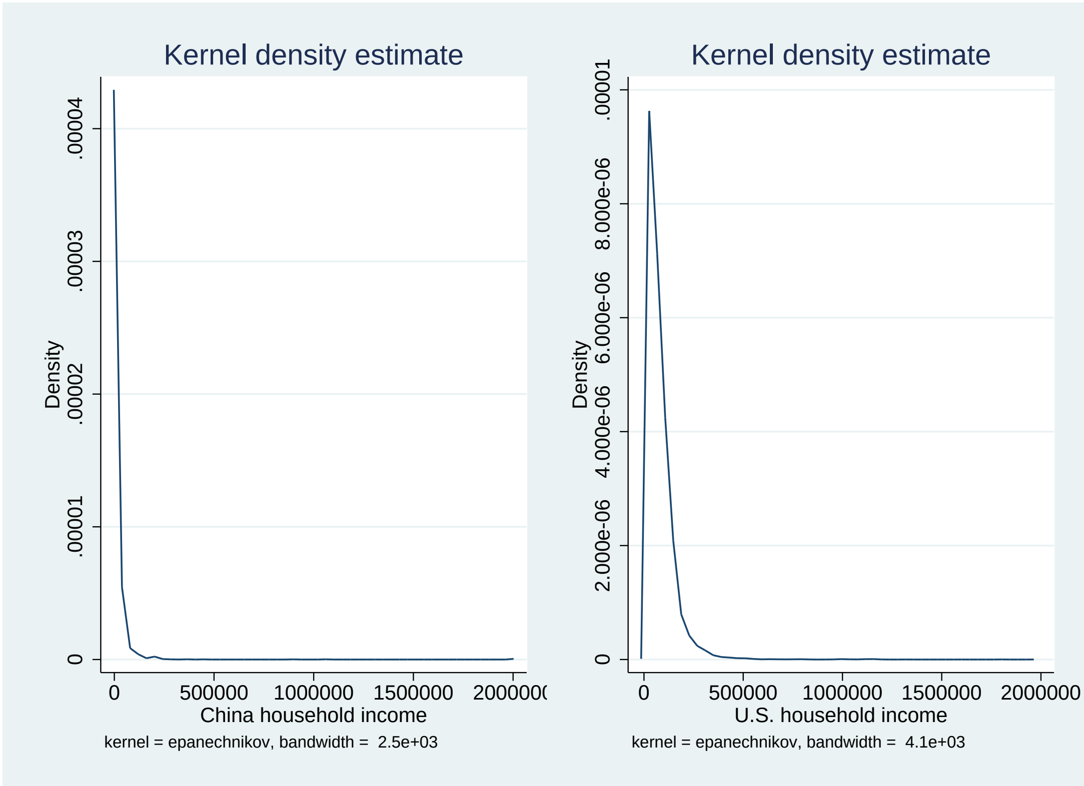
Note: in this example, we use the Baidu Maps (http://map.baidu.com/), an online map search engine like Google Maps but which has a higher precision for China's locations, to search for the bank branches around the community office of Xinyuan community in Beijing. The procedure for constructing the community-level market concentration is the following: we enter the address of a community office on Baidu Maps, then search "Yinhang (bank in Chinese)" in the "Locations Nearby" and can find the names of bank branches within 2 kilometers around the community office. Although the search results also include ATMs, we do not keep them because they cannot grant a loan.

Figure 4: Beauty ratings by gender and market



Note: The distributions of beauty ratings. The unit of the vertical axis is the share of the sampled individuals with each rating in percentage points. The ratings range from 1 to 10 with a lower rating representing a worse-looking individual. C/I loans and M loans indicate the two major samples we use to analyze commercial/industrial loan markets and mortgage loan markets, respectively. Data source: 2013 China Household Finance Survey.

Figure 5: A comparison of income distributions in China and the U.S.



Note: The left graph is the income distribution for China, from 2011 China Household Finance Survey; The right graph is the income distribution for the United States, from 2011 Current Population Survey March supplement. The large right skewness is visible for China's income distribution, while the density declines to 0 as the family income is close to 0 for the U.S. income distribution.

