The Role of Digital Credit in Building Trust:

A Case Study of Zhima Credit's Inclusive Housing Initiative in China[1]

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Abstract

This paper explores the extent to which digital credit scoring—an innovative digital technology—can foster social trust, bridge financial and information gaps and expand greater access to resources and facilities. The analysis is based on an in-depth case study of Zhima Credit's efforts to promote inclusive housing in China. Findings from a unique survey at individual user-level show that digital credit users exhibit greater trust in their economic activities and report higher satisfaction in their overall life conditions.

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1. Introduction

The inclusion of marginalized or disadvantaged groups into the development process requires improving their access to resources, information, housing, and facilities. While there has been increasing research on urban poverty (Baker and Schuler 2004; Chamhuri, Karim, and Hamdan 2012), the question of how to enable poor and relatively poor urban communities to access to housing and other essential facilities remains underexplored (World Bank 2012).

There is a growing body of literature on the role of digital technology in poverty reduction and inclusive development. Digital technologies have been shown to help poor communities access education, financial assistance, and agricultural extension services, while also facilitating greater market participation (Fu and Akter 2016; Heeks 2010; Narayan 2002). More recently, , digital platforms have created opportunities for marginalized communities to participate in market transactions and sell their products more efficiently (He 2019; Leong, Pan, and Cui 2016) or even develop businesses and generate income without requiring initial capital investment (Fu et al. 2023). Additionally, there are also some interesting studies on digital credit through mobile banking. For instance, Suri, Bharadwaj, and Jack (2021) find that fintech tools, particularly digital loans, can significantly improve financial access and household resilience, based on data from Kenya. However, some critics argue that digital credit does not consistently improve lives, and its lack of transparency raises concerns about predatory lending practices.[2]

While these studies provide useful insights, they overlook some important factors. One key obstacle to inclusive development is the lack of trust, which leads to transaction costs. This

[2] "The Impact of Digital Credit in Low-Income Countries", *VoxEU column*, March 2022.

lack of trust often serves as an entry barrier to engagement in various economic and social activities, limiting access to resources and facilities, and reducing economic efficiency. Distrust between service providers and poor communities contributes to the exclusion of these groups from essential facilities and services. To what extend can digital technologies help build the much-needed trust between the poor and service providers, lower transaction costs, and enable disadvantaged communities to access the services and resources they need to make a decent living?

This paper examines the role of innovative digital technology, specifically digital credit scoring, in promoting trust using big data. Drawing from the literature on machine learning (ML) technologies in rural finance, Kumar, Sharma, and Mahdavi (2021) argue that machine learning-based technology offers new opportunities for small farmers, rural youth, and women farmers, who have been left out of traditional banking systems. Additionally, some researchers evaluate the value of digital footprints for credit scoring and find that easily accessible variables from such footprints have predictive power comparable to or even exceeding that of traditional credit bureau scores.[3] This presents a significant opportunity for enhancing financial inclusion in developing countries, where many unbanked individuals lack credit records with traditional credit bureau.

In the context of China, Kostka (2019) finds a surprisingly high level of approval for Social Credit Systems (SCSs) across various demographic groups. More socially advantaged citizens and older individuals, in particular, show the strongest support for SCSs because they see them as beneficial for promoting honest deals in society. Despite these insights, the extent

[3] "Digital Footprints and Credit Scoring", *VoxEU column*, August 2018.

to which digital credit scoring can help the poor access services they otherwise would not be able to, by enhancing trust and reducing transaction costs, remains under-researched.

This paper aims to fill this gap in the literature by examining whether digital credit can help build trust between individuals and service providers in economic transactions, through lowering transaction cost and increasing access to resources, thus promoting greater inclusion. The analysis draws on survey data collected from Zhima Credit in China; a credit scoring mechanism assigned by private sector entities. Zhima Credit is widely used in commercial scenarios such as renting, leasing, transportation, and shopping, to provide faster and more convenient access to service through waiver of deposits, which is usually required in renting.

The paper finds that digital credit users have higher levels of trust in the economic activity they engage with. For example, individuals who use deposit-free services for renting housing through Zhima credit show higher levels of trust in landlords and real estate agents. They also show higher levels of satisfaction in their overall life conditions. These effects on trust are particularly strong among lower middle-income groups. This paper contributes to the literature by offering a pioneering theoretical framework and providing the first empirical evidence on how digital credit scoring technology can promote inclusive housing through re-invented trust building.

2. Theoretical framework: Digital credit and trust in digital age

2.1 Digital trust in institutions

Trust is a social relationship in which we believe that the trusted person, object or information has the right intentions toward us and is competent to fulfill that trust (Hardin 2006). It involves a cognitive evaluation based on relevant knowledge of the subject's trustworthiness. The internet and digitalization have transformed how trust is perceived and developed in social relationships and provided new contexts in which trust is built and tested (O'Neill 2012). Digitalization replaces many face-to-face physical interactions and challenges traditional models of trust in two key ways: first, there is often lacks relevant prior knowledge about the potentially trusted subjects in the digital space, making it harder to assess the authenticity of their identities and intentions. Second, even when knowledge is available, it is gathered and evaluated in ways that are qualitatively different from face-to-face interactions.

Trust in the digital age can be categorized based on the trusted subject, including trust in digital technologies, service providers and institutions, and other individuals and groups online. The development of digital trust carries significant policy implications regarding the quality and transparency of relationships between people, institutions and society (Cohen-Almagor 2010). This paper focuses on the transformation of trust in institutions, especially service providers such as firms and governments, based on the "experience of technologies" (Dutton and Shepherd 2006). Trust has long been regarded as a central element in the political process and social participation that helps build stable and efficient institutions. Conversely, the lack of trust is often blamed for declining interest and engagement in civic life and online transactions (Beldad, de Jong, and Steehouder 2010; Deth, Montero, and Westholm 2007).

The evidence on the impact of digital technology on trust in institutions is mixed. Some studies suggest that the use of digital technologies in public institutions can increase trust by improving interactions with citizens and enhancing perceptions of responsiveness (Myeong, Kwon, and Seo 2014). However, risk perception and the intention to use digital services are not always correlated, and the findings vary in the context of e-government and e-commerce (Bélanger and Carter 2008). Both governments and firms are increasingly sensitive to trust strategies to manage information and services, creating a sense of security and stability for citizens and customers (Padua 2012).

It is important to recognize that the development and distribution of digital trust is not uniform across regions and demographic groups. Those who engage with digital services and form trust in institutions are diverse. Regions and communities with better access to and more willing to engage with digital technologies experience more shifts in their daily trust relationships. Younger generation, women, and early adopters generally exhibit higher trust in digital technologies, despite expressing more concerns over privacy (Malik, Dhir, and Nieminen 2016). Political orientation and social media usage also influences the trust in digital news sources (Verma, Fleischmann, and Koltai 2018). These unequal impacts across different groups raise concerns over the inclusiveness of digital technologies, and social justice, as seen in the growing cases of fraud and abuse of trust in digital platforms (Mansell and Collins 2005).

Building on the existing studies, this paper seeks to answer whether and how digital technologies influence trust in institutions. It argues that digital technologies can improve institutional trust, but their impact varies across social groups. Additionally, the paper examines to what extent people benefit from digital technology-enhanced trust, as reflected in

improved life satisfaction, and whether these benefits are distributed equally among different social groups.

2.2 Credit as infrastructure of trust

This paper explores digital credit as a case study to examine the relationship between trust and digital technology. If trust is seen as a "bond between past and future", credit serves as a measure of the strength and reliability of this bond (Padua 2012). Some scholars even argue that trust is the social component of credit (Lapavitsas 2007). Acknowledging interconnectedness between trust and credit, this paper focuses on how the recent wave of digital credit technologies are reshaping economic and societal landscapes in developing countries.[4]

Digital credit refers to the new types of credit services and products that use alternative sources of data and algorithms, to determine the creditworthiness of individuals and companies. The Center for Financial Services Innovation has identified more than 40 companies globally that use big data analytics to generate credit scores using non-traditional data.[5] Digital credit helps bridge the gap left by the traditional credit systems, particularly the low-income groups in developing countries with limited financial footprints at conventional credit bureaus. However, with the increasing use of mobile phones, these individuals can now be integrated into a credit system through their online activities. Their data can be collected, and services can be provided through mobile devices. In the world's six biggest emerging economies - China, Brazil, India, Mexico, Indonesia and Turkey - digital credit has the potential to provide formal credit access to between 325 million and 580 million people for the first time (Costa, Deb, and Kubzansky 2015).

