# Managerial Incentives and Consumer Lending:

# Evidence from a Natural Field Experiment[†]


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*Keywords*: Nonlinear incentives; Quotas; Credit card approval; Delinquency

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## Abstract

Using unique data from a major Chinese bank, we find that following the bank's adoption of a nonlinear incentive scheme for its credit card sales managers, the number of credit cards approved increases sharply at the end of each month. Further analysis shows that this occurs through a combination of lax screening in the approval process, a reduction in application processing times, and the creation of "zombie" borrowers. We also find that managers who are male, have a shorter tenure, are located further from the bank's headquarters, with better past performance are more likely to exhibit this gaming behavior. Overall, we provide ample evidence on the overall benefits and costs of nonlinear incentive schemes in the customer finance sector.



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# 1 Introduction

Nonlinear incentive systems based on quotas are commonly used in the workplace. Oyer (2000) demonstrates that discrete contracts stipulating specific sales quotas are optimal for salespersons with limited liability and rent sharing.[1] However, nonlinear incentive systems may also induce agents to engage in gaming as their incentives may change depending on the cumulative output (Holmström and Milgrom 1987). Empirically, Oyer (1998) shows that workers respond to this nonlinearity in incentive schemes by taking distortionary actions at the end of the period to bunch their outputs that increase their income at the cost of efficiency. For instance, workers may bunch production at nonlinear kink points. The finance literature also shows that bank loan officers are subject to this nonlinear incentive. Tzioumis and Gee (2013) show that to meet their monthly quotas, mortgage officers increase their output toward the end of the month; consequently, mortgages on the last working day of the month have the highest likelihood of delinquency.

However, there is limited knowledge on whether opportunistic behaviors induced by nonlinear incentives of a single agent exist in the consumer finance sector, where banks normally hire two agents in the credit card granting process: one is the credit card sales staff, whose primary incentive is to focus on credit card sales volume; the second is the risk control staff, whose job is to focus on managing the risk of credit cards.[2] And, if they do, their underlying mechanisms and economic consequences. This paper attempts to fill this void. Using daily credit

[1] There may be another explanation for firms adopting nonlinear incentive schemes. Some evidence suggests that firms typically opt for nonlinear incentives in the sales context to attract overconfident employees (e.g., Larkin and Leider (2012)). However, we believe the demand for overconfident employees is limited in the consumer finance sector.

[2] Prior research studying the mortgage (loan) officers' incentives has focused on the incentives of a single agent, the loan officer, who is subject to the nonlinear (high-powered) incentives (Cole, Kanz, and Klapper (2015), Tzioumis and Gee (2013), Agarwal and Ben-David (2018)). Berg (2015) studies the dual role of the risk manager and loan officer in the loan-granting process and documents the advantage of two-agent bank organizations over one agent.

card approval data from a Chinese commercial bank (hereafter, “the bank”), we explore whether the introduction of nonlinear incentives with a minimum quota system induces gaming behaviors in bank agents and the possible underlying mechanisms of these behaviors in the consumer credit market.

We focus on the incentive schemes of managers in the credit card sales team. Ideally, bank employees and managers should be compensated according to the quantity and quality of credit cards granted. However, the stronger market competition in consumer lending renders this type of contract design less practical. Indeed, the focal bank has changed its incentive scheme from placing little emphasis on credit card sales volumes to rewarding and punishing staff based on credit card sales quotas. Under the new incentive scheme, agents must increase their credit card sales by at least 20% at the end of each month compared with the same period in the previous year. Credit card sales team managers who meet this quota are rewarded with promotion opportunities, while those who fail to meet the quota for three consecutive months are subject to disciplinary action, including a reduction in salary, a cancelation of bonuses, and possible dismissal. Those who fail to meet the quota by a large margin may face disciplinary action at the end of one rather than three months.

We first analyze credit card approval timing following the introduction of the new nonlinear incentive scheme. We find strong evidence that employees in the credit card sales department (under the influence of their team managers) substantially vary their sales across the month following adopting the nonlinear incentive scheme in 2016. In contrast, there was no such pattern in the year before the incentive scheme was adopted. The magnitude of the monthly variations in employee output is economically significant, with employees increasing their aggregate output by 16.6% in the final week of the month, then immediately decreasing their output at the beginning of the following month. This pattern is persistent for all months during our one-year study period.

After documenting the increased number of credit card approvals in the final week of each month, we then analyze the mechanisms through which the nonlinear incentive scheme generates the end-of-month spikes and their potential economic consequences. We first show that the introduction of nonlinear incentives may increase the quantity of credit card applications to the bank while decreasing the quality of the applications the bank receives. We further posit that the minimum quota system may induce a lax screening of credit card applicants, incentivizing agents to approve credit card users on the margin. It is also plausible that credit card sales managers may work with the risk control department employees to relax their approval criteria for marginal credit card applications in the final week of each month.[3] We show that credit approval decisions made at the end of the month are less sensitive to applicants' income, employment status, and personal assets following the adoption of the new incentive scheme.

We then explore the possible consequences of lax screening. We find that lax screening leads to a higher likelihood of delinquency for credit cards granted at the end of each month. We also find that delinquent credit cards are less likely or take longer to be reinstated. Further analysis reveals that it is mainly low-income users whose credit cards have a higher (lower) likelihood of delinquency (reinstatement) and take longer to be reinstated. These findings suggest that nonlinear compensation may induce bank employees to approve the credit card

[3] Tzioumis and Gee (2013) find that mortgage officers may approve marginal bank loan applications when they are subject to minimum quota requirements under nonlinear incentive schemes. Agarwal and Ben-David (2018) find that bank loan officers who are incentivized based on loan volume tend to apply lax screening in their approval decisions. In our setting, credit sales managers are not directly responsible for the approval of the credit cards. However, the risk control and credit card sales departments are located in the same branch, and their staff frequently interact with each other, providing opportunities of collusion. We discuss this in Section 6.1 in details.

applications of high-risk users, ultimately increasing the bank's credit card–related risks and exposing some marginal credit cardholders to the risk of financial default.

A second possible channel is that nonlinear incentive contracts may lead to "zombie" credit cardholders, who are misled by credit card sales employees to open credit accounts. Given that credit card sales managers are incentivized to maximize their quotas, they may push their employees to lobby some preexisting customers to apply for a credit card, even they may not need one. Bank customers who have been unwittingly convinced to apply for a credit card may lose trust in the bank, and thus be reluctant to use their new credit cards.[4] We find evidence consistent with this conjecture. In particular, we find that cardholders make fewer transactions and spend less on credit cards issued in the final week of each month following the introduction of the nonlinear incentive scheme in 2016. Cards are also more likely to be inactive or canceled.[5] These findings highlight the negative impacts of the opportunistic behaviors induced by nonlinear incentives on credit card usage. That is, it can create "zombie" credit cardholders, who use their cards less frequently than typical users.

We further explore the possible consequences of misleading credit card sales behaviors, which may create consumer trust issues. Credit cardholders misled to use credit cards may have less trust in the bank.[6] Therefore, we posit that misled credit cardholders may also reduce their use of other banking services. Given that wealth management is one of the most important banking services in the customer finance sector in China (Acharya et al. (2019)), we use the end-

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[4] Several interviewees in the bank stated that their colleagues processed credit cards applications for customers who were not fully aware of the terms and conditions of the application (e.g., simply asking customers to sign their names on the application forms together with a bunch of other documents the customers are going to sign).

[5] Following Agarwal, Liu, and Souleles (2007), we define a credit card as inactive if the cardholder makes no financial transactions for more than six consecutive months.

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

of-month balance of assets under bank management to measure customers' use of the bank's other services. We find that cardholders whose credit cards were approved at the end of the month are less likely to use the bank's wealth management services. Further analysis reveals that the results are mainly driven by the group of low-frequency credit card users. Our results highlight the potentially negative consequences of gaming behaviors induced by nonlinear incentive schemes on other customer financial services.[7]

The third possible channel is the shorter credit card approval processing times. We posit that credit card sales managers may pressure the risk control department to bring forward the approval of credit cards from the beginning of the next month to the end of the focal month. To test this conjecture, we separately examine application processing times for credit cards that are approved and declined. Since the introduction of the incentive scheme in 2016, credit cards approved at the end of the month have shorter processing times, while there is no such pattern for declined applications. We further show that shorter processing times are related to adverse borrower outcomes, including lower credit quality and a lower willingness to invest with the bank.

Our final set of analyses focuses on the characteristics of credit card sales managers. We posit that male managers are more likely to be involved in opportunistic behaviors because males are more prone to aggressive behaviors induced by monetary incentives (Charness and Gneezy (2012), Dohmen et al. (2011), Huang and Bao (2020)). We find evidence supporting this conjecture. We also explore the effect of manager tenure—those with shorter tenure may have more career concerns and be more afraid of losing their jobs (Agarwal and Ben-David (2018)).

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[7] An alternative explanation for this result is that customers with more vulnerable that drive lower investments because their financial circumstances are negatively affected by credit cards. As we document in Appendix B, the income explanation is not supported.

