Nonlinear Incentives on Consumer Credit Market:

Evidence from a Natural Field Experiment

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Abstract

Using the unique data from a major Chinese bank that introduced a nonlinear incentive scheme for credit card sales managers, we find that the number of credit cards approved increases sharply at the end of each month. Further analysis shows this occurs through a combination of lax screening in the approval process, reduction in the processing time of the application and creation of "zombie" borrowers. We also find that male managers, managers with shorter tenure, and managers who locate farther from the headquarter are more likely to be subject to this gaming behavior. Overall, we provide ample evidence on the overall benefits and costs of nonlinear incentive schemes in the customer finance sector.

Keywords: Nonlinear incentives; Quotas; Credit Card Approval; Delinquency

JEL classification: G21, J33, M52

1 Introduction

Nonlinear incentive systems with certain quotas are used widely in workplaces. Oyer (2000) demonstrates that a discrete contract for meeting a certain quota is optimal for salespersons with limited liability and rent sharing.[1] However, this nonlinear incentive system may also induce agents to game. An agent's incentives may change across time depending on her cumulative output to date (Holmström and Milgrom (1987)). Empirically, Oyer (1998) shows that workers respond to this non-linearity in incentive schemes by taking distortionary actions at the end of period to bunch their outputs that increase their income at the cost of efficiency. For instance, workers may bunch production at non-linear kink points. The finance literature has also shown that bank loan officers are subject to this type of non-linear incentive. Tzioumis and Gee (2013) show that mortgage officers increase output towards the end of a month to meet the monthly quota and as a result, mortgages on the last working day of a month have the highest likelihood of delinquency.

However, little is known if such opportunistic behavior induced by the nonlinear incentive exists in the consumer finance sector and through what mechanisms it works. This paper attempts to fill in the void. In particular, using daily credit card approval data from a Chinese commercial bank, we explore if the introduction of nonlinear incentives with a minimum quota system on bank agents may induce them to game and the possible economic consequences of this gaming in the consumer credit market.

[1] There could be another explanation why firms adopt a nonlinear incentive scheme. Some evidence exists that firms typically opt for nonlinear incentives in a sales context to attract overconfident employees (see, e.g., Larkin and Leider (2012)).

We focus on the incentive schemes of managers in the credit card sales team. Theoretically, bank employees and managers should optimally be compensated based on both quantity and quality of the granted credit cards. However, the keener market competition in consumer lending renders such contract design less practical. In fact, our focal bank changes its incentive scheme from little emphasize on credit card selling volumes to rewarding and punishing the staff based on a quota system that is related to the credit card selling volume. In the commercial bank we study, the new incentive scheme imposes a quota-based incentive for agents to reach a minimum of 20% increase in the issuance of credit cards by the end of each month compared with the same period last year. The bank rewards the credit card sales team managers who meet the standard with greater promotion opportunities in the job ladder compared with other managers. Those failing to meet the minimum quota for three consecutive months are subject to disciplinary actions, including decrease in fixed salary, cancelation of the bonus and a higher likelihood of dismissal. Also, disciplinary action can result at the end of a single month (not three consecutive months) if the credit card sales team managers fail to meet the quota by a large margin.

We first analyze credit card approval timing after the introduction of this new nonlinear incentive scheme. We find strong evidence that employees (under the influence of their team managers) in the credit card sales department substantially vary their output during the length of each month after the adoption of the nonlinear incentive scheme in 2016. Whereas for the year before the incentive scheme was adopted (Year 2015), there is no such a pattern. The magnitude of the monthly time series variation in employees' output is economically significant. Toward the end of each month, employees are increasing their aggregate output by 16.6 % in the last week of the month. This pattern is immediately reversed at the beginning of the next month and is persistent across all months during our one-year sample.

After documenting the temporary increase of credit card origination in the last week of each month induced by the nonlinear incentive schemes, we start to analyze the mechanisms through which the non-linear incentive may work to generate the last week spike and its potential economic consequences. We first posit that the minimum quota system may induce a lax screening of the credit card applicants, incentivizing the bank to approve some credit card users that are on the margin.[3] It is also plausible that the credit card sales managers may approach the risk control department to lax their approval criteria by including some marginal credit card applications in the last week of the month. As such, we may expect the credit cards users approved at the end of each have lower income and are less likely to have full time employment. We find evidence supporting this conjecture. To further shed light on the lax screening, we show that the credit approval decision is less sensitive to the applicant's income for the credit card approved by the end of each month after the new incentive scheme is introduced. We then explore the possible consequences of the lax screening. We find that the lax screening leads to higher likelihood of delinquency for the credit cards granted at the end of each month. We also find that after the delinquency occurs, the credit cards are less likely to reinstated or it takes longer time for these credit cards to be reinstated. Further analysis reveals that it is mainly those low-income users whose credit cards have higher (lower) likelihood of delinquency (reinstatement) and take longer time to be reinstated. Taken together, these evidence confirm that the nonlinear compensation design may induce employees in the bank to approve some

[3] Tzioumis and Gee (2013) finds that mortgage officers may approve some marginal bank loan applications when they are subject to the minimum quota requirements under their nonlinear incentive schemes. Agarwal and Ben-David (2018) finds that bank loan officers who were incentivized based on originated loan volume may tend to apply lax screening in their approval decisions.

marginal credit card users' credit application, which ultimately increase the risks of the bank's credit card products.

The second channel we conjecture is that the nonlinear incentive contracts may lead to some "zombie" credit card users who could be misled by the credit card sales employees to open the credit card accounts. As the credit card sales managers are incentivized to maximize a quota-based outcome, they may have incentives to ask staff under their management to lobby some pre-existing customers to apply for credit cards, who may not need the credit card products at all. In such a case, these credit card users who are misled to have the credit cards may feel discomfort once they realize they have the credit cards against their own intention. As a result, they may be reluctant to use their new credit cards.[4] We find evidence consistent with this conjecture. In particular, we find that for the credit cards which are open in the last week of each month in 2016 when the nonlinear incentive scheme is introduced, on average, the cardholders have fewer transactions and spend less. The cards are also more likely to be in the sleep mode or to be finally cancelled. These findings highlight the negative impacts of the opportunistic behavior induced by nonlinear incentives on the credit card usage. That is, it induces some "zombie" credit card users who use the cards less frequently than the normal users.

We further explore the possible consequences of this misleading sales behavior. We conjecture that it may create further trust issues among the consumers. The credit card users who are misled to use credit cards may feel less trustworthy in the bank.[6] Thereafter, we may

[4] In our interview with the several credit card sales managers and employees in the bank, they shared some experience that their colleagues may sometimes apply the credit cards for some customers who are not fully aware of the consequences of using credit cards (e.g., just asked the customers to sign off their names in the credit card application forms together with a bunch of other documents the customers are going to sign).

[6] As trust offers security against expropriation, theft or deception (Guiso, Sapienza, and Zingales (2008)), more trusting customers are more willing to invest in trust-intensive assets because they are less fearful of being cheated and less anxious about taking risks (Georgarakos and Inderst (2011), Gennaioli, Shleifer, and Vishny (2013), Dupas, Keats, and Robinson (2019)).

expect the misled credit card users may also reduce their usage of other banking service. We use the end-of-month balance of investments under management in the bank to measure customers' use of the bank's other services as wealth management is the one of the most important banking services in the customer finance sector in China (e.g., Acharya et al. (2020)). We find the last week credit card users are less likely to use the wealth management service. In additional analysis, we find it is the group of low-frequency credit card users whose credit cards are originated in the last week of the month that are less likely to use the wealth management service in the future. Overall, our results highlight that the possibly negative externalities of the gaming behavior induced by the nonlinear incentive scheme on other customer finance services.[7]

The third related channel we posit is the shorter processing time in the credit card approval process. We posit that the credit card sales managers may exert some influences on the risk control department to expediate the approval process of the credit card and shift some credit cards which are supposed to be approved at the beginning of the next month to the end of the focal month. To test this conjecture, we examine the processing time of the credit card applications for the approval case and declined case separately. We find the end-of-month approved cards have shorter processing time after the new incentive scheme is introduced in 2016 whereas for the declined application, there is no such a pattern. We further show that the fast-processing practice is related with borrower's ex-post outcome and highlight that the faster processing may be related with the relative worse credit quality and lower investment willingness within the bank.

[7] One alternative explanation of this result is that it is those customers whose income are more vulnerable that drive the less investment results as these marginal customers' personal financial conditions are negatively affected by the credit card. As we document in Appendix B, the income explanation is not supported.

Our last series of analysis focus on the heterogeneity of the credit card sales managers' characteristics. We posit that male managers are more likely to be involved in the opportunistic behavior as studies find male are more prone to aggressive behavior induced by monetary incentive. We find evidence supporting this conjecture. The next demographic characteristic we explore is the manager tenure. Mangers with shorter tenure may have more career concerns and are more afraid of losing their jobs. As such, we expect the end-of-month bunch is more obvious in these types of managers. We find consistent evidence to support this. Last, we conjecture that geographical proximity plays a role in the effects of the nonlinear contracts as it is easier for the headquarter (main branch in our case) to monitor and acquire information on those managers who are close to the main branch. Whereas for the employees who are farther away, the hard information (e.g., failure to meet the minimum sales quota) could be the main driver for their promotions/demotions. We find evidence supporting this view.

Our study contributes to the literature in the following ways. First, this paper documents the impacts of nonlinear incentive contracts in the context of consumer/household finance area. Prior studies in economics have shown that the nonlinear incentive contracts of salesperson and executive creates incentives for these agents to influence the timing of customer purchases and vary their effort over different periods (Oyer (1998), Larkin (2014), Kaur, Kremer, and Mullainathan (2015)). Studies in finance have also shown that bank loan officers, insurance agents and financial advisors are subject to the effect of these non-linear incentives and the effort-gaming may create significant risks to the financial institutions (Tzioumis and Gee (2013), Agarwal and Ben-David (2018), Freeman, Huang, and Li (2019), Inderst and Shaffer (2019)). We contribute to the exiting literature by documenting the credit card sales managers in the consumer banking sector who are subject to the nonlinear incentives also have gaming and timing effort behavior.

Second, we show the externality of the end-of-month timing effort behavior induced by the nonlinear incentive contracts in the consumer finance area (Baker (1992), Bénabou and Tirole (2016), Peek and Rosengren (2005)). We show that the incrementally granted credit cards in the last week of the month after the nonlinear incentive is introduced have higher delinquency rates, lower likelihood of reinstatement and it takes longer time for these credit cards to be reinstated. These externalities could be essential to the customer credit markets. In addition, we also document several negative externalities on the bank's other services/products. The new credit card users in the last week of the month may feel misled to have the credit cards and thereafter seldomly use their credit cards. Such discomforts may have a long-run effect in the reduced usage of other services in the bank (e,g, wealth management service). This highlights the negative externalities of nonlinear contracts from the bank's perspective.

