Gradual Optimization Against Heterogeneous Moral Hazard: Evidence from a Fintech Lending Firm

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Abstract

We relate a Fintech lending firm's actual behavior to its borrowers' heterogeneity in moral hazard. We analyze unique loan-level data from this firm, quantify moral hazard and heterogeneity in moral hazard between borrowers with high education and those with low education, and calculate optimal loan caps. We find the firm's daily average loan size was not far from the optimal cap. Moreover, it gradually moved from one size more optimal for the low education to one more optimal for the high education. The firm also gradually selected more borrowers with high education, because they were less prone to moral hazard.

Keyword: Moral Hazard; Heterogeneity; Optimization.

JEL codes: D82; G14; L21

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1 Introduction

Information asymmetries lead to problems of moral hazard and adverse selection and cause economic inefficiencies (Akerlof, 1970), especially in credit markets (Stiglitz and Weiss, 1981). Recent advances, rather than treating adverse selection and moral hazard as distinct phenomena, further discover that moral hazard effects are heterogeneous across individuals and individuals select on this heterogeneity (Einav et al., 2013). However, there has been relatively little work relating heterogeneity in moral hazard to economic agents' actual behavior.

In this paper, we use unique loan-level data from a Fintech lending firm in China to attempt to fill this gap. All loans originated by this firm are of the same interest rate and of the same loan term, and only differ in their sizes. Our study sample covers around 100,000 loan transactions; furthermore, once a loan transaction of an individual is drawn into our sample, all her subsequent loans, if any, would also be.

Taking advantage of the above feature of the loan product offered by this firm and the above sampling strategy, we first test two theoretical hypotheses regarding moral hazard: first, ceteris paribus, a larger loan size leads to a higher default probability; second, ceteris paribus, a higher level of ability, measured by education level in our empirical analysis, would reduce the positive association between loan size and default probability.

The fact that all loans only differ in their sizes helps our test satisfy the ceteris-paribus condition so that we could focus on testing the effect of loan size on default probability. The above sampling strategy further allows us to control for individual fixed effects in regression analysis. To address the potential endogeneity of loan size even after controlling for individual fixed effects, we instrument the size of a loan originated on a particular day by the average size of loans originated on its previous day. We argue that the variation in daily average loan size is mainly driven by supply side, i.e. the firm, rather than by demand side.

Our instrumental variable-fixed effect (IV-FE) analysis shows that a one-thousand-

CNY ($\sim$ 150 US dollars) increase in loan size would cause overdue rate to increase by 14.5% to 18.7%, number of collection calls to increase by 1.36 to 1.47, and non-repayment rate to increase by 12.6% to 14.2%. Nevertheless, lending to a borrower with higher education would mitigate the above effects by about 20%-30%.

With the above numbers in hand, we continue to directly quantify a loan's marginal cost if its size increases by one CNY. Further by equating its marginal cost with its marginal benefit—mainly deriving from more interest rate income when its size increases by one CNY—we calculate optimal loan caps both for an average borrower and for borrowers of different education levels. We find that, on the whole, the firm's daily average loan size was not far from the calculated optimal loan cap. Moreover, the firm shifted its lending strategy during our sample period: in the first half of the sample period, its daily average loan size was quite close to the one optimal for the low education; after the shift, it moved close to the one optimal for the high education. Meanwhile, the firm chose to select more and more borrowers with high education over time, because they were less prone to moral hazard.

Overall, these findings provide evidence on the role of heterogeneity in moral hazard in driving lending behavior.

Our research contributes to four strands of literature. First, our paper echoes the literature on selection on moral hazard. Einav et al. (2013) present evidence of heterogeneous moral hazard in health insurance, and find that agents, i.e. the insurees in their case, select insurance coverage based on this heterogeneity. In this study, we also find heterogeneity in moral hazard for borrowers of different education levels. Different from Einav et al. (2013), we present evidence that a principal, i.e. the lending firm in our context, could counter-select on moral hazard by gradually selecting out those of low education, because they were more prone to moral hazard.

Besides, our paper contributes to the literature that investigates the empirical importance of moral hazard. In credit markets, a challenge to identify moral hazard arises from the possibility that both adverse selection and moral hazard could explain the same phenomenon and thus it is difficult to disentangle the two.[1] For example, in our context, moral hazard implies that individual borrowers are more likely to default on larger loans, while adverse selection means that borrowers at high risk of default also desire large loans, given that they view repayment as less likely. In response to this challenge, Adams, Einav, and Levin (2009) test moral hazard with data from a large auto sales company and their identification relies on exogenous (to the individual) variation in car price and minimum downpayment.[2] Karlan and Zinman (2009) design a field experiment in a consumer credit market, and there they randomize both offer interest rates and contract interest rates to distinguish between hidden information and hidden action. We use data from a Fintech firm and test moral hazard in a new context with a different identification strategy, taking advantage of the features both of the context and of the sampling strategy.

Second, our study contributes to the understanding of firms' behavior. Many models of firms' behavior in the industrial organization literature directly assume that firms maximize profit and therefore equate marginal cost with marginal benefit. [3] For example, the literature on productivity estimation bases its identification strategy on the holding of first-order conditions in the choice of (intermediate) inputs (Olley and Pakes, 1996; Levinsohn and Petrin, 2003; Ackerberg, Caves, and Frazer, 2015; Gandhi, Navarro, and Rivers, 2020). Instead, our study directly calculates optimal loan caps according to the principle of marginal cost equalling marginal benefit and thus directly test firms' optimization behavior. Our findings broadly support the standard textbook view of firms' behavior that they pursue profit maximization and therefore equate marginal cost with marginal benefit.

Third, our results tie to the literature on credit rationing (Stiglitz and Weiss,

[1]Early tests of asymmetric information like Chiappori and Salanié (2000) do not try to distinguish between adverse selection and moral hazard.

[2]In fact, Adams, Einav, and Levin (2009) test exactly the same hypothesis with ours and find that borrowers are more likely to default on larger loans.

[3]In fact, this is our standard textbook model of firms' behavior.

1981). Ghosh, Mookherjee, and Ray (2000) emphasize the distinction between micro credit rationing, where a borrower' loan size is directly limited, and macro credit rationing, where a group of borrowers are denied access to any credit. Our analysis shows that the firm in our context, trying to optimize against heterogeneous moral hazard, not only imposed loan caps and thus micro-rationed credit, but also gradually selected out those more prone to moral hazard over time and thus also macro-rationed credit. In our context, macro credit rationing arises from the lending firm's counter-selection on moral hazard when it faces interest rate ceiling, different from explanations offered by previous literature.

Fourth, our study is also related to the research on the impact of modern financial technology. The rise of modern financial technology allows FinTech firms to mitigate traditional informational problems. On one hand, Fintech firms could access both hard and soft information (Iyer et al., 2016); nonstandard or soft information, including digital footprints (Berg et al., 2020), appearance (Duarte, Siegel, and Young, 2012) and friendships (Lin, Prabhala, and Viswanathan, 2013), supplements traditional hard information such as credit scores. On the other hand, with more information, big data and machine learning techniques offer FinTech firms an opportunity to design better screening algorithms and develop better monitoring technologies. The Fintech lending firm in our study also collects soft as well as hard information on all applicants. With this information as input, it invests significantly in machine learning technology and develops a proprietary algorithm to screen applicant before lending. Nevertheless, our results suggest that these efforts do not eliminate moral hazard problem. Our findings also raise the question of whether and how modern financial technology could cope with heterogeneity in moral hazard.

The remainder of this paper is organized as follows. Section 2 presents the conceptual framework we use and derives comparative statics. Section 3 describes our empirical setting and data. Section 4 and Section 5 present our main results and heterogeneity analysis respectively. Section 6 explores how the firm optimized its loan size when facing heterogeneous moral hazard. We discuss our findings in Section 7 and conclude in Section 8.

2 Model

2.1 Set-up

Our model builds on and extends that by Ghosh, Mookherjee, and Ray (2000) and Karlan and Zinman (2009). Consider an indivisible project requiring a loan of size L to be viable. A project here includes not only entrepreneurial activities, as traditionally defined, but also household activities, as that defined in Karlan and Zinman (2009). The project can either succeed or fail and thus its output is random. If it succeeds, the output is Q. Otherwise, the output is zero. The project succeeds with probability $p(e;a)$, and fails with probability $1-p(e;a)$. e is the effort level of the agent overseeing the project, and a is her ability level.[4] The probability of success $p(e;a)$ increases with effort level e at a diminishing rate. That is, $\frac{\partial p}{\partial e} > 0$ and $\frac{\partial^2 p}{\partial e^2} < 0$. It also increases with ability level a, i.e. $\frac{\partial p}{\partial a} > 0$. Let r, a positive constant, denote the interest rate. The problem for the agent if she is risk-neutral is to choose the effort level e^* to

$$\max_{e} p(e;a)[Q-(1+r)L]+[1-p(e;a)]\cdot 0-e. \tag{1}$$

If the project succeeds, the agent would get $Q-(1+r)L$, the output minus the principal and the loan interest. Otherwise, she gets nothing. In either case, the agent has to bear the cost of effort e. For simplicity, we assume the cost of effort is linear and is just e. Note the asymmetry when the project succeeds and when it fails. In the former case, the agent enjoys the output Q and pays the monetary cost $(1+r)L$. In the latter case, she still gets all the output ,

[4]Effort here is an abstract but "tractable way to model all borrower activities that impact repayment" (Karlan and Zinman, 2009). Ability here is also an abstract way to model all borrower characteristics that impact repayment given effort level. Therefore, ability could be interpreted as moral standard.

though it is zero now. But she does not have to pay the monetary cost because of limited liability. This asymmetry is one important assumption of our theoretical model. The other important assumption is that the lender could not observe the borrower's effort level e in any case, and could only observe the final result: either the project succeeds and the borrower pays back the loan, or the project fails and the borrower defaults.

Maximization of (1) implies that the optimal effort level e^* should satisfy the first-order condition

$$\frac{\partial p(e^*;a)}{\partial e} = \frac{1}{Q-(1+r)L}. \tag{2}$$

The optimal effort level e^* thus is a function of the project output Q when it succeeds, the loan size L, the interest rate r and the agent's ability level a.

Based on comparative static analysis, we propose the following two theoretical hypotheses. (Refer to Appendix A for details.)

Hypothesis I: Ceteris paribus, a larger loan size leads to a lower level of effort and a higher probability of default. That is, a higher debt burden causes a higher degree of moral hazard.

Hypothesis II: Ceteris paribus, a higher level of ability reduces the problem of moral hazard proposed in Hypothesis I.

Hypothesis I is the standard debt overhang problem in literature. Hypothesis II is the interactive effect indicating heterogeneity in moral hazard.To empirically test these two hypotheses, however, requires much more. An ideal scenario would be one in which for a given borrower, only her loan sizes vary at different time points; all the other aspects of her loans, including the interest rate and the loan term, stay constant. Fortunately, a Fintech lending firm provides a context that approximates this ideal scenario and also provides data for our study. Next we would describe its operation and the data.

3 Data

3.1 Fintech Lending Process

The Fintech lending firm was started by several wealthy men with their own money. This firm only offers a single product—short term consumption loans with annual interest rate 24% and loan term 14 days.[5] Figure 1 shows the operation process of the firm. Advertisements are deployed to attract potential applicants. Applicants just need to fill an application form. In the form, they provide personal information including identification number, monthly income, marriage status, occupation, education level, loan amount requested, purposes of loan, etc. The firm invests significantly in machine learning technology and designs a proprietary algorithm to review these applications, check the background of these applicants and decide the fate of these applications within seconds. The algorithm relies heavily on two credit scores to screen applicants. One is the Anti-Fraud score developed and maintained by Tencent, the company that develops and maintains the popular WeChat app in China. The firm employs the Anti-Fraud score to screen off potential frauds. The other is the Flash score developed by the firm itself. The Flash score is a sum of fourteen sub-scores. These sub-scores take into account every applicant' personal characteristics such as gender, education and her credit score as well as her behavior at other lending institutions such as how many lending institutions she has inquired before her current application and whether other lending institutions were able to deduct from her account in the previous month. The range of the Anti-Fraud score is from 0 to 100, and that of the Flash score is from 0 to 999. A larger Anti-Fraud score means a higher fraud risk, while a larger Flash score means a more trustworthy applicant. An applicant's Anti-Fraud score and Pi-Li score are not fixed, and could be updated each time she applies.