Thus, we expect opportunistic end-of-the-month behaviors to be more prevalent in managers with shorter tenure. We find consistent evidence to support this. Finally, we posit that geographical proximity plays a role in the effects of the nonlinear contracts because it is easier for bank headquarters (the main branch in our case) to monitor and acquire information about managers who are located close to the main branch (Giroud (2013)). In contrast, for employees who are further away, hard information (e.g., failure to meet the minimum sales quota) could be the main driver of their promotions or demotions. We find evidence supporting this view.

We further document the unintended consequences of the nonlinear incentive on the realized profit for credit card account holders. Using the before-after design, we estimate that the introduction of this incentive may increase the interest income (by 0.31 pp) and total cost (by 0.14 pp) while decreasing the interchange income (by 0.25 pp) and total fees (0.22 pp), yielding a total decline of realized profit by 0.26 percentage points. Taken together, we interpret the results as demonstrating that nonlinear incentives can bring about a significant drop in total income and a reduction in borrowing costs, leading to a decreased realized profit for the bank.

Our study contributes to the literature in the following ways. First, this paper documents the impacts of nonlinear incentive contracts in the area of the consumer/household finance section, where two agents play roles in the credit card granting process. Prior economics have shown that nonlinear incentive contracts incentivize salespersons and executives to manipulate the timing of customer purchases and vary their efforts over different periods (Oyer (1998), Larkin (2014), Kaur, Kremer, and Mullainathan (2015)). Finance studies show that bank loan officers, insurance agents, and financial advisors are subject to the gaming effect of nonlinear incentives, creating significant risks for financial institutions (Tzioumis and Gee (2013), Agarwal and Ben-David (2018), Inderst and Shaffer (2019), Berg, Puri, and Rocholl (2020), Cao et al. (2022)). We contribute to the existing literature by showing that credit card sales managers subject to nonlinear incentives also exhibit gaming and timing behaviors. Documenting the existence of these gaming behaviors in consumer/household finance is important because: 1. It demonstrates that the gaming behavior induced by the nonlinear incentives of one single agent could still exist in the two-agent model once the credit sales team and risk control team are located in the same area. 2. this gaming behavior can erode consumer trust in financial institutions, which may further impede the inclination of households to save and use financial institutions or markets (e.g., Guiso, Sapienza, and Zingales (2004)). In our case, misled consumers are less likely to use the bank's investment services.

Second, we show the externalities of end-of-month behaviors induced by nonlinear incentive contracts in the consumer finance sector (Baker (1992), Bénabou and Tirole (2016), Peek and Rosengren (2005)). We show that following the adoption of the nonlinear incentive scheme, credit cards granted in the final week of the month have higher delinquency rates, a lower likelihood of reinstatement, and longer reinstatement times. These externalities may be significant in the consumer credit market. Regulators and academics in the United States and Europe criticize financial institutions that take advantage of consumers' behavioral biases (e.g., myopia, present bias, and inattention) to earn large profits, especially from consumers who are uneducated or financially disadvantaged (Campbell et al. (2011)).[8] We provide further support to this claim because the gaming behaviors of bank staff may lead to lax screening, thus higher delinquency rates for financially vulnerable consumers.

[8] Senator Chris Dodd, lead sponsor of the *Credit Card Accountability, Responsibility, and Disclosure Act 2009* noted, "My colleague from New York, Senator Schumer, has called this 'trip-wire pricing,' saying the whole business model of the credit card industry is not designed to extend credit but to induce mistakes and trap consumers into debt. I think he is absolutely right, unfortunately. This is an industry that has been thriving on misleading its consumers and its customers" (US Senate, 2009).

Our findings have important implications for regulators of bank employee compensation contracts. Since the global financial crisis, financial institution regulators place a much greater focus on the compensation practices of senior bank executives (e.g., *The Financial Crisis Inquiry Report* of 2011). The academic literature also shows that risk-taking incentives and short-term compensation contracts for bank CEOs lead to greater risk-taking in the banking sector (DeYoung, Peng, and Yan (2013), Kolasinski and Yang (2018)). Our study shows that the design of incentives for mid-level managers and employees in the customer banking sector is also important. Nonlinearity in incentive contracts may expose the financial institution to increased risk in their credit card products and greater customer dissatisfaction.

The remainder of the paper is organized as follows. Section 2 describes the institutional background. Section 3 presents our data and variables. Section 4 details the methodology. Section 5 documents the end-of-month effect on credit card approvals. Section 6 investigates the potential channels and economic outcomes. Section 7 shows the effects of managerial characteristics. Section 8 presents the impact on bank profit. Section 9 concludes the paper and discusses the study's external validity.

# 2 Institutional Background

## 2.1 Credit Cards in China

Banks dominate the credit market in China (Song and Xiong (2018)). In 1985, the Bank of China issued China's first credit card, and commercial banks began to participate in the consumer lending market, making it a critical source of credit provision for borrowers. Since then, China has experienced rapid growth in the credit card market—the total number of active credit cards more than tripled between 2009 and 2014, with credit exceeding 15.20 trillion RMB at the end of this period. Delinquency rates have also increased substantially during this period, posing severe challenges for economists and policymakers.

Our focal bank is a leading state-owned commercial bank with a vast network of branches across all provinces and municipalities in China. Our data are collected from the bank's branches in a Chinese capital city covering more than 14,000 $km^2$, with around 16 million residents and a gross domestic product of 1.2 trillion RMB in 2015. Similar to other state-owned commercial banks, the bank has two branch 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 of the city ("Zhi Hang" in Chinese). The bank we obtain data from has one main branch in the capital city and 41 sub-branches across the city.

To apply for a credit card, an applicant must submit an application form with detailed personal information and supplementary documents, including photocopies of their national identification, an employment certificate, and proof of income.[9] Because there is no personal credit information sharing among financial intermediaries in China (see Bao and Huang (2021) for more details), the bank uses the information submitted by applicants to determine whether to approve the application and, if approved, the amount of credit. Credit card approval decisions are delegated to the sub-branch level (see Agarwal et al. (2020) and Keys and Wang (2019)).[10] To limit the number of credit cards issued to less solvent borrowers, each branch has a risk control

[9] In this bank, credit cards are divided into two types depending on whether customers are required to deposit reserve funds: quasi-credit cards and standard credit cards. Standard credit cards are further subdivided according to the type of customer: general purpose credit cards (issued to the general public) and private label credit cards (issued to partnering companies). We only consider the data of general-purpose credit cards because these are covered by the nonlinear incentive scheme.

[10] Since China's entry into the World Trade Organization in 2001, commercial banks have implemented reforms that delegate individual-level decision-making to each bank branch (see Qian, Strahan, and Yang (2015)).

department that screens new applicants and is authorized to contact applicants and their employers either by phone or in-person to confirm the authenticity of the application. During this screening process, the risk control department may frequently interact with the credit card sales department to discuss the application. If the branch determines that an applicant is unqualified, it can cancel the application. Approved applicants receive their credit card by mail and must activate it before gaining access to credit.

Once approved, cardholders can have multiple loans if the total credit does not exceed the prespecified amount. The bank requires each borrower to repay 10% of the monthly credit card balance. If the borrower fails to pay the minimum amount by the 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 related interest expenses and extra penalties for the delinquency. If the borrower does not reinstate the account within a certain period, the bank may either lower his/her credit rating or pursue the repayment through legal processes.

## 2.2 Adoption of the New Incentive Scheme

Our study bank has two main types of agents: employees and 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. Employees at each level are under the direct leadership of team and department managers. Within each sub-branch, there are four departments: a credit card sales department, which is responsible for credit card products; a loans department, which is responsible for originating new band loans and maintaining existing bank loans; a wealth management department, which is responsible for selling wealth management products such as deposits, mutual funds, and other investment products; and a risk control department, which is responsible for screening credit card and bank loan applications. Each department has several teams in charge of different areas. The four departments coordinate with each other in their daily business. For credit card approval, the credit card department will forward the application to the risk control department for screening, while the risk control department may contact the credit card sales department to request additional information.

In each sub-branch, the bank pays agents (employees) with a pre-determined basic salary based on their rung within the branch and lump-sum bonuses for fulfilling the bank's requirements.[11] The bank promotes or demotes employees semiannually based on their performance in the preceding months. Employees who have shown superior performance are promoted, while those who have failed to meet essential criteria are demoted. The remainder stays at the same level.

The bank's handbook, *Regulation of Agents*, outlines the compensation scheme, promotion protocol, and other aspects of agents' responsibilities. The bank occasionally updates its regulations based on guidance from the People's Bank of China, the China Banking Regulatory Commission (CBRC), and feedback from its branches all over China.[12] Given that neither managers nor employees at the sub-branch level know the timing and the substance of updates, we treat these changes as a natural field experiment that identifies agents' responsiveness to new incentive schemes.

