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# Research on SMEs' Reputation Mechanism and Default Risk Based on Investors' Financial Participation

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**Abstract:** Small and micro enterprises (SMEs) play a significant role in the market economy. While online lending has brought financial inclusion for SMEs' borrowers, it has also increased the default risk, which restricts the normative development of online lending. To explore the impact of the reputation mechanism on borrowers' default behavior, this paper provides a theoretical model of asymmetric information dynamic games under the online lending mechanism and an empirical study, which takes the number of bidders that reflects the investors' participation as a proxy variable for the reputation effect factor. The theoretical model showed the borrowers' default behavior is effectively restrained by the increase in the reputation effect factor in the reputation mechanism, and the empirical study found that an increase in the number of bidders can significantly reduce the risk of borrowers' default, which verifies the conclusion of the theoretical model.

**Keywords:** reputation mechanism; number of investors; SMEs; default risk

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## 1. Introduction

Traditional financial institutions decide whether to issue a loan on the borrower's credit review and related loan collateral, even using the collateral mechanism to restrict the borrower's performance for a long time. On the one hand, the high cost of a unit capital credit review for small-amount lending makes traditional financial institutions subjectively reluctant to implement related loans for the long-tail group; on the other hand, the lack of credit information and mortgage of the long-tail group means that the lending conditions of traditional financial institutions are thresholds that are too high to reach for low-income groups. Therefore, obtaining relevant financial support from formal finance for long-tail groups is not easy. However, it is critical to assist the long-tail group in becoming rich to reduce the gap between the rich and the poor in China.

Small and micro enterprises (SMEs) in the long tail group are an essential part of China's socialist market economy, and the health of their development is related to social stability, people's livelihood, and other aspects. However, SMEs also face the problem of difficult and expensive financing. To this end, the 18th National Congress of the Communist Party of China put forward the proposition of "inclusive finance", which aims to solve the problem of financing sources for vulnerable groups such as SMEs.

Financial technology based on Internet technology has developed rapidly, especially models such as crowdfunding and online lending in the absence of traditional financial services and the unmet funding needs of long-tail groups. However, while online lending is developing rapidly, problems such as the moral hazard caused by information asymmetry, platforms' operation, and the management mechanism that restricts the standardization of its development make the development encounter a bottleneck, especially the recent frequent "explosion" phenomena of platforms that have revealed the high risk of the online lending industry.

The source of the increased risk of default by borrowers damages the rights and interests of investors and becomes a stumbling block on the development of online lending. Therefore, effectively regulating borrowers' performance from the mechanism level has become a good medicine for the orderly development of online lending. The loan relationship is a contractual relationship. In addition to binding the borrowers through the terms of the formal contracts, the influence of the informal contracts on the borrowers' lending behavior should not be underestimated [1,2]. The research on reputation in invisible contracts as an incentive mechanism for honest execution of contracts can be traced back to Adam Smith [3,4]. Reputation determines the competitive advantage of an enterprise to some extent under the information asymmetry and provides essential information to customers at the same time. As an effective mechanism to alleviate the information asymmetry between borrowers and lenders, a reputation mechanism can help reduce the default risk of borrowers.

Therefore, it is necessary to deeply analyze the impact of online lending on the behavioral pattern of SMEs' borrowers, platforms, and investors compared with traditional lending and discuss what the impacts of the reputation mechanism are in online lending. Since there is more financial participation of investors in online lending than before, it is also worth studying whether it has an impact on the default risk. These have both important theoretical value and practical significance.

Compared with the existing research, the marginal contribution of this paper is in the following two aspects: First, this paper builds a micro-game theory model to simulate and analyze the behavior patterns of enterprise borrowers, investors, and platforms in online lending and theoretically analyzes the online lending based on the information sharing mechanism by increasing the participation of investors to form an incentive and punishment mechanism with reputation signal as the transmission path. It affects the behavior of borrowers to reduce the default risk of SMEs. Second, the validity and feasibility of the theoretical model are empirically tested from objective data, and the number of bidders is creatively used as a proxy variable of reputation effect factor to test the influence of the reputation of SMEs' borrowers on their default behavior. Simultaneously, suggestions to solve the problem of the current supply of financial resources "from the real to the virtual" are provided.

Following the brief introduction, a review of existing studies is found in Section 2. Section 3 deliberates a theoretical model with the model assumptions, parameter setting, and game analysis. The empirical study and result analysis are found in Section 4, and the paper is concluded with recommendations in Section 5.

## 2. Literature Review

Although online lending has experienced rapid development, incidents such as platform runaways, loan defaults, and cash withdrawal crises have emerged one after another, causing this financing method to be heavily criticized since the establishment of Paipaidai in 2007. Therefore, some scholars have also paid attention to this problem, trying to explore why the risk events frequently occur on the online lending platform compared with traditional lending from the behavioral motives and patterns of online lending participants in games.

On the basis of the assumption of rational economic people, dynamic games and static games are used to analyze the interest-driven behavior of online lending stakeholders. It is found that in the absence of supervision, the borrowers will choose the behavior strategy of "not providing" corresponding information, and the lenders will choose the behavioral strategy of "no review". Lenders have a motive for arbitrage trading, and the platform has the motive for black box operations in the evolutionary game between lenders, online lending platforms, and regulators [5]. The digital credit platform, as a supplement to traditional finance, has increased the effective supply of financial services [6], but fraud and increased dependence on technology have also exacerbated the related financial risks [7,8]. You et al. [9] discussed the conflict of interest between P2P lending participants by utilizing the stakeholder approach to address the P2P lending platforms that do not possess operational suitability owing to excessive defaults.

The main factor that impacts the online lending market are online lending platforms [10]. Online lending platforms as information intermediaries are plagued by adverse selection in the game between online lending platforms and lenders. Although the interest rate paid by the borrowers decreased as the loan size increased, high-interest rates may not bring about the expected high returns to lenders [11]. In simulating the platform and the behavior of investors by Matlab, it is found that the online lending platform should target customers with small capital needs and that risks can be diversified by increasing the number of customers [12]. The addition of guarantee institutions can diversify the risks of online lending platforms as well, which is beneficial to the increased expected returns of the platforms [13]. The relevant information of SMEs in the separation equilibrium state can be accurately disclosed through the signal game between the online lending platform and the borrowers. Still, the credit risk caused by the concealment of non-financial information aggravates the contradiction between the platform and the borrower in reality [14]. Najaf et al. [15] analyzed the influence of the COVID-19 pandemic on the determinants of Fin-Tech P2P lending due to P2P lending platforms having attracted borrowers with little to no access to the credit facilities, which have been offered through conventional banks during the COVID-19 pandemic. Therefore, in addition to the realizable value of patent collateral, the cost of information concealment is an essential factor affecting the equilibrium of the online lending market considering the asymmetry of information [16].