[5] The law in China protects loans with annual interest rates no greater than 24%, allows but does not protect loans with annual interest rates between 24% and 36%, and prohibits loans with annual interest rates greater than 36%. Debtors would only be forced by law to repay loans if they fail to do so when annual interest rates are no higher than 24%.

Most applications would be denied. Those whose applications are approved get loans with a fixed term of two weeks. At the expiration date, some loans turns out to be overdue. For those whose loans are overdue, the firm employs a team specializing in calling them to try to collect money back. The goal of the team is first to collect principals back. They do succeed in collecting back a portion of loans overdue. For the remaining loans overdue, the firm has to bear the loss of principals plus interest, when their borrowers refuse to repay the loans even after a dozen of calls from the collection team. The firm, of course, puts these borrowers on its blacklist and chooses to cut any connection with them in the future. The knowledge of one's default behavior could be shared by a number of similar online banking platforms. That is, these online banking firms might share a blacklist. However, as far as we know, one's default behavior on this platform does not affect her official credit score, i.e. the credit score reported by China's central bank.

Thus borrowers could be classified into three categories: those who repay loans on time, those who only repay loans after collection calls, and those who fail to repay any money no matter how many collection calls they have received. The first category, having proved themselves by repaying loans on time, subject to minor checks, could borrow from the firm the next time if they need. The final category, having failed to prove themselves by not repaying any money, are denied of any access to loans in the future by this firm. The accessibility to loans in the future for one in the second category depends on her overdue length. Only if one's overdue length is no more than three days, is her future access to loans from the firm possible. Indeed, we do not find any individual whose previous loans are overdue for more than three days in the data. We are informed that a three-day grace period would allow for borrowers' temporary neglect.

Figure 1 also shows various costs that the firm incurs as it goes through each stage of the lending process. First, the firm has to pay advertising cost. Second, for each applicant, it has to pay screening cost. The information input of the screening algorithm, including the Anti-Fraud score and the Flash score, is typically a purchase from other data providers. Third, if a loan is overdue, the firm has to pay collection costs, including labor costs of the collection team and direct communication costs of calling borrowers. If it is fortunate enough to collect principals back, the firm only has to lose interest. Otherwise, it has to bear a much greater loss of principal.

3.2 Summary Statistics

We draw a random sample of around 100,000 loan transactions from the database of this firm. It covers March 2018, when the firm started its business in online lending, through March 2019. Our sample only contains successful applicants, and does not include any individual whose application was rejected. Once a loan transaction of an individual is drawn into the sample, all her subsequent loans, if any, would also be. This sampling strategy allows us to track an individual's repayment performance over time and control for her fixed effect in the following regression analysis.

Table 1 summaries the statistics at loan level. The average loan amount applied is around 4.5 thousand CNY.[6] The average loan amount actually approved and borrowed is only around 1.2 thousand CNY. In the sample, loan amount applied is always no less than that actually approved and borrowed. That is, the gap between loan amount applied and that actually approved and borrowed is always non-negative. Among these loans, 11.2% of them is for the purpose of entertainment, 37.3% for purchases of clothes and cosmetics, 38.3% for purchases for electronics, and 12.2% for dining out. Note that the purposes here are reported by borrowers themselves when they fill online application forms, and in reality the firm lacks any means to monitor loans' usage.

Table 1 also summaries the Anti-Fraud score and the Flash score, the two aforementioned credit scores that the firm relies on heavily to screen applicants. The Anti-Fraud score has a mean of 46.9 and a standard deviation of 18.7, and is

[6] The exchange rate was between 6.3 CNY per US dollar and 7 CNY per US dollar during the study period.

distributed more or less evenly between 0 and 100.[7] In contrast, the Flash score has a mean of 602 and a standard deviation of 43.7, and most borrowers in our sample have a Flash score above 500. A more detailed examination reveals that only 1.55% of the 93,788 loans in the sample are approved with Flash scores less than 500.[8] We conclude from the distribution of these two credit scores that the firm relied more heavily on the Flash scores than on the Anti-Fraud scores for screening in practice.

Among the loans in the sample, 20.6% turns out to be overdue in the end. The aforementioned specialized collection team would call those whose loans are overdue in order to push them to repay loans as soon as possible. The number of collection calls is 3.5 on average for individuals with overdue loans. After these collection calls, a major 67.1% of overdue loans would be repaid in the end, and the average overdue length for them is 2.8 days; 32.9% of overdue loans would not be repaid at all in the end, and the average overdue length for them is 188.2 days.[9] For the whole sample, the firm calls each borrower 0.72 times on average, the average overdue length is 13.2 days and 6.8% of all loans are not repaid in the end.

Table 2 summaries the statistics at borrower level. It shows that during the study period, 64.7% of individuals borrowed only once, 23.4% twice, 8.3% three times, 2.7% four times, and the remaining 1.0% five or more times. The borrowers are between 21 and 47 years old with the average being 30.5 years old. 63.0% of them are male, 53.3% have a spouse, and 58.9% are urban residents. All borrowers report their monthly income bracket in the application form. 0.6% report their

[7]Tencent Inc. suggests adopting a certain threshold and rejecting anyone whose Anti-Fraud score is above the threshold. Nevertheless, the firm does not follow this suggestion at all. For the suggestion, see `https://cloud.tencent.com/document/product/668/14641`.

[8]A document details each of the fourteen sub-scores and the usage of the Flash score in practice. According to the document, the firm should directly approve the applications of those with Flash scores more than or equal to 645, turn those applicants with Flash scores greater than or equal to 630 but less than 645 to human agents for further checks, and reject those applicants with Flash scores less than 630. Again, the firm did not strictly follow this advice.

[9]Strictly speaking, the overdue length reported in the database for a loan that has never been repaid does not have any practical meaning. It should be understood as the length of the time between a loan's expiration date and the date that the firm completely gives up on collecting it back.

monthly income less than or equal to 1000 CNY, 0.2% between 1001 CNY and 2000 CNY, 11.2% between 2001 CNY and 4000 CNY, 31.9% between 4001 CNY and 6000 CNY, 25.4% between 6001 CNY and 8000 CNY, 16.6% between 8001 CNY and 10000 CNY, 8.2% between 10001 CNY and 15000 CNY, 3.4% between 15000 CNY and 20000 CNY, and the remaining 2.5% above 20000 CNY. They also report their occupations. 3.8% are in agriculture, forestry, animal husbandry, or fishery, 14.9% in manufacturing, 4.6% in IT sector, 5.3% in individual business, 4.1% in transportation sector, 6.1% in education or health sector, 9.3% in real estate industry, 16.5% in wholesale or retail trade, 6.2% in governmental or public institutions, 4.1% in banking, insurance or finance, 12.4% in catering, cosmetology, services or agencies, and 12.7% in other occupations unspecified. The borrowers' education levels, on the whole, are relatively high. Only 6.5% of them are of middle school or below, 34.6% of high school or technical secondary school, 41.4% of college education for professional training, and 17.5% have bachelor degree or above.

In Table 3, we summarize nonrepayment by loan order up to the fifth order. The nonrepayment rate is 6.85% for loans of the 1st order, 6.81% for loans of the 2nd order, 6.57% for loans of the 3rd order, 6.30% for loans of the 4th order and 5.60% for loans of the 5th order. This decreasing nonrepayment rate by loan order arises from positive dynamic selection: once a borrower fails to repay her loan, she would be denied of any future access to loans by the firm. This positive dynamic selection makes the pool of qualified borrowers of the n-th loan more credible than those of the $n-1$-th loan. Borrowers eligible for the n-th loan have proved themselves by repaying all their previous $n-1$ loans.

Table 1 and Table 2 report rich statistics on borrowers, but the firm collects much more. For example, we are informed that through a borrower's telephone directory, the firm could potentially know her personal network. The firm even knows the percentage of power remaining in a borrower's telephone when she fills the online application form.[10] Consequently, the information we researchers have is only a subset of that of the firm, a limitation we would take into account when we design our empirical strategy.

Though not perfectly complete, the data we have has two critical features for our following empirical analysis. First, as mentioned above, the firm only offers a single product—short term consumption loans with a fixed annual interest 24% and a fixed loan term 14 days. Therefore the only difference between loans is in their size. All the other aspects, including loan terms and interest rates, are the same. Second, the sampling scheme allows us to observe multiple loans for the same individual over time. Again, the only difference between these multiple loans is their size. We would utilize these two features in the following empirical analysis.

4 Empirical Tests

4.1 Econometric Model

Consider the following linear probability model,

$$D_{it+\Delta} = \alpha + \beta L_{it} + \gamma X_{it} + u_i + \epsilon_{it+\Delta}. \tag{3}$$

i denotes individual; t and $t + \Delta$ denotes date and $\Delta = 14$ is the fixed loan term. $D_{it+\Delta}$ is an default indicator, being one if individual i defaults 14 days later on the loan that she borrows on date t and being zero otherwise. L_{it} is the loan size that individual i borrows on date t. X_{it} denotes control variables including purposes of loan, the loan amount that individual i applies for, and her Flash score and Anti-Fraud score on date t. u_i represents i's individual heterogeneity. u_i could capture individual i's ability level as in the model (1), family background, personal network, etc. A borrower with a high ability level is more likely to earn enough

[10]A borrower with little power remaining in her telephone when she fills the online application form is treated as less reliable by the firm.

to repay her loan and thus is less likely to default. Similarly, an individual with a good family background and personal network is better able to get additional funds when she finds it difficult to repay her loan on her own, and thus is also less likely to default. $\epsilon_{it+\Delta}$ represents individual i's idiosyncratic shock on date $t+\Delta$. Individual i might suddenly fall ill or get fired then, and therefore be unable to repay her loan.

β, the coefficient of loan size L_{it}, is the parameter we are interested in. It measures the ceteris-paribus impact of an increase in loan size on default probability. Moral hazard implies a positive β, and a positive β confirms Hypothesis I. The magnitude of β measures the degree of moral hazard.

Note that in equation (3), L_{it} is the loan amount actually approved by the firm and borrowed by individual i on date t, rather than the amount individual i requests at application. The latter is included in X_{it} as a control variable. Now the key question is to understand how the firm decides on the loan amount L_{it} for individual i on date t. We propose the following model for the firm's decision on the loan amount approved for individual i,

$$L_{it} = f(X_{it}, \mu_i, s_t, v_{it}). \tag{4}$$

Here X_{it} denotes the same control variables as those in equation (3). μ_i again denotes i's individual heterogeneity. Remember that the firm knows much more than we researchers. In this sense, μ_i denotes individual i's characteristics that the firm knows but we researchers do not. s_t denotes supply shifters. The firm might change or update its lending strategy over time.[11] v_{it} denotes other new information collected by the firm on date t when individual i applies for a loan. As shown in Figure 1, the firm still collects new information even borrowers have applied and been screened before.

[11] We are informed that there is no fixed formula to determine loan size, and the firm would adjust its lending strategy from time to time if it feels the time is right. Though the algorithm employed by the firm is fixed, it seems that the firm could change the parameters of the algorithm and thus change the daily average loan size.

Next we examine the relationship between the lending decision rule (4) and the determinants of default likelihood (3). First, u_i in (3) and μ_i in (4) are obviously correlated with each other, since both denote individual i's individual heterogeneity and the factors they each capture could have some in common. Second, $\epsilon_{it+\Delta}$ in (3) and v_{it} in (4) might also be correlated. v_{it} is the innovation on date t influencing the loan amount that the firm decides to lend to individual i; $\epsilon_{it+\Delta}$ is the innovation $\Delta(=14)$ days later influencing individual i's default probability. A correlation between v_{it} and ϵ_{it} and a serial correlation between ϵ_{it} and $\epsilon_{it+\Delta}$ could cause the correlation between v_{it} and $\epsilon_{it+\Delta}$. The correlation between v_{it} and ϵ_{it} could be because they two, both innovations on date t, might capture something in common. The correlation between ϵ_{it} and $\epsilon_{it+\Delta}$ might be because ϵ_{it} persists over time and this persistence does not vanish $\Delta(=14)$ days later.