Before 2016, the bank did not reward agents in the credit card sales department for the number of credit cards issued because of the CBRC's advice against quota-based incentive

[11] Salaries and bonuses for each bank branch are determined by the main branch and district managers and can vary within a certain range.
[12] In practice, details can vary between provinces, with province-level headquarters (*sheng hang*) having the final say. The main city branch and sub-branches have no influence on changes to the handbook regulations.

systems.[13] As shown in Figure 1, the number of credit cards issued grew considerably from 2009 to 2014 but then suffered a sharp decline, with a negative growth rate of -5.05% in 2015.[14]

[Insert Figure 1 about here]

In response to a decline in credit card sales in 2015, our focal bank, updated its incentive scheme in the *Regulation of Agents* and enacted it in January 2016. The new nonlinear incentive scheme introduced a quota-based incentive for team managers in the credit card sales department to increase their monthly credit card sales by 20% compared with the same period in the previous year. The bank rewards credit card sales team managers who meet this quota with promotion opportunities, increased salaries, and bonuses compared with other managers.[15] The bank punishes team managers who fail to meet the standard for three consecutive months with disciplinary action, including demotions and decreases in salaries and bonuses.[16] The new regulation imposes strong nonlinear incentives for agents. Credit card sales team managers who are promoted to departmental managers earn around five times more and eight times more than managers demoted to employees (see Table 2 for more details).

[13] 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 2010, the CBRC chair, Liu Mingkang, spoke out against the quota-based system at the commission's second-quarter economic analysis meeting (http://money.sohu.com/20100607/n272617017.shtml).

[14] This decline may have been largely attributable to the rapid growth in fintech (peer-to-peer) lending and the popularity of virtual credit cards launched by fintech companies, including Ant Financial Group and Jingdong Digits. In 2015, the Supreme People's Court in China clarified the legal status of peer-to-peer lending, facilitating its growth (see http://www.court.gov.cn/fabu-xiangqing-15146.html for details).

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

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

# 3 Data and Variables

## 3.1 Data

The bank provided us with three sets of data. The first set includes information on all customers who applied for a credit card between January 2015 and December 2016 from all 41 branches in the focal capital city. We gather the demographic details of each credit card applicant, including age, gender, marital status, education, employment, income, and place of residence. We also have the information on the credit card approval process for each application during our sample period, including the duration and outcome of each application, with details on dates and assignees.

The second set of data includes the credit card information for approved borrowers 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. It also contains the realized profit information of credit card account holders, including daily balance, incomes, and costs. The data also include cardholders' additional activities in the study bank, including assets under management, number of bank accounts, and investment account balance (if any).

The third set of data captures bank branch information. It contains information about employees and managers in all branches, including age, gender, education, job level, salary, and work tenure.

## 3.2 Variables

Table 1 presents the descriptive statistics for borrower-level variables for the sample period (see Appendix A for detailed definitions). We analyze three sets of variables pertaining to borrowers' demographics, credit card characteristics, and other banking services. To study the effect of the new incentive scheme, we include cardholders in the final-week sample if their credit card approval date falls in the last week of each month; otherwise, they are included in the non–last-week sample.[17] Therefore, we split the data into a two-by-two matrix: 2015 vs. 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 borrowers have different credit outcomes—those in last-week sample are less likely to use the new credit card, more likely to be delinquent, and less likely to have their accounts reinstated because of their delinquency. Finally, concerning other banking services, the borrowers in last week are less likely to engage in asset management within the bank compared with those borrowers in non-last-week sample. Our summary statistics suggest that the nonlinear incentive scheme may have differential effects on the credit outcomes of borrowers in last-week and non-last-week samples.

[Insert Table 1 about here]

Table 2 presents the summary statistics for branch-level information. In Panel A, we show that bank agents, on average, are aged 35 years, 48% have a bachelor's degree or higher, 63% are male, and have 6.93 years of work tenure. In terms of salary, there are large gaps between employees and managers. Moreover, among these two groups, there is very wide salary

[17] 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 holiday arrangement in 2015. With consideration of leave in lieu, there is an average of 20.83 days each month. Within each month, there are five days in last-week sample and 15.83 days in non-last-week sample during our sample period.

gap with low and high rungs on the job ladder. For instance, the monthly salary for department managers may be five times that of team managers. In Panel B, we show that the average approval rate is 61%, and the mean duration for acceptance and rejection are 7.31 and 3.34 days, respectively with respect to credit card approvals. In Panel C, we show the key summary statistics on average account-level credit card issuer income, costs, and profits at the branch month level. The average daily balance is RMB 2894. On average, the interchange income, total fees, total cost, and realized profit consist of about 16.37%, 3.72%, 8.05%, 26.31%, and 1.83% of the annualized average daily balance.

[Insert Table 2 about here]

## 4 Identification and Empirical Methodology

Our identification strategy exploits the adoption of the new incentive scheme in 2016 that imposed quota-based incentives on the bank's credit card sales team managers. Given that the change-imposed end-of-the-month incentives, we presume that last-week borrowers in 2016 would be directly affected by this change.

To assess the effects on borrowers' credit outcomes, we test whether the total number of credit card origination in the last week of each month is statistically different from that in the non-last week of the month at the 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 the branch level:

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

where $\text{Number}_{bt}$ is the number of credit cards issued at branch $b$ on date $t$.[18] We use $\log(1 + \text{Number}_{bt})$ as the dependent variable to measure overall credit card approvals at the branch–day level, so that zero values are defined. The variable of interest, $\text{LastWeek}_t$ is a set of dummy variables equal to 1 if date $t$ falls in the final week of each month $d$. We also consider the following fixed effects: day of the week ($\text{dow}_t$), day of the month ($\text{dom}_t$), month ($\tau_m$), and branch ($\delta_b$). To calculate the confidence intervals of 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 non-last-week observations) and branch level.

To examine the effects on borrowers' credit outcomes, we use the standard difference-in-differences specification at the individual borrower level. This method enables us to compare the effect of the new incentive scheme on two groups: one directly affected by the event (treatment group) and one not directly affected by the event (control group). The differences-in-differences approach then relies on measuring the differential effect of the nonlinear incentive across the two groups:

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

where the dependent variable $Y_{i,b,t}$ is the economic outcomes of a borrower $i$ issued by branch $b$ at month $t$, including credit card use, loan delinquency behaviors, and the use of other banking services.[19] $\text{After}_t$ is an indicator variable that equals 1 if month $t$ is after January 2016 and zero otherwise. $\text{LastWeek}_i$ is an indicator variable that equals 1 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

[18] We aggregate the individual credit card approval number to the branch level because each branch manager is awarded at the branch level (including the main branch and sub-branches).
[19] 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 variables. However, the estimation of nonlinear models may be unstable given the large sample size; thus, we adopt a linear econometric specification that provides highly accurate estimates for the marginal effects.

variables. For most of our analyses, we include branch–time fixed effects ($\theta_{b,t}$) that capture common variations at branch level for each month to rule out a series of identification concerns and we also include the manager fixed effects to control for time-invariant manager-level attributes associated with the credit conditions for each city. The error term $\epsilon_{i,b,t}$ is clustered at the borrower and time levels, accounting for serial correlations in credit outcomes and possible correlations in borrowers' behaviors in the same branch. For simplicity, we denote the interaction term $\text{After}_t \times \text{LastWeek}_i$ as Treatment. The coefficient $\beta_2$ on the interaction term Treatment is the difference-in-differences estimate, which measures the effect of the new incentive scheme when controlling for all time-varying, observed and unobserved branch-level heterogeneities.[20]

# 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 affecting credit card approvals.

## 5.1 Graphic Evidence

Figure 2 shows the end-of-month effect on the number of credit card approvals. Figure 2a is the subsample period from January 2015 to December 2015, and Figure 2b is the subsample period from January 2016 to December 2016. Date 0 on the horizontal axis is the final day of each

[20] For brevity, we do not report the estimates for control variables in all difference-in-differences specifications. Interested readers can refer to the online appendix for the full estimation results.

month. The graph omits weekends and Chinese official holidays.[21] Therefore, 10 days on the horizontal axis represent two calendar weeks after the final day of each month. On the vertical axis, we graph the average number of new credit card approvals at day $t$. The vertical axis is at log level. The figure shows a surprising regularity for the sample in 2016: the number of credit card approvals is much higher at the end and lower at the beginning compared with the middle of each month. Our results are consistent with our theoretical predictions for agents under nonlinear incentive contracts, showing the differences between last-week and non-last-week borrowers (see Lazear and Oyer (2004)).

[Insert Figure 2 about here]

Figure 3 shows the average daily credit card approvals for last-week and non-last-week samples 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. $t$ = 0 represents the month in which the incentive scheme was introduced, and the negative and positive numbers represent the months before and after, respectively. The vertical axis is the average (log) number of daily credit cards issued by the 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 to 2015, while the number increased sharply after the enaction of the 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 graphic evidence suggests that agents respond to the change in the incentive scheme by increasing the number of credit cards issued to meet their monthly quotas.

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[21] The dates for official holidays in China are available at 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 because of holiday arrangements.