Our findings can bring particularly important implications for financial regulators. The recent regulations in financial institutions pay greater attention and exert greater effort to the compensation practices in the senior executives of the banks after the GFC (e.g., The Financial Crisis Inquiry Report 2011). Academic literature also shows that Bank CEO risk-taking incentives and compensation contract short-termism leads to greater risk taking in the banking sectors (DeYoung, Peng, and Yan (2013), Kolasinski and Yang (2018)). Our study shows that the incentive design of the mid-level managers and employees in the customer banking section is also important. The nonlinearity in the incentive contracts might expose the financial institution to increasing amount of risk in their credit card products and greater customer dissatisfaction.

The remainder of the paper is organized as follows. We describe our instituional background in Section 2. Section 3 presents our data and variables. Section 4 details the identification and empirical specification. Section 5 documents the end of month effect on credit card origination. Section 6 investigates the potential channels and economic outcome. Section 7 shows additional heterogeneity results on managerial characteristics. Section 8 discuss the external validity. Section 9 concludes the paper.

2 Institutional Background

2.1 Credit Card in China

Banks dominate the credit market in China (Song and Xiong (2018)). In 1985, the Bank of China issued the first credit card in China and commercial banks began to participate in the consumer lending market, making it a critical source of credit provision for borrowers. Since then, China experienced rapid growth in credit card market – the total number of active credit cards more than tripled between 2009 and 2018 and the entire credit line exceeding RMB 15.40 trillion at the end of this period. The delinquency rate also increases substantially during this period, posing severe challenges to economists and policymakers.

The bank we study is one of the leading state-owned commercial banks. It possesses a vast branch network that covers all provinces and municipalities in China. Our data are from the bank's branches in one of the capital cities in China. This capital city covers more than 14,000 km^2, houses about 16 million residences, and produces 1.2 trillion RMB GDP in 2015. As with many state-owned commercial banks, the bank has two types of branches: the first one is one main branch for each city ("Fen Hang" in Chinese), and the second type is sub-branches located in districts or counties in the city ("Zhi Hang" in Chinese). The bank has one main branch and forty-one sub-branches in this capital city.

To apply for a credit card from the bank we study, an applicant must submit the application form with detailed personal information and supplementary documents, including his/her photocopy of national identification, employment certificate, and proof of income.[8] As there is no personal credit information sharing among different financial intermediations in China (see Bao and Huang (2021), for more details), the bank uses these pieces of information submitted by the applicants to determine whether to approve the application and, upon the approval, the credit lines for the approved borrower. The borrower's credit card approval decision is delegated at the bank sub-branch level (see Agarwal et al. (2020)).[9] To limit the number of credit cards provided to less solvent borrowers, each branch has the risk control department to screen the qualification of new applicants with the authority to contact applicants and their employers either by phone or in-person to confirm the authenticity of the application materials. The branch cancels the application if it judges the applicant as unqualified and approves the application otherwise. The approved borrower receives the credit card by mail and has to activate the card following the instructions before having access to any credit. During this screening process, the risk control department may have frequent interactions with the credit card sales department to discuss the application cases.

[8] In this bank, the credit cards are classified into two types according to whether customers are required to deposit reserve funds: the quasi-credit cards and the standard credit cards. The standard credit cards are further classified into two sub-types according to the types of customers: the general-purpose credit cards (issued to the general public) and the private label credit cards (issued to the partnering companies). We consider the data of general-purpose credit cards as this type of credit cards is covered by the nonlinear incentive scheme.

[9] Since China's entrance into WTO in 2001, commercial banks implemented reforms that delegate individual level decision-making to each bank branch (see Qian, Strahan, and Yang (2015)).

After these procedures, the borrower can have (multiple) loan originations as long as the total credit amount does not exceed the pre-specified credit line. The bank requires each borrower to repay a minimum 10% of the credit card balance per month. If a borrower fails to pay the minimum amount by the given deadline, s/he receives a delinquent record. The borrower cannot borrow further from the credit card unless s/he reinstates the loan account to normal status by paying the corresponding interest expenses and extra penalties for the delinquency. If the borrower does not reinstate the account within a certain period, the bank branch may either lower the internal credit rating or pursue the repayment through legal processes.

2.2 Change in the Incentive Scheme

In the bank we study, there are two main types of agents: the first one is employees and the second one is managers. There are four rungs for employees ranging from the lowest level I to the highest level IV and three rungs for managers, including the team, department, and sub-branch managers with the sub-branch is highest and the team is lowest. The employees of each rung are under direct leadership of the team managers and department managers. Within each sub-branch, there are four departments: credit card sales department which is responsible for credit card products, loan department which is responsible for originating new band loans and maintaining existing bank loans, wealth management department which is responsible for attracting/maintaining customers to purchase wealth management products including deposits, mutual fund subscriptions and other investment products purchase, and risk control department which is responsible for screening credit card and bank loan applications. There are several teams within each department in charge of different subjects. The four departments coordinate with together in its daily business. For instance, in the credit card approval procedure, the credit card department will forward the application to the risk control department for screening. Sometimes, the risk control department may contact the credit card sales department to request for additional material for screening process.

In each sub-branch, the bank pays agents (employees) with a pre-determined basic salary based on his/her rung within the branch and lump-sum bonuses for fulfilling the bank's requirements.[10] The bank promotes or demotes agents semi-annually based on its protocol that evaluates agents' performance in the previous months and, as a result, agents are promoted on the bank job ladder for superior performances, demoted for falling below an essential requirement, and left on the same rung otherwise.

The bank's handbook "Regulation of Agents" outlines the compensation scheme, promotion protocol, and other aspects of the agents' responsibility. The bank updates the regulations irregularly based on the guidance from the People's Bank of China (PBOC, hereafter) and China Banking Regulatory Commission (CBRC, hereafter) and the feedback from its branches all over China.[11] As neither managers nor employees at the sub-branch know the timing of an update or the substance of the changes, we treat the change as a nature field experiment that identifies agents' responsiveness to new incentive schemes.

Prior to 2016, the bank did not reward agents on the issuance number of credit cards due to the guidance from CBRC against quota-based incentive systems.[12] As shown by Figure 1, the

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[10] The salary and bonus for each bank branch is determined by the main branch and district managers and can vary within a certain range.

[11] In real practice, the details in the bank may vary across different provinces. The province level headquarter ("Sheng Hang" in Chinese) has the final say on the details. Sub-branches and the main branch in the city we study have no influence on the change of the rules listed in the handbook.

[12] The quota-based system in the banking industry is widely discussed by regulators. In June 2009, the CBRC issued a notice emphasizing that all commercial banks should abolish end-of-month assessment practices and quota-based incentive systems (http://finance.sina.com.cn/g/20090624/22386394864.shtml). In October 2011, the Chairman of CBRC, Liu Mingkang spoke at the CEO Organization Summit against the quota-based system to hit presumed targets (https://www.cbirc.gov.cn/cn/view/pages/ItemDetail.html?docId=1998&itemId=919&generaltype=0).

issuance number of credit cards has been in a high growth rate with more than double digits from 2009 to 2014 while suffers a sharp decline with a negative growth rate of -5.05% in 2015.[13]

[FIGURE 1 ABOUT HERE]

To cope with the decline in credit card sales volume in 2015, our focal bank, updated its incentive scheme in the "Regulation of Agents" Handbook and enacted the new incentive scheme in January 2016. The new incentive scheme introduces a non-linear compensation for the credit card sales department. The new incentive scheme imposes a quota-based incentive for team managers to reach a 20% increase in the issuance of credit cards by the end of each month compared with the same period last year. The bank reward sales team managers who meet the standard with greater promotion opportunities in the job ladder and increase in salary and bonuses compared with other managers.[14] The bank punish team managers who fail to meet the standard for three consecutive months with disciplinary action, including the demotion in the job ladder and decrease in salary and bonuses.[15] The new regulation imposes strong non-linear incentives for agents. The credit card sales team managers who are promoted to department manager may earn about five times more monthly income than other team managers and eight times more than the managers who are demoted to employees (see Table 2 for more details).

[13] The decline may be largely due to the fast development of FinTech lending (P2P lending) and the popularity of virtual credit cards launched by FinTech companies, including the Ant Financial Group and Jingdong Digits. In 2015, the supreme court in China also clarify the legal status of P2P lending which facilitates the development of P2P lending in 2015.See the legal reform on P2P lending in 2015 for details. (http://www.court.gov.cn/fabu-xiangqing-15146.html)

[14] The credit card contract is standard so that agents cannot game the bank by lowering the transaction fees and service charges of credit card when a few extra issuances would reach a hurdle (see Larkin, 2014).

[15] For managers who fail to meet the quota, the deficit in previous month is not carried over to the subsequent month and will not augment future quota.

3 Data and Variables

3.1 Data

The bank provided us with two sets of data. The first set of data include the information on all credit card borrowers whose origination date between 2015:01 and 2016:12 from all forty-one branches in this capital city. For each borrower, we observe the details about his/her demographics, including age, gender, marital status, education, employment, income, and place of residence. In addition, the data include the borrower's credit card information at the monthly frequency for one-year length since origination, including the transaction records, the amount of credit line, credit balance, and monthly repayment status. The data also include the borrower's additional banking service records within this bank, for instance, the asset under management, number of bank accounts, and balance in investment accounts (if any).

The second set of data include the information on the bank branch. The data include the credit card approval process for each application during our sample period, include the application duration and application outcome with detailed date and assignee branch. The data also contain information on employees and managers for all branches including age, gender, education, job ladder salary, and work tenure.

3.2 Variables

Table 1 presents the descriptive statistics for borrower-level variables during the entire sample period. The detailed definitions of these variables are available at Appendix A. We analyze three sets of variables that pertain to the borrower's demographics, credit card characteristics, and other banking service variables. To study the effect of change in incentive scheme, we define a borrower belongs to the last-week sample if his/her credit card origination date is within the last week of each month and the non-last-week sample otherwise.[16] Therefore, we split the data into a two-by-two matrix: 2015 versus 2016, and last-week versus non-last-week.