Consequently, loan size L_{it} in (3) is endogenous, and it is correlated not only with individual i's fixed effect u_i, but might also with the innovation term $\epsilon_{it+\Delta}$. Further analysis reveals that u_i and L_{it} are negatively correlated: a larger u_i means that i herself is more likely to default, and thus she would have to receive a smaller amount of loan L_{it} from the firm. Ignoring this negative correlation would bias the estimate of β downward. Similar reasoning applies to the correlation between L_{it} and $\epsilon_{it+\Delta}$: these two are also negatively correlated, and thus an estimation of β even after controlling for individual heterogeneity by fixed effects might still be biased downward.

With the above endogeneity problem in mind, we would next show our empirical strategy and results. We would first compare OLS and Fixed Effects (FE) estimations, and then show how to augment the FE method with an instrumental variable (IV) strategy.

4.2 OLS and FE

Table 4 intuitively illustrates our estimation strategy. Here we first classify all loans according to their order. For a borrower's n-th loan, we compare its size with the same borrower's $n-1$-th loan. The comparison yields either zero or positive difference. According to the comparison, we further categorize all loans of the same order into two groups: one with the same size as the previous loan by the same borrower, denoted as Group 1, and one with a larger size than the previous loan by the same borrower, denoted as Group 2. Table 4 shows that the nonrepayment rate of Group 2 is always larger than that of Group 1. In particular, the first panel shows that conditional on loans being of the 2nd order, the nonrepayment rate of Group 2 is 6.84%, slightly higher than that of Group 1. The second panel shows that conditional on loans being of the 3rd order, the nonrepayment rate of Group 2 is 7.24%, higher than that of Group 1 by 1.1 percentage points. The third panel shows that conditional on loans being of the 4th order, the nonrepayment rate of Group 2 is 6.97%, higher than that of Group 1 by 1.2 percentage points. Therefore, s borrower' likelihood of default increases when she happens to get a larger loans than her previous one. Note that the above comparison of the nonrepayment rates of these two groups is conditional on loans' order. By conditioning on loans' order, we have partially controlled for borrowers' unobserved heterogeneity arising from positive dynamic selection suggested by Table 3.

Further regression results of estimating (3) are shown in Table 5. Here we measure the dependent variable D_{it} by whether i's loan has been overdue or not by its expiration date.

In order to control for borrowers' unobserved heterogeneity arising from positive dynamic selection, we again classify loans by their orders; the first panel, the second panel and the third panel of Table 5 only consider loans of the 1st and the 2nd order, loans of the 2nd and the 3rd order and loans of the 3rd and the 4th order, respectively. Since the results across these three panels are similar, we would only focus on the first panel in our following discussion.

The first column reports the estimation results by OLS with no control variable. It shows that a one-thousand-CNY increase in loan size decreases overdue rate by about 5.20%. Further estimation with control variables included in the second column lowers the estimate to 4.31%. Both results, however, are contrary to Hypothesis I. The third column controls for individual heterogeneity by fixed effects, and now the estimation becomes positive: a one-thousand-CNY increase in loan size increases overdue rate by about 15.7%. Further controlling for other covariates in the final column lowers the estimate slightly to 13.7%. The contrast between the first two columns and the last two columns tells the importance of individual heterogeneity in determining loan size and default likelihood. An individual with more positive heterogeneity, i.e. a higher μ, would receive a larger loan according to (4). Meanwhile, a higher μ in (4) implies a lower u in (3), and a lower u decreases default probability. Therefore, without controlling for individual heterogeneity, loan size and default likelihood are more likely to be negatively correlated, as confirmed by the regression results in the first two columns of Table 5. Controlling for individual heterogeneity would make the estimate more close to the true value, as confirmed by the regression result in the final column of Table 5.

Here it is worth emphasizing that in the control variables, we have included loan amount applied. The loan amount requested by a borrower on a particular date might reflect some of her idiosyncrasies then and these idiosyncrasies might influence her later default behavior. For example, illness or temporary unemployment necessitates a larger amount of borrowing, and these temporary shocks might also make later repayment on time more difficult. By including loan amount applied in the covariates, we have controlled for the potential impact of these idiosyncrasies on later default behavior.

Moreover, after we have controlled for loan amount requested by borrowers, the remaining variation in the main dependent variable in (3), i.e. loan amount actually approved, is largely caused by supply side rather than by demand side, that is, by the firm rather than by borrowers. This requires us to examine the variation in loan amount from the supply side perspective, as we do in (4).

Next in Table 6, we use number of collection calls after one defaults on her loan as a second proxy for the default indicator D_{it} in (3). As mentioned above, the firm employs a team specialized in calling those who default on their loans. The team would call debtors time after time either until they repay their loans or until the firm gives up hope of collecting money back. Again for the same reason as above, we would only focus on the first panel in our following discussion.

The first column in Table 6 shows that a one-thousand-CNY increase in loan size decreases number of collection calls by 0.11. When we include control variables in the regression in the second column, the estimate changes to -0.04, and becomes insignificant. The third column controls for individual heterogeneity by fixed effects, and now the estimate becomes positive and significant: a one-thousand-CNY increase in loan size now costs 0.92 extra collection calls. Further controlling for other covariates in the final column lowers the estimate slightly to 0.78. Once again, as that in Table 5, the contrast between the first two columns and the last two columns of Table 6 tells the importance of controlling for individual heterogeneity when we test moral hazard.

Finally in Table 7 we use a dummy variable denoting whether a loan is repaid or not eventually as a proxy for the default indicator. If an overdue loan is not repaid eventually, the dummy variable is unity. Otherwise, it is zero. For the same reason as above, we would only focus on the first panel in our following discussion.

The first column in Table 7 shows that a one-thousand-CNY increase in loan size decreases nonrepayment rate by about 0.86%. Controlling for potential relevant variables makes the estimate close to zero and insignificant, as shown in the second column. The third column shows that once we have controlled for individual heterogeneity by fixed effects, the estimate becomes positive and significant: now a one-thousand-CNY increase in loan size increases nonrepayment rate by 8.74%. Further controlling for other covariates in the final column lowers the estimate slightly to about 7.34%.

No matter how we measure the default indicator, all the results from Table 5 to Table 7 show a similar pattern: the estimates by OLS and by FE differ substantially and the signs of the estimates by these two methods are often opposite to each other. The estimates by OLS do not support Hypothesis I. However, once we have controlled for individual heterogeneity by FE, all estimates change substantially: all of them become positive and relatively large in magnitude. In contrast to the estimates by OLS, the estimates by FE provide strong support for Hypothesis I.

Nevertheless, as analyzed above, the estimates by FE might still be biased downward. Next we would show how to address this potential bias with an IV strategy.

4.3 IV-FE

For a loan of size L_{it}, we use the average loan size originated on its previous day, denoted as $\bar{L}_{t-1}$, as the instrument for L_{it}. Figure 2 shows daily average loan size over time. The daily average loan size initially centered around 0.5 thousand CNY. Then in May 2018, it jumped to around 1 thousand CNY and had been staying at that level for about 5 months through Oct 2018. Starting from then, the daily average loan size had been gradually increasing until Dec 2018. After that, it stayed around 1.7 thousand CNY. This pattern suggests that the variation in the daily loan size is mainly driven by the supply side rather than by the demand side. By employing average loan size of the previous day, $\bar{L}_{t-1}$, as the instrument for loan size L_{it}, intuitively we make use of a shifter from the supply side as an instrument for the equilibrium loan size to examine the response by the demand side,i.e., borrowers' default behaviour. Next we would argue for the validity of the instrument.

For simplicity, consider individual i who borrows from this firm first on date t_1 and then again on a later date t_2 with $t_2 > t_1 + \Delta > t_1$. A differenced version of (3) is

$$D_{it_2+\Delta} - D_{it_1+\Delta} = \beta(L_{it_2} - L_{it_1}) + \gamma(X_{it_2} - X_{it_1}) + (\epsilon_{it_2+\Delta} - \epsilon_{it_1+\Delta}). \qquad (5)$$

As analyzed above, the difference in the loan size $L_{it_2} - L_{it_1}$ in (5) is endogenous because loan size on date t_2, L_{it_2}, could be correlated with individual idiosyncratic shock on date $t_2+\Delta$, $\epsilon_{it_2+\Delta}$. Similarly, loan size on date t_1, L_{it_1}, could be correlated with individual idiosyncratic shock on date $t_1 + \Delta$, $\epsilon_{it_1+\Delta}$. By employing average loan size of the previous day, $\bar{L}_{t-1}$, as the instrument for the loan size, L_{it}, we actually instrument the difference in loan size, $L_{it_2} - L_{it_1}$, with the difference in average loan size of the previous day, $\bar{L}_{t_2-1} - \bar{L}_{t_1-1}$. The average loan size on date $t_2 - 1$ (or on date $t_1 - 1$) is the average over those who borrows on date $t_2 - 1$ (or on date $t_1 - 1$). Borrowers on date $t_2 - 1$ (or on date $t_1 - 1$) and those on date t_2 (or on date t_1) are two distinct groups. Under the assumption that idiosyncratic shocks are independent across persons, i.e. $\epsilon_{it} \perp \epsilon_{js}$ for any $i \neq j$ and any t and s, average loan size on date $t_2 - 1$, $\bar{L}_{t_2-1}$ (or on date $t_1 - 1$, $\bar{L}_{t_1-1}$), is not only uncorrelated with individual i's idiosyncratic shock on date $t_2 + \Delta$, $\epsilon_{it_2+\Delta}$ (or on date $t_1+\Delta$, $\epsilon_{it_1+\Delta}$), but also uncorrelated with individual i's idiosyncratic shock on date $t_1 + \Delta$, $\epsilon_{it_1+\Delta}$ (or on date $t_2 + \Delta$, $\epsilon_{it_2+\Delta}$). Therefore, the difference in average loan size of the previous day, $\bar{L}_{t_2-1} - \bar{L}_{t_1-1}$, is uncorrelated with the difference in individual idiosyncratic shock, $\epsilon_{it_2+\Delta} - \epsilon_{it_1+\Delta}$, and thus is a valid instrument for the difference in loan size, $L_{it_2} - L_{it_1}$ in (5).

Table A.1 in the appendix examines determinants of loan size and confirms the strong impact of the instrument on the instrumented. Note that Table A.1 also shows that loan amount applied has a minimal impact on loan amount approved. Besides, the sign is opposite to our expectation: a one-thousand CNY increase in loan amount applied decreases—rather than increases—the amount finally approved by about seven CNY. This again suggests that most variation in loan amount approved and borrowed is not driven by the demand side.

Table 8 shows the regression results estimated by instrumental-variable fixed-effects (IV-FE) method.[12] Similarly as before, the first panel, the second panel and the third panel only considers loans of the 1st and the 2nd order, loans of the 2nd and the 3rd order and loans of the 3rd and the 4th order, respectively. Again since the results across these three panels are similar, we would focus on the first panel in our following discussion.

All the estimates by IV-FE are larger in magnitude than the corresponding ones by FE. The first column shows that a one-thousand-CNY increase in loan size increases overdue rate by about 18.70%, larger than the estimate by FE—13.73% in the final column of Table 5. The second column shows that the same increase in loan size increases number of collection calls by 1.36, again larger than the corresponding FE estimate—0.78 in the final column of Table 6. The final column shows that a one-thousand-CNY increase in loan amount increases nonrepayment rate by 12.62%, much larger than the corresponding FE estimate—7.34% in the final column of Table 7.

Note that in all the regressions in Table 8, we also control for loan amount applied. All the results, however, show that the impact of loan amount applied on borrowers' default behavior, no matter how we measure it, is tiny and insignificant.

All the above IV-FE estimates confirm the downward bias of the FE estimates analyzed in Section 4.1. Therefore, even after controlling for individual heterogeneity we should still treat loan amount as endogenous , and address the problem with an appropriate instrument.

The empirical analysis in Table 8 strongly supports Hypothesis I. Nevertheless, it has not exhausted all theoretical implications. Hypothesis II further proposes that the degree of moral hazard depends on borrowers' ability level. Next we would explore this heterogeneity.

[12] The IV-FE method also solves the problem of nonrandom attrition, if any.

5 Heterogeneity

To test the interactive effect proposed in Hypothesis II, we modify (3) slightly and add an interactive term,

$$D_{it+\Delta} = \alpha + \beta L_{it} + \theta L_{it} * \text{ability}_i + \gamma X_{it} + u_i + \epsilon_{it+\Delta}. \tag{6}$$

Hypothesis II implies that $\theta < 0$. To estimate Equation (6), we choose education level as a measure of ability.