[4] It is not limited to developing countries. For an example in developed countries, see https://neweconomics.org/2018/07/whats-your-score.

[5] "Big Data, Big Potential: Harnessing Data Technology for the Underserved Market", *Prosper Canada Learning Hub*, March 2015.

Given its rapid expansion and broad impact, this paper recognizes digital credit as part of the "infrastructure of trust" in the digital age. Digital credit provides the measurement, yardstick, and foundation for trust-related activities and transactions. It differs from traditional credit in three key ways: it offers instant, automated, and remote credit services that are distributed through online platforms without in-person visits.[6] This allows users to access credit faster and with lower transaction costs.

Globally, the primary applications of digital credit are still in finance. Evidence from lending and micro-finance demonstrates the impact of this digital credit system. In collaboration with financial institutions, digital credit companies often provide small short-term loans directly to customers through existing mobile money ecosystem (Francis, Blumenstock, and Robinson 2017). This financial innovation reduces the transaction costs of lending and expands the access of users to credit, allowing them to seize opportunities and manage risks (Suri and Jack 2016). In some cases, digital credit fosters market competition and lowers interest rates for both individuals and enterprises (Moro and Fink 2013). For example, the Commercial Bank of Africa disbursed KES40 billion ($495 million) in loans through the M-Shwari online platform in Kenya in 2015, with a non-performing loan ratio of 2.0% compared to 4.3% globally and 5.4% in Sub-Saharan Africa (GSMA 2017).

By providing access to finance, this kind of digital credit helps alleviate poverty by improving consumption and labor allocation efficiency (Suri and Jack 2016). Nonetheless, the benefits of digital credit are not evenly distributed. Early adopters of digital credit technologies tend to be "young, male, urban, educated, stably employed, and bank account

[6] "Instant, Automated, Remote: The Key Attributes of Digital Credit", *CGAP Blog*, February 2016.

holders" (Costa, Deb, and Kubzansky 2015). A cross-regional comparison shows that the major beneficiaries of digital credit are younger individual aged 34 or below and more educated population with at least secondary diploma or vocational training. However, evidence also shows that digital credit promotes financial inclusion for previously excluded groups, particularly women, with stronger positive impacts in female-headed households (Suri and Jack 2016).

Beyond financial applications, digital credit is also being integrated into other sectors. For instance, in Kenya, digital credit is being used in clean water distribution and renewable energy solutions (Francis, Blumenstock, and Robinson 2017). Despite its growing relevance, the broader implications of digital credit on economic and social life remain underexplored. Moreover, new risks are emerging. Users are concerned about the privacy and confidentiality of their data. Incidents of data theft, unauthorized sharing, and data sales can easily erode trust in digital credit platforms. Additionally, users of digital credit may not fully understand the costs or conditions associated with digital credit product before agreeing to terms online.[7] A regulatory framework for customer protection in digital credit is still lacking.

The use of alternative data, such as non-financial payment streams, academic records, behavioral signals from social media footprints and psychometric testing to score "the unbanked", may produce questionable categories and interventions, potentially leading to new forms of social stratification and exclusion (Aitken 2017). Such risks may undermine the positive impacts of digital credit and reinforce existing social inequalities.

[7] "Digital Credit: Consumer Protection for M-Shwari and M-Pawa Users", *CGAP Blog*, April 2015.

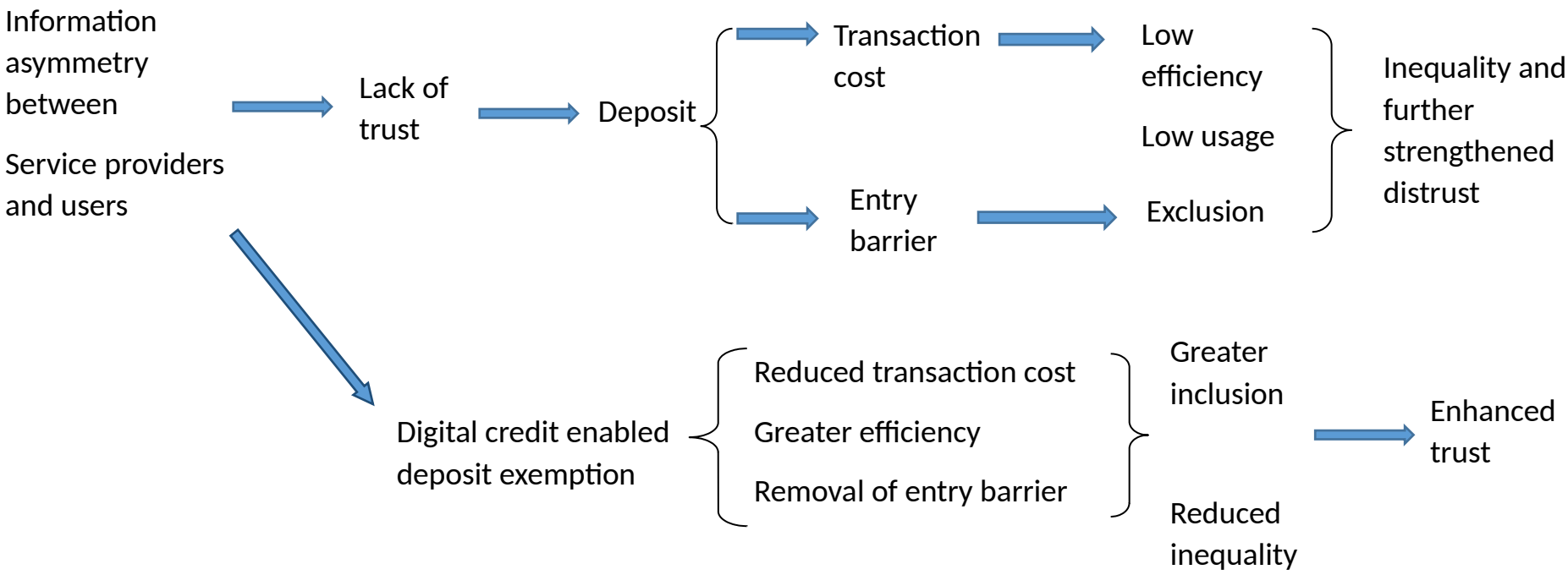
2.3 Bridging the trust gap and promoting social inclusion: The role of digital credit

Trust and inclusion are interconnected, as trust enables individuals to access and leverage previously untapped resources, which, in turn, can enhance trust once these resources are utilized (Cook 2020). Studies show a clear link between users' experiences with public services and the level of trust they develop in those services. Therefore, encouraging user engagement with public services can be an effective strategy to promote social inclusion (Grimsley, Meehan, and Tan 2004). Trust also facilitates economic activities by lowering transaction costs, creating opportunities for those who were previously marginalized in the market to become more engaged. How trust positively affects financial inclusion is a prime example showing the importance of trust for inclusion (Xu 2020).

The rapid development of digital technologies has created new opportunities to bridge the trust gap and promote social inclusion. For example, digital credit can be used in lending activities to help unbanked populations gain access to quality financial services. This not only builds their trust in unfamiliar financing activities but also improves financial service providers' confidence in the creditworthiness of these previously unbanked individuals. Beyond financial services, digital credit can also be applied in other non-financial activities, such as allowing tenants with high digital credit scores to rent properties without a deposit.