[Insert Figure 3 about here]

### 5.2 Statistical Significance

Table 3 presents the results for 2016 (Panel A) and 2015 (Panel B). Column (1) of Panel A shows the relationship between last-week days and credit cards origination. The positive coefficient on $\text{LastWeek}_t$ indicates that the number of credit cards originated during the last-week days of the month is larger than the rest days of the month. The coefficient of 0.154 indicates that the probability of a credit card being issued in the final week of the month is 16.6% (= exp(0.154) - 1) greater than in the rest of the month. Column (2) includes the month fixed effect, which has little effect on the magnitude and statistical significance of the coefficient on $\text{LastWeek}_t$. Our results are robust to adding day of week and day of month fixed effects in Column (3) and branch fixed effects in Column (4). The coefficient on $\text{LastWeek}_t$ is significant at the 1% level across all specifications. Panel B shows that the coefficient is not significant at any specification, and the magnitude is much lower than that in Panel A, suggesting that the end-of-the-month effect becomes economically and statistically significant following the introduction of the incentive scheme.

[Insert 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 four non-mutually exclusive channels through which the change in managerial incentives may affect end-of-the-month behaviors: (i) change in application flow and lax screening, (ii) fast processing times, and (iii) agency issues. We further explore the economic outcomes of nonlinear incentives on card usage, credit outcome, and other banking services associated with borrowers.

## 6.1 Change in application flow

The objective of the nonlinear incentive is to induce bank managers to seek new business; hence, they may improve the quantity and quality of the application flow. On the one hand, managers may attract strong but hesitant potential applicants by increasing the awareness of credit cards. On the other hand, weak potential applicants may learn from bank's behavior and strategically apply for credit cards in the last week of each month.

We first investigate whether the nonlinear incentive influences the quantity of application flow. In Column (1) of Panel A in Table 4, we analyze whether the application volume is statistically different between the treatment and control groups. We calculate the number of applications for each branch month and perform difference-in-differences specifications on this number. The point estimates show an increase of up to 11.7% for the number of applications, and the effects are economically and statistically significant.

We next explore whether nonlinear incentive influences the quality of application flow by examining whether the applications' characteristics change for the treatment group. To do so, we show the difference-in-differences estimates of the effect on their characteristics in Columns (2)-(9) of Panel A in Table 4. The point estimates indicate no statistically significant differences in the demographic characteristics between the two groups. For credit characteristics (income, employment, asset, and liability), the point estimates show a drop in monthly income of 461.5, a decline in employment probability of 3.2 percentage points, a 2.7 percentage point decline in asset indicator, and a 1.1 percentage point increase in liability indicator. Our results suggest that nonlinear incentive increases the applicant quantity while decreasing the quality of the bank's applications. Overall, our findings indicate that the introduction of nonlinear incentive may attract more applications to the bank while decreasing the quality of the applications received.

[Insert Table 4 about here]

## 6.2 Lax Screening

To limit the issuance of credit cards to insolvent borrowers, the study bank has a risk control department that screens new applicants (see Berg (2015)). The number of credit cards issued increases dramatically during last-week days when we control for a potential change in demand for credit cards, suggesting that the risk control department at the sub-branch level may have different screening criteria or risk tolerance for applicants (Agarwal and Ben-David (2018)).[22] Using the available information, we test this hypothesis and explore whether credit approval decisions differ between the last-week and non-last-week groups using the difference-in-differences specification.

In Panel B of Table 4, we regress the approval indicators for all applications on the interaction term Treatment and observed characteristics. Columns (1) and (2) present the base regressions, showing that applications in the treatment group were 12% more likely to be approved. In Columns (3) to (6), we interact the Treatment dummy with income, employment status, and personal assets. Our results show that the weight on income, employment status, and

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[22] Prior literature has also shown that risk-management involvement reduces loan default rates by more than 50% (Berg (2015)). These findings suggest that a two-agent model can help to facilitate efficient screening decisions (Landier, Sraer, and Thesmar (2009)). In our focal bank, staff and managers in the risk control department were not subject to the minimum quota incentive scheme in 2016 but other incentives. For instance, they may get a penalty if the delinquency rates and card use frequencies are at the bottom 10% of their approved credit cards. However, at the sub-branch level, it is plausible that credit card sales managers persuaded staff in the risk control department to relax their approval criteria, given that they share the same office and their day-to-day interactions are frequent. There are two personal benefits that the staff in the risk control department may obtain from this collusion. The first one is a certain amount of honorarium paid by the staff of the credit sales department and the second one is their future career opportunity if the managers in the credit card sales department get promoted to the sub-branch managers in the future if they manage to meet the quota listed in the new incentive scheme.

personal assets decline for the last-week group and is approximately 25% to 45% lower than that of the non-last-week group.

Our results suggest that risk control departments may relax their screening of final-week credit card applications and place less emphasis on hard information (e.g., applicants' income, personal assets, and employment status) during approval processes. The declining emphasis on hard information may lead to a higher delinquency rate and, in the case of delinquency, a lower reinstatement rate (Liberti and Petersen (2019)).

We explore whether nonlinear incentives lead to a change in credit quality. Columns (1) and (2) in Table 5 show the effect of nonlinear incentives on borrowers' delinquency behaviors. Following Gross and Souleles (2002) and Chatterjee et al. (2007), we define delinquency as credit repayments being at least three months past their due dates. The coefficients on the Treatment dummy are both positive, similar in magnitude (0.373% and 0.347%), and statistically significant. This effect is economically meaningful, with delinquency rates of last-week borrowers being 17% higher than those among non–last-week borrowers. In Columns (3) and (4), we estimate Equation (1) with time to delinquency as the dependent variable. Time to delinquency is defined as the duration between the issuance of credit cards and delinquency. The coefficients on the Treatment dummy range from -0.586 to -0.545, and the duration between card issuance and delinquency is 6.4% shorter for last-week borrowers than for non–last-week borrowers.

We next examine whether any difference exists in borrowers' ex-post behaviors conditional on delinquency. First, we study whether the delinquent last-week borrowers are more likely to have their accounts reinstated than non-last-week borrowers. In Columns (5) and (6), the coefficient on the Treatment dummy ranges from -8.152 to -8.116 and is statistically significant, showing that last-week borrowers are 10.02% less likely than non–last-week borrowers to reinstate their accounts. Second, for reinstated credit card accounts, we examine whether there is any difference in time to reinstatement between the two groups of borrowers. In Columns (7) to (8), we show that it takes an additional 0.4 months for last-week borrowers to reinstate their credit accounts, which is 12.2% higher than the average reinstatement duration for non–last-week borrowers (3.27 months). 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. In addition, it takes longer for the last-week borrowers to reinstate their accounts.

[Insert Table 5 about here]

We further explore the effect of reduced emphasis on hard information income during approval process on the future delinquency likelihood. We classify low-income borrowers as those whose income is in the lowest quintile of all approved borrowers in the same month and high-income borrowers as the remainder.[23] We then explore whether there are noticeable differences between income and credit outcomes. Specifically, we repeat the specifications used in Table 5 by decomposing the Treatment dummy into low-income and high-income dummies following the econometric specification in Agarwal et al. (2020). The results are reported in Table 6. Column (1) shows that those with a low income largely drive the higher delinquency rate observed in last-week borrowers. Further, among last-week borrowers, shorter delinquency times (Column (2)), lower reinstatement rates (Column (3)), and longer reinstatement times (Column (4)) are concentrated in low-income borrowers.

[Insert Table 6 about here]

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[23] Our results are robust to the hard information for borrowers, including the borrowers' income, personal assets, and employment status. We show robust results using borrowers' personal assets and employment status in Appendix B.

### 6.3 Creation of Zombie Cardholders

As bank managers are incentivized to maximize a quota-based outcome, this practice may lead to agency issues against the welfare of bank at the margins of credit card origination (Dobbie et al. (2021)). Bank managers may pressure their staff to provide misleading information to preexisting and new customers who do not want to use credit cards to convince them to apply for credit cards, leading to credit cardholders losing trust in the bank.[24] While our data do not reveal actual communications between bank staff and customers, we use credit card usage patterns to capture possible misleading behaviors.

We first examine the effect of nonlinear incentives on borrowers' behaviors using different measures of credit card usage as the dependent variable (see Table 7). We first show the effect on borrowers' monthly credit card usage frequency. 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 and time fixed effects and control for borrowers' 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 is slightly less at -0.512, implying that borrowers' credit card usage decreases by 9.25%. In Columns (3) and (4), we re-estimate the specifications using monthly credit card transaction amount as the dependent variable. The coefficient on the Treatment ranges from -

[24] Several interviewees (managers and employers) stated that they occasionally put in an application for a credit card on behalf of long-term bank customers who were not fully aware that they were applying for a credit card by simply asking the customer to sign their names on the application form along with other documents. Similarly in US, Senator Chris Dodd has noted "The whole business model of the credit card industry is not designed to extend credit but to induce mistakes and trap consumers into debt. This is an industry that has been thriving on misleading consumers."

394.5 to -388.3, implying that the monthly average transaction amount decreases by 8.21% to 8.34%. These results indicate that our results are robust to borrower-level characteristics and time-varying heterogeneities. We further consider the effect of nonlinear incentives on the probability of credit cards being inactive or canceled within one year of their origination. Following Agarwal, Liu, and Souleles (2007), we define a credit card as inactive if the cardholder has made no financial transactions for more than six consecutive months. In Columns (5) to (8), we report the coefficients of each of the two dependent dummy variables (equal to 1 if the credit card is inactive or canceled, respectively) on Treatment. The estimates are both economically and statistically significant, suggesting that credit cards issued in the final week of the month are 17% more likely to be inactive and 13% more likely to be canceled compared with those issued in the rest of the month.