Table 1: Descriptive statistics: commercial/industrial loan markets

	GL Male	BL Male	t	GL Female	BL Female	t	Male	Female	t
Approved	0.84	0.85	-0.2	0.96	0.83	1.8	0.83	0.85	-0.8
Interest rate (percentage)	4.25	7.29	-3.5	3.66	6.96	-2.3	6.35	6.27	0.2
With collateral	0.29	0.29	0.0	0.11	0.29	-1.9	0.26	0.25	0.2
Interest rate adjustable	0.34	0.34	0.1	0.4	0.25	1.2	0.34	0.30	0.7
HHI (community)	0.35	0.41	-1.1	0.32	0.35	-0.4	0.42	0.37	2.1
Age	40.9	43.9	-1.7	36	39.8	-1.8	44.7	40.9	4.4
Ethnic Han	0.98	0.87	2.2	1	0.9	1.7	0.92	0.94	-0.5
Educational attainment	11.9	10.9	1.7	12.3	11.2	1.4	10.8	11.3	-1.9
Marital status	0.92	0.89	0.6	0.78	0.86	-1.1	0.91	0.87	1.8
Healthy	0.94	0.92	0.5	0.89	0.93	-0.7	0.91	0.90	0.4
Party member	0.23	0.18	0.8	0.04	0.05	-0.4	0.18	0.08	3.5
Home ownership	0.81	0.76	0.7	0.70	0.73	-0.2	0.81	0.74	1.9
Rural status	0.27	0.36	-1.2	0.19	0.21	-0.3	0.39	0.24	3.8
Agri Hukou	0.44	0.61	-2.2	0.67	0.51	1.5	0.61	0.51	2.4
N	48	189		27	110		426	220	
M	29	107		13	48		230	96	

Note: Descriptive statistics for the mean values of different beauty and gender groups in commercial/industrial loan markets. N is the number of observations for regressions with bank loan approval as the dependent variable, and M is the number of observations for regressions with credit terms such as interest rate as the dependent variable. t is the t statistic for the hypothesis that the mean difference is equal to 0. HHI is the average community-level Herfindahl index during 2009-2013. Data source: 2013 China Household Finance Survey and China Banking Regulatory Commission (CBRC).

Table 2: Descriptive statistics: mortgage loan markets

	GL Male	BL Male	t	GL Female	BL Female	t	Male	Female	t
Approved	0.96	0.90	2.6	0.99	0.92	3.0	0.90	0.93	-2.8
Interest rate (percentage)	4.87	6.18	-3.5	5.21	5.45	-0.7	5.72	5.30	2.3
Down payment ratio	0.41	0.42	-0.5	0.42	0.42	0.0	0.42	0.42	0.2
Public housing fund loan	0.62	0.74	-3.4	0.57	0.66	-1.9	0.73	0.65	5.0
HHI (prefecture)	0.12	0.11	4.4	0.13	0.11	4.4	0.12	0.12	0.9
Age	42.2	45.6	-3.6	38.6	43.6	-4.0	45.8	43.1	5.8
Ethnic Han	0.98	0.90	3.7	0.96	0.93	1.5	0.91	0.93	-1.6
Educational attainment	13.4	12.1	4.0	14.5	12.2	5.7	11.7	12.3	-3.7
Marital status	0.90	0.92	-1.2	0.76	0.84	-2.0	0.93	0.82	9.3
Healthy	0.93	0.88	1.9	0.92	0.87	1.7	0.87	0.86	1.0
Party member	0.35	0.26	2.7	0.18	0.13	1.6	0.26	0.15	6.9
Log family income	8.44	6.96	3.5	8.96	6.71	4.3	6.91	7.01	-0.4
Retired	0.08	0.08	0.2	0.10	0.14	-1.2	0.07	0.13	-5.3
Rural status	0.16	0.31	-4.3	0.05	0.21	-4.3	0.34	0.19	8.4
Agri Hukou	0.29	0.42	-3.4	0.23	0.34	-2.4	0.46	0.33	6.8
N	197	1168		129	565		2185	1007	
M	95	424		63	211		822	381	

Note: Descriptive statistics for the mean values of different beauty and gender groups in mortgage loan markets. N is the number of observations for regressions with bank loan approval as the dependent variable, and M is the number of observations for regressions with credit terms such as interest rate and down payment ratio as the dependent variables. t is the t statistic for the hypothesis that the mean difference is equal to 0. HHI is the average prefecture-level Herfindahl index during 2009-2013. Data source: 2013 China Household Finance Survey and China Banking Regulatory Commission (CBRC).