This paper focuses on such non-financial applications, particularly how deposit exemption through digital credit can enhance trust in the rental market, real estate agents and landlords. Many tenants may have encountered unpleasant experiences, such as the loss of deposit, without this service. By eliminating the need for a deposit, transaction costs are reduced, and greater efficiency is achieved in pairing tenants and landlords, thereby promoting greater inclusion (Figure 1).

Figure 1. Mechanism on how deposit exemption experience enabled by digital credit can enhance people's trust



User & economy

3. Case study: Zhima Credit in China

To further explore the relationship between digital credit and trust, we examine the case of Zhima Credit in China. Based on a review of China's credit system, we distinguish between the social credit system, managed by the government, and the credit systems issued by private sector. Zhima Credit was chosen for three key reasons. First, the scale of digital credit and its policy implications are more significant in China than other countries. Second, China's Zhima Credit offers a unique case study of credit-based services beyond the financial sector, driven partly by unexpected policy change in China, and thus highlighting the broader impact of digital credit on economic and social life. Third, we have secured exclusive access to Zhima Credit through a university-industry collaborative research project, which provides data that is unavailable elsewhere.

According to the World Bank, 21% of China's population did not have an account at a financial institution in 2014. China's existing credit scoring system, the Credit Reference Center, covers around 300 million people out of an estimated 800 million potential borrowers.[8] The establishment of a social credit system has been a major focus of governance reform in China, as highlighted in the official directives like the 13th Five-Year Plan and the State Council Notice concerning Issuance of the Planning Outline for the Construction of a Social Credit System (2014-2020). Under the coordination of the Central Leading Small Group for Comprehensively Deepening Reform, China has launched a series of pilot urban projects across the country since August 2015 and expected to establish a national credit

[8] "China Planning to Set up Personal Credit Reporting Agency". *Reuters*, January 2018.

system by 2020. The 2017 official paper by the Chinese Information Center used data from 295 cities to address the recent progress on the construction of a social credit system and the decrease in "trust-breaking behaviors". In 2020, the social credit system covered 1.1 billion people through an integrated China social credit system.[9] In building social trust through the credit system, the application of digital technologies is defined as a strategic priority (Chinese Information Center 2017). In July 2017, China's State Council released the "Next Generation Artificial Intelligence Development Plan", emphasizing the role of AI and blockchain technologies in transforming social government and establishing a more efficient social credit system that reduces the costs and risks of human interaction (State Council of the People's Republic of China 2017).

However, the social credit system has sparked intense debates and controversies both within China and internationally. Often perceived as a comprehensive government-managed credit rating mechanism for citizens, concerns have been raised about its mass surveillance and potential punitive measures, such as restricting individuals with low credit records from accessing flights or high-speed trains.

It is important to distinguish between the credit system developed by the state and those developed by the private sector, despite some areas of overlap. Currently, 137 commercial credit rating companies are actively in the market, in 2015, the People's Bank of China issued provisional licenses to eight of them to pilot credit scoring.[10] This was part of the initiative to enhance access to small business loans and consumer credit without collateral or financial history. In 2017, none of the companies was given the licenses to continue financial service

[9] "China's Ides of Control and Social Credit System", *ICS Research Blog*, January 2022.

[10] The list of the eight companies included the forerunners in this field: Ant Financial's Zhima Credit, Tencent, Sinoway Credit, Lakala Payment Co, Intellicredit Inc, China Chengxin Credit, Pengyuan Credit Service Co Ltd, and Qianhai Zhengxin, a unit of Ping An Insurance.

credit rating. The conflicts of interest and lack of independence among third-party rating agencies have led to the suspension of the pilot credit system associated with internet financing. In other words, there has yet to be a unified stance between governmental agencies and private firms on the standard and application of the digital credit system, as each places varying emphasis on its use. Despite collaboration in several areas, as mentioned in open sources, the objective and direction of the digital credit system in the private sector remain distinct from those of the government.[11]

This paper focuses on the innovative methods and impacts of digital credit in the private sector, avoiding the tendency to conflate the activities of commercial companies with the government's social credit system (Creemers 2018). A few key distinctions serve as starting points: private firms' digital credit services are mostly voluntary, depending on customers' choice to open accounts; they collect data from uploaded documents and activities limited to relevant online platforms; and their credit-rating predominantly to reward, rather than punish users, thus establishing an operating eco-system between business, consumers and credit platforms. In this respect, the development of digital credit in China is comparable to global trends that prioritizing big data and algorithms in credit ranking and access to services and goods.

Zhima Credit, part of Ant Financial Services Group (associated with the Alibaba Group), provides one of the most comprehensive digital credit services in China. With over 700 million domestic users on its mobile payment platform. Alipay, the company offers a wide

[11] Such as the cooperation between the Supreme Court and Zhima Credit on the blacklist of debtors. "China Focus: Chinese courts use technology to tighten noose on debt defaulters", *Xinhua Net*, October 2017.

range of services, including innovative methods of credit rating for its users (Huang, Wang, and Wang 2020).[12] Credit scores range from 350 to 950, indicating the likelihood of the users adhering to agreements, aiming to minimize the trust gap between consumers and business. By using cloud computing and machine learning technologies to evaluate the creditworthiness of individuals and enterprises, Zhima Credit facilitates faster and more convenient services, particularly by offering deposit waivers or reductions for credit users in commercial scenarios like renting, leasing, transportation, and shopping.

These features make Zhima Credit's case relevant and unique in the digital credit landscape. It covers a large number of users in a highly vibrant digital economy, providing a unique opportunity to observe large-scale social impacts. However, driven by changes in the policy environment, the private firm has had to expand its credit services beyond finance. This opens new avenues for examining the social implications of digital credit systems, as they extend into key sectors such as housing and transportation, allowing a broader analysis of their social-economic impact.

Before presenting the results, this paper will explain the credit service developed by Zhima Credit, focusing on its data sources, rating mechanisms, business model, and current applications. With users' authorization, the data is mainly extracted from several sources: business partners in finance, transportation, hotel and housing when they use the credit rating of Zhima Credit for risk control; governmental and public institutions; online transactional records, including payment, transfer and investment on its associated payment platform. Based on the collected data, Zhima Credit evaluates the "compliance probability", with final

[12] Data updated with Zhima Credit in February 2019.

credit scores depending on the volume of data and users' behavior. Users with good compliance records will see their scores increase, while violations or overdue payments will decrease scores. Inactivity may also result in a slight decline in scores.

By drawing data from multiple sources and applying diverse measurements, Zhima Credit distinguishes itself from the traditional credit system, which primarily relies on formal financial records. Its reliance on mobile-enabled data indicates its potential to reach more than 700 million mobile phone users, whereas traditional credit agencies access only fewer than 400 million people with formal financial loan histories. The major difference as highlighted in interviews with experts and internal managers, is that Zhima Credit evaluates credit through the lens of "compliance probability", which refers to the "willingness to comply" as assessed by data processing. In contrast, traditional credit agencies emphasize the "capacity to comply", based on personal income and assets. This means that, theoretically, the digital credit system broadens the scope of credit rating, offering opportunities to individuals without formal financial records but who are deemed trustworthy.

However, this approach also introduces two significant risks. First, it raises concerns about how to manage users who may not have the capacity to repay yet still access services and goods through the credit platform. Second, and more importantly, is the institutionalized bias in mobile-enabled credit rating. Users' credit scores depend largely on data contribution, but disparities in internet access and the volume of personal data produced across different social groups and regions may aggravate existing inequalities in access to digital infrastructure and services.

By submitting their data to Zhima Credit and its business partners, users can access services and goods more rapidly and conveniently, such as small loans and deposit reductions or waivers in vehicle and housing rentals. Common applications include using shared bikes without a deposit and renting hotels and apartments without a deposit.[13] Since transportation and housing are closely associated with basic human needs, the expansion of the digital services in these areas is expected to influence larger social groups and populations. The next section explores the empirical evidence on Zhima's credit effects in housing sector, particularly examining the impact of the applications across different groups of users, and the risks associated with them.