There is competition between platforms as well. Compliant and benign platform competition will enhance compliance operations to a certain extent, but the scale of lenders will decrease in the face of borrowers. In contrast, competition between platforms will increase platform credit risks in the face of lenders [17]. The existence of illegal operating platforms will force compliant platforms to tend to operate illegally [18], which will make online lending fall into a disordered and chaotic development state. It is concluded that network externalities will compress the profit space of multi-attribution platforms through the analysis of the two-sided market pricing theory and the two-stage dynamic game model, which aims at the pricing and profit model of online lending platforms. The two-part charging model is better than the single membership charging model from the perspective of protecting the interests of lenders. At the same time, the mode of guaranteeing the principal is not desirable [19]. Therefore, effective supervision is necessary [20].

Online lending platforms generally serve as an information intermediary to facilitate transactions between borrowers and lenders in the financing process of online lending [21]. More importantly, the online lending platform is an interactive platform [22], making it possible for users, including borrowers and lenders, to participate in the value creation of the platform [23]. Ma et al. [24] found that the value co-creation of consumers and sharing platforms plays an important role in the good development of the industry. The game between borrowers, lenders, and online lending platforms directly determines the financing efficiency or degree of friction.

From the review of existing studies, there are still some limitations. To sum up, a large number of scholars have paid more attention to the game between the platform and borrowers, as well as the dominant role of the platform in online lending, so in view of the value co-creation of consumers, is the value of investors' participation only in providing funds? If not, what mechanism is used to realize the other value of investors' participation in online lending compared with traditional lending? Because of this, this article attempts to reveal the influence of the reputation mechanism of investors' financial participation in online lending on the default risk of borrowers by constructing a game theoretical model and empirical analysis from the perspective of the dynamic game theory of information asymmetry.

## 3. A theoretical Model

### 3.1. Model Assumptions

Online lending participants mainly include investors, lending platforms, and borrowers. A borrower is a participant who aims to obtain a loan. An enterprise, as an example, will be a good enterprise (that is, an enterprise with more self-owned funds and strong comprehensive capabilities such as repayment willingness and operation management) or a poor enterprise (that is, an enterprise with less self-owned funds and weaker comprehensive capabilities such as repayment willingness and operation management). A good enterprise can repay the principal and interest on time, while a poor enterprise cannot repay on time due to its operation or credit problems, which will bring certain losses to investors. Investors are participants who lend funds to obtain corresponding returns. The online lending platform is an intermediary that provides investment information to investors during the lending process and provides verification information, credit evaluation, and other services for loan applications provided by borrowers.

Borrowers submit the loan application materials to the online lending platform, and the lending platform will verify the information and credit evaluation of the application materials, then announce the relevant information to the investors under normal circumstances. Investors choose whether to invest or not on the basis of the published investment information. If they choose to invest, they will transfer the investment funds to the third-party payment institution entrusted by the lending platform, and the third-party payment institution will transfer the funds to the corresponding borrowers. Suppose the sum of the investor's investment amount is more or equal to the borrower's application loan amount, then the borrower's loan is successful; otherwise, it is unsuccessful, and thus multiple investors may be in the same successful loan order. The borrower transfers the funds to the third-party payment institution to repay the principal and interest after the loan expires, and the third-party payment institution repays the funds to the investor. The loan relationship is then terminated. The specific process is shown in Figure 1.

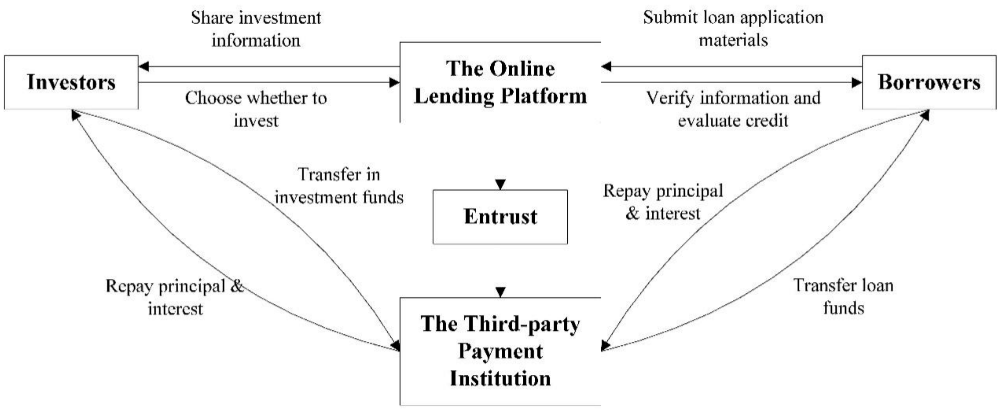


**Figure 1.** The online lending platform and customers' relationships.

The difference between online lending and traditional commercial banks is that online lending exogenizes and marketizes traditional commercial banks' endogenous financial production process. Commercial banks do not pass on the borrowers' loan information to the lenders, and there is a serious information asymmetry between the supply and demand sides of funds. In addition, due to the limitations of the credit approval system and incentive mechanism of commercial banks, excessive administrative approval procedures can easily lead to high loan time costs and aggravate the financing difficulties of SMEs [25]. After the emergence of online lending, fund lenders bypassed commercial bank intermediaries directly to achieve financial participation that matches their utility. This direct information acquisition and fund lending avoid traditional financial intermediaries and have "financial disintermediation effect" properties [26]. The specific process is shown in Figure 2.