Table 9 shows the heterogeneity in moral hazard when we employ the dummy of higher education as the measure of ability and estimate (6) by FE. We classify those borrowers who attend college for professional training or receive a bachelor degree or above as those of higher education, and others as those of lower education. The three panels of Table 9 report regression results for loans of the 1st and the 2nd order, loans of the 2nd and the 3rd order and loans of the 3rd and the 4th order, respectively. Again we would only focus on the first panel in our following discussion.

The first column in Table 9 shows that for a borrower with higher education, the main effect of a one-thousand-CNY increase in loan size on overdue rate, a 15.25% increase, decreases by 2.51 percentage points, though insignificant. The second column shows that the main effect on number of collection calls, a one increase, decreases by 0.36 for a borrower with higher education. The final column shows that the main effect on nonrepayment rate, a 9.30% increase, decreases by 3.08 percentage points for a borrower with higher education. Two thirds of all estimates of the interactive effect in Table 9 are significant and large in magnitude.

However, as before, loan size L_{it} is endogenous in (6), and this additionally causes the endogeneity of the interaction term $L_{it} * \text{ability}_i$. To deal with this endogeneity problem, we use the same strategy as before: we instrument loan size L_{it} by average loan size of the previous day, $\bar{L}_{t-1}$, and additionally instrument the interaction term $L_{it} * \text{ability}_i$ by $\bar{L}_{t-1} * \text{ability}_i$, the interaction between average loan size of the previous day and individual i's ability level.

Table 10 shows the heterogeneity in moral hazard when we use the education level as the measurement of ability. Most estimates in the first two panels are significant and large in magnitude, while those estimates in the third panel, though similar in magnitude, are insignificant because of a smaller sample size. In the first panel of Table 10, the first column shows that the main effect of a one-thousand-CNY increase in loan size on overdue rate, a 20.75% increase, decreases by 4.08 percentage points for a borrower with higher education. The second column shows that the main effect on number of collection calls, a 1.63 increase, decreases by 0.46 in absolute value for a borrower with higher education. The final column shows that the main effect on nonrepayment rate, a 15.09% increase, decreases by 4.39 percentage points for a borrower with higher education.

Overall, the results in Table 9 and Table 10 support Hypothesis II, especially when we focus on loans of order up to three.

Now that a larger loan size leads to a higher default rate, in principle loan price, i.e., interest rate, should increase with loan size. However, the interest rate charged by this firm, 24% uniformly for all loans, is already the maximum allowed by law in China. Still, one remaining option is to impose a loan cap. According to Figure 2, the firm does impose loan caps in practice. Next we would examine whether local caps imposed by the firm are optimal.

6 Gradual Optimization Against Heterogeneous Moral Hazard

To check whether the loan caps imposed the firm are optimal, we would first quantify a loan's marginal cost and marginal benefit and then compare the two. The above regression results have already provided key parameters that our quantification needs.

6.1 Quantifying Marginal Benefit and Marginal Cost

First consider marginal benefit. If the firm lends out one CNY more, it would get more interest payment, but only when the loan gets repaid in the end. That is, we need to discount the interest rate($\equiv r$) by the actual nonrepayment rate($\equiv NR$). Therefore, we calculate marginal benefit at time t as

$$MB_t = r \times [1 - (NR_t + \Delta NR)]. \tag{7}$$

r in Equation (7) denotes the interest rate charged by the firm, 24% in our case; NR_t denotes the nonrepayment rate realized at time t, and ΔNR denotes the marginal impact of one CNY on nonrepayment rate. Note that the marginal impact of one CNY here is negligible: though the estimated marginal impact of a one-thousand-CNY on nonrepayment rate is both significant and large in magnitude, we need to multiply this estimated marginal impact by one thousandth in Equation (7) when calculating the marginal impact of one CNY instead.

Next consider marginal cost. Table 8 shows that an increase in loan size causes an increase in nonrepayment rate. This increase in nonrepayment rate not only reduces the firm's marginal benefit by increasing the likelihood of a borrower not paying the interest of her loan, which has already been taken into account in Equation (7), but also directly causes a loss of principal by increasing the borrower's likelihood of not repaying the principal. Suppose the amount of principal is L thousand CNY, the resulting marginal cost of one CNY is

$$\begin{aligned} MC_t =& (L + 0.001) \times 1000 \times (NR_t + \Delta NR) - L \times 1000 \times NR_t \\ \approx& L \times 1000 \times \Delta NR + NR_t. \end{aligned} \tag{8}$$

Though the marginal impact of one CNY on nonrepayment rate is minuscule, 0.1262/1000 in our case, the principal L is in the order of one thousand and thus the resulting expected loss becomes large in magnitude.

With marginal benefit calculated as that in Equation (7) and marginal cost calculated as that in Equation (8), we next calculate the optimal loan cap.

6.2 Optimal Loan Cap

By equating marginal benefit in Equation (7) with marginal cost in Equation (8), we calculate the optimal loan cap at time t as

$$\begin{aligned} L_t^{\text{opt}} \times 1000 \times \Delta NR + NR_t =& r \times [1 - (NR_t + \Delta NR)], \\ L_t^{\text{opt}} =& \frac{r \times [1 - (NR_t + \Delta NR)] - NR_t}{1000 \times \Delta NR}. \end{aligned} \tag{9}$$

If we take NR_t to be the average nonrepayment rate during the sample period, 6.8% as summarized in Table 1, and further take ΔNR to be the estimated marginal effect of a one CNY on nonrepayment rate, 12.62% as shown in the first panel of Table 8 divided by one thousand, the implied optimal loan cap would be 1.236 thousand CNY, which is surprisingly close to the average loan size during the sample period, 1.181 thousand CNY as shown in Table 1.

In the above calculation of the optimal loan cap, we researchers hold an unfair advantage in that we use ex post data on overdue and nonrepayment realizations, something that is unavailable to the firm at the time of loan origination. NR_t should in principle be the *expected* nonrepayment rate at time t, while 6.8% in the above calculation is the ex post sample nonrepayment rate. What matters then is how the firm forms its expectation of nonrepayment rate when it decides on loan size.

We assume two models of expectation formation process for the firm: one is heuristic and the other is Markov. With heuristic expectation, the firm uses the nonrepayment rate *up to* date t as its then expectation of nonrepayment rate. With Markov expectation, the firm only uses the nonrepayment rate during the previous credit cycle (the previous fourteen days) as its then expectation of nonrepayment rate.

With these two expectation models, we continue to calculate daily average marginal benefit according to equation (7), where r is taken to be 24%, NR_t is the heuristic expectation or the Markov expectation of nonrepayment rate at time t and ΔNR is the same as before, i.e., 12.62% divided by one thousand. We also calculate daily average marginal cost according to equation (8), where NR_t and ΔNR are the same as that in the calculation of daily average marginal benefit and L is taken to be the daily average loan size.

Figure 3 shows the calculated daily average marginal benefit and marginal cost, with the left sub-figure employing the heuristic expectation model and the right one employing the Markov expectation model. Though the one employing the Markov expectation model is more bumpy, both sub-figures show a similar pattern. Initially daily average marginal cost was less than daily average marginal cost, implying that daily average loan size then was lower than the optimal size. This continued for about half year until Oct. 2018. Then it seems that the firm recognized this sub-optimality and began to increase its loan limit. As a result, daily average marginal cost began to move close to daily average marginal benefit. However, the firm continued to increase its daily average loan size even after daily average marginal cost had caught up with daily average marginal benefit. The increase stopped around Dec. 2018, after which daily average loan size stayed around constant. Therefore, daily average marginal cost also stayed around constant after that, but at a level above daily average marginal benefit.

The above analysis examines the equalization of marginal benefit and marginal cost globally for the whole sample. Next we investigate the equalization of this two separately for the high education and the low education, which is also required by optimization.

6.3 Optimal Loan Caps by Education Group

Our analysis in Section 5 shows that the degree of moral hazard depends on borrowers' education level. This heterogeneity implies that for a given loan size, the high education and the low education would incur different marginal benefits and marginal costs according to (7) and (8).

Denote the high education as H, and the low education as L. Optimization across groups requires that

$$MB_H = MC_H = MB_L = MC_L, \tag{10}$$

where MB_H and MB_L denote marginal benefit for the high education and the low education respectively, and MC_H and MC_L denote marginal cost for the high education and the low education respectively.

By (7), $MB_H = MB_L$ requires that the nonrepayment rate of the high education and of the low education should approximately be the same. That is, we should have

$$NR_t^H \approx NR_t^L, \tag{11}$$

where NR_t^H and NR_t^L denote the nonrepaymanet rate of the high education at time t and of the low education at time t respectively. Given (11), by (8), $MC_H = MC_L$ further requires that

$$\bar{L}_H \times \Delta NR_H = \bar{L}_L \times \Delta NR_L, \tag{12}$$

where $\bar{L}_H$ and $\bar{L}_L$ denote average loan size of the high education and of the low education respectively, and ΔNR_H and ΔNR_L denote the marginal effect of one-thousand CNY on nonrepayment rate of the high education and of the low education respectively. If we take ΔNR_L to be 0.1509 and ΔNR_H to be 0.1070 (=0.1509-0.0439), as that estimated in the first panel of Table 10, (12) implies that

$$\frac{\bar{L}_H}{\bar{L}_L} = \frac{\Delta NR_L}{\Delta NR_H} = \frac{0.1509}{0.1070} = 1.4. \tag{13}$$

That is, average loan size of the high education should be about 40% larger than that of the low education.

However, Figure 4 shows that daily average loan size of the high education and that of the low education were quite close to each other all the time. Apparently the firm failed to optimize across this two distinct groups.[13]

Nevertheless, the failure to optimize across groups does not necessarily leads to failure to optimize within groups. Optimization within groups only requires that

$$MB_H = MC_H, \tag{14}$$

$$MB_L = MC_L. \tag{15}$$

To check the possibility of optimization within the high education group, we compare the calculated daily average marginal benefit and marginal cost for the high education in Figure 5, with the left sub-figure employing the heuristic expectation model and the right one employing the Markov expectation model. In the calculation of daily average marginal benefit for the high education according to (7), we take interest rate, r, to be 24%, NR_t to be the heuristic expectation or the Markov expectation of the nonrepayment rate at time t of *the high education*, and ΔNR to be 0.1070/1000—the estimated marginal effect of one-thousand CNY on the nonrepayment rate of *the high education* (0.1070=0.1509-0.0439), as shown in the first panel of Table 10, divided by one thousand. Similarly in the calculation of daily average marginal cost for the high education according to (8), NR_t and ΔNR are the same as that in the calculation of daily average marginal benefit and L is taken to be daily average loan size of *the high education*.

Both sub-figures show a similar and interesting pattern. Initially marginal cost was lower than marginal benefit. As the firm increased its daily average loan size for the high education (also for the low education, as Figure 4 shows that the loan amount of this two groups moved together) after Oct. 2018, marginal

[13] Information constraint is likely to be the cause for this failure. Note that this online lending firm lacks direct means to verify the education level reported by applicants. Given this information constraint and the fact that loan amount actually approved is always no more than what borrowers applies in the first place, if the firm chooses to discriminate in favour of the high education by means of a larger loan size, all applicants would have pretended to be of high education when they fill the application form.

cost gradually caught up with marginal benefit. After Dec. 2018, daily average loan size stayed around constant and thus the calculated daily average marginal cost also stayed around constant, but surprisingly, at a level quite close to the calculated daily average marginal benefit.

Next we turn to examine the degree of optimization within the low education. We compare the calculated daily average marginal benefit and marginal cost for the low education in Figure 6. In the calculation, we take r to be 24%, L to be daily average loan size of *the low education*, NR_t to be the heuristic expectation or the Markov expectation of the nonrepayment rate at time t of *the low education*, and ΔNR to be 0.1509—the estimated marginal effect of one-thousand CNY on nonrepayment rate of *the low education*, as shown in the first panel of Table 10, divided by one thousand.

Again, both sub-figures show a similar pattern, but in a way opposite to that shown in Figure 5. Here initially marginal cost was quite close to marginal benefit. As the firm began to increase its daily average loan size for the low education after Oct.2018, marginal cost began to increase and diverge from marginal benefit. After Dec. 2018, daily average loan size stayed around constant and thus the calculated daily average marginal cost also stayed around constant, but at a level quite above the calculated daily average marginal benefit.