In Table 1, we find that while the characteristics for samples of last-week and non-last-week before the new incentive scheme are of similar magnitude, those for borrowers in 2016 differ substantially: First, we exploit the ex-ante heterogeneity in demographic characteristics and show that the borrowers in last-week sample are more likely to be older, less likely to earn a high income, less likely to have a college degree or higher than those in non-last-week sample. Second, we find that these borrowers have different ex-post credit outcomes as the borrowers in last-week sample are less likely to use the new issued credit card, more likely to be delinquent, and less likely to reinstate account conditional on his/her delinquency. Finally, among other banking services, the borrowers in last week are less likely to engage in the asset management within the bank compared with those borrowers in non-last-week sample. Our summary statistics suggest that the non-linear incentive scheme may have differential effects on the credit outcomes of borrowers in last-week and non-last-week samples.

[TABLE 1 ABOUT HERE]

Table 2 presents the summary statistics for branch-level information. On average, bank agents are 35 years old, 48% have a bachelor's degree or higher, 63% of them are male, and have 6.93 years of work tenure. As for salary, there are large differences between employees and managers. Moreover, among these two groups, there are very wide salary gap with low and high rungs in the job ladder. For instance, the monthly salary for department managers can be five

[16] We omit the weekends and official holidays when dividing the last-week and non-last-week samples. See http://www.gov.cn/zhengce/content/2014-12/16/content_9302.htm for the official holidays arrangement in 2015. As there exists leave in lieu practice, during our sample period, there are on average 20.83 days for each month, and within each month, there are 5 days in last-week sample and 15.83 days in non-last-week sample.

times larger than that for team managers. As for credit card approval, the average approval rate is about 61% and the mean duration for acceptance and rejection are 7.31 days and 3.34 days, respectively.

[TABLE 2 ABOUT HERE]

4 Identification and Empirical Methodology

Our identification strategy exploits the change in the incentive scheme in 2016 that imposed quota-based incentives on bank's credit card sales team managers. Since the change induces the end-of-month incentives on agents, we presume that last-week borrowers in 2016 should have been directly affected by this change.

To assess the effects on borrower's credit outcomes, we test whether the total number of credit card origination in the last-week days of each month is statistically different from that in the non-last-week days of each month at bank branch level. We use the following econometric approach that regresses the daily number of credit card origination on dummies for the last-week of each month at branch level:

$$\log(1 + \mathrm{Number}_{bt}) = \beta * \mathrm{LastWeek}_t + \mathrm{dow}_t + \mathrm{dom}_t + \delta_b + \tau_m + \epsilon_{bt},$$

where Number_{bt} are the number of credit card issued at branch b on date t.[17] We use the $\log(1 + \mathrm{Number}_{bt})$ as dependent variable to measure the overall credit card origination at the branch-day level, so that zero values are defined. The variables of interest, $\mathrm{LastWeek}_t$, are a set of dummy variables that equal to one if the date t is on the last-week days of each month d. In

[17] We aggregate the individual credit card origination number to the branch-level since each branch manager is awarded in branch level (including the main branch and sub-branch).

most specification, we also consider the day of week fixed effects (dow_t), day of month fixed effects (dom_t), month fixed effects (τ_m), and branch fixed effects (δ_b). To calculate confidence intervals on the coefficients, we cluster the standard error at both five-day periods (with a given five-day period consisting of only last-week observations or only non-last-week observations) and branch level.

To examine the effects on borrower's credit outcomes, we use the standard difference-in-differences specification at the individual borrower level. This methodology compares the effect of new incentive scheme on two groups: A group that should be directly affected by the event, which we will call "the treated group", and a group that should not be directly affected by the event, which we call "the control group". The differences-in-differences approach then relies on measuring the differential effect of the nonlinear incentive across the two groups:

$$Y_{i,b,t} = \alpha + \beta_1 \text{After}_t + \beta_2 \text{LastWeek}_i + \beta_3 \text{After}_t \times \text{LastWeek}_i + \gamma X_{i,b,t} + \theta_{b,t} + \epsilon_{i,b,t},$$

where the dependent variable $Y_{i,b,t}$ is the credit outcome of a borrower i, issued by branch b, at month t, including the usage of credit cards, the loan delinquency behavior, and other banking services.[18] After_t is an indicator variable that equals one if the month t is after January 2016 and zero otherwise. LastWeek_i is an indicator variable that equals one if the credit card of borrower i is issued during the last week and zero otherwise. The independent variables $X_{i,b,t}$ are control variables. For most of our analyses, we include branch-time fixed effects ($\theta_{b,t}$) that capture any common variation in branch-level for each month to rule out a series of identification concerns. The error term $\epsilon_{i,b,t}$ is clustered at the borrower and time levels, accounting for the serial

[18] Our dependent variables include both continuous and binary variables. It is desirable to fit a probability model (i.e., Logit and Probit models) for binary dependent variable. However, the estimation of non-linear models may be unstable given the large sample size and we adopt linear econometric specification that provides highly accurate estimates for the marginal effects.

correlation in the credit outcomes and the possible correlation of borrowers' behavior in the same branch. The coefficient β on the interaction term $\text{After}_t \times \text{LastWeek}_i$ is the difference-in-differences estimate, measuring how the effect of the introduction of new incentive scheme when controlling for all time-varying, observed and unobserved, branch-level heterogeneities.[19]

5 Empirical Results

In this section, we explore the differences between last-week and non-last-week samples using the event study approach and regression analyses that control for potential confounders may affect credit card originations.

5.1 Graphic Evidence

Figure 2 shows the end-of-month effect in the number of credit card origination. The Figure 2a is the subsample period from January 2015 to December 2015 and the Figure 2b is the subsample period from January 2016 to December 2016. Date 0 on the horizontal axis is the end day of each month. The graph omits weekends and Chinese official holidays.[20] Therefore, 10 days on the horizontal axis represent two calendar weeks after the end day of each month, and so on. On the vertical axis, we graph the average number of new credit card origination at day t. The vertical axis is in log level. The figure shows a surprising regularity for the sample in 2016: the number of credit card origination is much higher at the end, and lower at the beginning, than in the

[19] For concision, we do not report the estimates for control variables in all difference-in-differences specification. Interest readers may find the Internet Appendix for the full estimation results.
[20] The dates for official holidays in China are available in http://www.gov.cn/zhengce/content/2014-12/16/content_9302.htm and http://www.gov.cn/zhengce/content/2015-12/10/content_10394.htm. Some weekends are workdays due to the holiday arrangement.

middle of each month. Our results are consistent with the theoretical predictions of agents who face nonlinear incentive contracts and, therefore, identify the differences between last-week and non-last-week borrowers (see Oyer (1998), Lazear and Oyer (2004)).

[FIGURE 2 ABOUT HERE]

In Figure 3, we show the average daily number of credit card origination for last-week and non-last-week samples in each month from January 2015 to December 2016. The horizontal axis measures time (in month) relative to the new incentive scheme in this bank in January 2016. The event time t = 0 represents the month when the incentive scheme was enacted, and the negative and positive numbers represent the months before and after the enaction, respectively. The vertical axis is the average (log) number of daily credit card issued by this bank during the last-week and non-last-week for each month. We find that the total number of credit card origination for last-week and non-last-week days is similar in 2015 while increases sharply after the enaction of incentive scheme. Moreover, the increase in the total number of credit card origination during last-week days is higher than that of the non-last-week days. Our event study graphic evidence suggest that agents responded to the change in incentive scheme by raising the origination number of credit cards to meet the non-linear hurdles and monthly quota-based requirements.

[FIGURE 3 ABOUT HERE]

5.2 Statistical Significance

We present the results for sample period in 2016 at Panel (A) and in 2015 at Panel (B) of Table 3. We first focus on Panel (A), column (1) shows the bivariate relation between last-week days and credit cards origination. The positive coefficient on LastWeek_t indicates that the number of credit card originated during the last-week days of month is larger than the rest days of month.

Its value of 0.154 indicates that the probability of a credit card issuance at end of month is about 16.6 (= exp(0.154) - 1) percent greater than the rest of the month. In column (2), the inclusion of the month fixed effects does not change much on the magnitude and statistical significance of the coefficient on LastWeek_t. Our results are robust when we add day of week and day of month fixed effects in column (3) and branch fixed effects in column (4). The coefficient on LastWeek_t is significant at 1% level across all specifications. In Panel (B), we find that the coefficient is not significant at any specifications and the magnitude is much smaller compared with that in Panel (A), suggesting the end-of-month effect becomes economically and statistically significant after the introduction of new incentive scheme.

[TABLE 3 ABOUT HERE]

6 Potential Mechanisms and Economic Outcomes

In this section, we use the data on credit card borrowers and bank branch agents to discuss three non-mutually exclusive channels through which change in managerial incentive may affect the end-of-month behaviors: (1) lax screening, (2) fast processing, and (3) agency issues. We further explore the economic outcome of nonlinear incentives on card usage, credit outcome, and other banking services associated with borrowers.

6.1 Lax Screening

To limit the issuance of credit cards to insolvent borrowers, the bank has risk control department to screen the qualification of new applicants (see Berg (2015)). The number of credit card origination increases dramatically during last-week days when we control for the potential change in demand for credit card, suggesting that this department may exact different screening criteria or risk tolerance on applicants (Agarwal and Ben-David (2018)). We test this hypothesis using the information available to approve the credit card applicants and explore whether the observable characteristics of credit card borrowers are different across the last-week and non-last-week groups using the difference-in-differences specification.

We first consider the observed characteristics for each customer in Table 4. In column (1) and (2), we show that the borrowers in the two groups have statistically distinguishable characteristics in income and employment. The last-week borrowers are less likely to be employed and have fewer income than non-last-week counterparts. In column (3) to (6), they are indistinguishable in demographical characteristics including age, gender, and marital status.

[TABLE 4 ABOUT HERE]

We next examine whether there are changes in credit card approval decisions of these two groups. In Table 5, we regress the approval indicator for all applications on Treatment dummy and observed characteristics. Columns (1) and (2) present the base regressions, showing that the applications were about 12% more likely to be approved under the treatment. In columns (3) to (6), we interact the Treatment dummy with income. Our results show that the weight on income declines for the last-week group and is 25% lower than that of the non-last-week group (-0.001 + 0.004 = 0.003 in the last-week relative to 0.004 in the non-last-week group). Moreover, the weight of income in the last-week group is not statistically different from zero.

[TABLE 5 ABOUT HERE]

Our results suggest that the risk control departments may impose lax screening on last-week credit card applications and the hard information became less important during the approval process. Such decline in the importance of hard information may lead to a higher delinquency rate, and conditional on delinquent, lower reinstatement rate (Liberti and Petersen (2019)).