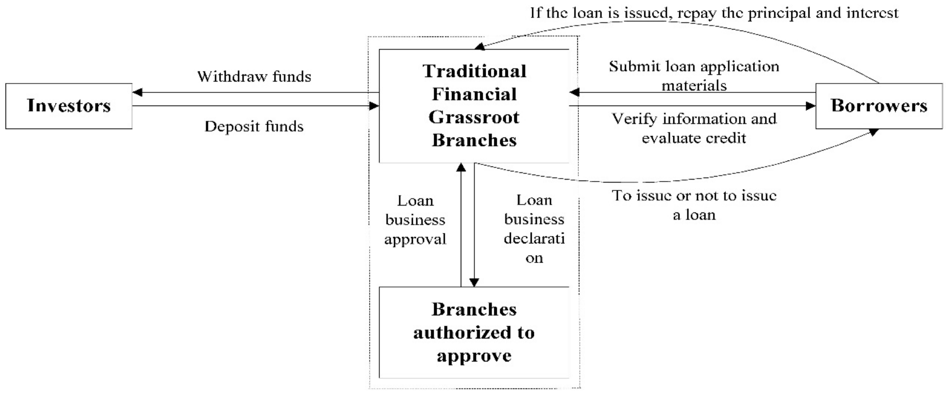


**Figure 2.** Traditional financial institutions' and customers' relationships.

The information of investors and borrowers is often asymmetric in real life, and investors are usually in a position of information disadvantage, which may lead to rejecting high-quality companies or lending to companies with poor credit. Then, this creates direct risks for investors and the lending platform itself. Therefore, the information between investors, online lending platforms, and enterprise borrowers is asymmetric in the game of incomplete information: enterprise borrowers accurately know their operating conditions and profitability. In contrast, investors and online lending platforms cannot obtain critical information. Although lending platforms and investors do not have sufficient information on borrowers, they can classify borrowers into "good enterprises" and "bad enterprises" on the basis of the information provided by the borrowers. Concurrently, all game participants are risk-averse people and can make rational decisions that maximize their benefits; they can constantly revise their previous decisions; they all have independent decision-making power without government intervention; and there is no form of collusion, that is, non-cooperative games.

Online lending is a dynamic game under asymmetric information that is based on the above. In a game of incomplete information, all parties in the game only know the probability of the opponent's type distribution but cannot know the exact type and the opponent's choice; thus, they cannot judge the actual strategic choice made by the opponent. The strategic goal of the game participants is to maximize their expected benefits as much as possible given the opponent type and the set of strategic choices. The specific game process is the natural selection of the type of borrowers, which is whether the SME is good or bad. The online lending platform publishes the corresponding financing information to investors after reviewing and evaluating the loan materials submitted by the borrower, and then investors judge whether the borrower is a good enterprise or bad enterprise according to the financing information received, and following this, they decide whether to lend or not. The game process is shown in Figure 3.

### *3.2. Parameters Setting*

#### 3.2.1. The Reputation Effect Factor $\mu$

The premise of the reputation mechanism to work is the repeated transactions, the effective transmission of information, and the sound punishment mechanism [27,28]. The existence and effectiveness of these conditions will affect the functioning of the reputation mechanism. Most of the borrowers who borrow online have a high risk of overflowing from traditional lending. The emergence of suitable financial products and lending channels will motivate them to repeat borrowing [29]. At the same time, one of the most outstanding advantages of online lending technology is information sharing. The lending information is almost directly transmitted between borrowers and investors in an efficient and timely manner, which significantly saves the cost of traditional financial media [30] and information searching [31], making the decision-making power of lending return to investors [32]. This change makes online lending a participatory financial democracy paradigm [33], allowing more people to participate in the financial system. Secondly, the reputation mechanism itself is a part of the punishment mechanism. Due to reputation damage, borrowers with high default risk or default records will lose corresponding trading opportunities.

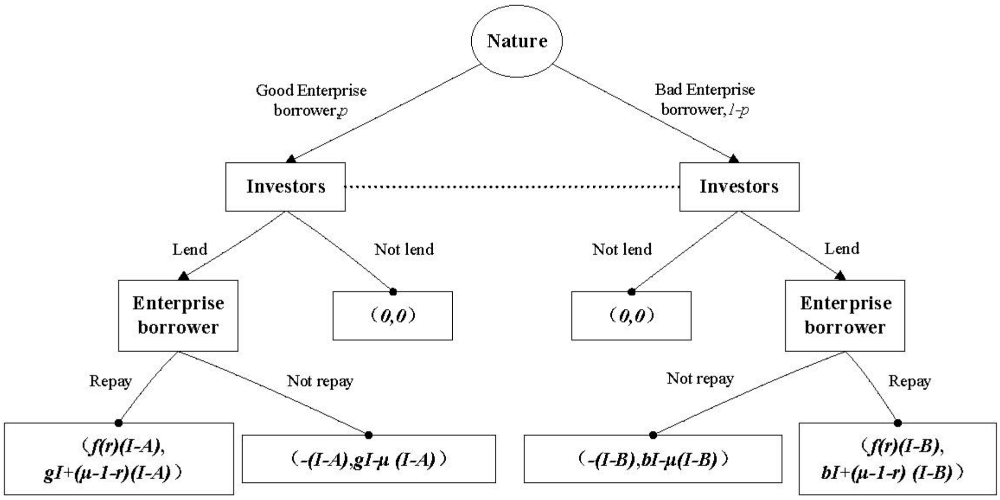


**Figure 3.** The online lending game tree.

Reputation is an intangible asset of an enterprise. However, there is no standardized evaluation system to evaluate an enterprise's reputation. Most of the current research constructs an enterprise reputation evaluation index system from the perspective of economics, politics, and social responsibility [34]. Some scholars have incorporated the evaluations of customers that have been served into the reputation evaluation system [35]. Obviously, the positive evaluation of past customers served helps enterprises establish a good reputation. Online lending is essentially a lending behavior, and it is also a consumer behavior for investors to purchase financial commodities from the perspective of the financial commodity attributes of online lending. As a new type of financial lending product, online lending, affects the reputation of borrowers and has a significant impact on later buyers under the influence of word in mouth [36].

Clearly, for a certain loan target, the amount involved in the borrower's default is related to the degree of reputation damage. Therefore, this paper uses the product of the reputation effect factor μ and the principal loan amount to represent the change in reputation, which is $\Delta reputation = \pm\mu \cdot amount$. Simultaneously, if the borrower performs the contract on time, the positive evaluation of the earlier buyers will enhance the purchase intention of the later buyers through the reputation mechanism and vice versa. Therefore, if the borrower performs the contract on time, $\Delta reputation > 0$; if the borrower defaults, $\Delta reputation < 0$.