4. Data and methodology

This paper provides a comprehensive investigation into the impact of Zhima Credit's deposit-free housing rental service by combining both quantitative and qualitative methods. A mobile phone-based survey conducted between December 2018 and January 2019, funded by the UNDP and carried out by a European university, forms the core of the quantitative data. The survey targeted Zhima Credit users who can use their credit scores for a deposit-free rental service in housing (referred to as housing rental survey). The survey was designed to be representative in terms of age, gender and location. Information on demographic characteristics was also collected. This is the first survey designed to measure the impact of a mobile credit system on social trust and satisfaction. Admittedly, the data has limitations such as sample selection bias due to the collection method used as well as its reliance on one

[13] Data provided by Zhima Credit.

single digital finance platform firm. Users of Zhima credit may not be representative of the general public in China but could potentially serve as a proxy of those who are actively engaged in digital economic activities. The findings from the survey are complemented with data from a qualitative fieldwork took place in July-August 2018, including semi-structured interviews and focus groups of internal staff, business partners and individual users. As the face-to-face interviews took place in Hangzhou City, individual users selected for the research are identified as frequent users of Zhima Credit products and urban residents living in the greater region of Hangzhou for more than two years.

The survey has a response rate of 4.7%, with 1,411 responses from 30,000 questionnaires sent. Out of these 1,411, 151 of them used Zhima Credit for deposit-free housing rentals. Table 1 presents the summary descriptive statistics of users and deposit-free users in the survey. Most respondents (84%) earned less than ¥200,000 (approximately US$ 28,368), indicating the prevalence of low to lower middle-income demographic. The survey also collected information about respondents' trust in the housing rental market, including trust on landlord, as well as his/her satisfaction with the current living conditions. Summary statistics show an average trust score of 66.5 out of 100, suggesting significant room for further improvement.

[Insert Table 1 here]

The survey results suggest that the main impact of deposit-free is a reduction in financial pressure, with over 60% of respondents reporting this benefit (Figure 2). Those who utilized the deposit-free service saved an average of ¥1,554 on housing deposit. In contrast, respondents who did not use the Zhima Credit's deposit-free service paid deposits amounting to an average of 1.5 times their monthly rent.

[Insert Figure 2 here]

The deposit-free service is also found to positively impact individuals' life satisfaction (Figure 3). Sub-group analyses show that respondents who received deposit-free services reported a significantly higher increase in life satisfaction compared to those who had to pay a rental deposit. The contrast is particularly noticeable among single people and those renting properties near their current residences.

[Insert Figure 3 here]

Similar observations are found from interviews, where respondents cited reduced financial pressure is a key factor in trying out deposit-free services, particularly in the face of rising rental costs in cities.[14] Users also report an increase in life satisfaction. However, this improvement is not directly correlated with a reduction in financial pressure. Instead, all users interviewed emphasize convenience and effectiveness as the main factors that make deposit-free services appealing and hence contributing to the improved quality of life.

4.1 Models

We estimate the effect of using deposit-free services on an individual's trust and satisfaction levels using the following Ordinary Least Squares (OLS) models, respectively:

$$Trust=\alpha_0+ \alpha_1(Zhima\_Use)+\alpha_2\{Individual\ Characteristics\}+ \alpha_3\{Controls\}+ \epsilon \quad (1)$$

$$Satisfaction=\alpha_0+ \alpha_1(Zhima\_Use)+\alpha_2\{Individual\ Characteristics\}+ \alpha_3\{Controls\}+ \epsilon \quad (2)$$

Trust is measured by respondents' self-assessment of trust in the housing rental industry, on a scale from 0 to 100, with 0 being low trust and 100 being high; *Satisfaction* reflects respondents' self-assessment of their living conditions; and the variable *Zhima_Use* is a

[14] Interviewed users in group 6 on 19 August 2019.

dummy variable that equals 1 if an individual has used Zhima Credit's deposit-free services for housing rental. We also control for individual characteristics such as age, sex, income level, education level, and marital status. *Age* is a continuous variable from 18-65. *Sex* and *Marital status* are dummy variables. *Income* is a categorical variable, ranging from less than RMB10,000, to above RMB 5 million. *Education* is also a categorical variable from 1-5, where 1 represent junior high school or below, and 5 represents a master's degree or higher. Other control variables include the number of months prepaid for rent, migration status, and current residence location (rural/urban). *Migration status* is a dummy variable that equals 1 if the respondent has migrated from a rural area to a city and 0 otherwise. These controls are included in the estimated models. Clearer descriptions are summarized in Table 2.

[Insert Table 2 here]

Given the concerns on potential endogeneity in the cross-sectional data, Rosenbaum and Rubin (1983)tested the pattern using the propensity score matching (PSM) method (1983). PSM estimates the effect of a treatment or intervention, such as using Zhima Credit's deposit-free service, by matching treated units (those who used the service) with untreated units (those who did not) based on the similarity of their predicted probabilities of using the service when renting a house. These predicted probabilities are referred to as propensity scores.

This method does not rely on a parametric model linking the digital credit usage to the outcome, such as individual's trust in landlords or real estate agents. Instead, it uses matched observations based on propensity scores to calculate the average treatment effect on the treated (ATT) for those who used the deposit-free service enabled by the digital credit.

5. Findings

Table 3 presents the estimated results of using deposit-free service on users' trust in the business and their satisfaction with living conditions. Columns (1) and (2) show the estimated impacts on an individual's trust in the housing rental industry and their satisfaction with living conditions, respectively. The estimated results show that the use of deposit-free services is positively associated with both trust and satisfaction, significant at 1% and 5%, respectively. Married individuals tend to report higher levels of trust and satisfaction, while migrants generally have a lower level of trust. Interestingly, higher income or education levels do not necessarily correspond to increased trust or satisfaction. Only when income surpasses RMB2 million does it positively impact trust or satisfaction. In contrast, education levels are negatively associated with trust, possibly due to concerns about risks associated with digital activities, such as data privacy, or their general critical perspective on society. Most of the interviewees who have higher education express a strong awareness and sensitivity to potential privacy risks, particularly regarding the sharing and misuse of personal data. They also question whether it is fair to be excluded from a deposit-free service due to past behavior, such as criminal records.[15] Users also recognize trade-off between personal privacy and the convenience of digital services, with some seeing it as "a choice to give up personal data for trust in online platforms".[16]

In interviews, users express a high level of trust in credit-based renting services, although this attitude could be biased as they are already frequent users of Zhima Credit. However, they emphasize that this increase in trust was not immediate but developed gradually through the frequent use of other online services, such as Alipay online payment and the deposit-free renting of shared phone chargers or bikes.[17] Business partners of Zhima Credit in the housing

[15] Interviewed users in group 2 on 18 August 2019.
[16] Interviewed users in group 7 on 19 August 2019.
[17] Interviewed users in group 1 on 18 August 2019.

industry, such as online renting platforms, also highlight the significant reduction in transaction costs as a key driver for the popularity of deposit-free services.

All business partners report a substantial increase in active users. For example, an online renting agency observed a 50-60% increase in the number of rental contracts after the introduction of Zhima Credit. The number of properties available for deposit-free services is about 20% of the total properties but it accounts for up to 80% of all the renting contracts.[18] Both tenants and landlords feel more secure with credit rating, as it reveals the characteristics of users to landlords, preventing the risks of losing deposits from tenants.

[Insert Table 3 here]

6. Robustness

Admittedly, it is challenging to determine the causal impact of using Zhima credit for deposit-free services on trust and satisfaction levels in models (1) and (2). The estimation faces potential endogeneity issues. Individuals who are more likely to use digital credit for deposit-free services may already possess higher levels of trust, particularly given their willing to try new types of products or services. This general trust could extend to trust in rental market, such as landlords or real estate agents. Additionally, other omitted variables, such as previous experiences with landlords or real estate agents, may affect trust levels.

The identification strategy employed is unlikely to address all concerns of simultaneity bias between the use of digital credit for deposit exemption in renting a house and the individual's trust in landlords or real estate agents in the rental market, given the cross-sectional nature of the data. The survey data were collected in a non-experimental setting, where the use of

[18] Interviewed company M on 25 August 2019.