We explore whether the impact of nonlinear incentives caused the change of credit quality. We first present our results for the change in credit quality in Table 6. In column (1) and (2), we show the effect of nonlinear incentives on borrower's delinquency behavior. Following Gross and Souleles (2002) and Chatterjee et al. (2007), we define the delinquency for the borrower's credit card if the repayments are at least three months past due. As shown, the coefficients on the Treatment dummy are both positive, similar in magnitude (0.373% and 0.347%), and statistically significant. The effect is economically meaningful: the differential in delinquency rate corresponds to about 17% increase in the average delinquency rate among non-last-week borrowers. In columns (3) to (4), we estimate the specifications (1) with time to delinquency as the dependent variable. Time to delinquency measures the duration between the issuance of credit cards and delinquency incidence. The coefficients on the Treatment dummy are between -0.586 and -0.545 and the duration between card origination and delinquency incidence is 6.4% shorter for last-week than non-last-week borrowers.

We next examine whether there exists any difference for borrowers' ex-post behaviors conditional on delinquency. First, we study whether the delinquent last-week borrowers have a greater likelihood to have their account reinstated compared with those non-last-week borrowers. In columns (5) to (6), the coefficient on Treatment dummy is between -8.152 and -8.116 and statistically significant, showing that last-week borrowers are 10.02% less likely to reinstate their accounts compared with others. Second, for reinstated credit card accounts, whether there are any differences between two groups of borrowers regarding the time to reinstatement. In columns (7) to (8), we show that conditional on reinstatement, last-week borrowers take an additional 0.4 months to reinstate their credit accounts. As the average duration for non-last-week borrowers who reinstate their credit accounts is 3.27 months, the last-week borrowers' accounts are 12.2% less likely to reinstate. Overall, our results suggest that last-week borrowers are more likely to become delinquent on their credit cards than non-last week borrowers and are less likely to have their delinquent accounts reinstated conditional on delinquency.

[TABLE 6 ABOUT HERE]

We further explore the implication of the decline importance of income during the approval process in the increase in delinquency. We classify low-income borrowers as those whose income belongs to the lowest quintile of all originated borrowers in the same month and high-income borrowers as the rest. We then explore whether there are noticeable differences between the income and the credit outcomes. Specifically, we repeat the specifications for Tables 6 by decomposing the Treatment dummy into the low-income and the high-income dummy and report the results in Table 7. Column (1) show that our results on the higher delinquency rate of last-week borrowers relative to others are largely driven by low-income borrowers. Furthermore, the shorter time to delinquency (Column 2), the lower reinstatement rate (Column 3), and the longer time to reinstatement (Column 4) associated with last-week borrowers are concentrated among low-income borrowers.

[TABLE 7 ABOUT HERE]

6.2 Agency Problem

As bank managers are incentivized to maximize a quota-based outcome, this practice may lead to agency issue against the welfare of whole bank at the margins of credit card origination (Dobbie et al. (2019)). Bank managers may mislead pre-existing and new customers to apply for credit cards, and, as a result, these credit card borrowers may feel less trustworthy on bank.[21]

We first examine the effect of nonlinear incentives on borrower's behaviors using different measures of credit card usage as the dependent variable in Table 8. We first show the effect on the borrower's monthly number of credit card usage. In column (1), the coefficient on the Treatment is -0.52 and statistically significant. The magnitude is economically meaningful: given the mean of non-last-week borrowers' monthly credit card usage is 5.53, a decrease of 0.52 implies that the average credit card usage declined by 9.40%. We also account for the possibility of shocks at the branch level (by including branch-time fixed effects) and control for borrower's observed variables in column (2). As shown, the results are not sensitive to the inclusion of these control variables and fixed effects. If anything, the coefficient on the Treatment dummy becomes slightly smaller: the coefficient is now -0.512, which implies that borrower's credit card usage decreases by 9.25%. In columns (3) to (4), we re-estimate the specifications with the monthly amount of credit card transaction as the dependent variable. The coefficient on the Treatment dummy is between -394.5 and -388.3, implying the monthly average transaction amount decrease by 8.21% to 8.34%, respectively. These results indicates that our results are robust to the borrower-level characteristics and the time-varying heterogeneities. We further consider the effect of nonlinear incentives on the probability of credit card being inactive or canceled within one year since its origination. Following Agarwal, Liu, and Souleles (2007), we define a credit card is inactive if the card holder has no financial transactions for more than six consecutive months. In column (5) to (8), we report the coefficient for Treatment for each of the two

[21] During our interview with the several bank managers and employees, they sometimes will apply the credit cards for some of the senior bank customers who are not fully aware of the consequences of using credit cards (e.g., just asked the customers to sign off their names in the credit card application forms together with a bunch of other documents the customers are going to sign).

dependent variables: a dummy equal to one if the credit card being inactive (Columns 5 and 6) and being canceled (Columns 7 and 8). The estimates are both economically and statistically significant, suggesting that last-week credit cards are 17% more likely to be inactive and 13% more likely to be canceled compared with non-last-week credit cards.

[TABLE 8 ABOUT HERE]

We also explore whether the change in incentive schemes caused a decrease in borrower's other banking service from period to period. We use the end-of-month balance of investments under management with the bank as the measure for customer's monthly investment, as wealth management is the one of the most important trust-intensive banking services. In Table 9, we present our results for the change in investment. The effect of change in incentive schemes on the average stock of investment combines two effects: the impact on the probability of investment (extensive margins) and, conditional on investment, the amount of investment in the bank (intensive margins). We report the coefficients using our baseline specification for each of the two dependent variables: a dummy equal to one if the customer has any investment (Columns 1 and 2) and the amount of investment (Columns 3 and 4). Our estimates indicate that all measures of investment decrease more for last-week compared with non-last-week customers after the enaction of new incentive scheme, and the effect is both economically and statistically significant.

[TABLE 9 ABOUT HERE]

As trust offers security against expropriation, theft or deception (Guiso, Sapienza, and Zingales (2008)), more trusting customers are more willing to invest in trust-intensive assets because they are less fearful of being cheated and less anxious about taking risks (Georgarakos and Inderst (2011), Gennaioli, Shleifer, and Vishny (2013), Dupas, Keats, and Robinson (2019)).

We test this hypothesis using the relative few usages and card cancellation as proxy for the mistrust in bank (Mester, Nakamura, and Renault (2005)). We classify low-frequency customers as those whose monthly average number of credit card usage belongs to the lowest quintile and then explore whether there are differences between the credit card usage and the investment outcomes.[22] Specifically, we decompose the Treatment into the low-frequency and the high-frequency dummies and report the results in Table 10. We examine how the effect of new incentive on the probability that a customer will investment in the bank, and conditional on investment, how it affects the amount given is differentiated by different types of customers. Column (1) to (2) show that the lower investment is concentrated among lower frequency last-week customers. Our results are robust when we use the cancellation indicator as a proxy for mistrust as shown in column (3) to (4). Overall, we highlight that the relationship between the effect of managerial incentive and investment outcome may be driven by the group of customers who have less trust in the bank.

[TABLE 10 ABOUT HERE]

6.3 Fast Processing

As nonlinear incentive imposes end of month requirements on bank managers, it may lead to faster processing for credit card application approval to notch for deadline (Chen et al. (2021) and DeFusco and Paciorek (2017)). We examine this hypothesis by studying the effect of new incentive scheme on the duration for application process in Table 11. We divide all credit card applications into two groups based on their outcome: approved sample and denied sample.

[22] Similarly, we also classify high-frequency customers as those whose average number of credit card usage belongs to the non-lowest quintile.

Column (1) and (2) show that the duration decreases significantly for approved sample. The coefficients on the Treatment are statistically significant and the magnitude is economically meaningful: the new incentive reduced the approval duration by about 3 days, or approximately 39% of the pre-period average. The impact of new incentive on rejected sample, presented in column (3) and (4), is much less and statistical insignificant. Our results suggest that the employees and managers are more likely to increase the processing speed for approval decision rather than rejection to bunch for end of month quotas.

[TABLE 11 ABOUT HERE]

We next study whether the fast-processing practice is related with borrower's ex-post outcome. We classify fast-process borrowers as those whose approval duration of credit card usage belongs to the lowest quintile and decompose the Treatment into the fast-process and the other dummies and report the results in Table 12. Column (1) to (4) show that the deteriorate in credit quality is concentrated among fast-process borrowers. Column (5) to (6) present that lower investment outcome is also driven by fast-process borrowers. Our results highlight that the faster processing may be related with the relative worse credit quality and lower investment willingness within the bank.

[TABLE 12 ABOUT HERE]

7 Managerial Characteristics

In this section, we examine the relation between the characteristics of managers and the credit outcome and focus on three main characteristics: gender, tenure, and distance to main branch. Women tend to be more risk-averse and less prone to monetary incentive (Charness and Gneezy, 2012; Dohmen et al., 2011; Bao and Huang, 2021). Male managers may therefore be more willing to push origination outcome aggressively through the system (Beck, Behr, and Guettler (2013), Adams and Ferreira (2009)). We decompose the Treatment dummy into the male/female dummies based on manager's gender and report the results in Panel A of Table 13. Indeed, we find that male managers are related with the deterioration of credit outcome and investment behaviors while we don't find such effects is significant with female managers.

As managers with longer work tenure have greater familiarity with pre-existing customers and fewer career concerns, managers who have been the job longer may exhibit less opportunistic behavior than other managers after the new incentive scheme (Mas and Moretti (2009), Griffith and Neely (2009)). We test this hypothesis in Panel B of Table 13 by classifying short tenure managers as those whose work tenure belongs to the lowest quintile. We decompose the Treatment dummy into the long/short tenure dummies and our results show that longer work tenure managers are associated with worsen in credit quality and investment outcomes.

Proximity to main branch makes it easier for headquarters to monitor and acquire information about sub-branch (Drexler and Schoar (2014), Giroud (2013)). Hence, we expect managers far away from the main branch are more probable to game the system (Kalnins and Lafontaine (2013), Chhaochharia, Kumar, and Niessen-Ruenzi (2012)). We decompose the Treatment dummy into the away/near branch dummies where we define the away branches that are the furthest quintile away from main branch. We report the results in Panel C of Table 13 and show that the higher delinquency rate and lower investment willingness of last-week borrowers are largely associated with managers who are away main branch.

[TABLE 13 ABOUT HERE]

8 Discussion

As our results are based on data from one single bank, we discuss whether these findings can be generalized to different stimuli, institutions, and time periods. We clarify the external validity using the conditions proposed by List (2020). First, our sample is based on borrowers from one of the leading commercial banks in China and is highly similar to the underlying population and bank customers in terms of relevant observables. Second, there is no attrition as we have all credit card borrowing records from this bank. Third, due to the nature of our natural field experiment setup, participants do not know they are being observed, and therefore, all borrowers make their decisions in a natural environment, alleviating the concern for the unobserved change in participants. As a result, we expect our findings to be valid for larger samples and borrowers from other banks.