### 3.2.2. The Other Parameter Settings

$I$ is the total amount of funds required for enterprise project investment, representing the size of the project; $p$ or $1 - p$ is the probability that the company is a good or bad enterprise, and $p$ obeys the uniform distribution of [0, 1], $0 \le p \le 1$; $A$ is the amount of self-owned capital of a good enterprise; $B$ is the amount of self-owned capital of a bad enterprise, and according to the definition of good or bad enterprise, $A > B$ and $I > A$; $f(r)$ is the rate of return obtained by the investor through lending, being a function of the borrowing rate $r$, and $f'(r) \ge 0$, $f''(r) < 0$ [37,38]; $g$ is the project operating return rate of a good enterprise; and $b$ is the project operating return rate of a bad enterprise, and $g > b$.

## *3.3. The Game Analysis*

According to the basic assumptions and parameter settings, the online lending game tree is shown in Figure 3.

It can be seen from the game tree that the enterprise borrower's strategy space is {Repay, Not repay}, and the investor's strategy space is {Lend, Not lend}, so all the action sets of both sides of the game are: (Lend, Repay), (Lend, Not repay), (Not lend, Repay), (Not lend, Not repay). However, if the investor does not lend, there is no follow-up enterprise to choose whether to repay the loan; thus, the game ends if the investor chooses not to lend. The return matrices are shown in Tables 1 and 2:

**Table 1.** The return matrix of investors and the "good enterprise" borrower.

| | | The "Good Enterprise" Borrower | |
|---|---|---|---|
| | | **Repay** | **Not Repay** |
| Investors | Lend | *(f(r) (I-A), gI + (μ-1-r)(I-A))* | *(-(I-A), gI-μ(I-A))* |
| | Not lend | *(0,0)* | *(0,0)* |

**Table 2.** The return matrix of investors and the "bad enterprise" borrower.

| | | The "Bad Enterprise" Borrower | |
|---|---|---|---|
| | | **Repay** | **Not Repay** |
| Investors | Lend | *(f(r) (I-B), bI + (μ-1-r)(I-B))* | *(-(I-B), bI-μ(I-B))* |
| | Not lend | *(0,0)* | *(0,0)* |

If it is assumed that good enterprises repay the loan and bad enterprises do not repay the loan, then the expected return of the investor choosing to issue the loan is

$$E(R)_{\text{Lend}} = pf(r)(I-A) + (1-p)(-(I-B))$$

The expected return for an investor who chooses not to issue a loan is.

Make $E(R)_{\text{Lend}} > E(R)_{\text{Notlend}}$, which is $pf(r)(I-A) + (1-p)(-(I-B)) > 0$, obtaining

$$p > \frac{1}{1 + f(r)\left(1 - \frac{A-B}{I-B}\right)}$$

The investor will issue loans under this condition; otherwise, the investor will not issue loans. When the other conditions remain unchanged, the greater the interest rate $r$, the greater the probability that the investor will issue loans, and vice versa. When $A$, $I$, and $r$ are fixed, the larger the self-owned capital $B$ of the bad enterprise, the smaller the value of the right formula of the inequality, and the greater the probability that the investor will issue loans.

Investors will choose to lend in the face of good enterprises; on the contrary, investors' strategy is not to lend in the face of bad companies. For the enterprise borrower, the expected return on loan repayment is

$$E(R)_{\text{Repay}} = p(gI + (\mu - 1 - r)(I-A))$$

The expected return on non-payment of the loan is $E(R)_{\text{Not repay}} = p(gI - \mu(I-A))$.

Make $E(R)_{\text{Repay}} > E(R)_{\text{Not repay}}$, finding that when the reputation effect factor $\mu > \frac{1+r}{2}$, the enterprise borrower chooses to repay the loan and when the reputation effect factor $\mu < \frac{1+r}{2}$, the enterprise borrower chooses not to repay the loan. Obviously, the higher the borrowing rate, the more likely the borrower will default. However, the greater the reputation effect factor μ, the greater the motivation of the borrower to perform the repayment. Since the size of the reputation effect factor is affected by the number of early buyer reviews, it means that the more investors purchase a certain loan target under the new information-sharing mechanism of online lending, the more motivation the borrower has to give up the short-term benefits of default and actively maintain a good reputation, which is similar to the work of Ye et al. [36]. Investors' participation not only provides a loan principal, but they also could use their own knowledge and experience to identify potential default orders, which attracts and affects potential customers, further reducing the possibility of the borrowers' default. This is the investors' value co-creation, which is important for the long-term development of the loan market.

## 4. The Empirical Study and Result Analysis

### *4.1. The Hypotheses*

On the basis of the above, more investors participate in the lending relationship [39], which means more potential comments. The reputation mechanism with the increased reputation effect factor restricts the borrower's default behavior [23], which can reduce the borrower's default risk due to the information asymmetry [11]. The number of bidders for an order can be a good indicator of the financial participation of investors [40]. Therefore, in general, the greater the number of bidders in the order, that is, the higher the financial participation of investors, the more inclined the borrower is to sign the contract; on the contrary, the fewer the number of bidders in the order, the greater the risk of borrower default. Then, we can make the following hypothesis:

**Hypothesis 1 (H1)**. *The greater the number of bidders for a loan order, the lower the default risk of the order.*

We also found that when the investment amount of each investor is certain, the order financing amount is closely related to the number of bidders. The larger the order financing amount, the more bidders are required, and the larger financing amount of the order will increase the repayment pressure of the borrower and the default risk [41], which reduces the binding force of the investors' financing participation by the reputation mechanism on the borrower's credit behavior. Then, we introduce the number of bidders per unit of the loan amount, $pbids = \ln(bids/amount)$, that is, the number of bidders corresponding to each 1 yuan of financing. The more the number of bidders per unit of the loan amount, the lower the borrower's default risk and vice versa. Due to the large standard deviation of the number of bidders and the order amount, this paper treats both bids and amount as logarithmic. Then, we can make the following hypothesis:

**Hypothesis 2 (H2)**. *The greater the number of bidders for an order per unit loan amount, the lower the default risk of the order.*

On the basis of the above theoretical model and hypotheses, we designed a research process, as shown in Figure 4. We present the empirical *study* that was conducted following the research process.