Zhima Credit for a deposit-free service was not random. This introduce selection bias, as the likelihood of using Zhima Credit may depend on other unobserved factors.

To mitigate the non-experimental setting, we adopt propensity score matching (PSM) which estimates the probability of receiving treatment (in this case, using Zhima Credit for deposit-free services) conditional on observed covariates (Rosenbaum and Rubin 1983). Besides Rosenbaum and Rubin (1983), the PSM method has been used in a few economic studies and some argue that it produces similar results to randomized control trials (Chiputwa, Spielman, and Qaim 2015; Jalan and Ravallion 2003; Luo and Niu 2019; Olmos and Govindasamy 2015).

We proceed by estimating a logit model to analyze the decision to use Zhima Credit for deposit-free service based on a set of observed characteristics (Table 4). Variables included in the logit model are age, education level, income level, sex, marital status, migrant status, urban or rural residence, and amount of rental prepayment. The results show that individuals living in urban areas and those residing locally are more likely to use Zhima Credit for deposit-free services. Additionally, a higher amount of rental prepayment is associated with a higher likelihood of using deposit-free services, consistent with the descriptive statistics indicating that these deposit-free services help reduce financial pressure.

[Insert Table 4 here]

A propensity score for using Zhima Credit's deposit-free services is obtained through the logit model (Figure 4). Then, nearest neighbor matching is performed to pair those who used Zhima Credit for deposit-free services with those who did not. These matched-observations

are then used to calculate the average treatment effect on the treated (ATT) for deposit-free service usage enabled by Zhima Credit.

[Insert Figure 4 here]

The matching results are presented in Table 5, where propensity scores are divided into five blocks. Relatively fewer deposit-free service users are found in blocks 3, 4, and 5, which is aligned with the generally low estimated propensity scores for deposit-free service users, as shown in Figure 3. Additionally, balancing tests are conducted to verify if variables or individual characteristics used to construct propensity scores are similar between those who used the services and those who did not (Table 6). The results from the tests show that matched individuals have similar characteristics even if they differ in the usage of deposit-free services. The mean differences between those who use Zhima Credit for deposit exemptions and those who are not significantly significant indicating that no single variable can perfectly predict the treatment.

[Insert Table 5 here]

[Insert Table 6 here]

After the matching and balancing procedure, 150 observations in the treatment group (those who used deposit-free services through Zhima Credit) were matched with 134 observations in the control group to estimate the ATT for trust levels. Similarly, 150 observations in the treatment group (those who used deposit-free services through Zhima Credit) were matched with 128 observations in the control group to estimate the ATT for satisfaction level. The results show that using deposit-free services through Zhima Credit has a trust score of 10.84, which is 16.7% higher than the average trust score of the control group. The estimate of the

using deposit-free services through Zhima Credit has satisfaction score of 7.55, which is 9.7% higher than the average satisfaction score of the control group (Tables 7 and 8).

[Insert Tables 7 and 8 here]

Our subsample analysis shows that the effects on trust are particularly high for those with an annual income between RMB 50,000 and RMB100,000, suggesting indicating that lower middle-income groups establish more trust from the services. For migrant individuals, deposit-free services have significant impact on their satisfaction with living conditions, but not on their trust levels. Additionally, the effects of these deposit-free services are significant for those who are living in cities but not for those in rural areas, likely due to housing shortages and high financial pressures in urban environments. Deposit-free services have positive effects on both trust and satisfaction levels of single individuals. This may be related to cultural norms in China because married couples typically prefer to buy and not rent houses.

Although the interview sample with business partners is not large enough to differentiate the impact across social groups based on residential or marital status, business partners with access to large-scale data on their platforms confirm that deposit-free services reach social groups differently. They report that the young people, particularly recent university graduates, many of whom are single, are the primary beneficiaries of deposit-free services. However, due to their financial status, they may not have sufficient credit scores to access the services. In response, business partners may implement new strategies to include this social group, such as offering lower deposit or giving exemptions specifically for graduates.[19] Alternatively, they could adjust thresholds for different user profiles, such as lowering the score requirement for rural or younger users.[20]

[19] Interviewed enterprises, company M on 25 August 2019.
[20] Interviewed enterprises, company X on 27 August 2019.

It is important to note that while the PSM method yields results consistent with the OLS model, readers should exercise caution when interpreting the observed patterns found between digital credit and trust as causal inference. The PSM method relies on the key assumption of unconfoundedness, meaning that all variables that influence treatment assignment and potential outcomes must be observed. However, the survey data may not be able to capture all relevant variables. Future research could explore alternative methods, such as instrumental variable estimators, when more comprehensive data is available, to further validate the findings.

7. Conclusions

Digital technology advances offer new opportunities for inclusive development. Digital credit scoring mechanisms developed by private sector entities show great potential in reducing financial pressure and improving welfare. Unlike traditional credit scoring, which mainly applies to lending activities, digital credit is used across various commercial activities, such as renting, transportation, and shopping, enabling faster and more convenient services through deposit exemption or reductions for users based on their digital credit scores.

Using data from Zhima Credit, a digital credit mechanism developed by Ant Financial, this study finds that deposit-free services enabled by digital credit is positively associated with an individual's trust in economic activities and their overall life satisfaction. For instance, those who use Zhima Credit's deposit-free services for house renting show higher trust in the

housing rental industry and greater satisfaction with their living conditions than those who do not use digital credit.

However, this impact is not uniform across social groups. Married individuals generally have higher levels of trust and satisfaction. Single individuals show a significant increase in trust and satisfaction levels when using deposit-free services, likely due to stronger need for renting houses among singles, as married people in China are more likely to buy houses. Interestingly, higher income or education levels do not necessarily correlate with greater trust or satisfaction, with education levels even negatively associated with trust. Lower middle-income groups are primary beneficiaries of deposit-free services, implying the development impact on inclusion from digital credit. For migrants, the impacts of deposit-free services satisfaction level, but have little impact on trust. Additionally, these impacts of deposit-free services are more pronounced in urban areas than in rural ones.

These heterogenous impacts of digital credit across social groups offers a few policy implications. First, although fiber optic and 4G networks reached more than 98%of China by 2019, a significant gap remains between urban and rural areas and between the elderly and the youth. Internet adoption is 55.9% in rural areas compared to 79.8% in urban ones, with the elderly above 60 accounting for almost half of the non-internet users. This digital divide suggests a growing gap in access to social services and welfare benefits.

Second, the lack of correlation between education levels and trust may reflect concern about data privacy in digital credit. Most individuals do not fully understand how the data are shared across different platforms or how their credit score is calculated. A robust data

governance regulatory environment and transparency of algorithms are critical for further utilizing big data and analytics in economic and social activities. clear and consistent rules on data sharing and platform interoperability will further enhance the uses of digital credit across sectors.

Third, with more than 290 million internal rural-urban migrants in China, ensuring their social integration remain a key policy agenda for the government. Digital technologies can engage this group in economic activities, as seen by the impact of deposit-free services on their living satisfaction. However, further efforts are needed to address cultural and social barriers to building trust, as the impact of trust levels for migrants remains limited in deposit-free services.

Due to data limitation, the paper only examines the impact of digital credit in one commercial activity - the housing rental market. Since digital credit can be applied to economic activities, further research could explore the wider developmental impact of digital credit in other applications, especially the shared and circular economy. Additionally, research could investigate whether trust gained in one context influences trust in broader organizations and communities. Given the cross-sectional nature of data and potential endogeneity issues, the patterns found between digital credit and tryst should be interpreted cautiously. Future multidisciplinary research should address ethical and regulatory concerns about data use, ensuring privacy protection while enabling data to drive value creation and social inclusion. It is crucial to ensure that the algorithm used to estimate digital credit scores do not discriminate against any social groups in the society.