[Insert Table 7 about here]

We also explore whether the new incentive scheme causes a decrease in borrowers' use of other banking services. We use the end-of-month balance of investments under management with the bank management as the measure of customer's monthly investment, as wealth management is one of the most important trust-intensive banking services in China (Acharya et al. (2019)). In Table 8, we present our results for changes in investments—both the probability and amount of investment—following the adoption of the new incentive scheme. Using our baseline specification, we report the coefficients on each of the two dependent variables, a dummy equaling one if the customer has any investments (Columns (1) and (2)) and the amount of investment (Columns (3) and (4)), respectively. Our results show that both investment measures decrease more for last-week borrowers than for non-last-week borrowers following the adoption of the new incentive scheme, and the effect is both economically and statistically significant.

[Insert Table 8 about here]

Given that trust offers security against misbehaviors (Guiso, Sapienza, and Zingales (2008)), customers are more willing to invest in assets based on trust because they are less fearful about 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 low card usage and card cancelations as proxies for mistrust in the bank (Mester, Nakamura, and Renault (2005)). We define 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.[25] Specifically, we decompose the treatment group into low-frequency and high-frequency dummies and report the results in Table 9. We examine how the effect of new incentive on the probability that a customer will invest in the bank, and conditional on investment, how it affects the investment amount is differentiated by different types of customers. Columns (1) to (2) show that the lower investment is concentrated among lower frequency last-week customers. Our results are robust when we use the cancelation indicator as a proxy for mistrust, as shown in Columns (3) and (4). Overall, we highlight that the relationship between managerial incentives and investment outcomes may be driven by customers with less trust in the bank.

[Insert Table 9 about here]

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

### 6.4 Fast Processing

Given that nonlinear incentives impose end-of-month requirements on bank managers, they may result in faster credit card application processing times to meet the deadline (Chen et al. (2021); DeFusco and Paciorek (2017)).[26] We examine this hypothesis by studying the effect of the new incentive scheme on application processing time in Table 10. We divide all credit card applications into approved and rejected applications. Columns (1) and (2) show that duration decreases significantly in the approved sample. The coefficients on the Treatment are statistically significant and the magnitude is economically meaningful: the new incentive scheme reduces approval duration by about three days (approximately 39%) compared with the pre–incentive scheme period. The impact of new incentives on declined sample, presented in Columns (3) and (4), is much less and statistically insignificant. Our results suggest that employees and managers are more likely to increase processing speeds for approvals than rejections to meet their end-of-month quotas.

[Insert Table 10 about here]

We next study whether fast processing times are related to borrowers' credit outcomes. We define fast-approval borrowers as those whose approval time is in the lowest quintile. We decompose the treatment group into fast-approval borrowers and other dummies and report the results in Table 11. Columns (1) to (4) show that low credit quality is concentrated among fast-approval borrowers. Columns (5) to (6) show that lower investment outcome is also driven by fast-process borrowers. Our results highlight that faster processing may be related to lower credit quality and willingness to invest with the bank.

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[26] The faster processing time also needs cooperation from the staff in the risk control department. As we discuss in footnote 21, this type of cooperation is plausible.

[Insert Table 11 about here]

## 7 Managerial Characteristics

In this section, we examine the relationship between three managerial characteristics—gender, tenure, distance to the main branch, and past performance—and the gaming behavior we have found under the new incentive schemes.

Women tend to be more risk-averse and less prone to monetary incentives (Charness and Gneezy (2012), Dohmen et al. (2011), Huang and Bao (2020)). Male managers may therefore be more willing to push origination outcomes aggressively through the system by pressing the staff in the risk control department to apply lax screening criteria and mislead the customers (Beck, Behr, and Guettler (2013), Adams and Ferreira (2009)). We decompose the Treatment dummy into male and female dummies based on manager gender and report the results in Panel A of Table 12. We find that male managers, but not female managers, are significantly associated with a deterioration in credit outcomes and a reduction in wealth management services.

Managers with a longer tenure have greater familiarity with preexisting customers and fewer career concerns, thus may be less likely to exhibit opportunistic behaviors following the enactment of the new incentive scheme (Mas and Moretti (2009), Griffith and Neely (2009)). We test this hypothesis in Panel B of Table 12 by defining short-tenure managers as those whose tenure is in the lowest quintile. We decompose the Treatment dummy into long- and short-tenure dummies. Our results show that managers with longer tenure are associated with worse credit quality and investment outcomes.

Being close to the main branch makes it easier for headquarters to acquire information about and monitor sub-branches (Drexler and Schoar (2014), Giroud (2013)). Hence, we expect that managers who are located far from the main branch are more likely to game the system (Kalnins and Lafontaine (2013), Chhaochharia, Kumar, and Niessen-Ruenzi (2012)). We decompose the Treatment dummy into near and far branch dummies, where far branches are those in the furthest quintile from the main branch. We report the results in Panel C of Table 12, which shows that the higher delinquency rates and lower investment willingness among final-week borrowers are largely associated with managers located further from the main branch.

Lastly, we study how manager's past performance is related with their opportunistic behavior. We decompose the Treatment dummy into above and below median dummies based on managers' performance in the year of 2015. We report the results in Panel D and show that managers with better past performance are associated with the declined credit quality and lower investment amount.

[Insert Table 12 about here]

## 8 Bank Profit

In this section, we examine the unintended consequences of the nonlinear incentive, focusing on its effects on the total income, total costs, and overall profit for credit card account holders. We collapse the account-level data to means at branch and month level.

Following Agarwal, Liu, and Souleles (2007), we calculate related variables as an annualized percentage of average daily balance to make a comparison across different components. We first analyze the total income of account holder, which include three parts: interest charges, interchange income, and total fees. Column (1) of Table 13 shows the before-after specifications with interest charges, defined as an annualized percentage of average daily balance, as the dependent variable. The point estimates indicate that interest income increased by 0.31 percentage points on a base of 16.37% for the average account holder and are statistically distinguishable from zero at conventional levels. We next focus on the interchange income and total fees and present the regression estimates in columns (2) and (3) of Table 13, respectively. The corresponding coefficient estimates indicate that over the implementation of nonlinear incentive, interchange income dropped by 0.25 percentage points and total fees declined by 0.22 percentage points. Both estimates are statistically distinguishable from zero. Therefore, the introduction of nonlinear incentives may translate into a decline in total income for credit card account holders.

We further analyze the total costs for the account holder, including realized net charge-offs, the cost of funds, rewards and fraud expenses, and operational costs. Column (4) of Table 13 shows before-after specifications with total costs as the dependent variable. The point estimates show an increase in total costs of 0.14 percentage points on a base of 27.11%. The reduction in fee revenue and the rise of account costs suggest that the nonlinear incentive may reduce banks' profit. We examine this potential response by estimating before-after specifications where the dependent variable is realized profit, which is defined for a credit card account as the difference between total income and total costs. The estimates in column (5) of Table 13 show evidence of an economically significant decline in realized profit by 0.26 percentage points on a base of 1.87%.

[Insert Table 13 about here]

## 9 Discussion and Conclusion

Understanding how incentive schemes affect the consumer lending market is a question of prime importance in finance. In this paper, we conduct a natural field experiment on bank managers to identify the effect of quota-based incentives on credit quantity. We find that nonlinear incentives have a strong and economically significant effect on credit card origination at the end of each month.

We also document several mechanisms that explain how nonlinear incentives affect credit card origination. First, we show that bank employees may relax the screening criteria for credit card approvals and reduce their emphasis on hard information in the final week of the month. Moreover, we find that credit cards granted at the end of each month because of lax screening have a higher likelihood of delinquency and conditional on delinquency, the borrowers are less likely to reinstate their credit cards.

Second, we find that nonlinear incentives may induce bank managers to mislead customers into opening credit card accounts. We find that, on average, the last-week borrowers are less likely to use their credit cards or invest with the bank after adopting the new incentive scheme. In addition, we find that low-frequency credit cardholders are less likely to use wealth management services in the future. These findings highlight the negative effects of opportunistic behaviors induced by nonlinear incentives on overall bank welfare.

Third, we show that nonlinear incentives may induce faster credit card approval processing times. Following the adoption of the new incentive scheme, cards approved at the end of the month have a shorter processing time, while there is no significant change for declined applications. Our further analysis shows that the gaming behavior is more pronounced for male managers, managers with shorter tenure and managers located further away from headquarter.

Our findings have important implications for incentive schemes in the consumer lending market. Banks are increasingly relying on sophisticated incentive schemes for their managers. However, it is unclear whether and how such schemes change the behaviors of bank agents and borrowers, particularly in real-world credit markets, nor is it clear how managerial characteristics are associated with the performance of incentive schemes. The results presented in this paper are a first step toward answering these important questions. We further discuss whether our results can be generalized to different stimuli, institutions, and time periods given that our findings are based on data from a single bank. We check external validity using the criteria proposed by List (2020). First, our sample is based on borrowers at one of China's leading commercial banks. This sample is highly similar to the wider population and other bank customers in terms of relevant observables. Second, there is no attrition because we include all credit card approval records from the bank. Third, because of the design of our natural field experiment, participants do not know they are being observed; therefore, all bank staff and borrowers make decisions in a natural environment, alleviating concerns about unobserved changes in participants. As a result, we expect our findings to be valid for larger samples and borrowers from other banks.