### *4.2. The Empirical Model Settings*

As illustrated in Figure 1 above, the Renrendai platform requires the legal representative or person in charge of the borrowing enterprise to provide the order information such as the loan interest rate and loan amount; personal characteristic information such as age, marriage, and gender; asset information such as business and income certificates; and personal credit reports, income certification (Online lending platforms have different credit evaluation methods for the identity of borrowers. For the credit evaluation of online business and private business owners, identity authentication, a personal credit report, a business certificate, and an income certificate are required. In addition, the online store address, online store account number, and even the corresponding video certification sometimes need to be submitted), and other credit information. Therefore, we adopted the Probit model to examine the influence of the number of order bidders (*lnbids*) and the number of bidders per unit loan amount (*pbids*) on whether the borrower defaults. We define the borrower's *age*, *gender*, marital status (*marriage*), education (*degree)*, asset status, and user's name (*user_name*) as personal characteristic information (*BI*); define credit reports (*credit*), job certifications (*c_work*), income certifications (*c_income*), and field certifications (*c_location*) as credit information (*CI*); and define loan amount (*amount*), loan interest rate (*interest*), loan term (*months*), and loan creation time (*ftime*) as order information (*OI*). The empirical model is set as follows:

$$\Pr(default = 1) = \alpha + \beta_1 \cdot lnbids/pbids + \beta_2 \cdot BI + \beta_3 \cdot CI + \beta_4 \cdot OI + \varepsilon$$

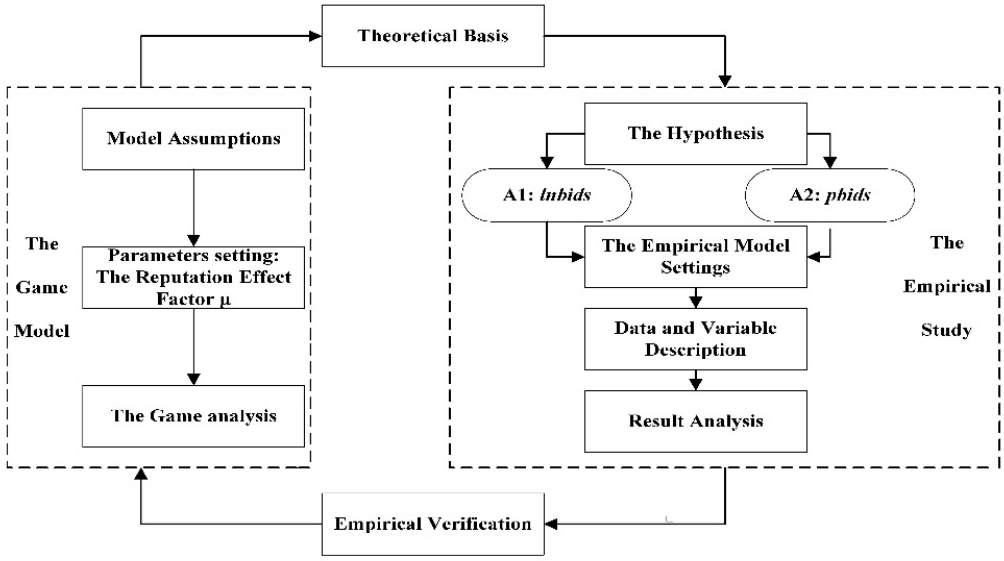


**Figure 4.** The research process.

*4.3. Data and Variable Description*

Online lending platforms mainly provide financing channels for natural persons and SME customer groups. We select the loan transaction data of an online lending platform, namely, Renrendai, from May 2015 to June 2016, including 205,152 natural individual borrowers and borrowers from SMEs. We draw on the practice of Zhuang et al. [41] and filter the loan titles such as "company", "enterprise", "shop", "scale up", "production", "business turnover", and "entrepreneurship" to determine the data samples of the research objects of SMEs, resulting in 46,500 samples. The research objects of SMEs mainly include online merchants and private enterprises, because the financing customer groups of SMEs in the online lending platform mainly have these two types. Generally speaking, these two forms of corporate legal persons usually raise funds for enterprises in the name of personal credit loans in online lending platforms. Correspondingly, the borrower information mentioned in the empirical part below refers to the basic information of the legal person of the enterprise or the person in charge of the enterprise. In fact, the online lending platform usually defines SMEs into two forms: online merchants and private enterprises. Moreover, the legal persons of these two forms of enterprises often use credit loans to raise funds for enterprises in their personal names. Therefore, when we investigate the credit of SMEs on the lending platform, we use business owners to represent SMEs. Since the order (Wait_open) that is being opened for bidding is in the state of being in progress, we remove them with a total of 30 samples, the valid sample was 46,470 order data points. Among them, the number of orders with the number of bidders greater than 0 was 17,392.

The explained variable *default* is whether the loan defaults. The loan defaults if the order is overdue or bad debt, then the value is 1, and the other status of the order is 0. It is worth noting that the Renrendai loan platform has four financing states, namely, failed order financing (Failed), successful order financing and successful repayment of principal and interest (Closed), successful order financing but overdue default (Over_due), and order financing is successful but the default is advanced by the platform (Bad_debt). Therefore, this paper considers both Over_due and Bad_debt as loan defaults when examining whether the loan defaults. The explanatory variable *lnbids* is the number of bidders for an order, and *pbids* is the number of bidders for an order per unit loan amount, with both being used as proxy variables of the reputation effect factor $\mu$.

The existing literature shows that the borrower's personal characteristic information, credit information, and order information can also affect the borrower's default risk [42,43]. Therefore, this paper introduces the personal characteristics information (*BI*), credit information (*CI*), and order information (*OI*) as control variables.

For the personal characteristic information (*BI*), *gender* is a dummy variable, where 0 is female, 1 is male; marital status (*marriage*) contains divorced, widowed, married, and single, where 0 is single, 1 is divorced or widowed or married; education status (*degree)* includes high school and below, college, undergraduate, and postgraduate students or above, where 0 means no relevant information is provided, 1 means high school and below, 2 means college, 3 means undergraduate, 4 means postgraduate or above. The asset status is represented by the presence or absence of real estate (*estate*) and mortgage (*mortgage*), where 0 means no real estate, 1 means owning real estate, and 0 means no mortgage, 1 means owning mortgage; user's names (*user_name*) are divided into two categories according to whether there are Chinese characters, where 0 means no Chinese characters, and 1 means there are Chinese characters.

For the credit information (*CI*), credit report, job certification, income certification, and field certification indicate whether the borrower has submitted relevant certification materials, where 0 means not submitted, 1 means submission. Since all borrowers are required to authenticate, we did not consider this.