9 Conclusion

Understanding how incentive scheme affects consumer lending market is a question of first-order importance in finance. In this paper, we use a natural field experiment with bank managers to identify the effect of quota-based incentive on credit quantity. We find a strong and economically significant effect of nonlinear incentive on credit card origination at the end of each month.

At the same time, we document several mechanisms that explain how the nonlinear incentive affects credit origination. First, we show that the bank may lax screening criteria for credit card approval and reduce the weight for hard information in the last week of each month. This important change may explain why borrowers approved at the end of each month have lower income and are less likely to have employment. Moreover, we find that the lax screening may lead to higher likelihood of delinquency for the credit cards granted at the end of each month, and conditional on delinquency, the borrowers are less likely to reinstate their credit cards.

Second, we find that the nonlinear incentive may induce the agency issues of bank managers who mislead customers to open credit card accounts. We find that, on average, the last-week borrowers are less likely to use credit card and invest within this bank after the new incentive scheme. In addition, we find that low-frequency credit card borrowers are less likely to use the wealth management service in the future. These findings highlight the negative externalities of the opportunistic behavior induced by nonlinear incentives on the overall bank welfare.

Third, we show that nonlinear incentive may induce faster processing in the credit card approval process. We study the processing time of the credit card applications and find that the end-of-month approved cards have shorter processing time after the new incentive scheme while there is no significant change for declined application.

Our findings have important implications for incentive scheme in consumer lending market. Banks have increasingly relied on sophisticate incentive schemes on their managers. But it is unclear whether, what, and how such schemes may change the behaviors of bank agents and borrowers, particularly in real-world credit markets such as the one we study. Nor is it obvious what managerial characteristics are associated with the performance of new incentives. Our results in this paper are a first step toward answering these important questions.

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Figure 1: Credit card in China

This figure reports the cumulative number and growth rate of credit card origination in China from 2009 through 2018. Data source: People's Bank of China.

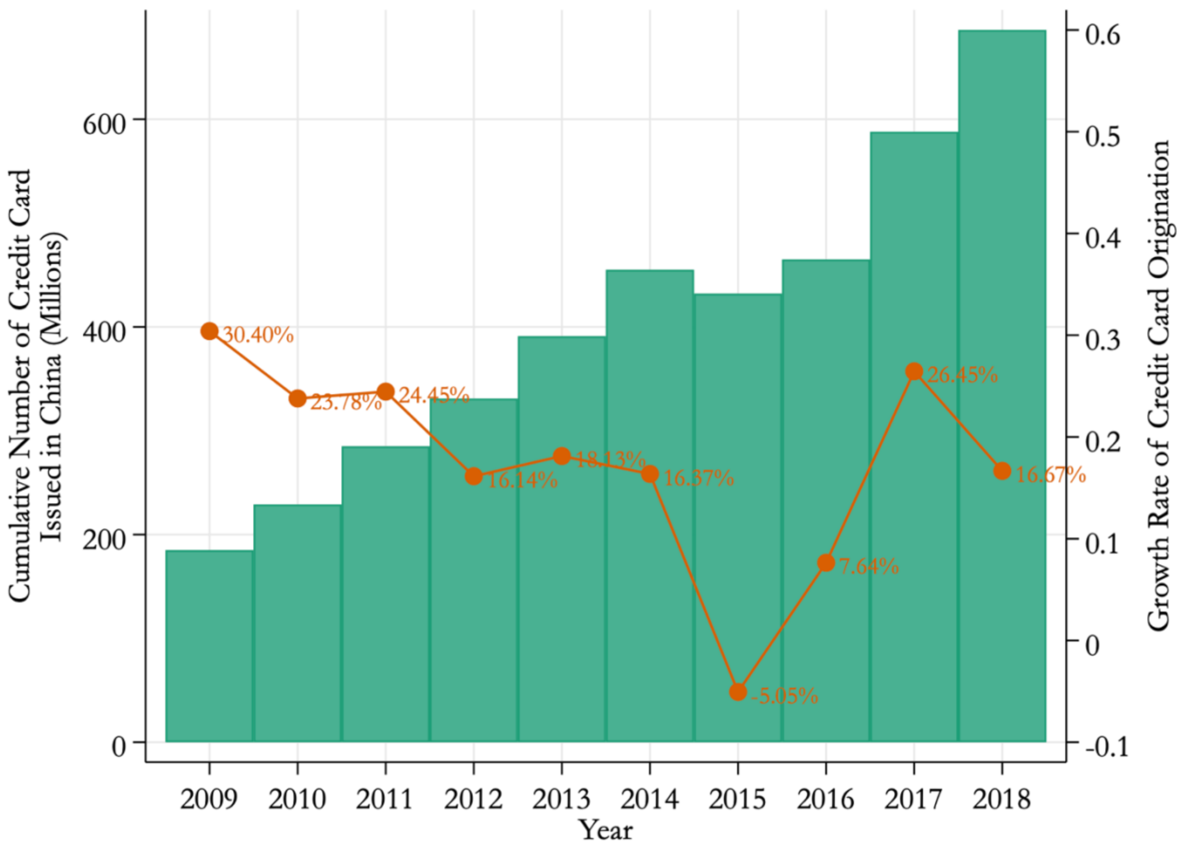


Figure 2: Daily origination of credit cards

This figure shows the daily credit card origination (aggregated to branch level) at the Year 2015 (upper panel) and Year 2016 (bottom panel).

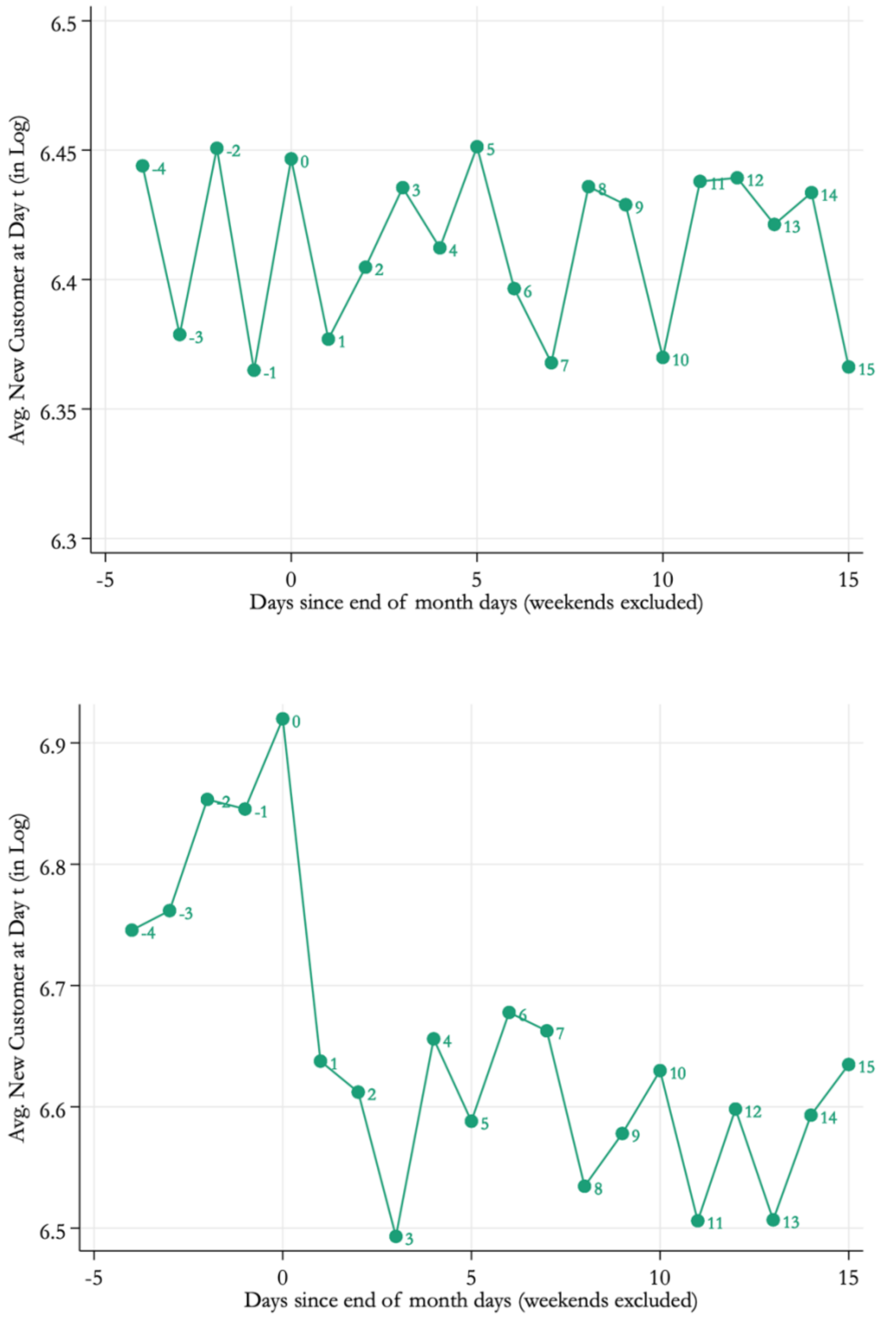


Figure 3: Credit card origination for last-week and non-last-week days

This figure shows the monthly average credit card origination of last-week and non-last-week days (aggregated to branch level) from 2015:01 to 2016:12.