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Table 1. Descriptive statistics

	Entire sample		Those who have used Zhima Credit to obtain deposit exemption service	
VARIABLES	Mean	Std dev	Mean	Std dev
Zhima_Use (A dummy variable that equals 1 if the individual uses Zhima credit to obtain deposit exemption service)	0.166	0.372		
Trust score (0-100)	66.54	27.10	74.96	26.69
Satisfaction score (0-100)	78.71	21.78	84.16	21.59
Age	26.91	5.418	27.27	5.919
Male	0.620	0.486	0.669	0.472
Married	0.234	0.424	0.278	0.450
Urban	0.408	0.492	0.589	0.494
Migrant	0.768	0.423	0.583	0.495
Income level less than RMB 10,000	0.111	0.314	0.146	0.354
Income level RMB10,000-20,000	0.086	0.280	0.099	0.300
Income level RMB20,000-50,000	0.135	0.342	0.152	0.361
Income level RMB50,000-100,000	0.276	0.447	0.245	0.432
Income level RMB100,000-200,000	0.233	0.423	0.199	0.400
Income level RMB200,000-300,000	0.080	0.272	0.086	0.281
Income level RMB300,000-500,000	0.042	0.200	0.066	0.250
Income level RMB500,000-1,000,000	0.023	0.150	0.000	0.000
Income level RMB1,000,000-2,000,000	0.004	0.066	0.000	0.000
Income level RMB2,000,000-5,000,000	0.002	0.047	0.000	0.000
Income level above RMB5,000,000	0.007	0.081	0.007	0.081
Education level: Junior high school or below	0.042	0.200	0.060	0.238
Education level: High school	0.198	0.399	0.205	0.405
Education level: Associate college	0.344	0.475	0.318	0.467
Education level: Undergraduate	0.382	0.486	0.377	0.486
Education level: Master or above	0.034	0.182	0.040	0.196
Occupation: Professional	0.166	0.372	0.172	0.379
Occupation: Sole proprietorship	0.122	0.328	0.100	0.300
Occupation: Corporate Management	0.094	0.291	0.146	0.354
Occupation: Public servant	0.017	0.127	0.033	0.180
Occupation: Student	0.029	0.167	0.060	0.238
Occupation: Unemployed	0.008	0.088	0.000	0.000
Occupation: White collar	0.387	0.487	0.344	0.477
Occupation: Blue collar	0.100	0.300	0.080	0.271
Occupation: Other	0.078	0.268	0.066	0.250

Table 2. Data description

Variable	Definition
Trust	Respondent's score on trust in the housing rental industry or landlord (0-100, with 100 representing the highest level of trust)
Satisfaction	Respondent's score on satisfaction in the living conditions (0-100, with 100 representing the highest level of satisfaction)
Zhima_Use	A dummy variable equals 1 for the respondents who have used Zhima credit to obtain deposit-free services for housing rental and equals 0 for the respondents who have not used Zhima credit for the services.
Individual characteristics	
Gender	Equals 1 if respondent is male, and equals 0 if respondent is female
Age	Respondent age
Income	Income level of respondent (categorized from 1-11; representing income levels of less than RMB10,000, 10,000-20,000, 20,000-50,000, 50,000-100,000, 100,000-200,000, 200,000-300,000, 300,000-500,000, 500,000-1,000,000, 1,000,000-2,000,000, 2,000,000-5,000,000, and above 5,000,000)
Education	Education level of respondent (categorized from 1-5; representing education levels of junior high school or below, high school, associate college, undergraduate, and master or above.)
Marital status	Equals 1 if respondent is married, equals 0 if respondent is not married
Other controls	
Mrent	Prepayments of monthly rental (by number of monthly rental)
Migration status	Equals 1 if respondent is a migrant, and equals to 0 if respondent is not a migrant
Residence location	Equals 1 if respondent is currently living in the city, and equals 0 if respondent is currently living in the rural area

Table 3. **The impact of digital credit on Trust and Satisfaction: OLS Regression results**

VARIABLES	(1) Trust	(2) Satisfaction
Zhima_Use	9.302***	5.603**
	(2.680)	(2.336)
Marriage	4.980**	3.586*
	(2.382)	(1.889)
Education level: High school	-8.529*	0.624
	(4.521)	(5.052)
Education level: Associate college	-11.08**	-0.742
	(4.419)	(4.935)
Education level: Undergraduate	-11.92***	-1.024
	(4.438)	(4.893)
Education level: Master or above	-17.16***	-3.336
	(6.280)	(5.450)
Age	0.175	0.00185
	(0.188)	(0.163)
Male	2.006	5.422***
	(1.922)	(1.650)
Urban	0.682	1.838
	(2.068)	(1.680)
Payment of monthly rental	-0.836	-0.0537
	(0.597)	(0.441)
Migrant	-5.181**	0.343
	(2.289)	(1.947)
Income percentile dummies	Yes	Yes
Constant	74.99***	72.51***
	(7.110)	(7.140)
Observations	882	813
R-squared	0.071	0.044

Note: *income is a categorical variable ranging from 1 to 11, representing income levels of less than RMB10,000, 10,000-20,000, 20,000-50,000, 50,000-100,000, 100,000-200,000, 200,000-300,000, 300,000-500,000, 500,000-1,000,000, 1,000,000-2,000,000, 2,000,000-5,000,000, and above 5,000,000. Edu is a categorical variable ranging from 1 to 5, representing education levels of junior high school or below, high school, associate college, undergraduate, and master or above.*

Table 4. **Determinants of the adoption of Digital credit: Logit model estimation results**

VARIABLES	(1) Use Zhima dummy (1=use)
Age	-0.0288
	(0.0200)
Education level: High school	-0.493
	(0.467)
Education level: Associate college	-0.572
	(0.453)
Education level: Undergraduate	-0.561
	(0.457)
Education level: Master or above	-0.680
	(0.666)
Urban	0.732***
	(0.206)
Male	0.378*
	(0.204)
Marriage	0.235
	(0.252)
Migrant	-0.897***
	(0.217)
Payment of monthly rental	0.293***
	(0.0584)
Income percentile dummies	Yes
Constant	-0.922
	(0.742)
Observations	880

Note: *income is a categorical variable ranging from 1 to 11, representing income levels of less than RMB10,000, 10,000-20,000, 20,000-50,000, 50,000-100,000, 100,000-200,000, 200,000-300,000, 300,000-500,000, 500,000-1,000,000, 1,000,000-2,000,000, 2,000,000-5,000,000, and above 5,000,000. The interaction effects of the income level and using deposit-free services are not significant. Edu is a categorical variable ranging from 1 to 5, representing education levels of junior high school or below, high school, associate college, undergraduate, and master or above.*

Table 5. Matched observations in control and treatment groups

Block ID	Inferior of block of propensity score	Deposit paying users	Deposit free users	Total
1	0.045	543	65	608
2	0.2	140	58	198
3	0.4	21	18	39
4	0.6	1	6	7
5	0.8	1	3	4
Number of observations		706	150	856

Table 6. Balancing test

Mean difference between the matched individuals who use Zhima credit for deposit-exemption services and those who do not use Zhima credit					
	Block 1	Block 2	Block 3	Block 4	Block 5
Respondent age	1.053	-1.555	0.024	-2.333	-2.333
Education level - Junior high school or below	-0.036	0.058	-0.063	-0.167	0.000
Education level - High school	0.020	-0.049	0.079	-0.333	0.000
Education level - Associate college	-0.024	0.035	0.111	-0.167	-0.333
Education level - Undergraduate	0.022	-0.039	-0.056	0.667	0.333
Education level - Master or above	0.018	-0.006	-0.071	0.000	0.000
Residence location-urban area	0.065	-0.123*	-0.190*	0.000	0.000
Male	0.040	-0.014	-0.159	0.167	-1.000
Married	0.003	-0.023	0.103	0.500	-0.333
Migrant	0.043	0.000	-0.024	-0.167	-0.667
Annual income - less than RMB10,000	0.023	-0.008	-0.127	-0.333	0.000
Annual income - RMB 10,000-20,000	-0.021	0.024	0.032	-0.333	0.000
Annual income - RMB 20,000-50,000	0.038	-0.110**	0.127	0.000	-0.333
Annual income - RMB 50,000-100,000	-0.068	0.110	0.135	-0.167	0.667
Annual income - RMB 100,000-200,000	0.048	-0.060	0.032	-0.167	0.000
Annual income - RMB 200,000-300,000	-0.021	0.044	-0.175	1.000	0.000
Annual income - RMB 300,000-500,000	-0.007	-0.000	0.032	0.000	-0.333
Annual income - RMB 500,000-1,000,000	0.000	0.000	0.000	0.000	0.000
Annual income - RMB 1,000,000-2,000,000	0.000	0.000	0.000	0.000	0.000
Annual income - RMB 2,000,000-5,000,000	0.000	0.000	0.000	0.000	0.000
Annual income - RMB above 5,000,000	0.009	0.000	-0.056	0.000	0.000
Prepayments of monthly rental	-0.247*	0.013	0.413	-1.167	0.000
Observations	608	198	39	7	4