For the order information (*OI*), the loan term (*months*) is a dummy variable, where 0 means the order loan term is less than or equal to 18 months, and 1 means the order loan term is greater than 18 months. Since there may be a nonlinear relationship between the borrowing rate and the order status, this paper also controls the square of the loan interest rate (*interest*). The statistical description and MANOVA of the relevant variables are shown in Table 3. We can see that although the main effect of bids was not significant, the main effects of *lnbids* and *pbids* were both significant, which was consistent with our expectations and indicated that *lnbids* and *pbids* will affect whether the borrower defaults. At the same time, the overall effects of the three models were very significant.

**Table 3.** The statistical description and MANOVA of the main variables.

| Variable | Number of Samples | Mean | Standard Deviation | Min | Max | MANOVA F-Value | MANOVA F-Value | MANOVA F-Value |
|---|---|---|---|---|---|---|---|---|
| *default* | 46,470 | 0.0029481 | 0.0542173 | 0 | 1 | | | |
| *bids* | 46,470 | 32.89301 | 69.14479 | 0 | 1777 | 0.95 (0.3299) | | |
| *lnbids* | 17,392 | 4.07377 | 0.946285 | 0 | 7.482682 | | 6.42 ** (0.0113) | |
| *pbids* | 17,392 | −6.999648 | 0.8179377 | −11.74086 | −4.508543 | | | 3.47 * (0.0626) |
| *age* | 46,470 | 34.26002 | 8.021573 | 22 | 61 | 0.88 (0.6860) | 0.89 (0.6714) | 0.88 (0.6769) |
| *gender* | 46,470 | 0.8012912 | 0.3990327 | 0 | 1 | 1.09 (0.2968) | 1.07 (0.3014) | 1.09 (0.2964) |
| *marriage* | 46,470 | 0.6673983 | 0.4620647 | 0 | 1 | 2.86 * (0.090) | 3.08 * (0.0792) | 2.96 * (0.0856) |
| *degree* | 46,470 | 1.610286 | 0.8982575 | 0 | 4 | 0.63 (0.5931) | 0.63 (0.5961) | 0.64 (0.5893) |
| *estate* | 46,470 | 0.4326017 | 0.495442 | 0 | 1 | 6.85 *** (0.0089) | 6.96 *** (0.0083) | 6.90 *** (0.0086) |
| *mortgage* | 46,470 | 0.2456208 | 0.4304593 | 0 | 1 | 22.82 *** (0.0000) | 22.71 *** (0.0000) | 23.00 *** (0.0000) |

**Table 3.** *Cont.*

| Variable | Number of Samples | Mean | Standard Deviation | Min | Max | MANOVA F-Value | MANOVA F-Value | MANOVA F-Value |
|---|---|---|---|---|---|---|---|---|
| *user_name* | 46,470 | 0.380396 | 0.4854894 | 0 | 1 | 771.01 *** (0.0000) | 761.43 *** (0.0000) | 768.68 *** (0.0000) |
| *credit* | 46,470 | 0.4243168 | 0.4942442 | 0 | 1 | 4.08 ** (0.0435) | 3.78 * (0.0519) | 4.10 ** (0.0428) |
| *c_work* | 46,470 | 0.3783086 | 0.4849704 | 0 | 1 | 0.61 (0.4335) | 0.43 (0.5138) | 0.58 (0.4461) |
| *c_income* | 46,470 | 0.372111 | 0.483373 | 0 | 1 | 2.71 * (0.0994) | 2.50 (0.1139) | 2.64 (0.1045) |
| *c_location* | 46,470 | 0.0199053 | 0.1396765 | 0 | 1 | 224.35 *** (0.0000) | 221.66 *** (0.0000) | 223.29 *** (0.0000) |
| *amount (yuan)* | 46,470 | 81665.6 | 95042.52 | 3000 | 500000 | 0.61 (0.4349) | 0.01 (0.9183) | 1.66 (0.1979) |
| *months* | 46,470 | 0.4868302 | 0.4998319 | 0 | 1 | 7.72 *** (0.0055) | 9.09 *** (0.0026) | 8.68 *** (0.0032) |
| *interest (%)* | 46,470 | 11.69388 | 1.096909 | 8 | 13.2 | 78.04 *** (0.0000) | 78.81 *** (0.0000) | 78.63 *** (0.0000) |
| *ftime* | 17,392 | 13.71171 | 6.089081 | 0 | 23 | 2.70 *** (0.0000) | 2.67 *** (0.0000) | 2.68 *** (0.0000) |
| Model | | | | | | 31.12 *** (0.0000) | 31.21 *** (0.0000) | 31.16 *** (0.0000) |
| $R^2$ | | | | | | 0.1202 | 0.1205 | 0.1203 |
| Adj-$R^2$ | | | | | | 0.1163 | 0.1166 | 0.1165 |

Note: ***, **, * represent significant levels at 1%, 5%, and 10%, respectively, and the data in parentheses correspond to the *p*-value of the MANOVA.

### 4.4. Result Analysis

This paper used STATA14.1 software to perform empirical regression on the data, and the regression results are shown in Table 4:

According to the estimation results of the model in the table above, we see that the coefficient of the explanatory variable *lnbids* was −0.124 and was significant at the 1% confidence level. This means that when the participation of investors increases, which is reflected in the rise in the number of bidders for loan orders, the borrowers of SMEs are more likely to repay due to being afraid of the easy-to-destroy reputation of the information sharing mechanism. Therefore, H1 was verified.

**Table 4.** The model regression results.

| Variable | | | | | Robust Analysis |
|---|---|---|---|---|---|
| | Probit | Probit | IVprobit | IVprobit -2step | Cloglog |
| *pbids* | | −0.107 ** (0.0466) | −1.154 *** (0.133) | −2.361 * (1.310) | −0.218 ** (0.106) |
| *lnbids* | −0.124 *** (0.0454) | | | | |
| *BI* | controlled | controlled | controlled | controlled | controlled |
| *CI* | controlled | controlled | controlled | controlled | controlled |
| *OI* | controlled | controlled | controlled | controlled | controlled |
| *_cons* | controlled | controlled | controlled | controlled | controlled |
| *Obs* | 17,392 | 17,392 | 17,392 | 17,392 | 17,392 |

Note: ***, **, * represent significant levels at 1%, 5%, and 10%, respectively, and the data in parentheses correspond to the robust standard errors of the estimated coefficients. Due to the limited space, the regression results of the variables in the main text are not listed; please refer to the Appendix A for details.