## References


Acharya, Viral V, Jun Qian, Yang Su, and Zhishu Yang, 2019, In the Shadow of Banks: Wealth Management Products and Issuing Banks' Risk in China, *SSRN Electronic Journal*.

Adams, Renée B, and Daniel Ferreira, 2009, Women in the boardroom and their impact on governance and performance, *Journal of Financial Economics* 94, 291–309.

Agarwal, Sumit, and Itzhak Ben-David, 2018, Loan prospecting and the loss of soft information, *Journal of Financial Economics* 129, 608–628.

Agarwal, Sumit, Chunlin Liu, and Nicholas S Souleles, 2007, The Reaction of Consumer Spending and Debt to Tax Rebates—Evidence From Consumer Credit Data, *Journal of Political Economy* 115, 986–1019.

Agarwal, Sumit, Wenlan Qian, Amit Seru, and Jian Zhang, 2020, Disguised corruption: Evidence from consumer credit in China, *Journal of Financial Economics* 137, 430–450.

Baker, George P, 1992, Incentive Contracts and Performance Measurement, *Journal of Political Economy* 100, 598–614.

Bao, Zhengyang, and Difang Huang, 2021, Shadow Banking in a Crisis: Evidence from FinTech During COVID-19, *Journal of Financial and Quantitative Analysis*, 1–57.

Beck, Thorsten, Patrick Behr, and Andre Guettler, 2013, Gender and Banking: Are Women Better Loan Officers?, *Review of Finance* 17, 1279–1321.

Bénabou, Roland, and Jean Tirole, 2016, Bonus Culture: Competitive Pay, Screening, and Multitasking, *Journal of Political Economy* 124, 305–370.

Berg, Tobias, 2015, Playing the Devil's Advocate: The Causal Effect of Risk Management on Loan Quality, *Review of Financial Studies* 28, 3367–3406.

Berg, Tobias, Manju Puri, and Jörg Rocholl, 2020, Loan Officer Incentives, Internal Rating Models, and Default Rates, *Review of Finance* 24, 529–578.

Campbell, John Y., Howell E. Jackson, Brigitte C. Madrian, and Peter Tufano, 2011, Consumer Financial Protection, *Journal of Economic Perspectives* 25, 91–114.

Cao, Yiming, Raymond Fisman, Hui Lin, and Yongxiang Wang, 2022, SOEs and Soft Incentive Constraints in State Lending, *American Economic Journal: Economic Policy*.

Charness, Gary, and Uri Gneezy, 2012, Strong Evidence for Gender Differences in Risk Taking, *Journal of Economic Behavior and Organization* 83, 50–58.

Chatterjee, Satyajit, Dean Corbae, Makoto Nakajima, and José-Víctor Ríos-Rull, 2007, A Quantitative Theory of Unsecured Consumer Credit with Risk of Default, *Econometrica* 75, 1525–1589.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suárez Serrato, and Daniel Yi Xu, 2021, Notching R&D investment with corporate income tax cuts in China, *American Economic Review* 111, 2065–2100.

Chhaochharia, Vidhi, Alok Kumar, and Alexandra Niessen-Ruenzi, 2012, Local investors and corporate governance, *Journal of Accounting and Economics* 54, 42–67.

Cole, Shawn, Martin Kanz, and Leora Klapper, 2015, Incentivizing Calculated Risk-Taking: Evidence from an Experiment with Commercial Bank Loan Officers, *Journal of Finance* 70, 537–575.

DeFusco, Anthony A., and Andrew Paciorek, 2017, The interest rate elasticity of mortgage demand: Evidence from bunching at the conforming loan limit, *American Economic Journal: Economic Policy* 9, 210–240.

DeYoung, Robert, Emma Y Peng, and Meng Yan, 2013, Executive Compensation and Business Policy Choices at U.S. Commercial Banks, *Journal of Financial and Quantitative Analysis* 48, 165–196.

Dobbie, Will, Andres Liberman, Daniel Paravisini, and Vikram S Pathania, 2021, Measuring Bias in Consumer Lending, *The Review of Economic Studies*.

Dohmen, Thomas J, Armin Falk, David Huffman, Uwe Sunde, Jürgen Schupp, and Gert G Wagner, 2011, Individual Risk Attitudes: Measurement, Determinants and Behavioral Consequences, *Journal of the European Economic Association* 9, 522–550.

Drexler, Alejandro, and Antoinette Schoar, 2014, Do Relationships Matter? Evidence from Loan Officer Turnover, *Management Science* 60, 2722–2736.

Dupas, Pascaline, Anthony Keats, and Jonathan Robinson, 2019, The Effect of Savings Accounts on Interpersonal Financial Relationships: Evidence from a Field Experiment in Rural Kenya, *The Economic Journal* 129, 273–310.

Gennaioli, Nicola, Andrei Shleifer, and Robert W Vishny, 2013, A Model of Shadow Banking, *Journal of Finance* 68, 1331–1363.

Georgarakos, Dimitris, and Roman Inderst, 2011, Financial Advice and Stock Market Participation, *SSRN Electronic Journal*.

Giroud, Xavier, 2013, Proximity and Investment: Evidence from Plant-Level Data, *The Quarterly Journal of Economics* 128, 861–915.

Griffith, Rachel, and Andrew Neely, 2009, Performance pay and managerial experience in multitask teams: evidence from within a firm, *Journal of Labor Economics* 27, 49–82.

Gross, David B, and Nicholas S Souleles, 2002, Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence from Credit Card Data, *Quarterly Journal of Economics* 117, 149–185.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2004, The role of social capital in financial development, *American Economic Review* 94, 526–556.

Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2008, Trusting the stock market, *Journal of Finance* 63, 2557–2600.

Holmstrom, Bengt, and Paul Milgrom, 1987, Aggregation and Linearity in the Provision of Intertemporal Incentives, *Econometrica* 55, 303.

Huang, Difang, and Zhengyang Bao, 2020, Gender Differences In Reaction To Enforcement Mechanisms: A Large-Scale Natural Field Experiment, *SSRN Electronic Journal*.

Inderst, Roman, and Greg Shaffer, 2019, Managing Channel Profits When Retailers Have Profitable Outside Options, *Management Science* 65, 642–659.

Kalnins, Arturs, and Francine Lafontaine, 2013, Too Far Away? The Effect of Distance to Headquarters on Business Establishment Performance, *American Economic Journal: Microeconomics* 5, 157–179.

Kaur, Supreet, Michael Kremer, and Sendhil Mullainathan, 2015, Self-Control at Work, *Journal of Political Economy* 123, 1227–1277.

Keys, Benjamin J, and Jialan Wang, 2019, Minimum payments and debt paydown in consumer credit cards, *Journal of Financial Economics* 131, 528–548.

Kolasinski, Adam C, and Nan Yang, 2018, Managerial myopia and the mortgage meltdown, *Journal of Financial Economics* 128, 466–485.

Landier, Augustin, David Sraer, and David Thesmar, 2009, Financial Risk Management: When Does Independence Fail?, *American Economic Review* 99, 454–458.

Larkin, Ian, 2014, The Cost of High-Powered Incentives: Employee Gaming in Enterprise Software Sales, *Journal of Labor Economics* 32, 199–227.

Larkin, Ian, and Stephen Leider, 2012, Incentive Schemes, Sorting, and Behavioral Biases of Employees: Experimental Evidence, *American Economic Journal: Microeconomics* 4, 184–214.

Lazear, Edward P, and Paul Oyer, 2004, Internal and external labor markets: a personnel economics approach, *Labour Economics* 11, 527–554.

Liberti, Jose Marıa, and Mitchell A. Petersen, 2019, Information: Hard and soft, *Review of Corporate Finance Studies* 8, 1–41.

List, John A, 2020, Non est Disputandum de Generalizability? A Glimpse into The External Validity Trial, *Artefactual Field Experiments*.

Mas, Alexandre, and Enrico Moretti, 2009, Peers at Work, *The American Economic Review* 99, 112–145.

Mester, Loretta J, Leonard I Nakamura, and Micheline Renault, 2005, Transactions Accounts and Loan Monitoring, *Review of Financial Studies* 20, 529–556.

Oyer, Paul, 1998, Fiscal Year Ends and Nonlinear Incentive, *Quarterly Journal of Economics* 113, 149–185.

Oyer, Paul, 2000, A Theory of Sales Quotas with Limited Liability and Rent Sharing, *Journal of Labor Economics* 18, 405–426.

Peek, Joe, and Eric S Rosengren, 2005, Unnatural Selection: Perverse Incentives and the Misallocation of Credit in Japan, *The American Economic Review* 95, 1144–1166.

Qian, Jun Qj, Philip E. Strahan, and Zhishu Yang, 2015, The Impact of Incentives and Communication Costs on Information Production and Use: Evidence from Bank Lending, *Journal of Finance* 70, 1457–1493.