Note: **** p<0.01, ** p<0.05, * p<0.1.*

Table 7. **Propensity score matching results: Trust score**

	Average trust score of the control group	Deposit free service effect	Percentage of improvement	t-stat	Number of users in the deposit-paying control group	Number of users in the deposit-free treatment group
All sample	64.92	10.84	16.70%	3.17	134	150
Income:50,000-100,000RMB	65.70	15.77	24.00%	2.14	37	37
Migrant	63.87	6.75	-2.40%	1.46	94	88
Local	69.36	17.10	10.60%	2.43	46	62
Rural	65.00	7.24	24.70%	1.10	65	61
Urban	64.78	17.77	11.10%	3.34	61	89
Male	65.76	11.84	27.40%	2.31	81	100
Female	63.51	5.23	18.00%	0.89	48	50
Single	63.03	13.34	8.20%	2.98	102	108
Married	71.03	6.17	21.20%	1.12	29	42
High education level	62.11	19.42	8.70%	3.14	51	63
Low education level	66.86	5.50	31.30%	1.34	75	87

Note: *High education level refers to individuals reported having a bachelor or master's degree or above.*

Table 8. **Propensity score matching results: Satisfaction score**

	Average satisfaction score of the control group	Deposit free service effect	Improvement Magnitude	t-stat	Number of users in the deposit-paying control group	Number of users in the deposit-free treatment group
All sample	77.98	7.55	9.70%	2.38	128	150
Income:50,000-100,000RMB	77.20	3.24	4.20%	0.45	34	37
Migrant	77.94	7.91	10.20%	2.18	90	88
Local	78.19	10.24	13.10%	1.62	43	62
Rural	77.79	7.38	9.50%	1.59	60	61
Urban	78.31	10.20	13.00%	2.06	59	89
Male	79.81	4.80	6.00%	1.12	76	100
Female	74.98	5.17	6.90%	0.98	46	50
Single	76.65	11.78	15.40%	2.79	98	108
Married	82.29	-3.27	-4.00%	-0.56	27	42
High education level	77.60	10.17	13.10%	2.11	49	63
Low education level	78.26	3.76	4.80%	0.89	70	87

Note: *High education level refers to individuals reported having a bachelor's or master's degree or above.*

Figure 2. Impact of deposit-free housing on living conditions (% of respondents)