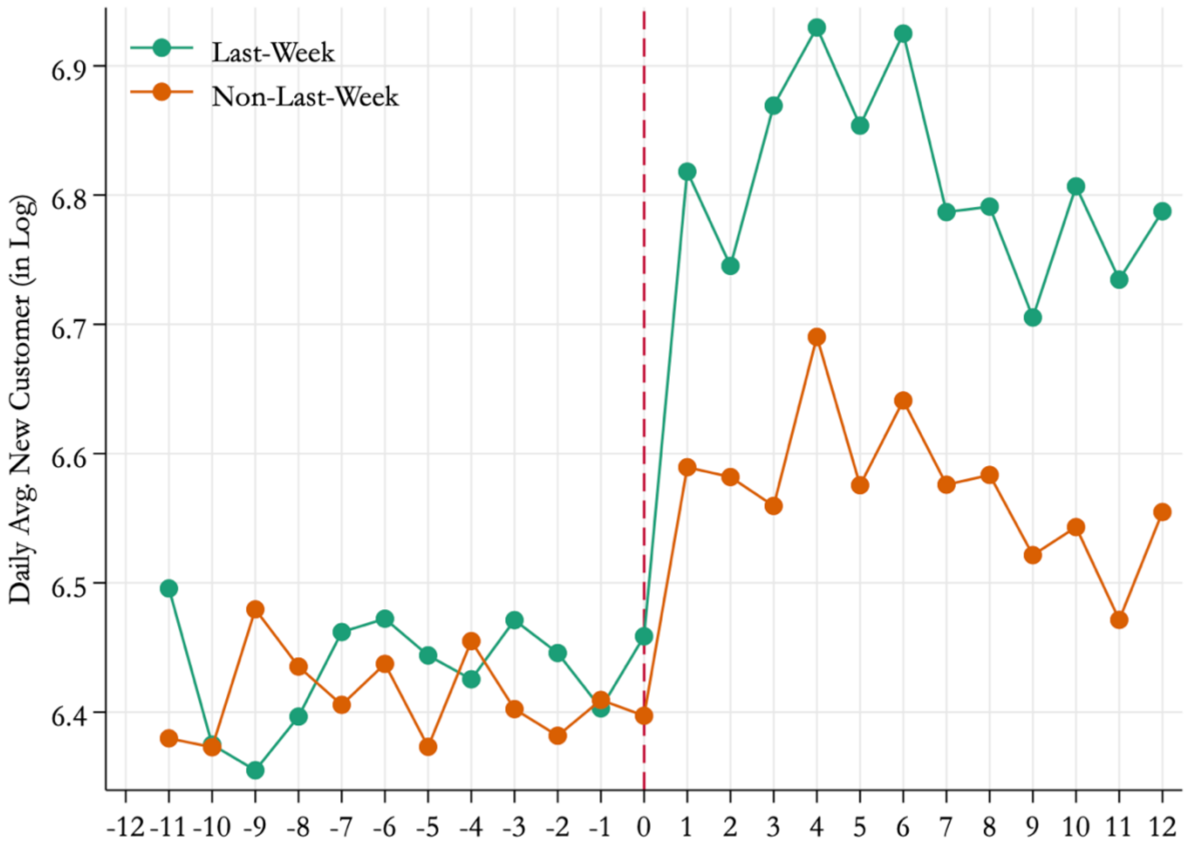


Table 1: Summary statistics (borrower-level)

This table reports the summary statistics for the borrower-level variables. All variables are measured at a monthly frequency from 2015:01 to 2016:12. We report the mean and standard deviation for each variable. The detailed variable definitions are presented in Appendix A.

	Year 2015				Year 2016			
	LastWeek Sample		Non LastWeek Sample		LastWeek Sample		Non LastWeek Sample	
Variable	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Panel A: Borrower Characteristics								
Age	38.44	6.13	38.72	6.92	38.57	5.89	37.69	7.87
Income	6153	3276	6205	3712	5721	3048	6207	3302
Employment	0.68	0.47	0.69	0.46	0.63	0.46	0.68	0.46
College	0.35	0.48	0.36	0.48	0.32	0.47	0.37	0.48
Gender	0.48	0.50	0.48	0.50	0.49	0.50	0.49	0.50
Married	0.67	0.47	0.69	0.46	0.67	0.47	0.66	0.48
Car Loan	0.04	0.20	0.05	0.22	0.06	0.24	0.05	0.22
Car	0.41	0.49	0.43	0.50	0.42	0.49	0.43	0.50
House	0.61	0.49	0.63	0.48	0.61	0.49	0.62	0.49
Mortgage	0.18	0.38	0.19	0.39	0.20	0.40	0.18	0.38
Panel B: Credit Card Characteristics								
Transaction number	5.54	12.74	5.52	11.60	5.06	15.24	5.53	13.67
Transaction amount	3693	4372	3707	4372	3320	4031	3728	4478
Inactive	0.11	0.30	0.11	0.31	0.13	0.36	0.11	0.31
Cancellation	0.09	0.28	0.09	0.29	0.11	0.34	0.09	0.28
Delinquency	0.02	0.13	0.02	0.14	0.03	0.16	0.02	0.14
Time to delinquency	8.40	4.00	8.28	3.97	8.02	4.24	8.49	4.50
Reinstatement	0.81	0.39	0.79	0.41	0.75	0.43	0.81	0.39
Time to reinstatement	3.01	2.56	3.17	2.67	3.55	2.06	3.27	2.93
Credit line	37149	26739	37208	26908	36570	26873	37344	27259
Panel C: Other Banking Characteristics								
Investment	5269	5534	5613	6498	4715	5227	5661	6628
AUM	18971	23488	19941	27910	17753	20968	19027	25832
Number of accounts	2.55	3.92	2.57	3.51	2.47	3.31	2.56	4.01

Sophistication	5.56	4.80	5.60	3.92	5.40	3.88	5.56	2.13
Closing	3.01	2.38	3.02	1.89	2.93	1.77	2.99	1.81
Banking relationship	14.32	8.70	14.43	8.75	14.07	8.91	14.39	8.70

Table 2: Summary statistics (branch-level)

This table reports the summary statistics for the branch-level variables. Our sample period starts from 2015:01 to 2016:12. We report the mean, standard deviation, minimum and maximum for each variable. The detailed variable definitions are presented in Appendix A.

Variable	Mean	SD	Min	Max
Age	35.21	11.04	20	59
College	0.48	0.50	0	1
Gender	0.63	0.48	0	1
Work Tenure (Year)	6.93	7.91	0	28
Employee Level I Salary	1347.87	210.12	1200	1500
Employee Level II Salary	1831.65	146.48	1600	1950
Employee Level III Salary	2164.18	174.69	2000	2350
Employee Level IV Salary	2750.98	146.55	2400	2950
Manager (Team) Salary	5748.12	3412.61	4000	12000
Manager (Department) Salary	16432.23	4367.90	13500	20000
Manager (Branch) Salary	30713.41	11294.85	25000	60000
Monthly Bonus	1648.58	3718.26	0	40000
Approval Rate	0.61	0.49	0	1
Accepted Duration	7.31	6.45	0	21
Rejected Duration	3.34	2.19	0	11

Table 3: Nonlinear incentives and credit card origination

This table presents the estimation results for the balanced panel regression on credit card origination aggregated to the branch level in Year 2016 (Panel A) and Year 2015 (Panel B), respectively. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

Panel A: Year 2016				
	Log daily number of credit card origination			
	(1)	(2)	(3)	(4)
Dummy=1 in LastWeek	0.154***	0.153***	0.161***	0.157***
	(0.000)	(0.000)	(0.000)	(0.000)
Month FEs	No	Yes	Yes	Yes
Day of Week FEs	No	No	Yes	Yes
Day of Month FEs	No	No	Yes	Yes
Branch FEs	No	No	No	Yes
Cluster SE	Yes	Yes	Yes	Yes
Mean (Dep.var)	2.884	2.884	2.884	2.884
Observations	10,500	10,500	10,500	10,500
R^2	0.055	0.111	0.136	0.548
Panel B: Year 2015				
	Log daily number of credit card origination			
	(1)	(2)	(3)	(4)
Dummy=1 in LastWeek	0.004	0.005	0.003	0.002
	(0.512)	(0.473)	(0.429)	(0.397)
Month FEs	No	Yes	Yes	Yes
Day of Week FEs	No	No	Yes	Yes
Day of Month FEs	No	No	Yes	Yes
Branch FEs	No	No	No	Yes
Cluster SE	Yes	Yes	Yes	Yes
Mean (Dep.var)	2.665	2.665	2.665	2.665
Observations	10,500	10,500	10,500	10,500
R^2	0.084	0.124	0.193	0.447

Table 4: Borrower's characteristics

In this table, we report the estimation results for the difference-in-differences regressions that explore whether the borrower's characteristics are different before and after new incentive schemes. Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Employment	Income	Age	College	Gender	Married
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.053**	-466.5***	0.010	-0.041	-0.008	0.004
	(0.019)	(0.000)	(0.817)	(0.114)	(0.169)	(0.310)
LastWeek	0.001	-11.7	0.022	-0.003	0.005	0.021
	(0.291)	(0.559)	(0.541)	(0.405)	(0.151)	(0.178)
After	-0.002	48.9	-0.034	0.012	0.004*	0.001
	(0.147)	(0.152)	(0.618)	(0.586)	(0.072)	(0.283)
Constant	0.687***	6104.6***	38.2***	0.364***	0.483***	0.665***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Branch*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	350,805	350,805	350,805	350,805	350,805	350,805
R^2	0.013	0.028	0.014	0.099	0.015	0.011

Table 5: Credit card applications approval

In this table, we show the estimation results for the difference-in-differences regressions studying how the nonlinear incentive affects the bank's credit card applications approval standards with respect to hard information (income). The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Approval Indicator					
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	0.121**	0.113**	0.086***	0.083***	0.074***	0.078***
	(0.007)	(0.009)	(0.000)	(0.001)	(0.004)	(0.001)
Treatment*Log(Income)			-0.002	-0.001	-0.003	-0.001
			(0.172)	(0.163)	(0.125)	(0.219)
Log(Income)			0.004**	0.003**	0.005**	0.004**
			(0.021)	(0.017)	(0.023)	(0.012)
Constant	0.527***	0.519***	0.524***	0.513***	0.517***	0.507***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Controls	No	No	No	No	Yes	Yes
Branch*Time FEs	No	Yes	No	Yes	No	Yes
Observations	616,189	616,189	616,189	616,189	616,189	616,189
R^2	0.092	0.113	0.101	0.172	0.184	0.217

Table 6: Nonlinear incentives and credit outcomes

In this table, we show the estimation results for the difference-in-differences regressions that investigate the impact of the nonlinear incentives on the credit outcome using the delinquency likelihood (%) (Column 1-2), the number of months between card origination and delinquency (Column 3-4), reinstatement likelihood (%) (Column 5-6), and the number of months between card delinquency and reinstatement (Column 7-8). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Delinquency		Time to Delinquency		Reinstatement		Time to Reinstatement	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.373***	0.347***	-0.586***	-0.545***	-8.152***	-8.116***	0.434***	0.428***
	(0.000)	(0.002)	(0.001)	(0.003)	(0.003)	(0.004)	(0.001)	(0.000)
LastWeek	-0.164*	-0.169*	0.118	0.129	2.685	2.597	-0.162*	-0.177**
	(0.066)	(0.059)	(0.512)	(0.471)	(0.147)	(0.160)	(0.062)	(0.043)
After	-0.111*	-0.105*	0.206	0.196	2.092*	2.338*	0.109*	0.111*
	(0.097)	(0.081)	(0.115)	(0.132)	(0.095)	(0.067)	(0.082)	(0.079)
Constant	1.986***	2.005***	8.282***	8.745***	78.58***	75.48***	3.165***	3.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Controls	No	Yes	No	Yes	No	Yes	No	Yes
Branch*Time FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,019,660	4,019,660	84,984	84,984	84,984	84,984	67,080	67,080
R^2	0.032	0.162	0.036	0.164	0.027	0.135	0.048	0.179