Based on Figure 5 and Figure 6, we are able to conclude that eventually the firm chose to optimize within the high education, and sacrificed optimization within the low education. It turns out that this strategy shift is justified by more borrowers with high education among the pool of borrowers over time. We plot the proportion of first-time borrowers with high education over time in Figure 7 and find that this is indeed the case: the proportion of first-time borrowers with high education gradually increased from around 50% at the beginning of the sample period to around 70% at the end of the sample period. The selection of more first-time borrowers with high education turns out to make perfect sense: when the firm did not distinguish the high education from the low education in terms of loan size, the firm should prioritize lending to the high education if the two groups were identical in other respects, because the high education was less likely to default ex ante. Figure 8 compares cumulative nonrepayment rates by education group and confirms that the high education was indeed always less likely to default. Therefore, for a loan of given size, it was more profitable for the firm to lend it to the high education.

Based on the above analysis, we arrive at the following conclusions. First, on the whole, in terms of average loan size, the firm was not far from optimality. The calculated optimal loan cap (1.236 thousand CNY) and the actual daily average loan size during the sample period (1.181 thousand CNY) were quite close to each other, and this two differed by less than 5%. Second, the firm's daily average loan size in the first half of the sample period was close to that required by the optimization within the low education. Later the firm gradually increased its daily average loan size. After the gradual increase, its daily average loan size stabilized at a level quite close to the optimal one for the high education. In the meantime, the firm selected more borrowers with high education over time.

On the one hand, initially the firm was unaware of the heterogeneity in moral hazard between the high education and the low education, did not distinguish between the two groups in terms of loan size, and thus failed to optimize across them. On the other hand, during the second half of the sample period, the firm recognized this failure, gradually increased its daily average loan size to a level close to the optimal size for the high education, and counter-selected on moral hazard by selecting in more borrowers with high education over time.

We have examined the firm's gradual optimization against moral hazard in detail, but the examination is still with some limitations. Next we would discuss these limitations.

7 Discussion

7.1 Voluntary vs. Involuntary Defaults

A main threat to online lending business is voluntary or strategic defaults by some borrowers, i.e. borrowing without any plan or intention to repay loans later. The firm could sue these intentional defaulters later to recover losses. However, because of the cost of suing itself and the weak legal enforcement in China, the effectiveness of this strategy is limited. Note that once a borrower chooses voluntary default and refuses to repay her loan, the firm would never lend to her again. So one could only default strategically once. Then a willful but rational borrower should choose to default on the loan whose discounted principal is the largest. If the discounted loan size one expects to get is not any larger in the future, she should default immediately on the first loan; Otherwise, she should always postpone voluntary default and have no reason to default within any limited horizon, especially within our one-year sample period.

Based on this reasoning and taking advantage of the rich information offered by the firm, we infer the proportion of possible voluntary defaults in our data. The data records not only whether one defaults on her loan, but also whether the firm loses contact with her in the end. Losing contact means that one changes her phone number later and thus she voluntarily choose not to be reached. Losing contact, especially immediately after one's first loan, strongly indicates voluntary default.

Therefore, we define a loan default as voluntary if this loan's borrower has no other loan within the study period, fails to repay this only loan in the end, and could not be reached any longer by the firm after one, two or three collection calls. Under this definition, 0.59% of all loans are voluntarily defaulted in the end, and they account for only 8.7% (=0.59%/6.8%) of all bad debts.[14] In other words,

[14]This estimate of the proportion of voluntary defaults could be biased upward. If we further restrict voluntary defaults to those loans whose borrowers could not be reached any more by the firm after only one collection call, only 0.08% of all loans are voluntarily defaulted, and they account for only 1.2% (=0.08%/6.8%) of all bad debts.

more than 90% defaults are involuntary in our sample.

Further note that our estimation strategy employs fixed effect. Since fixed effect requires at least two observations for a single borrower during our study period, voluntary defaults defined in the above way contribute nothing to our estimation results. For these two reasons, we focus on involuntary defaults in our modeling approach.

7.2 Price vs. Quantity

Our calculation of marginal benefits and marginal costs is all conditional on the interest rate set by the firm. Since the annual interest rate was always fixed at 24% during our study period and there was no variation in it, we could not answer the question whether the price, i.e. the interest rate, charged by the firm was the optimal one. What we have done in this paper is to analyze in detail that conditional on the fixed price, whether the firm's quantity strategy in terms of loan caps imposed is close to being optimal.

7.3 Adverse Selection vs. Moral Hazard

Besides the problem of moral hazard facing this Fintech lending firm, the other informational problem is adverse selection—the possibility that a higher interest rate would attract borrowers of higher risk.

We are able to exclude adverse selection in the traditional sense from our consideration for the following two reasons. First, as mentioned above, the interest rate was fixed during our study period, and therefore the pool of applicants that the firm attracted in terms of riskiness could also be considered to be fixed over time. Second, when measuring moral hazard, we adopt FE method and thus we compare the same individual's default behavior when she gets loans of different size. Therefore, any individual unobserved heterogeneity, including individual riskiness, has been controlled for in our empirical analysis.

Nonetheless, our analysis of heterogeneity in moral hazard and the firm's counter-selection on moral hazard based on this heterogeneity blur the traditional line between adverse selection and moral hazard, a point also suggested in Einav et al. (2013). Moral hazard, like riskiness, contains an element of unobserved heterogeneity on which either agents could select or principals could counter-select.

8 Conclusion

Our paper relates a Fintech Lending firm's actual behavior to its borrowers' heterogeneity in moral hazard. Our results reveal the firm's gradual optimizing effort against heterogeneous moral hazard by changing loan caps imposed and changing composition of borrowers over time.

Needless to say, out quantitative estimates are highly specific to our study context. Nonetheless, at a broad level they illustrate the role of heterogeneity in moral hazard in driving lending behavior, including loans caps imposed, changes in loan caps, and changes in composition of borrowers in terms of proneness to moral hazard. We hope that future work could go beyond testing adverse selection, or moral hazard, or heterogeneity in moral hazard, and directly relate economic agents' actual behavior to these informational problems.

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Table 1. Summary Statistics: Loan Level

	Obs	Mean	Std. Dev.	Min	Max
Overdue	95426	0.206	0.405	0	1
Number of Collections					
Full Sample	95426	0.718	2.574	0	48
Overdue Sample	19701	3.479	4.742	0	48
Days Overdue					
Full Sample	95426	13.180	51.780	0	350
Overdue Sample	19701	63.838	98.758	1	350
Been-Repaid	13214	2.784	9.997	1	296
Not-Been-Repaid	6487	188.206	79.724	1	350
Not-Been-Repaid					
Full Sample	95426	0.068	0.252	0	1
Overdue Sample	19701	0.329	0.470	0	1
Loan Amount (Thousand CNY)					
At Application	95426	4.526	5.767	0.5	20
Actually Approved and Borrowed	95426	1.181	0.355	0.5	3
Gap Between the Above Two	95426	3.345	5.859	0	19
Purposes of Loan					
Entertainment	95426	0.112	0.315	0	1
Clothes and Cosmetics	95426	0.373	0.484	0	1
Electronics	95426	0.383	0.486	0	1
Dining Out	95426	0.122	0.327	0	1
Others	95426	0.011	0.102	0	1
Credit Scores					
Anti-Fraud Score	94360	46.903	18.661	0	98
Flash Score	93787	602.028	43.693	269.16	756.93

Table 2. Summary Statistics: Borrowers' Characteristics

	Obs	Mean	Std. Dev.	Min	Max
No. of Loans Borrowed					
One	63338	0.647	0.478	0	1
Two	63338	0.234	0.423	0	1
Three	63338	0.083	0.276	0	1
Four	63338	0.027	0.162	0	1
$\geq$ Five	63338	0.010	0.098	0	1
Age	63338	30.460	5.486	21	47
Male	63338	0.630	0.483	0	1
Spouse	59234	0.533	0.499	0	1
Urban Hukou	63338	0.589	0.492	0	1
Monthly Income (CNY)					
[0,1000]	59428	0.006	0.080	0	1
[1001,2000]	59428	0.002	0.049	0	1
[2001,4000]	59428	0.112	0.315	0	1
[4001,6000]	59428	0.319	0.466	0	1
[6001,8000]	59428	0.254	0.435	0	1
[8001,10000]	59428	0.166	0.372	0	1
[10001,15000]	59428	0.082	0.275	0	1
[15001,20000]	59428	0.034	0.180	0	1
[20001,$+\infty$]	59428	0.025	0.157	0	1

Table 2. Summary Statistics: Borrowers' Characteristics (continued)

	Obs	Mean	Std. Dev.	Min	Max
Occupations					
Agriculture, Forestry, Animal Husbandry, Fishery	63338	0.038	0.192	0	1
Manufacturing	63338	0.149	0.356	0	1
IT	63338	0.046	0.210	0	1
Individual Business	63338	0.053	0.223	0	1
Transportation	63338	0.041	0.199	0	1
Education and Health	63338	0.061	0.239	0	1
Real Estate Industry	63338	0.093	0.291	0	1
Wholesale and Retail Trade	63338	0.165	0.371	0	1
Govermental and Public Institution	63338	0.062	0.241	0	1
Banking, Insurance, Finance	63338	0.041	0.198	0	1
Catering, Cosmetology, Services, Agents	63338	0.124	0.329	0	1
Others	63338	0.127	0.333	0	1
Education					
Middle School or Below	59431	0.065	0.246	0	1
High School or Technical Secondary School	59431	0.346	0.476	0	1
College for Professional Training	59431	0.414	0.492	0	1
Bachelor Degreee or Above	59431	0.175	0.380	0	1

Table 3. Nonrepayment by Loan Order

Loan Order	Repayment	Nonrepayment	Total
1	58999	4336	63335
	(93.15%)	(6.85%)	(100.00%)
2	20456	1496	21952
	(93.19%)	(6.81%)	(100.00%)
3	6771	476	7247
	(93.43%)	(6.57%)	(100.00%)
4	2039	137	2176
	(93.70%)	(6.30%)	(100.00%)
5	523	31	554
	(94.40%)	(5.60%)	(100.00%)
Total	88788	6476	95264
	(93.20%)	(6.80%)	(100.00%)

Row Percentages in Parentheses

Table 4. Nonrepayment by Difference in Loan Amount

	Difference in Loan Amount		Total
2^{nd} Loan	$2^{nd} - 1^{st} = 0$	$2^{nd} - 1^{st} > 0$	
Repayment	12,393	8,017	20,410
	(93.22%)	(93.16%)	(93.19%)
Nonrepayment	902	589	1,491
	(6.78%)	(6.84%)	(6.81%)
3^{rd} Loan	$3^{rd} - 2^{nd} = 0$	$3^{rd} - 2^{nd} > 0$	
Repayment	3,852	2,869	6,721
	(93.86%)	(92.76%)	(93.39%)
Nonrepayment	252	224	476
	(6.14%)	(7.24%)	(6.61%)
4^{th} Loan	$4^{th} - 3^{rd} = 0$	$4^{th} - 3^{rd} > 0$	
Repayment	1,171	854	2,025
	(94.21%)	(93.03%)	(93.71%)
Nonrepayment	72	64	136
	(5.79%)	(6.97%)	(6.29%)

Column Percentages in Parentheses

Table 5. Loan Amount on Overdue Rate

Overdue	(1) OLS	(2) OLS	(3) FE	(4) FE
1st and 2nd Loans:				
Loan Amount	-0.0520***	-0.0431***	0.1566***	0.1373***
	(0.0041)	(0.0043)	(0.0072)	(0.0078)
Observations	85,287	78,924	85,287	83,571
2nd and 3rd Loans:				
Loan Amount	-0.0728***	-0.0692***	0.1739***	0.1634***
	(0.0056)	(0.0061)	(0.0128)	(0.0138)
Observations	29,199	28,211	29,199	28,885
3rd and 4th Loans:				
Loan Amount	-0.0840***	-0.0832***	0.1085***	0.1092***
	(0.0095)	(0.0104)	(0.0228)	(0.0250)
Observations	9,423	9,219	9,423	9,330
Controls	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the OLS regressions include loan amount at application, purpose of loan, age, gender, marriage status, urban or rural residence, monthly income, occupation, education, Anti-Fraud score and Flash score; controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score.