Song, Zheng Michael, and Wei Xiong, 2018, Risks in China's Financial System, *Annual Review of Financial Economics* 10, 261–286.

Tzioumis, Konstantinos, and Matthew Gee, 2013, Nonlinear incentives and mortgage officers' decisions, *Journal of Financial Economics* 107, 436–453.

**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.

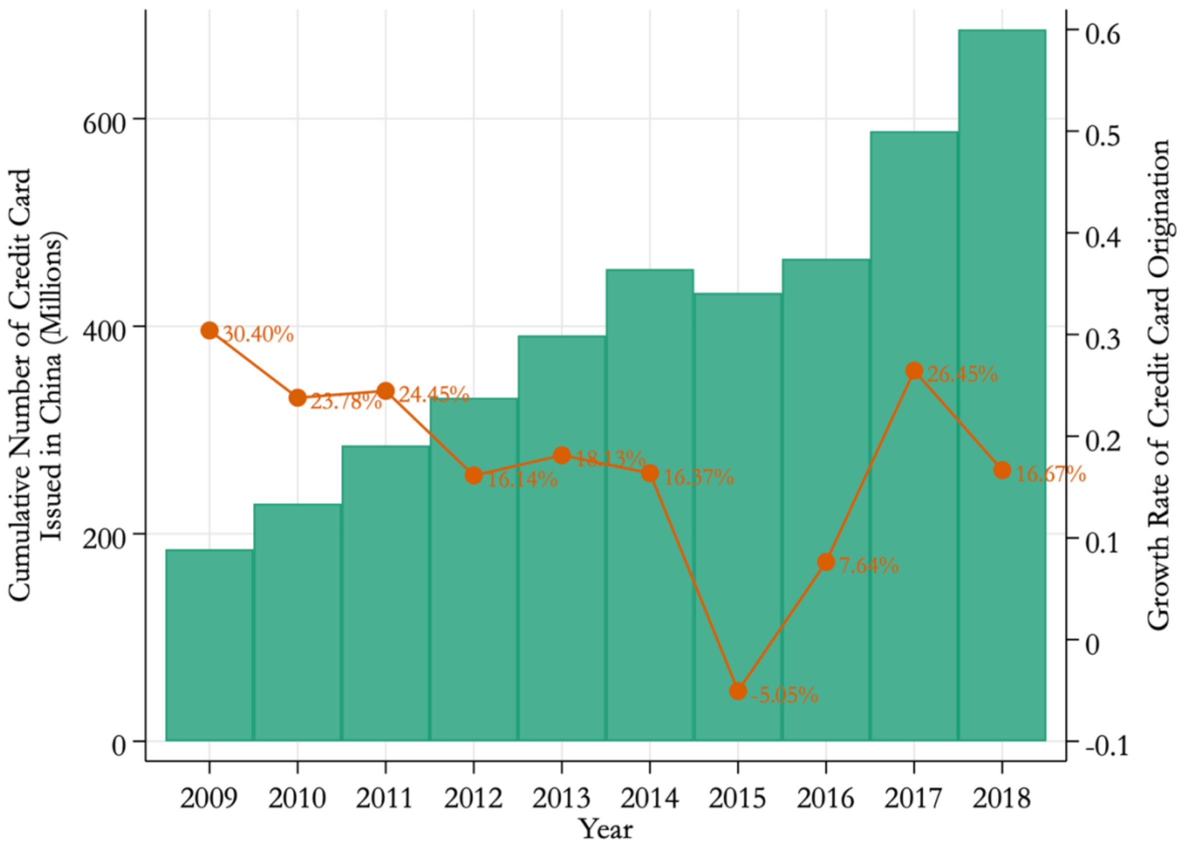


**Figure 2: Daily origination of credit cards**

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

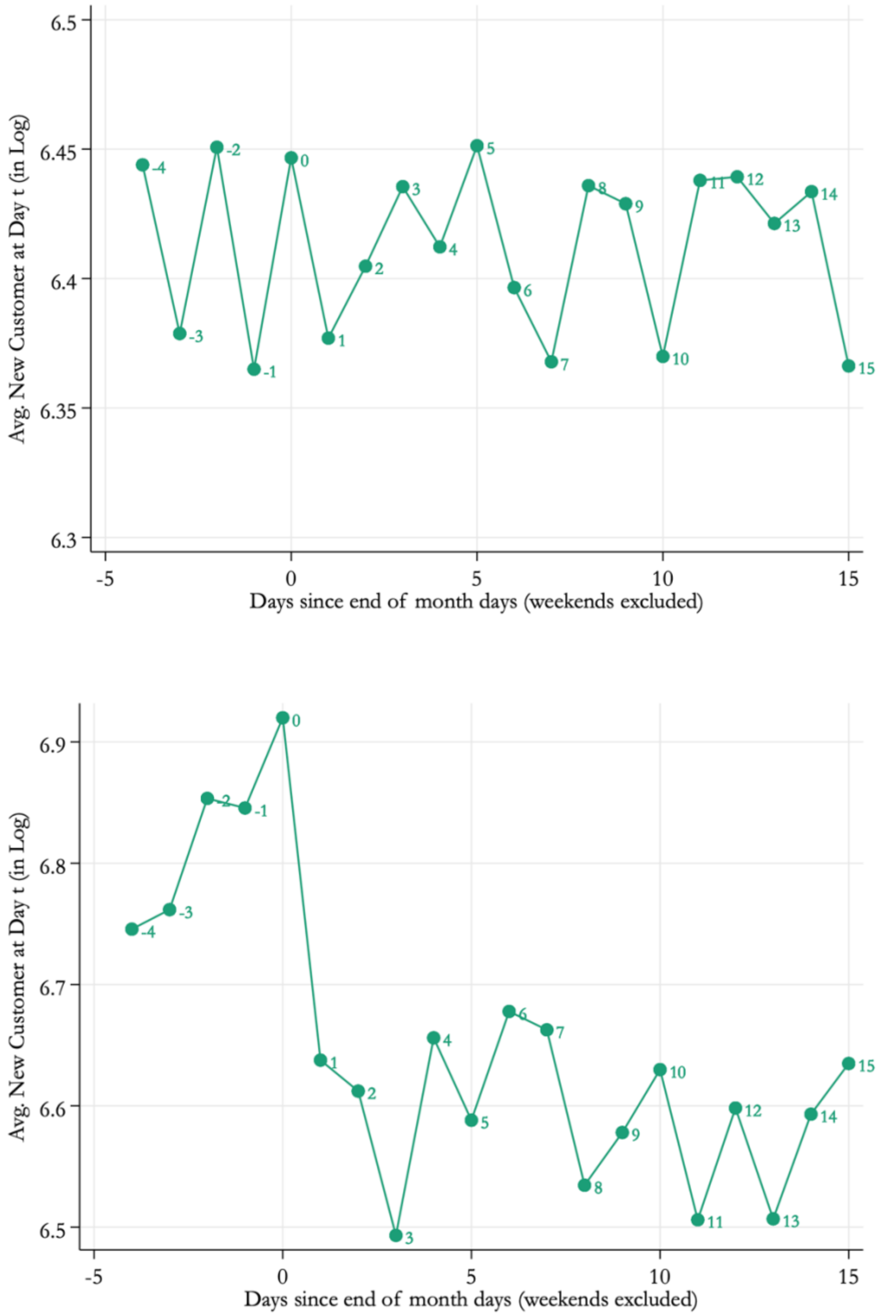
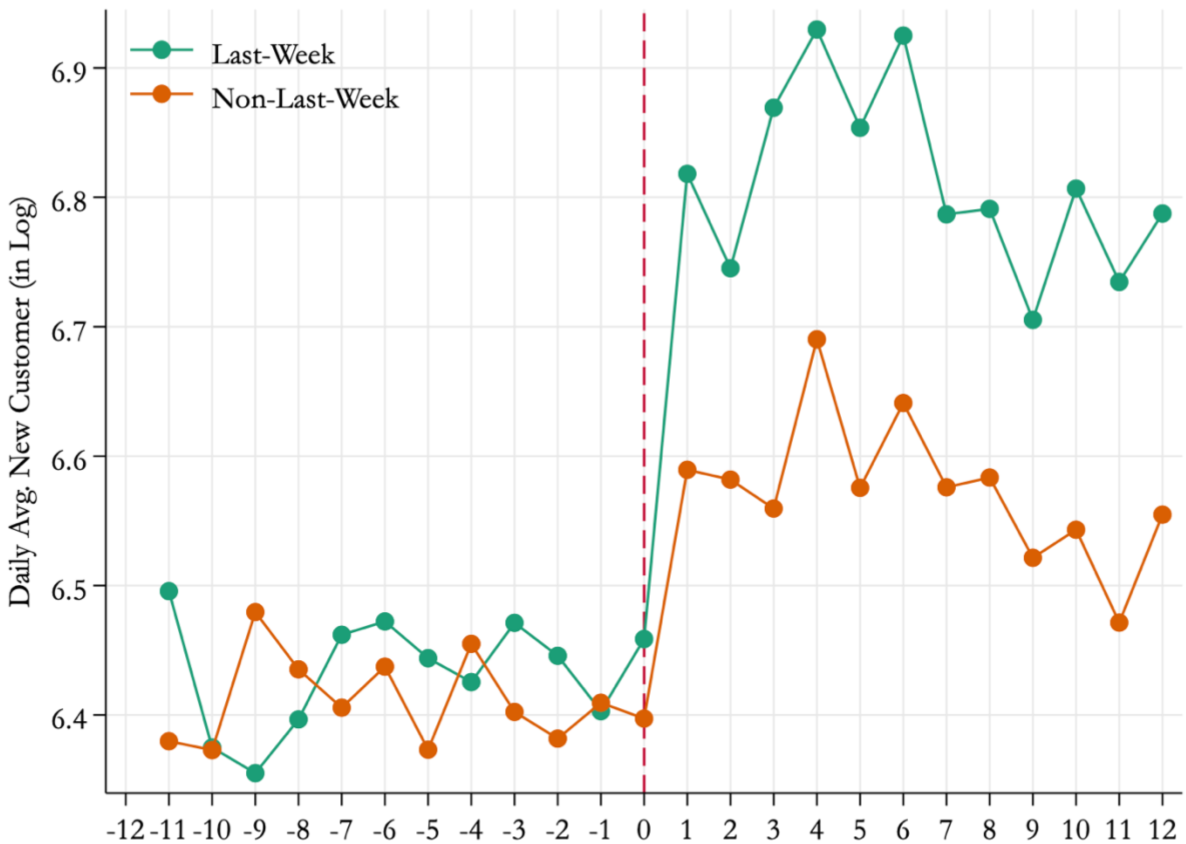