Table 7: Credit outcomes by the income of borrowers

In this table, we present the estimation results for the difference-in-differences regressions studying the influence of the nonlinear incentives on the credit outcome by borrower's income. We decompose the Treatment into Low Income and High Income. The dependent variables are delinquency likelihood (%) (Column 1), the number of months between card origination and delinquency (Column 2), reinstatement likelihood (%) (Column 3), and the number of months between card delinquency and reinstatement (Column 4). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Delinquency	Time to Delinquency	Reinstatement	Time to Reinstatement
	(1)	(2)	(3)	(4)
Low Income	0.549***	-0.704***	-11.781**	0.785***
	(0.000)	(0.002)	(0.014)	(0.000)
High Income	0.297*	-0.505	-7.198*	0.339*
	(0.071)	(0.115)	(0.053)	(0.079)
LastWeek	-0.169*	0.129	2.597	-0.177**
	(0.059)	(0.477)	(0.160)	(0.043)
After	-0.105*	0.196	2.338*	0.111*
	(0.081)	(0.132)	(0.067)	(0.079)
Constant	2.005***	8.745***	75.48***	3.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Controls	Yes	Yes	Yes	Yes
Branch*Time FEs	Yes	Yes	Yes	Yes
Observations	4,019,660	84,984	84,984	67,080
R^2	0.162	0.104	0.135	0.179

Table 8: Nonlinear incentives and credit card usage

In this table, we report the estimation results for the difference-in-differences regressions that investigate the effect of the nonlinear incentives on the credit card usage when the dependent variables are the monthly number of credit card usage (Column 1-2), the monthly amount of credit card usage (Column 3-4), credit card inactive likelihood (%) within six months (Column 5-6), and credit card cancellation likelihood (%) within twelve months (Column 7-8). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Number		Amount		Inactive		Cancellation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.520***	-0.512***	-394.5***	-388.3***	1.992***	1.894***	1.871***	1.764***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
LastWeek	0.020	0.021	-13.58	-13.37	0.134	0.132	-0.038	-0.039
	(0.418)	(0.402)	(0.739)	(0.743)	(0.485)	(0.492)	(0.827)	(0.823)
After	0.019	0.023	20.85	20.98	-0.019	-0.028	-0.076	-0.073
	(0.272)	(0.208)	(0.489)	(0.514)	(0.874)	(0.822)	(0.329)	(0.449)
Constant	5.516***	5.448***	4706.8***	4745.7***	10.80***	11.09***	9.288***	9.610***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Controls	No	Yes	No	Yes	No	Yes	No	Yes
Branch*Time FEs	No	Yes	No	Yes	No	Yes	No	Yes
Observations	4,019,660	4,019,660	4,019,660	4,019,660	4,019,660	4,019,660	4,019,660	4,019,660
R^2	0.021	0.121	0.035	0.159	0.064	0.257	0.032	0.128

Table 9: Nonlinear incentives and investment outcomes

In this table, we report the estimation results for the difference-in-differences regressions studying the effect of the nonlinear incentives on the credit card borrower's investment outcomes. The dependent variables are the indicator that a borrower has investment within the bank (Column 1-2), and the amount of investment within the bank (Column 3-4). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Dummy = 1 if Amount>0		Investment Amount	
	(1)	(2)	(3)	(4)
Treatment	-0.021***	-0.019***	-896.6**	-843.6**
	(0.000)	(0.003)	(0.022)	(0.031)
LastWeek	-0.001	-0.002	-342.5	-373.9
	(0.282)	(0.217)	(0.186)	(0.152)
After	0.001	0.001	48.73	20.35
	(0.674)	(0.994)	(0.768)	(0.903)
Constant	0.122***	0.106**	9912.6***	9332.7***
	(0.000)	(0.054)	(0.000)	(0.000)
Borrower Controls	No	Yes	No	Yes
Branch*Time FEs	No	Yes	No	Yes
Observations	4,019,660	4,019,660	4,019,660	4,019,660
R^2	0.011	0.042	0.093	0.161

Table 10: Investment outcomes by card usage

In this table, we report the estimation results for the difference-in-differences regressions studying the influence of the nonlinear incentives on the investment outcome by borrower's credit card usage. We decompose the Treatment into Low Income and High Income, and Cancellation and No Cancellation. The dependent variables are the indicator that a borrower has investment within the bank (Column 1 and 3), and the amount of investment within the bank (Column 2 and 4). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Dummy = 1 if Amount>0	Investment Amount	Dummy = 1 if Amount>0	Investment Amount
	(1)	(2)	(3)	(4)
Low Frequency	-0.039***	-1387.94***		
	(0.000)	(0.000)		
High Frequency	-0.017*	-707.54*		
	(0.063)	(0.057)		
Cancellation			-0.034***	-1662.68***
			(0.000)	(0.000)
No Cancellation			-0.018	-752.59
			(0.213)	(0.121)
LastWeek	-0.002	-373.9	-0.002	-373.9
	(0.217)	(0.152)	(0.217)	(0.152)
After	0.001	20.35	0.001	20.35
	(0.994)	(0.903)	(0.994)	(0.903)
Constant	0.106**	9332.7***	0.106**	9332.7***
	(0.054)	(0.000)	(0.054)	(0.000)
Borrower Controls	Yes	Yes	Yes	Yes
Branch*Time FEs	Yes	Yes	Yes	Yes
Observations	4,019,660	4,019,660	4,019,660	4,019,660
R^2	0.042	0.161	0.042	0.161

Table 11: Nonlinear incentive and application processing

In this table, we report the estimation results for the difference-in-differences regressions that study the impact of the nonlinear incentives on the credit card application processing time. We split the data sample into approved sample (Column 1-2) and denied sample (Column 3-4). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Approved Sample		Denied Sample	
	(1)	(2)	(3)	(4)
Treatment	-3.732***	-3.324***	-0.073	-0.071
	(0.001)	(0.000)	(0.211)	(0.183)
LastWeek	-0.385	-0.319	-0.038	-0.032
	(0.261)	(0.227)	(0.382)	(0.303)
After	0.812	0.731	0.056	0.054
	(0.376)	(0.348)	(0.297)	(0.495)
Constant	8.412***	8.121***	3.288***	3.160***
	(0.000)	(0.000)	(0.000)	(0.000)
Borrower Controls	No	Yes	No	Yes
Branch*Time FEs	No	Yes	No	Yes
Observations	350,805	350,805	265,384	265,384
R^2	0.063	0.212	0.054	0.147

Table 12: Application processing and borrower's behaviors

In this table, we report the estimation results for the difference-in-differences regressions that study the impact of the nonlinear incentives on the borrower's credit and investment outcome by application processing time. The dependent variables are delinquency likelihood (%) (Column 1), the number of months between card origination and delinquency (Column 2), reinstatement likelihood (%) (Column 3), the number of months between card delinquency and reinstatement (Column 4), the indicator that a borrower has investment within the bank (Column 5), and the amount of investment within the bank (Column 6). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Delinquency	Time to Delinquency	Reinstatement	Time to Reinstatement	Dummy = 1 if Amount>0	Investment Amount
	(1)	(2)	(3)	(4)	(5)	(6)
Fast Process	0.517***	-0.675***	-10.223***	0.725***	-0.035***	-1247.9**
	(0.010)	(0.000)	(0.005)	(0.001)	(0.000)	(0.035)
Slow Process	0.305*	-0.513*	-7.589	0.353*	-0.015	-742.6
	(0.051)	(0.095)	(0.106)	(0.073)	(0.174)	(0.135)
LastWeek	-0.169*	0.129	2.597	-0.177**	-0.002	-373.9
	(0.059)	(0.477)	(0.160)	(0.043)	(0.217)	(0.152)
After	-0.105*	0.196	2.338*	0.111*	0.001	20.35
	(0.081)	(0.132)	(0.067)	(0.079)	(0.994)	(0.903)
Constant	2.005***	8.745***	75.48***	3.003***	0.106**	5332.7***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.054)	(0.000)
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes
Branch*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,019,660	84,984	84,984	67,080	4,019,660	4,019,660
R^2	0.162	0.164	0.135	0.179	0.042	0.161

Table 13: Managerial characteristics and borrower's behaviors

In this table, we report the estimation results for the difference-in-differences regressions that study the heterogeneity impact of the nonlinear incentives on the borrower's outcome by manager's gender (Panel A), tenure (Panel B), and distance to headquarters (Panel C). Variables are defined in Appendix A. The p-values are reported in parentheses below coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the branch and time level.

	Number	Amount	Inactive	Cancellation	DLQ	Time to DLQ	Reinstatement	Time	Dummy = 1	Investment
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Manager's gender										
Male	-0.627***	-514.2***	2.471***	2.266***	0.429***	-0.624***	-8.781***	0.485***	-0.024***	-956.6***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.004)	(0.000)	(0.001)	(0.003)
Female	-0.298*	-148.3*	0.797	0.813	0.207*	-0.410	-6.984*	0.331*	-0.011	-651.2
	(0.091)	(0.054)	(0.237)	(0.155)	(0.072)	(0.115)	(0.064)	(0.083)	(0.104)	(0.031)
Panel B: Manager's tenure										
Short Tenure	-0.713***	-649.4***	2.974***	2.961***	0.487***	-0.693***	-9.543***	0.725***	-0.035***	-1247.9**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)	(0.005)	(0.001)	(0.000)	(0.035)
Long Tenure	-0.462	-323.1	1.624**	1.465*	0.312	-0.508*	-7.589	0.353*	-0.015	-742.6*
	(0.115)	(0.132)	(0.042)	(0.079)	(0.256)	(0.095)	(0.106)	(0.063)	(0.174)	(0.071)
Panel C: Manager's distance to headquarter										
Away Main Branch	-0.649***	-572.8***	2.734***	2.625***	0.517***	-0.675***	-10.223***	0.773***	-0.027***	-1071.4***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.010)	(0.000)	(0.004)	(0.001)	(0.000)	(0.002)
Near Main Branch	-0.477*	-342.2*	1.685	1.549*	0.305*	-0.513	-7.589**	0.341*	-0.017**	-786.7*
	(0.065)	(0.073)	(0.129)	(0.079)	(0.051)	(0.115)	(0.036)	(0.071)	(0.142)	(0.135)
Borrower Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Branch*Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,019,660	4,019,660	4,019,660	4,019,660	4,019,660	84,984	84,984	67,080	4,019,660	4,019,660
R^2	0.121	0.159	0.257	0.128	0.162	0.164	0.135	0.179	0.042	0.161

Appendix

Appendix A. Variable Definitions

A1. Borrower-level variable definitions:

Age is the card holder's age as of the card's origination time.