Table 6. Loan Amount on Number of Collection Calls

No. of Collection Calls	(1) OLS	(2) OLS	(3) FE	(4) FE
1st and 2nd Loans:				
Loan Amount	-0.1098***	-0.0399	0.9166***	0.7807***
	(0.0300)	(0.0314)	(0.0461)	(0.0498)
Observations	85,287	78,924	85,287	83,571
2nd and 3rd Loans:				
Loan Amount	-0.0281	0.0007	1.1117***	1.0004***
	(0.0399)	(0.0434)	(0.0858)	(0.0915)
Observations	29,199	28,211	29,199	28,885
3rd and 4th Loans:				
Loan Amount	0.0386	0.0657	0.9280***	0.8206***
	(0.0711)	(0.0772)	(0.1503)	(0.1578)
Observations	9,423	9,219	9,423	9,330
Controls	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the OLS regressions include loan amount at application, purpose of loan, age, gender, marriage status, urban or rural residence, monthly income, occupation, education, Anti-Fraud score and Flash score; controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score.

Table 7. Loan Amount on Nonrepayment

Nonrepayment	(1) OLS	(2) OLS	(3) FE	(4) FE
1st and 2nd Loans:				
Loan Amount	-0.0086***	-0.0019	0.0874***	0.0734***
	(0.0026)	(0.0027)	(0.0041)	(0.0044)
Observations	85,287	78,924	85,287	83,571
2nd and 3rd Loans:				
Loan Amount	-0.0035	-0.0011	0.1104***	0.0996***
	(0.0035)	(0.0038)	(0.0080)	(0.0084)
Observations	29,199	28,211	29,199	28,885
3rd and 4th Loans:				
Loan Amount	0.0082	0.0092	0.0959***	0.0923***
	(0.0058)	(0.0064)	(0.0140)	(0.0151)
Observations	9,423	9,219	9,423	9,330
Controls	No	Yes	No	Yes
Individual FE	No	No	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the OLS regressions include loan amount at application, purpose of loan, age, gender, marriage status, urban or rural residence, monthly income, occupation, education, Anti-Fraud score and Flash score; controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score.

Table 8. Loan Amount on Defaults: IV-FE

	Overdue	No. Collections	Nonrepayment
1st and 2nd Loans:			
Loan Amount Approved	0.1870***	1.3647***	0.1262***
	(0.0115)	(0.0770)	(0.0062)
Loan Amount Applied	-0.0001	0.0028	0.0002
	(0.0005)	(0.0028)	(0.0003)
Observations	83,335	83,335	83,335
2nd and 3rd Loans:			
Loan Amount Approved	0.1721***	1.4336***	0.1393***
	(0.0205)	(0.1206)	(0.0108)
Loan Amount Applied	-0.0014	0.0014	0.0005
	(0.0011)	(0.0063)	(0.0006)
Observations	28,719	28,719	28,719
3rd and 4th Loans:			
Loan Amount Approved	0.1446***	1.3734***	0.1424***
	(0.0379)	(0.2586)	(0.0207)
Loan Amount Applied	0.0024	0.0115	0.0011
	(0.0022)	(0.0143)	(0.0013)
Observations	9,259	9,259	9,259
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score. (4) The IV for loan amount is lag average loan amount.

Table 9. Heterogeneity in Education

	Overdue	No. Collections	Nonrepayment
1st and 2nd Loans:			
Loan Amount	0.1525***	1.0028***	0.0930***
	(0.0125)	(0.0885)	(0.0076)
Loan Amount∗Higher Education	-0.0251	-0.3579***	-0.0308***
	(0.0154)	(0.1041)	(0.0090)
Observations	79,184	79,184	79,184
2nd and 3rd Loans:			
Loan Amount	0.2219***	1.3765***	0.1436***
	(0.0238)	(0.1581)	(0.0162)
Loan Amount∗Higher Education	-0.0913***	-0.5738***	-0.0674***
	(0.0280)	(0.1890)	(0.0184)
Observations	28,301	28,301	28,301
3rd and 4th Loans:			
Loan Amount	0.1422***	1.0332***	0.1248***
	(0.0398)	(0.2850)	(0.0259)
Loan Amount∗Higher Education	-0.0573	-0.3561	-0.0566*
	(0.0490)	(0.3370)	(0.0302)
Observations	9,248	9,248	9,248
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score.

Table 10. Heterogeneity in Education: IV-FE

	Overdue	No. Collections	Nonrepayment
1st and 2nd Loans:			
Loan Amount	0.2075***	1.6275***	0.1509***
	(0.0176)	(0.1268)	(0.0103)
Loan Amount∗Higher Education	-0.0408*	-0.4630***	-0.0439***
	(0.0220)	(0.1536)	(0.0124)
Observations	78,963	78,966	78,966
2nd and 3rd Loans:			
Loan Amount	0.2074***	1.8553***	0.1867***
	(0.0347)	(0.2063)	(0.0198)
Loan Amount∗Higher Education	-0.0540	-0.6402***	-0.0727***
	(0.0408)	(0.2464)	(0.0228)
Observations	28,141	28,141	28,141
3rd and 4th Loans:			
Loan Amount	0.1674***	1.4817***	0.1738***
	(0.0591)	(0.3362)	(0.0334)
Loan Amount∗Higher Education	-0.0419	-0.1881	-0.0560
	(0.0724)	(0.4697)	(0.0401)
Observations	9,178	9,178	9,178
Controls	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes

(1) Robust standard errors in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Controls in the FE regressions include loan amount at application, purpose of loan, Anti-Fraud score and Flash score. (4) The IV for loan amount is lag average loan amount. Correspondingly,the IV for the interaction between loan amount and dummy of higher education is the interaction between lag average loan amount and dummy of higher education.