Table 3: Competition and commercial/industrial loan approval

Dep. variable:	Male		Female		Male & Female	
Application was approved	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	0.0357	0.668**	0.596**	0.646**		
	(0.153)	(0.323)	(0.267)	(0.362)		
Bad looks*HHI	-0.110	-0.241	0.160	0.219		
	(0.111)	(0.184)	(0.259)	(0.292)		
Male*HHI					0.232**	0.338**
					(0.101)	(0.137)
Good looks (at mean HHI)	0.022	0.046	0.247***	0.211**		
	(0.058)	(0.053)	(0.086)	(0.088)		
Bad looks (at mean HHI)	0.070	0.077	-0.033	-0.032		
	(0.044)	(0.046)	(0.068)	(0.066)		
Male (at mean HHI)					-0.012	-0.014
					(0.030)	(0.029)
N	423	420	218	215	646	640
Adj R-sq	0.072	0.071	0.052	0.036	0.080	0.068

Note: HHI is the average community-level Herfindahl index in 2011 (odd columns), and the HHI residual from a regression of HHI on the community type (rural area, small town, small city, median city and big city) (even columns); mean HHI=0.4, and mean HHI residual=0. Good looks (at mean HHI) is the marginal effect of being good-looking at the mean HHI; similarly for Bad looks (at mean HHI) and Male (at mean HHI). Other covariates include an indicator for agricultural Hukou, rural status, home ownership, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, their interaction terms with HHI, HHI (main effect), and province fixed effects. Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 4: Competition and commercial/industrial loan interest rate

Dep. variable:	Male		Female		Male & Female	
Interest rate	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	-3.941	-3.222	-1.368	21.63		
	(2.691)	(4.692)	(7.108)	(13.40)		
Bad looks*HHI	-0.256	-1.687	11.29***	16.56**		
	(1.751)	(2.206)	(3.722)	(7.316)		
Male*HHI					1.840	2.556
					(1.590)	(1.611)
Good looks (at mean HHI)	-0.695	-0.349	0.786	-0.397		
	(0.836)	(0.844)	(2.481)	(1.663)		
Bad looks (at mean HHI)	3.197***	3.108***	4.130***	3.645***		
	(1.017)	(0.957)	(1.427)	(1.195)		
Male (at mean HHI)					-0.428	-0.602
					(0.687)	(0.734)
N	225	223	95	93	321	317
Adj R-sq	0.141	0.143	0.238	0.243	0.103	0.092

Dep. variable:	Male		Male & Female	
	Collateral	No Collateral	Collateral	No Collateral
Interest rate	(1)	(2)	(3)	(4)
Good looks*HHI	-1.122	-10.730*		
	11.570	(5.723)		
Bad looks*HHI	3.254	-3.164		
	6.461)	(2.366)		
Male*HHI			-5.525	3.362
			(4.586)	(2.673)

Note: HHI is the community-level Herfindahl index in the year the loan of the largest amount was granted (odd columns of the upper part), and the HHI residual from a regression of HHI on the community type (rural area, small town, small city, median city and big city) (even columns of the upper part); mean HHI=0.4, and mean HHI residual=0. Good looks (at mean HHI) is the marginal effect of being good-looking at the mean HHI; similarly for Bad looks (at mean HHI) and Male (at mean HHI). Other covariates include an indicator for agricultural Hukou, rural status, home ownership, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, an indicator for a loan with collateral, an indicator for whether the interest rate is adjustable, their interaction terms with HHI, HHI (main effect), province fixed effects and loan granted year fixed effects. Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* $p<0.10$, ** $p<0.05$, *** $p<0.01$. The lower part divides the samples into loans with collateral or not, where HHI always stands for the HHI residual.

Table 5: Subsample analysis: competition and commercial/industrial loan approval

Dep. variable:	Male		Female		Male & Female	
	age $\leq$ 35	age>35	age $\leq$ 35	age>35	age $\leq$ 35	age>35
Application was approved	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	-0.233	0.781**	-0.558	0.509		
	(0.573)	(0.359)	(2.419)	(0.517)		
Bad looks*HHI	-0.029	-0.183	-0.112	0.413		
	(0.856)	(0.199)	(1.224)	(0.364)		
Male*HHI					-0.476	0.379**
					(0.324)	(0.157)

Note: HHI is the HHI residual from a regression of average community-level Herfindahl index on the community type (rural area, small town, small city, median city and big city). Other covariates include an indicator for agricultural Hukou, rural status, home ownership, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, their interaction terms with HHI, HHI (main effect), and province fixed effects. Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 6: Competition and mortgage loan approval