Gender is a dummy variable that equals one if the individual is male and equals to zero otherwise.

Married is a dummy variable that equals one if the card holder is married as of the card's origination time and equals to zero otherwise.

Income is defined as the monthly income of the card holder (verified by the bank) as of the card's origination time.

College is a dummy variable that equals one if the card holder obtains a college degree or above and equals to zero if below college level.

Car is a dummy variable that equals one if the card holder owns a car and zero otherwise.

Car Loan is a dummy variable that equals one if the card holder has an unpaid car loan and zero otherwise.

House is a dummy variable that equals one if the card holder owns a piece of real-estate and zero otherwise.

Mortgage is a dummy variable that equals one if the card holder has an unpaid mortgage and zero otherwise.

Transaction amount is the card holder's total amount of credit transaction including consumption, cash deposit and withdrawal, or transfer for each month.

Transaction number is the card holder's total number of credit transaction for each month.

Inactive is a dummy variable that equals to one if the card holder has no financial transactions for more than 6 consecutive months and equals to zero otherwise.

Cancellation is a dummy variable that equals to one if the card holder cancels the credit card within 12 months since the card's origination time and equals to zero otherwise.

Delinquency is a dummy variable that equals one if the credit card account is more than 3 months past due and equals to zero otherwise.

Time to delinquency is the number of months between credit card origination and delinquency.

Reinstatement is a dummy variable that equals one if the delinquent account returns to normal status (either current or carrying a balance as shown in the data) and equals to zero otherwise.

Time to reinstatement is the number of months between delinquency and reinstatement.

Credit line is the credit limit of the card holder as of the card's origination date.

Investment is the total investment of the card holder in this bank for each quarter.

AUM is the total asset under management of the card holder in this bank for each quarter.

Number of accounts is the total number of bank accounts with which the card holder established.

Sophistication is the total number of banks with which the card holder established banking relationships through debit card, mortgage loan, or credit card account.

Closing is the total number of banks with which the individual has closed the banking relationships through debit card, mortgage loan, or credit card account.

Banking relationship is defined as the number of months since the card holder established a relationship with this bank through any banking service, including debit card and mortgage loan.

A2. Branch-level variable definitions:

Age is the age of bank agent at the beginning of data sample (January 2015).

College is a dummy variable that equals one if the bank agent obtains a college degree or above and equals to zero if below college level.

Gender is a dummy variable that equals one if the bank agent is male and equals to zero otherwise.

Work tenure is the number of years that bank agent had worked in this bank at the beginning of data sample (January 2015).

Salary is the monthly after-tax income of bank agent recorded at the beginning of data sample (January 2015).

Bonus is the monthly bonus of bank agent recorded at the beginning of data sample (January 2015).

Appendix B. Robustness

One concern for our results in credit outcome is the infra-marginal problem as we are considering the outcome tests for two groups of borrowers. We address this problem by comparing the differences of delinquency rate for last-week and non-last-week borrowers along with the credit line distribution. We divide the whole sample into deciles based on the credit line and perform the difference-in-differences analysis on the delinquency between two groups of borrowers within each decile. We plot the estimated coefficients and corresponding 95 percent confidence interval for each of these ten groups in Figure B1. For all levels of the credit line, last-week borrowers have a higher delinquency probability than non-last week borrowers. This positive differential for last week borrowers is robust in economic magnitude and statistical significance, indicating that the marginal delinquency rate is similar to the average delinquency rate.

[FIGURE B1 ABOUT HERE]

Another potential concern with our analysis is that the decrease in bank's services (investment) could be mechanically related to the borrower's deterioration in financial conditions. We address this issue by performing cross-sectional tests that investigate the relation between the reduced usage of bank's services and customers' personal income. We divide the whole sample into deciles based on the income and perform the difference-in-differences analysis on the extensive and intensive margins between two groups of borrowers within each decile. We present the estimated coefficients and corresponding 95 percent confidence interval for each of these ten groups in Figure B2. As it shown, for all levels of the income, the last-week customers have a lower probability than non-last-week customers to invest in this bank, and conditional on investment, they have fewer amount of investment than their counterpart. This negative differential is robust in economic magnitude and statistical significance, indicating that the marginal effect of change in incentive schemes on the investment is similar to the average effect.

[FIGURE B2 ABOUT HERE]

Figure B1: Delinquency difference between last-week and non-last-week borrowers.

In this figure, we show the estimated delinquency difference last-week and non-last-week borrowers. For each decile of the credit line distribution in our sample, we perform the differences-in-differences analysis in Table 6 and obtain the coefficients on Treatment, along with the 95% confidence intervals.

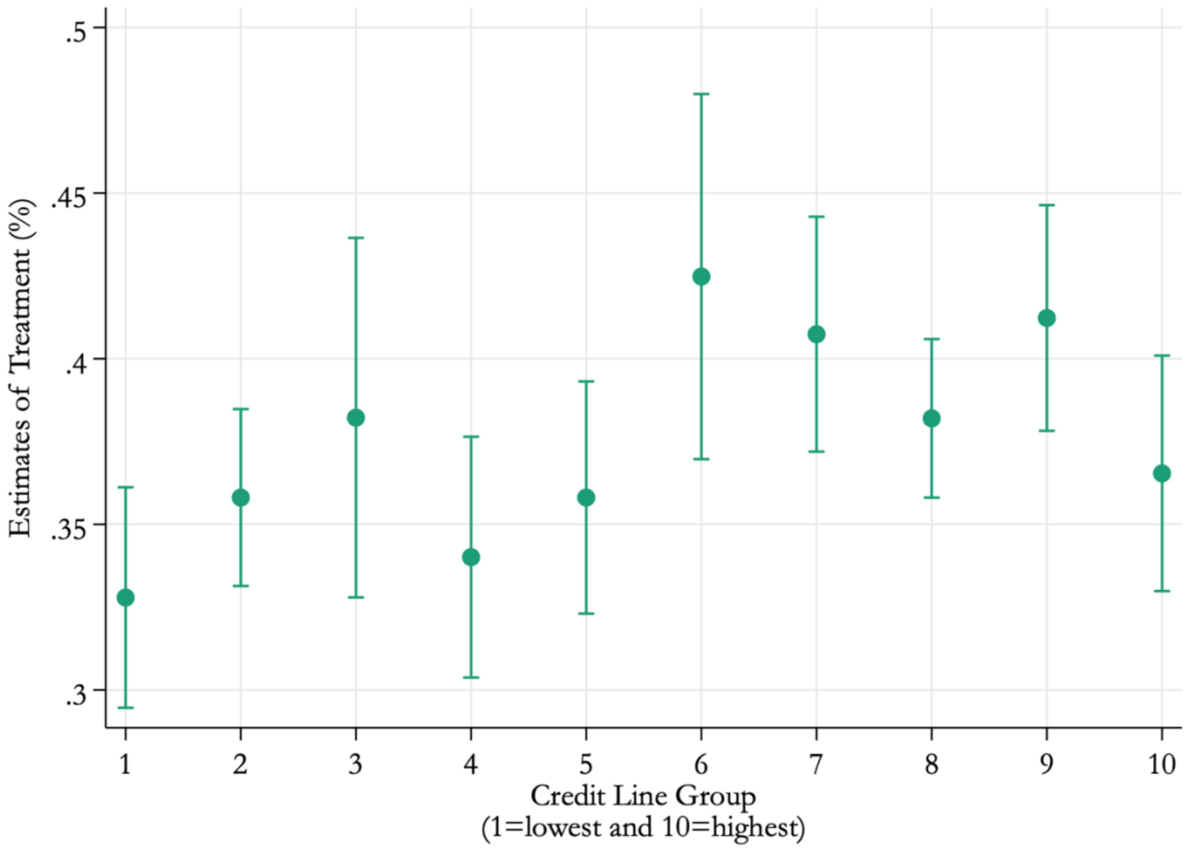
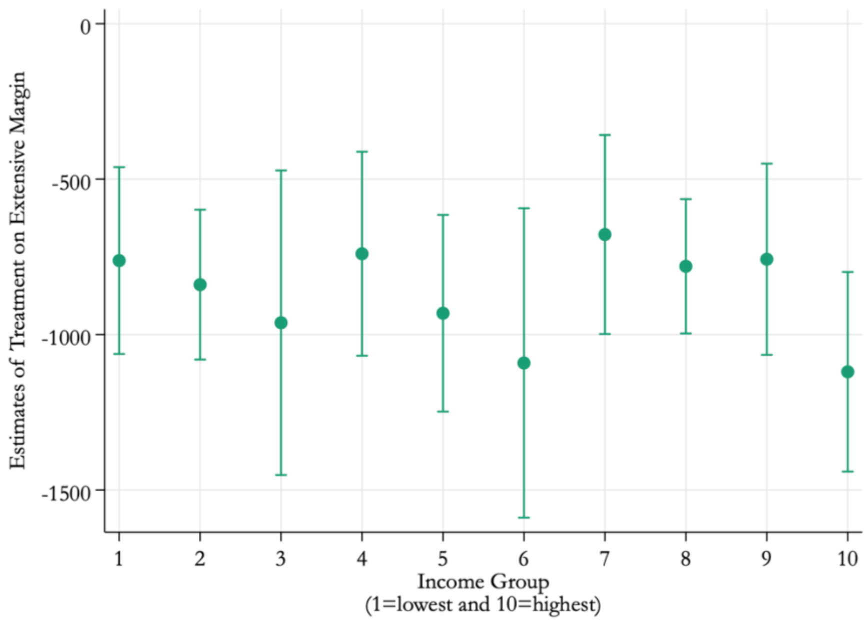


Figure B2: Investment difference between last-week and non-last-week borrowers.

In this figure, we show the estimated investment difference last-week and non-last-week borrowers. For each decile of the credit line distribution in our sample, we perform the differences-in-differences analysis in Table 9 and obtain the coefficients on Treatment, along with the 95% confidence intervals for extensive margin (Panel A) and intensive margin (Panel B).

Panel A: Extensive Margin



Panel B: Intensive Margin