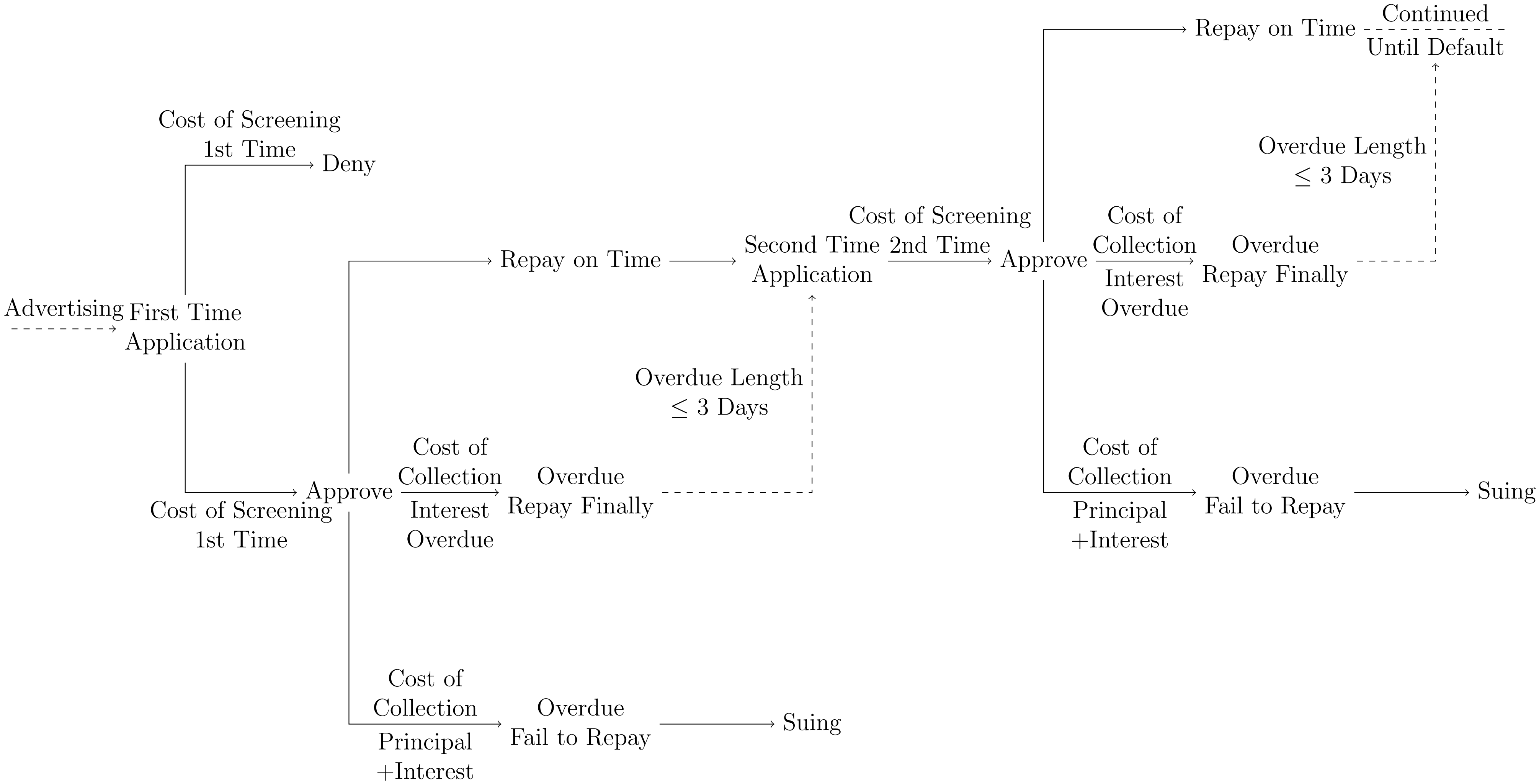

Figure 1. Operation Process of the Firm

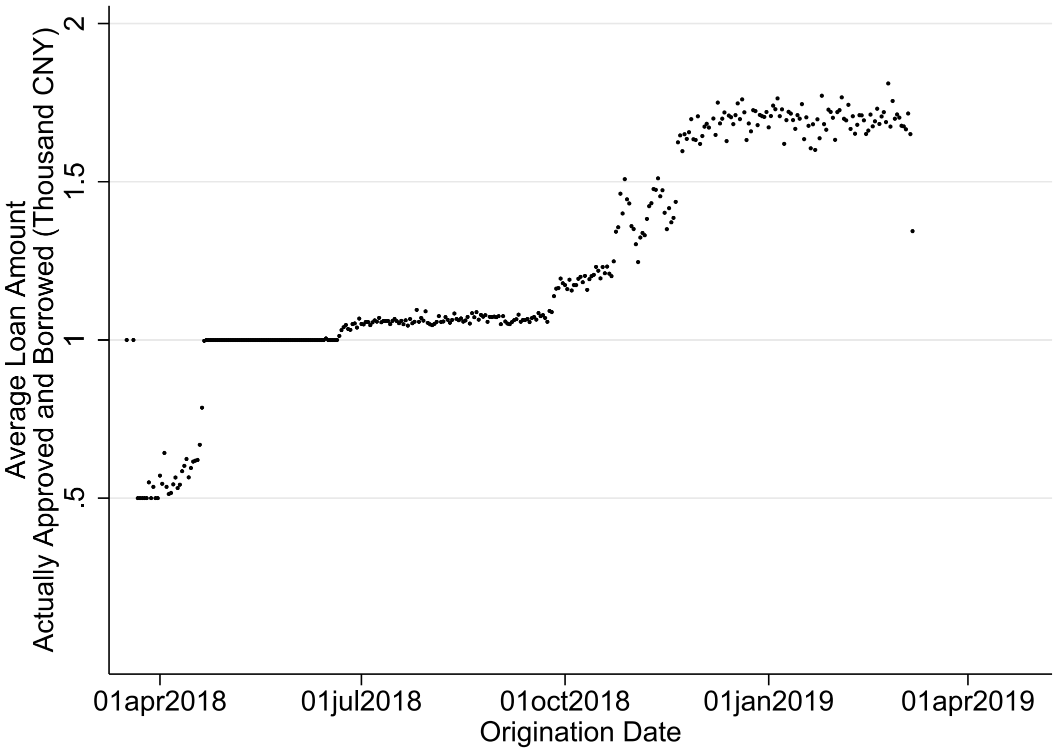

Figure 2. Daily Average Loan Amount

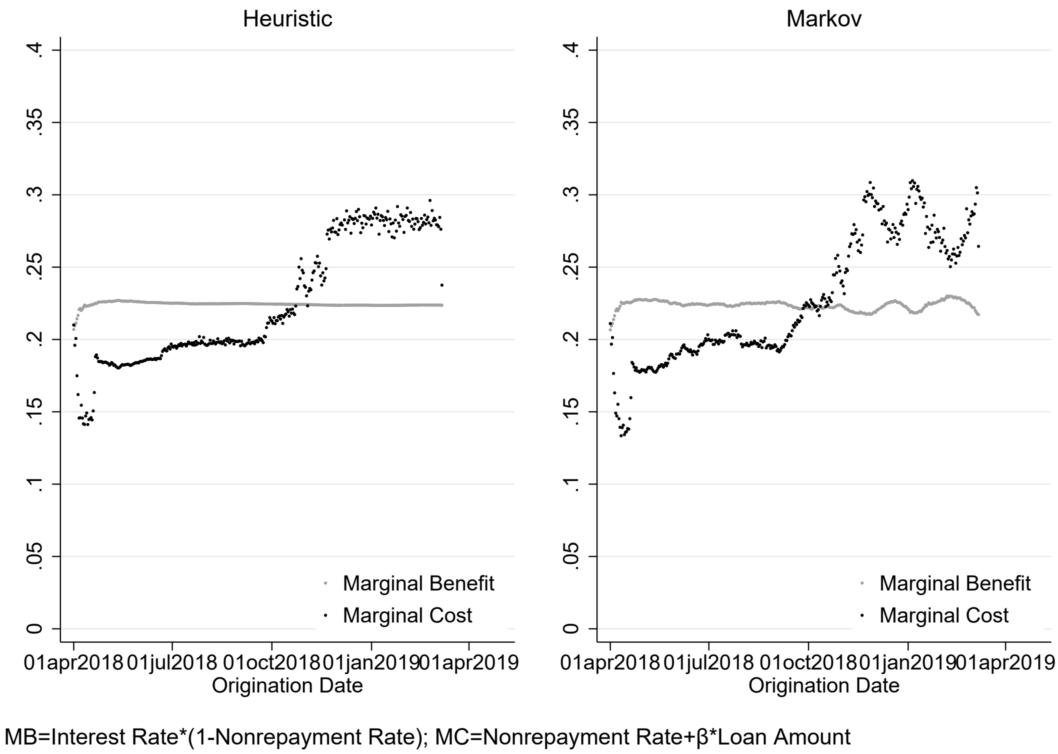

Figure 3. Daily Average MB and MC of the Whole Sample

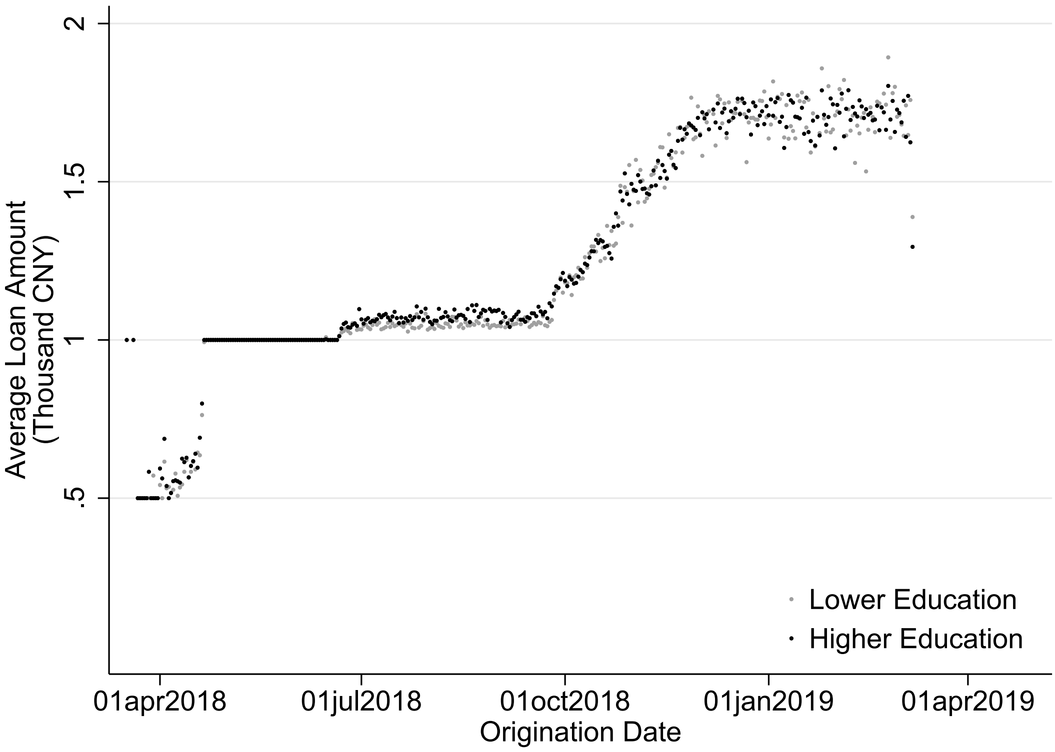

Figure 4. Daily Average Loan Amount by Education Group

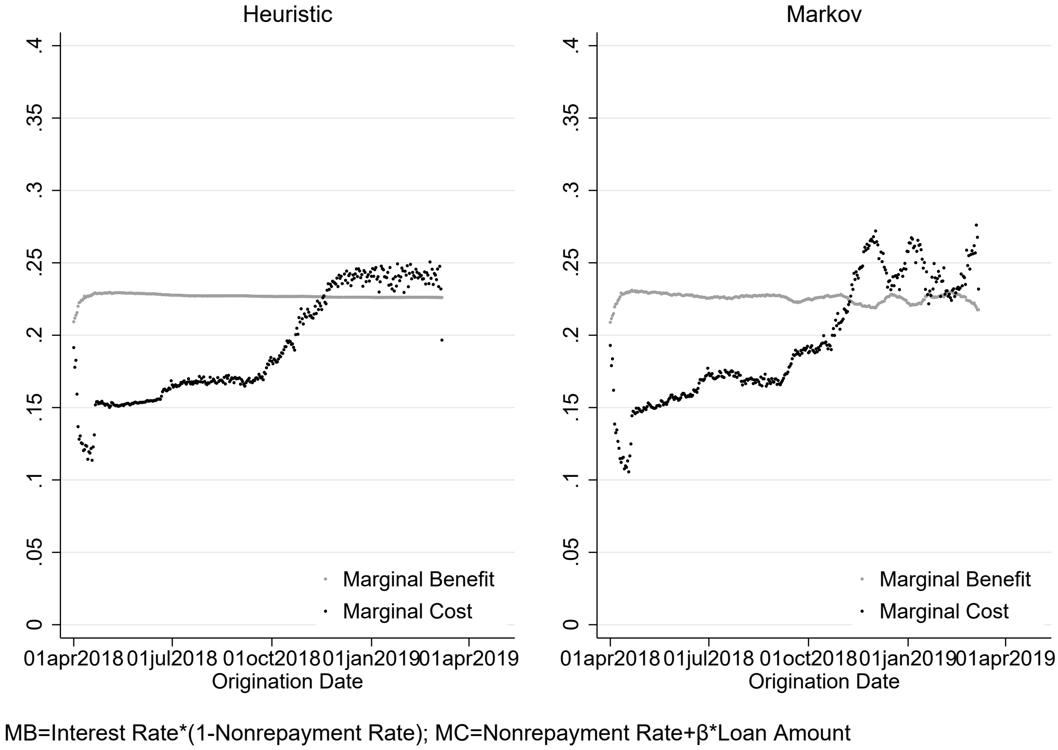

Figure 5. Daily Average MB and MC of the High Education

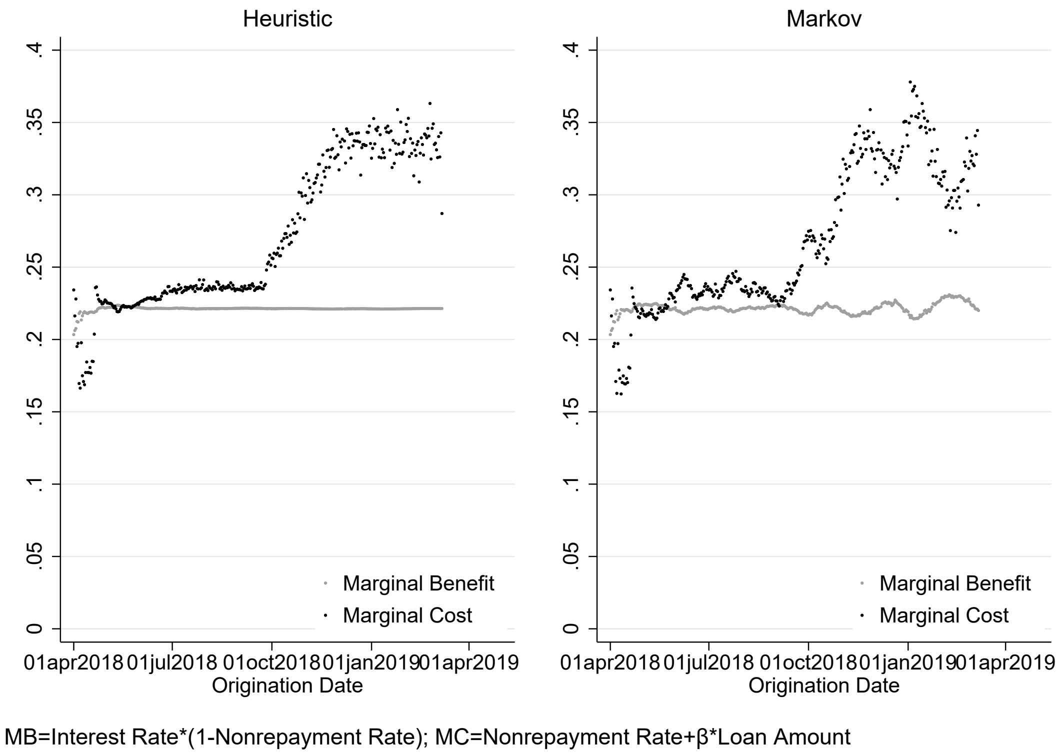

Figure 6. Daily Average MB and MC of the Low Education

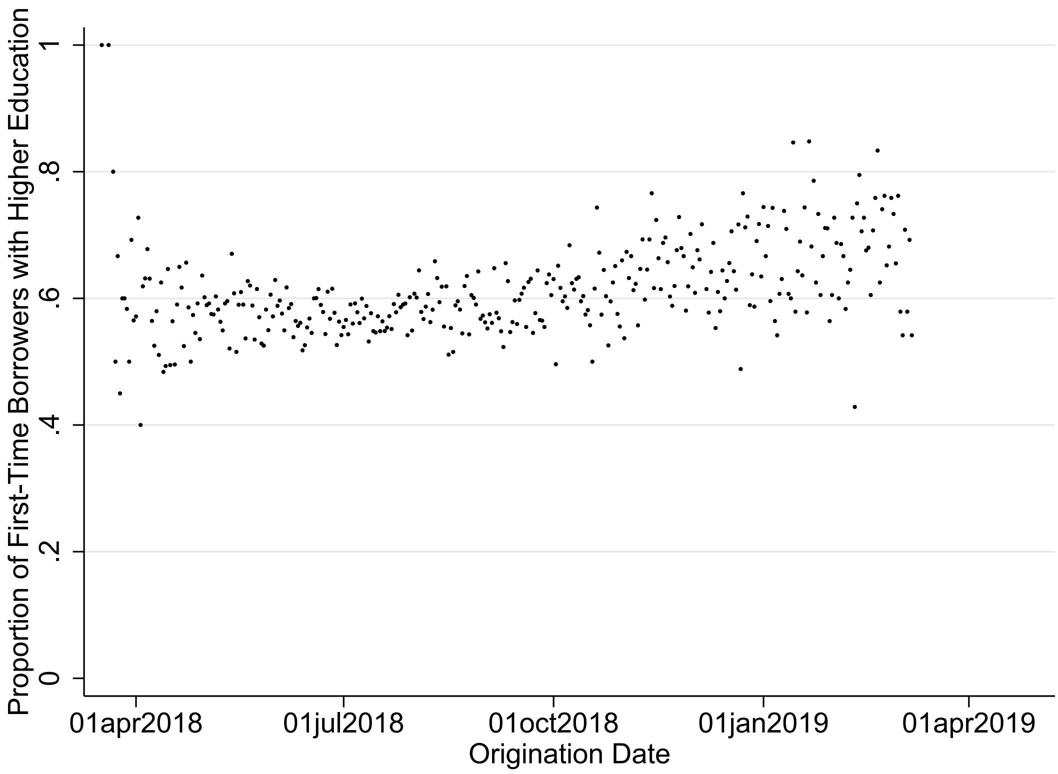

Figure 7. Proportion of First-Time Borrowers with High Education Over Time

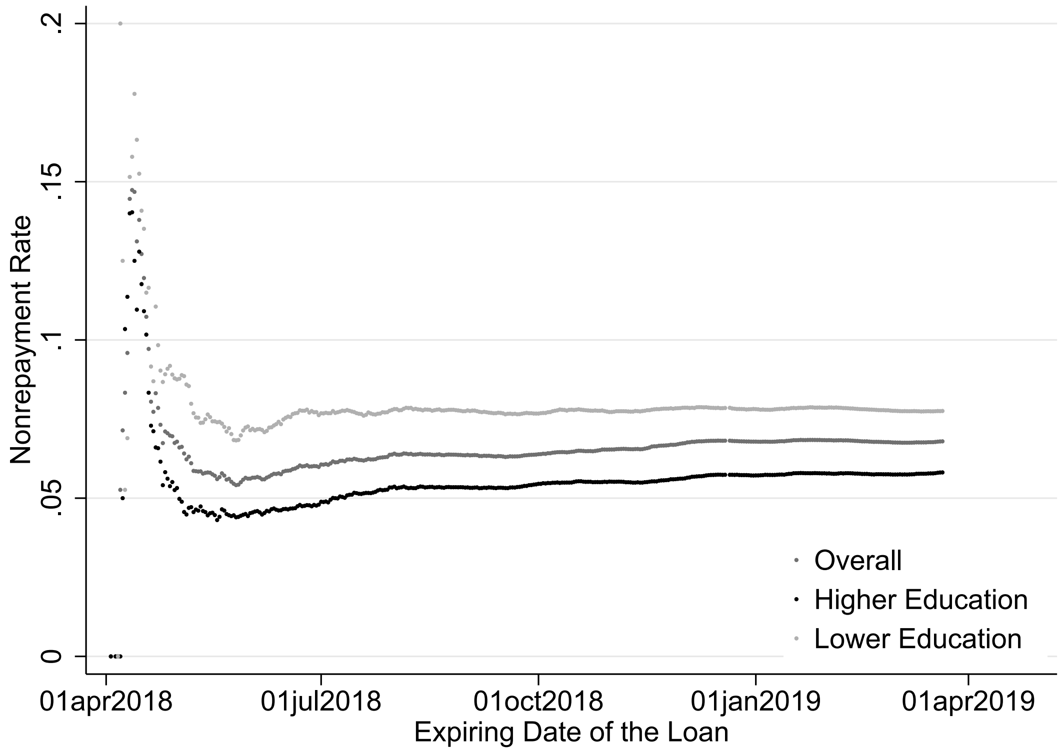

Figure 8. Cumulative Nonrepayment Rate by Education Group

A Appendix

A.1 Comparative Statics

Differentiating the first-order condition (2) with respect to loan size L at both sides leads to

$$\frac{\partial e^*}{\partial L} = \frac{(1+r)}{\frac{\partial^2 p}{\partial e^2}[Q-(1+r)L]^2} < 0. \tag{A.1}$$

Therefore as loan size L increases, effort level e decreases and default probability p increases. The intuition underlying this result is that a higher debt burden reduces the agent's payoff if the project succeeds, but not if the project fails. When the project succeeds, its output is Q, but the agent gets $Q-(1+r)L$, only a fraction of the total output. The larger the loan size L, the smaller the fraction. When the project fails, its output is zero, and the agent also gets zero, the total output in this case. In this sense, the problem here is similar to that in the classical rent-sharing model. There a tenant also only receives a fraction of output and thus chooses to exert less effort than the efficient one.[15]

Therefore, a larger loan size would weaken the agent's incentive to apply effort. To reduce this problem ex ante, the principal, i.e. the lender, could require more collateral. However, online banking in China typically lacks any means to impose collateral, which is different from traditional banking. Online credit is also uncollateralized in our study context. Therefore, we choose not to take collateral into account in our modelling.

Similarly, differentiating the first-order condition (2) with respect to ability level a at both sides leads to

$$\frac{\partial e^*}{\partial a} = -\frac{\frac{\partial^2 p}{\partial e \partial a}}{\frac{\partial^2 p}{\partial e^2}} > 0. \tag{A.2}$$

If $\frac{\partial^2 p}{\partial e \partial a} > 0$, that is, if a higher ability level a increases the effectiveness of effort e in making the project succeed, $\frac{\partial e^*}{\partial a} > 0$ and the agent would exert more effort

[15] For tests of moral hazard in such setting, see Burchardi et al. (2019).

if her ability level is higher. The intuition underlying this inference is that the effort e's marginal cost is one, a constant in the model specified (see equation (1)), while its marginal benefit is $\frac{\partial p}{\partial e}[Q-(1+r)L]$, the marginal impact of effort e on success probability p multiplied by the output left to the agent if the project succeeds. If $\frac{\partial^2 p}{\partial e \partial a} > 0$, as ability level a increases, the marginal impact of effort e on success probability p, $\frac{\partial p}{\partial e}$, would increase, so would the marginal benefit. A greater marginal benefit of effort e, with a constant marginal cost, leads the agent to exert more effort.

We could examine not only the effect of an increase in loan size L or an increase in ability level a on optimal effort level e^*, but also the interactive effect of an increase in loan size L *and* an increase in ability level a on optimal effort level e^*. Further differentiating the comparative-static result (A.1) with respect to ability level a (or differentiating (A.2) with respect to loan size L) leads to

$$\frac{\partial^2 e^*}{\partial L \partial a} = -\frac{\frac{\partial e}{\partial L}\left(\frac{\partial^3 p}{\partial e^3}\frac{\partial e}{\partial a} + \frac{\partial^3 p}{\partial e^2 \partial a}\right)}{\frac{\partial^2 p}{\partial e^2}} \tag{A.3}$$

$$= -\frac{\frac{\partial e}{\partial L}\frac{\partial^3 p}{\partial e^2 \partial a}}{\frac{\partial^2 p}{\partial e^2}} \qquad \text{if} \quad \frac{\partial^3 p}{\partial e^3} = 0; \tag{A.4}$$

$$> 0 \qquad \text{if} \quad \frac{\partial^3 p}{\partial e^2 \partial a} < 0. \tag{A.5}$$