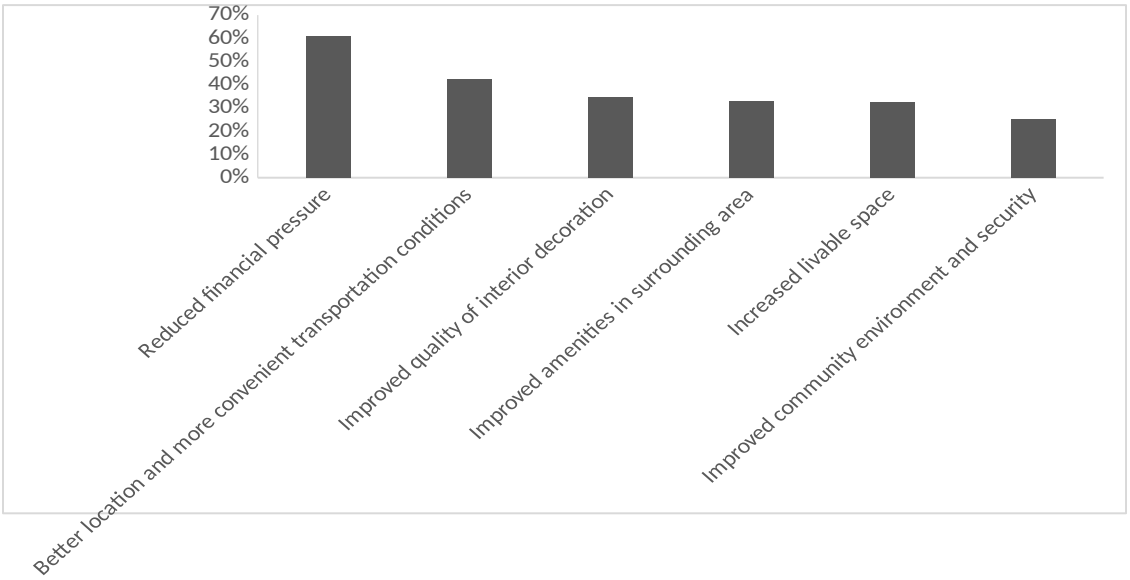
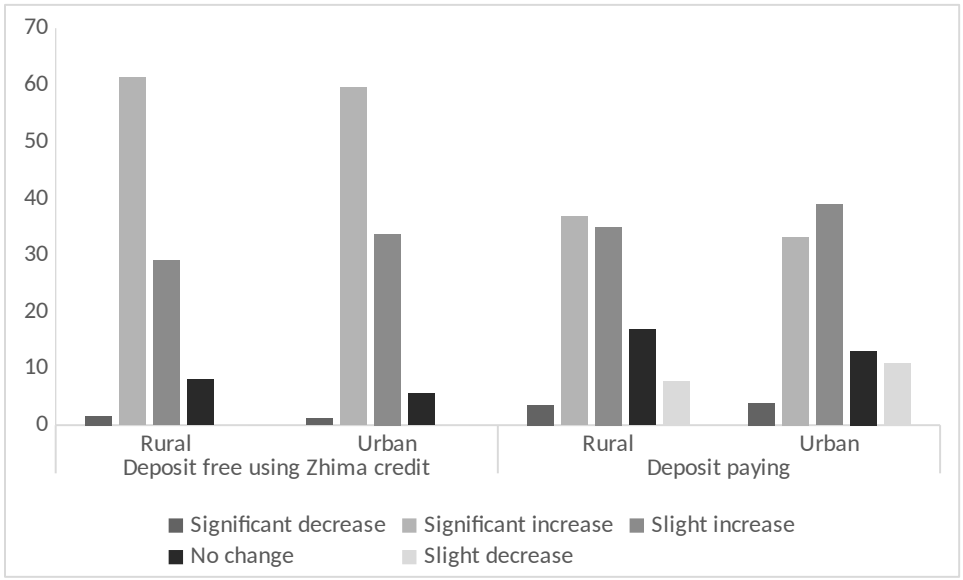
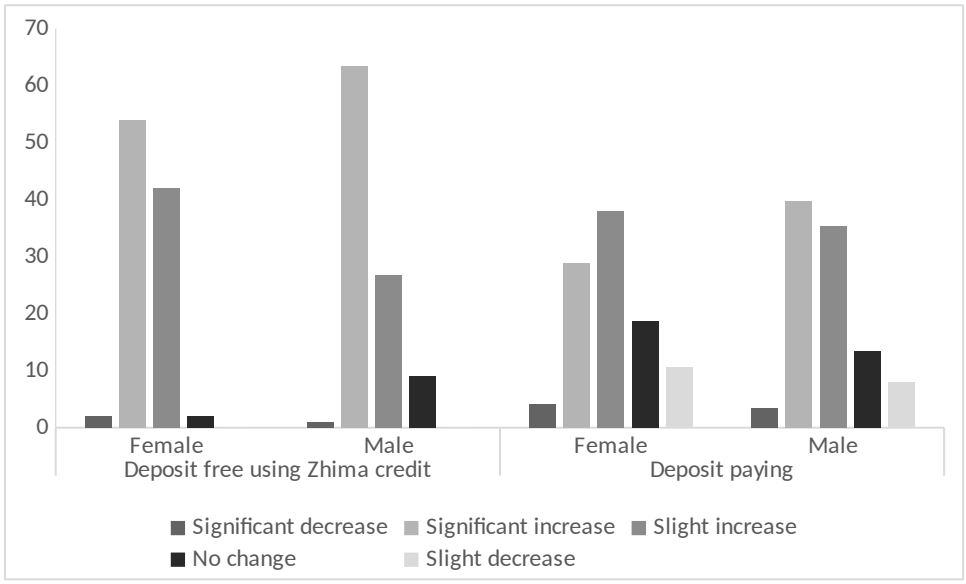
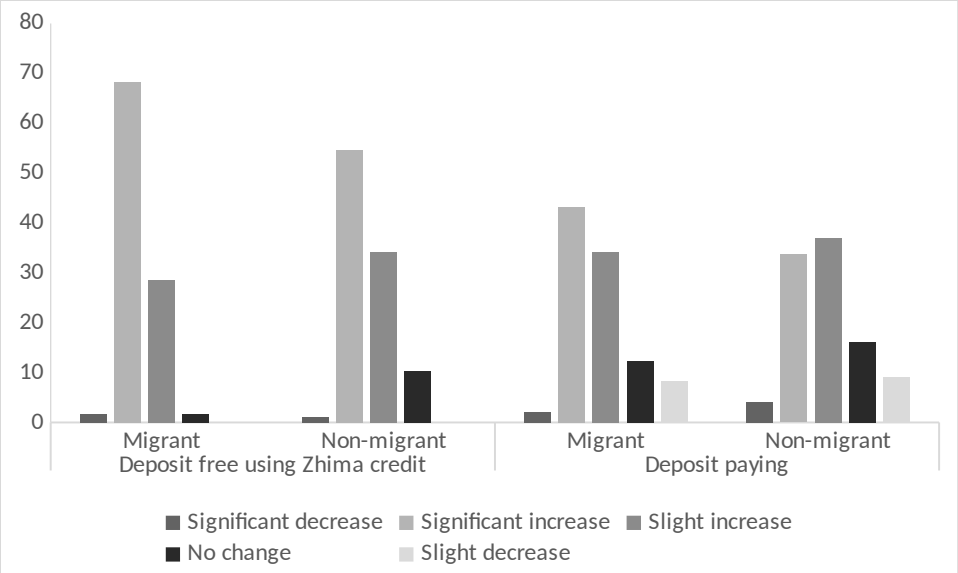
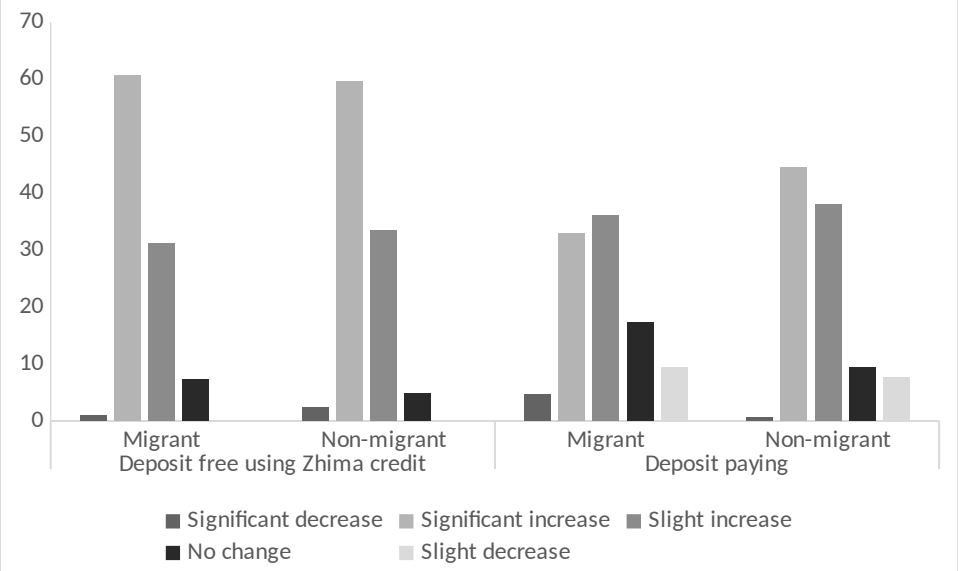


Figure 3. Impact of deposit-free service in housing rental on life satisfaction by sub-groups (% of respondents)






80
70
60
50
40
30
20
10
0
Migrant
Non-migrant
Migrant
Non-migrant
Deposit free using Zhima credit
Deposit paying
Significant decrease
Significant increase
Slight increase
No change
Slight decrease


70
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10
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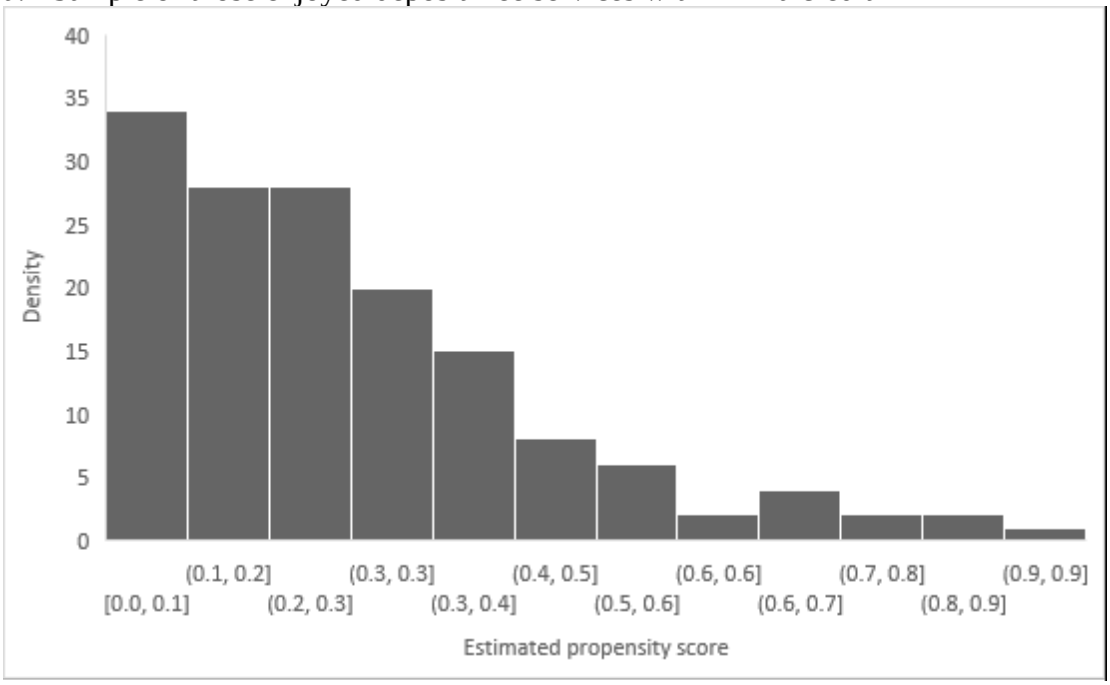
Migrant
Non-migrant
Migrant
Non-migrant
Deposit free using Zhima credit
Deposit paying
Significant decrease
Significant increase
Slight increase
No change
Slight decrease

Figure 4. **Histogram of propensity score**

a. Sample of those enjoyed deposit free services with Zhima credit



b. Sample of those who paid deposit when renting a house