Since the number of bidders for an order is affected by its borrowing amount, we introduced the number of bidders per unit loan amount as an explanatory variable. According to the results in the second column of Table 4, the coefficient of the number of bidders per unit loan amount was −0.107 and was significant at the 5% confidence level. We guess that this was because the borrowing enterprises realized that if they want to refinance continuously and cyclically on the online lending platform, they must "borrow and repay" and need to overcome the "gambling financing" that consumes the reputation on the platform one time. The greater the number of bidders involved in borrowing, the wider and faster the negative reputation pass-through effect brought by "gambling financing" will spread in the investor group, which in turn affects the subsequent benefits such as the financing cost of corporate refinancing. Thus, the greater the number of bidders per unit of the loan amount, the greater the deterrent effect of the reputation to a certain extent, which will directly increase the motivation of enterprise borrowers to repay the loan as promised. Therefore, H2 was verified, confirming that the larger the reputation effect factor μ, the more likely the enterprise borrower's repayment performance may increase, which is consistent with the conclusion of Yum et al. [12] and is the value co-creation of investors and platforms [22–24].

However, we found that on the one hand, the greater the number of bidders for an order per unit loan amount, the lower the default risk of the order. On the other hand, it is possible that the borrowing target with better qualifications will attract more bidders and thus reduce the subsequent default risk. Then, the above results may have endogeneity problems caused by the mutual causality between the explanatory variables and the explained variables. Therefore, we introduced the borrowing order's creation time (*ftime*) as an instrumental variable, wherein the creation time of the order is an integer. Due to the law of people's work and rest time, the creation time of a loan order is related to the number of bidders and does not directly affect whether the order defaults or not, so it satisfies the exogenous nature of instrumental variables. The correlation coefficient between the number of bidders per unit loan amount and the time of order creation was 0.0388 at the 1% confidence level, which significantly showed a strong positive correlation between them. On this basis, the IV Probit estimation was carried out. For the exogenous null hypothesis "$H_0$:$\rho$ = 0", the *p*-value of the Wald test result was 0.008, and thus *pbids* can be considered an endogenous variable at the 1% level. The estimated coefficient of *pbids* was −1.154, which was significant at the 1% level, and the coefficient sign was still negative in the IV Probit estimation, indicating that when using the general Probit model for estimation, the restraining effect of *pbids* on the order default risk was underestimated due to ignoring the endogeneity of *pbids*. Meanwhile, the regression results show that the instrumental variable *ftime* had strong explanatory power for the endogenous variable *pbids*. We also used the two-step method for estimation. The estimated coefficient was significantly −2.361, which was close to the MLE estimation result but larger than the absolute value of the latter. Thus, the previous results still hold.

Since order defaults in the Probit binary selection model were still "rare events", the MLE estimates used in Probit were consistent, but there was a rare event bias. Then, we performed a complemented log–log regression to test the robustness of the results. The estimated coefficient of *pbids* in the regression results was −0.218 and significant at the 5% level, and the results were robust.

Therefore, the empirical results show that more investors can participate in lending decisions through the borrower-related credit information released by the platform. This change can effectively reduce the default tendency of borrowers and confirms the conclusion of the previous theoretical model. The online lending platform effectively realizes more individual investors' participation in financial investment through the big data information sharing mechanism and enhances the interaction level among investors, platforms, and borrowers. Investors use their knowledge to identify the borrowers' information and decide whether to lend, which will affect potential customers and help enterprise borrowers more motivated to maintain their reputation and significantly reduce the occurrence of the "gambling financing" moral hazard. Its significance lies in that not only product providers create value, but also customers' participation and use will create value that should not be ignored such as the reduction of default, which will be conducive to the healthy development of the industry.

## 5. Conclusions and Recommendations

### 5.1. Conclusions

The existence of SMEs has a prominent and exclusive standing in the economy, wherein the prosperity of the economy is anchored over the growth and emergence of a flourishing SME sector. This paper constructed a micro-game theory model to discuss the behavior patterns of SME borrowers, investors, and platforms in online lending and found that online lending influences the behavior of borrowers by increasing the participation of investors to form an incentive and punishment mechanism with reputation signal as the transmission path. The following conclusions can be drawn:

Our analysis results confirmed that increasing the financial participation of individual investors, which is reflected in the increase in the number of bidders for the loan target, can change the reputation effect factor. Then, the incentives and punishments in the online lending market that use the reputation mechanism as a transmission channel are spontaneously formed, which urge enterprises to reduce the occurrence of moral hazard of "gambling financing". Moreover, because the degree of information asymmetry is alleviated, investors' concerns about the moral hazard of borrowers are reduced.

The theoretical implications are that the value creation mode under the commodity-oriented logic usually emphasize the value originality of enterprises; in fact, the participation of users and enterprises co-create the value, which can not only come from the effective use of operational resources, but also can be obtained through the transmission of objective resources by users. Therefore, activating the enthusiasm of users' participation is crucial for the long-term development of each industry.

### 5.2. Recommendations

On the basis of the above analysis and conclusions, the following suggestions are put forward:

First, it is necessary to strengthen and standardize the operation and management of enterprises themselves in order to improve the financial system and information disclosure from the perspective of SMEs. The most fundamental reason for the financing difficulties of SMEs is that the operation and management of SMEs are not standardized, and the financial system is not sound. This will lead to a lot of inconvenience for fund providers to obtain information on borrowing enterprises. Therefore, standardized business management and proper information channels with an excellent financial system can effectively help SMEs get out of the financing predicament.

Second, from the perspective of the lending model, the effective information communication mechanism between investors and borrowers should be technically improved, thereby increasing investor participation and increasing penalties for borrowers who break their trust and default. Repayment ability and willingness are the determinants of a borrower's untrustworthiness and default. Whether it is a traditional or a new lending model, efforts should be made to increase the punishment for untrustworthy borrowers and amplify the effect of the restraint and incentive mechanism. Simultaneously, it is necessary to improve borrowers' degree of information disclosure, innovate communication methods, provide corresponding technical support for online and offline interaction between investors and borrowers, increase investor participation, and optimize the ecological environment of financial services for SMEs in the process of lending and borrowing.

Third, from the perspective of traditional financial institutions, the traditional path dependence should be gotten rid of and replaced by actively adapting to the diversity of financial market needs under the new situation. They should master the latest financial technology in the increasingly fierce financial market and provide strong financial support for the strategic upgrade of the entity economy.