By (A.3), it is less straightforward to know the direction of the interactive effect. Further examination of (A.3) reveals that the direction of this interactive effect depends on the sign of the term in the parentheses $(\frac{\partial^3 p}{\partial e^3}\frac{\partial e}{\partial a} + \frac{\partial^3 p}{\partial e^2 \partial a})$, because the signs of the other two terms, $\frac{\partial e}{\partial L}$ in the numerator and $\frac{\partial^2 p}{\partial e^2}$ in the denominator, have been determined. $\frac{\partial e}{\partial L}$ in the numerator is negative by (A.1); $\frac{\partial^2 p}{\partial e^2}$ in the denominator is also negative by our assumption of the diminishing impact of effort e on success probability p. If we further assume that $\frac{\partial^3 p}{\partial e^3} = 0$, the term in the parentheses simplifies to $\frac{\partial^3 p}{\partial e^2 \partial a}$ as in (A.4). Now the direction of the interactive effect depends only on the sign of $\frac{\partial^3 p}{\partial e^2 \partial a}$. If it is negative, the interactive effect $\frac{\partial^2 e^*}{\partial L \partial a}$ would be positive, as in (A.5). Negativity of $\frac{\partial^3 p}{\partial e^2 \partial a}(= \frac{\partial(\frac{\partial^2 p}{\partial e^2})}{\partial a})$ means that the marginal impact

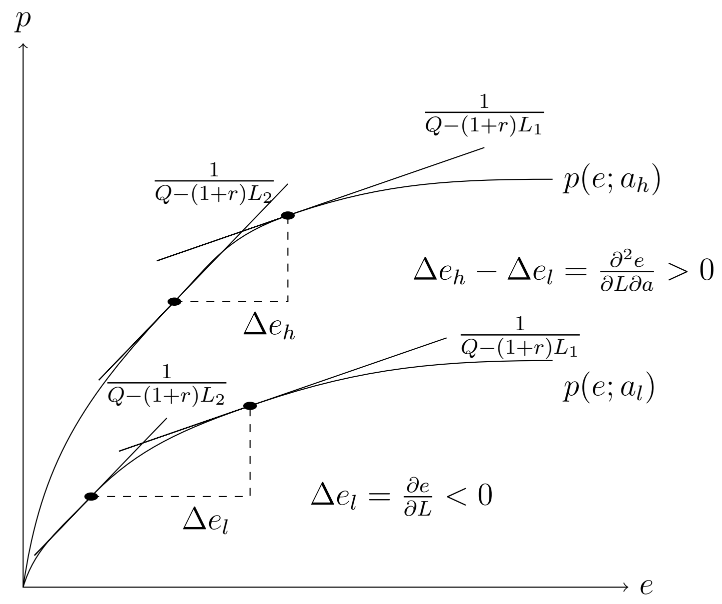

Figure A.1. Illustrative Graph of the Theoretical Framework

of effort e on success probability p is not only diminishing as the effort level e increases, but also diminishing more rapidly when ability a is higher.[16]

The intuition underlying this result is as follows. The marginal impact of effort e on success probability p should satisfy the first-order condition (2). When loan size L changes, the agent needs to adjust her effort level so that the marginal impact of changed effort level e on the success probability p could be matched to the changed right hand side of the first-order condition (2). If the marginal impact of effort e on success probability p becomes very sensitive to small changes in effort e as a result of higher ability a, then the agent is unwilling to change her effort much since the profile of marginal impact of effort e on success probability p can be matched to changed loan size L, and thus also changed right hand side of the first-order condition (2), with little change in effort.[17] See Figure A.1 for a graphical illustration of the above comparative statics.

[16] A simple example of $p(e;a)$ satisfying these assumptions is $p(e;a) = a(e-\frac{1}{2}e^2)$ with $a \in [0,1]$ and $e \in [0,1]$.

[17] The explanation here is similar to the intuitive explanation of the intertemporal elasticity of substitution. The intertemporal elasticity of substitution depends inversely on the curvature of the utility functions. "If the marginal utility of consumption is very sensitive to small changes in consumption, consumers are unwilling to change their consumption much to take advantage of intertemporal incentives since the profile of marginal utility can be matched to changed interest rates with little change in consumption." (See page 6, Deaton, 1992)

In Figure A.1, L_1 and L_2 are two loans with $L_1 < L_2$. a_l and a_h are two ability levels with $a_l < a_h$. The two curves depict the success probability $p(e; a_l)$ and $p(e; a_h)$ when the ability level is a_l and a_h respectively. Optimal effort level occurs where the slope of the two curves satisfies (2), as indicated by the small black points in the figure. If the agent's ability level is a_l, Δe_l measures the change in effort level when loan size increases from L_1 to L_2. Similarly, if the agent's ability level is a_h, Δe_h measures the change in effort level when loan size increases from L_1 to L_2. Note that these two differences, Δe_l and Δe_h, are both negative. That is, an increase in loan size would lead the agent to exert less effort. The difference between the two differences, i.e., $\Delta e_h - \Delta e_l$, then measures the interactive effect of an increase in loan size L from L_1 to L_2 and an increase in ability level from a_l to a_h on the effort level. $\Delta e_h - \Delta e_l$ is positive here. This is the case in the figure because the slope of the curve $p(e; a_h)$, i.e. $\frac{\partial p}{\partial e}$, changes more rapidly as effort level e changes than that of the curve $p(e; a_l)$ does. This is exactly what the assumption in (A.5) means.

Table A.1. Determinants of Loan Amount

	Loan Amount Approved and Borrowed
	FE
Lag Average Loan Amount Approved	0.9664***
	(0.0086)
Loan Amount Applied	-0.0070***
	(0.0002)
Credit Score: Anti-Fraud	0.0002
	(0.0002)
Credit Score: Flash	0.0003***
	(0.0001)
Controls	Yes
Individual FE	Yes
Observations	93,294

(1) Robust standard errors clustered at individual level in parentheses. (2) * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. (3) Purpose of loan and loan order are also controlled for in the FE regression.