Dep. variable:	Male		Female		Male & Female	
Application was approved	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	-0.090	-0.118	0.183	-0.470		
	(0.285)	(0.342)	(0.189)	(0.415)		
Bad looks*HHI	-0.334	0.471	-0.109	-0.576		
	(0.549)	(0.608)	(0.442)	(0.585)		
Male*HHI					-0.233	-0.115
					(0.165)	(0.246)
Good looks (at mean HHI)	0.037	0.043*	0.002	0.002		
	(0.023)	(0.023)	(0.021)	(0.021)		
Bad looks (at mean HHI)	0.008	0.009	0.040	0.040		
	(0.025)	(0.026)	(0.026)	(0.026)		
Male (at mean HHI)					-0.014	-0.014
					(0.011)	(0.011)
N	1720	1574	797	750	2533	2339
Adj R-sq	0.098	0.093	0.082	0.098	0.097	0.090

Note: HHI is the average prefecture-level Herfindahl index during 2009-2013 (odd columns) and the HHI residual from a regression of HHI on the logged prefecture GDP and logged prefecture population (even columns); mean HHI=0.12 and mean HHI residual=0. Good looks (at mean HHI) is the marginal effect of being good-looking at the mean HHI; similarly for Bad looks (at mean HHI) and Male (at mean HHI). Other covariates include an indicator for agricultural Hukou, rural status, logged family income, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, retirement status, their interaction terms with HHI, HHI (main effect), and province fixed effects. Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 7: Competition and mortgage loan interest rate

Dep. variable:	Male		Female		Male & Female	
Interest rate	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	-1.164	2.481	1.675	11.56		
	(5.484)	(7.009)	(11.68)	(12.48)		
Bad looks*HHI	5.788	0.918	4.380	15.07		
	(5.853)	(8.006)	(10.13)	(10.96)		
Male*HHI					8.445**	8.962**
					(3.704)	(4.452)
Good looks (at mean HHI)	-0.009	0.177	-0.260	-0.257		
	(0.312)	(0.290)	(0.492)	(0.492)		
Bad looks (at mean HHI)	1.037***	1.017***	-0.479	-0.556		
	(0.334)	(0.340)	(0.513)	(0.522)		
Male (at mean HHI)					0.225	0.135
					(0.182)	(0.209)
N	609	560	297	283	1145	852
Adj R-sq	0.079	0.066	0.029	0.060	0.047	0.045

Note: HHI is the prefecture-level Herfindahl index in the year the loan of the largest amount was granted (odd columns) and the HHI residual from a regression of HHI on the logged prefecture GDP and logged prefecture population (even columns); mean HHI=0.14 and mean HHI residual=0. Good looks (at mean HHI) is the marginal effect of being good-looking at the mean HHI; similarly for Bad looks (at mean HHI) and Male (at mean HHI). Other covariates include an indicator for agricultural Hukou, rural status, logged family income, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, retirement status, an indicator for public housing fund loan (gongjijin), their interaction terms with HHI, HHI (main effect), province fixed effects and loan granted year fixed effects. Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* p<0.10, ** p<0.05, *** p<0.01.

Table 8: Subsample analysis: competition and mortgage loan approval/interest rate

Dep. variable:	Male		Female		Male & Female	
	age $\leq$ 35	age>35	age $\leq$ 35	age>35	age $\leq$ 35	age>35
Application was approved	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	-0.509	0.174	0.635**	-0.562		
	(0.489)	(0.535)	(0.306)	(0.675)		
Bad looks*HHI	0.300	0.595	-0.814	-0.528		
	(0.634)	(0.723)	(0.901)	(0.673)		
Male*HHI					0.534	-0.252
					(0.395)	(0.322)
Interest rate	(1)	(2)	(3)	(4)	(5)	(6)
Good looks*HHI	4.475	0.542	12.555	17.623		
	(12.562)	(8.829)	(31.290)	(17.561)		
Bad looks*HHI	-7.855	-0.485	25.695	4.498		
	(11.932)	(9.320)	(23.996)	(14.504)		
Male*HHI					17.72***	4.573
					(6.372)	(4.378)

Note: HHI is the HHI residual from a regression of prefecture-level Herfindahl index on the logged prefecture GDP and logged prefecture population. Other covariates include an indicator for agricultural Hukou, rural status, logged family income, household head's age, ethnic Han indicator, educational attainment, marital status, health status, communist party member status, retirement status, their interaction terms with HHI, HHI (main effect), and province fixed effects (for approval), and in addition an indicator for public housing fund loan (gongjijin), its interaction term with HHI, and loan granted year fixed effects (for interest rate). Good look and bad look indicators are included in the regressions for column (1) to (4); male indicator is included in the regressions for column (5) to (6). Standard errors are clustered at prefecture,* p<0.10, ** p<0.05, *** p<0.01.