Fourth, a support strategy for SMEs according to local conditions and a matching preferential policy system should be formulated from the government's perspective. There are many SMEs in China, being the leading employer of laborers, but the operation of SMEs is complex. Therefore, the government's support strategy and policy system should escort SMEs' long-term and healthy development. Moreover, the government should also strengthen and standardize the construction of the credit reporting system, prevent the occurrence of default events of borrowers, and strengthen the protection of the rights of creditors.

### 5.3. Shortcomings and Prospects

Although this paper has some theoretical contributions and our empirical study also provides empirical evidence, there are still certain limitations. Our study focused on the behavior patterns in network lending, which is a part of financial technology (FinTech) or digital finance. Thus, this research topic can be expanded to mobile payments, online insurance, online funds, and other broader digital financial services in the future. It will bring about more inspiration to stakeholders and help the industry develop in an orderly fashion by analyzing the new characteristics of the behavior patterns of participants in different fields of FinTech.

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## Appendix A

**Table A1.** Model detailed regression results.

| Variable | | | | | Robust Analysis |
|---|---|---|---|---|---|
| | Probit | Probit | IVprobit | IVprobit -2step | Cloglog |
| *pbids* | | −0.107 ** | −1.154 *** | −2.361 * | −0.218 ** |
| | | (0.0466) | (0.133) | (1.310) | (0.106) |
| *lnbids* | −0.124 *** | | | | |
| | (0.0454) | | | | |
| *BI* | | | | | |
| *age* | −0.00498 | −0.00954 | −0.00708 ** | −0.0145 ** | −0.0152 |
| | (0.00594) | (0.00590) | (0.00357) | (0.00705) | (0.0137) |
| *gender* | 0.238 * | 0.288 ** | 0.139 | 0.284 ** | 0.725 ** |
| | (0.123) | (0.122) | (0.0884) | (0.129) | (0.291) |
| *marriage* | 0.259 * | 0.212 | 0.166 ** | 0.339 ** | 0.451 |
| | (0.147) | (0.146) | (0.0761) | (0.155) | (0.285) |
| *degree* | 0.00861 | −0.0164 | −0.0121 | −0.0248 | −0.175 |
| | (0.0648) | (0.0629) | (0.0308) | (0.0630) | (0.138) |
| *estate* | 0.284 *** | 0.280 *** | 0.148 * | 0.303 *** | 0.506 ** |
| | (0.105) | (0.103) | (0.0797) | (0.111) | (0.227) |
| *mortgage* | −0.455 *** | −0.514 *** | −0.279 ** | −0.570 *** | −1.052 *** |
| | (0.141) | (0.144) | (0.124) | (0.134) | (0.297) |
| *user_name* | 0.800 *** | 0.884 *** | 0.273 | 0.559 ** | 1.736 *** |
| | (0.131) | (0.131) | (0.225) | (0.241) | (0.318) |

**Table A1.** *Cont.*

| Variable | | | | | Robust Analysis |
|---|---|---|---|---|---|
| | Probit | Probit | IVprobit | IVprobit -2step | Cloglog |
| *CI* | | | | | |
| *credit* | −0.163 | −0.263 | −0.125 | −0.255 | −0.363 |
| | (0.225) | (0.233) | (0.136) | (0.254) | (0.481) |
| *c_income* | −0.104 | −0.119 | 0.141 | 0.289 | −0.232 |
| | (0.229) | (0.235) | (0.145) | (0.364) | (0.456) |
| *c_work* | −0.469 * | −0.421 * | −0.448 *** | −0.916 ** | −0.904 ** |
| | (0.243) | (0.237) | (0.145) | (0.397) | (0.432) |
| *c_location* | 0.802 *** | 0.872 *** | 0.181 | 0.371 | 1.485 *** |
| | (0.179) | (0.180) | (0.250) | (0.373) | (0.303) |
| *OI* | | | | | |
| *months* | −1.472 *** | −1.580 *** | −1.040 *** | −2.128 *** | −2.601 *** |
| | (0.213) | (0.218) | (0.321) | (0.388) | (0.308) |
| *interest* | −4.076 *** | −4.187 *** | 1.527 | 3.126 | −6.299 ** |
| | (1.197) | (1.285) | (1.514) | (4.405) | (2.910) |
| *interest^2* | 0.212 *** | 0.218 *** | −0.0551 | −0.113 | 0.339 *** |
| | (0.0525) | (0.0563) | (0.0741) | (0.199) | (0.124) |
| *amount* | −0.00000579 * | | | | −0.124 *** |
| | (0.00000302) | | | | (0.0454) |
| *_cons* | 17.87 *** | 17.14 ** | −18.74 ** | −38.35 | 23.07 |
| | (6.779) | (7.329) | (8.142) | (32.88) | (16.96) |
| | | | *pbids* | | |
| *age* | | | −0.00234 *** | | |
| | | | (0.000794) | | |
| *gender* | | | −0.00232 | | |
| | | | (0.0132) | | |
| *marriage* | | | 0.0555 *** | | |
| | | | (0.0210) | | |
| *degree* | | | −0.00378 | | |
| | | | (0.00843) | | |
| *estate* | | | 0.0105 | | |
| | | | (0.0176) | | |
| *mortgage* | | | −0.0250 | | |
| | | | (0.0183) | | |
| *user_name* | | | −0.146 *** | | |
| | | | (0.0476) | | |
| *credit* | | | 0.00147 | | |
| | | | (0.0771) | | |
| *c_income* | | | 0.182 ** | | |
| | | | (0.0849) | | |
| *c_work* | | | −0.216 *** | | |
| | | | (0.0754) | | |
| *c_location* | | | −0.223 *** | | |
| | | | (0.0789) | | |
| *months* | | | −0.247 *** | | |
| | | | (0.0160) | | |
| *interest* | | | 3.248 *** | | |
| | | | (0.160) | | |
| *interest^2* | | | −0.147 *** | | |
| | | | (0.00710) | | |
| *ftime* | | | 0.00623 *** | | |
| | | | (0.000997) | | |
| *_cons* | | | −24.72 *** | | |
| | | | (0.903) | | |
| *Obs* | 17,392 | 17,392 | 17,392 | 17,392 | 17,392 |

Note: ***, **, * represent significant levels at 1%, 5%, and 10%, respectively, and the data in parentheses correspond to the robust standard errors of the estimated coefficients.

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