**Figure 3: Credit card origination for last-week and non-last-week days**

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 borrower characteristics in Panel A, credit card characteristics in Panel B, and other bank characteristics in Panel C. 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 (years) | 38.44 | 6.13 | 38.72 | 6.92 | 38.57 | 5.89 | 37.69 | 7.87 |
| Income (RMB) | 6153 | 3276 | 6205 | 3712 | 5721 | 3048 | 6207 | 3302 |
| Employment (0/1) | 0.68 | 0.47 | 0.69 | 0.46 | 0.63 | 0.46 | 0.68 | 0.46 |
| College (0/1) | 0.35 | 0.48 | 0.36 | 0.48 | 0.32 | 0.47 | 0.37 | 0.48 |
| Gender (male=1) | 0.48 | 0.50 | 0.48 | 0.50 | 0.49 | 0.50 | 0.49 | 0.50 |
| Married (0/1) | 0.67 | 0.47 | 0.69 | 0.46 | 0.67 | 0.47 | 0.66 | 0.48 |
| Car Loan (0/1) | 0.04 | 0.20 | 0.05 | 0.22 | 0.06 | 0.24 | 0.05 | 0.22 |
| Car (0/1) | 0.41 | 0.49 | 0.43 | 0.50 | 0.42 | 0.49 | 0.43 | 0.50 |
| House (0/1) | 0.61 | 0.49 | 0.63 | 0.48 | 0.61 | 0.49 | 0.62 | 0.49 |
| Mortgage (0/1) | 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 (RMB) | 3693 | 4372 | 3707 | 4372 | 3320 | 4031 | 3728 | 4478 |
| Inactive (0/1) | 0.11 | 0.30 | 0.11 | 0.31 | 0.13 | 0.36 | 0.11 | 0.31 |
| Cancellation (0/1) | 0.09 | 0.28 | 0.09 | 0.29 | 0.11 | 0.34 | 0.09 | 0.28 |
| Delinquency (0/1) | 0.02 | 0.13 | 0.02 | 0.14 | 0.03 | 0.16 | 0.02 | 0.14 |
| Time to delinquency (months) | 8.40 | 4.00 | 8.28 | 3.97 | 8.02 | 4.24 | 8.49 | 4.50 |
| Reinstatement (0/1) | 0.81 | 0.39 | 0.79 | 0.41 | 0.75 | 0.43 | 0.81 | 0.39 |
| Time to reinstatement (months) | 3.01 | 2.56 | 3.17 | 2.67 | 3.55 | 2.06 | 3.27 | 2.93 |
| Credit line (RMB) | 37149 | 26739 | 37208 | 26908 | 36570 | 26873 | 37344 | 27259 |
| Panel C: Other Bank Characteristics | | | | | | | | |
| Investment (RMB) | 5269 | 5534 | 5613 | 6498 | 4715 | 5227 | 5661 | 6628 |
| AUM (RMB) | 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 (months) | 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 agents' characteristics in Panel A, credit card approval in Panel B, and credit card realized profits in Panel C. The detailed variable definitions are presented in Appendix A.

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| Panel A: Agents' Characteristics | | | | |
| Age (years) | 35.21 | 11.04 | 20 | 59 |
| College (0/1) | 0.48 | 0.50 | 0 | 1 |
| Gender (male=1) | 0.63 | 0.48 | 0 | 1 |
| Work tenure (years) | 6.93 | 7.91 | 0 | 28 |
| Employee level I salary (RMB) | 1347.87 | 210.12 | 1200 | 1500 |
| Employee level II salary (RMB) | 1831.65 | 146.48 | 1600 | 1950 |
| Employee level III salary (RMB) | 2164.18 | 174.69 | 2000 | 2350 |
| Employee level IV salary (RMB) | 2750.98 | 146.55 | 2400 | 2950 |
| Manager (Team) salary (RMB) | 5748.12 | 3412.61 | 4000 | 12000 |
| Manager (Department) salary (RMB) | 16432.23 | 4367.90 | 13500 | 20000 |
| Manager (Branch) salary (RMB) | 30713.41 | 11294.85 | 25000 | 60000 |
| Monthly bonus (RMB) | 1648.58 | 3718.26 | 0 | 40000 |
| Panel B: Credit Card Approval | | | | |
| Approval rate (0/1) | 0.61 | 0.49 | 0 | 1 |
| Accepted duration (days) | 7.31 | 6.45 | 0 | 21 |
| Rejected duration (days) | 3.34 | 2.19 | 0 | 11 |
| Panel C: Credit Card Realized Profit | | | | |
| Average daily balances (RMB) | 2894.73 | 5187.63 | 0 | 17095.79 |
| Interest charge (%) | 16.37 | 19.43 | 6.45 | 39.08 |
| Interchange income (%) | 3.72 | 4.68 | 0.67 | 13.52 |
| Total fees (%) | 8.05 | 14.71 | 2.25 | 28.18 |
| Total cost (%) | 26.31 | 19.42 | 12.41 | 47.84 |
| Realized profit (%) | 1.83 | 4.55 | -1.24 | 9.23 |

**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 |
| Manager FEs | No | No | No | Yes |
| Mean (Dep.var) | 2.884 | 2.884 | 2.884 | 2.884 |
| Observations | 10,500 | 10,500 | 10,500 | 10,500 |
| R-squared | 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 |
| Manager FEs | No | No | No | Yes |
| Mean (Dep.var) | 2.665 | 2.665 | 2.665 | 2.665 |
| Observations | 10,500 | 10,500 | 10,500 | 10,500 |
| R-squared | 0.084 | 0.124 | 0.193 | 0.447 |

## Table 4: Nonlinear incentives and credit card applications

In this table, we show the estimation results for the difference-in-differences regressions studying how the nonlinear incentive affects the quantity and quality of credit card application flow in Panel A and bank's credit card applications approval standards with respect to hard information in Panel B. 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: Quantity and quality of credit card applications

| | Log (# of Applicants) | Age | Income | Employment | College | Gender | Married | Asset | Liability |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| Treatment | 0.114*** | 0.015 | -461.5*** | -0.032*** | 0.005 | -0.013 | 0.016 | -0.027** | 0.011*** |
| | (0.002) | (0.217) | (0.005) | (0.004) | (0.173) | (0.169) | (0.104) | (0.031) | (0.004) |
| LastWeek | -0.005 | -0.027 | 253.4 | 0.021 | -0.003 | 0.009 | 0.021 | 0.019 | 0.005 |
| | (0.541) | (0.541) | (0.352) | (0.291) | (0.405) | (0.157) | (0.178) | (0.426) | (0.121) |
| Manager FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Branch*Time FEs | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 10,500 | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 |
| R-squared | 0.188 | 0.141 | 0.182 | 0.213 | 0.176 | 0.175 | 0.091 | 0.185 | 0.167 |

Panel B: Hard information during credit card approval

| | Approval Indicator | | | | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Treatment | 0.121*** | 0.113*** | 0.084*** | 0.079*** | 0.083*** | 0.075*** |
| | (0.007) | (0.009) | (0.000) | (0.001) | (0.004) | (0.002) |
| ×Log(Income) | | | -0.005** | -0.003** | -0.004** | -0.002** |
| | | | (0.034) | (0.029) | (0.023) | (0.017) |
| ×Employment | | | -0.011* | -0.008** | -0.019* | -0.015** |
| | | | (0.074) | (0.042) | (0.059) | (0.023) |
| ×Asset | | | -0.005* | -0.006** | -0.004* | -0.005* |
| | | | (0.084) | (0.027) | (0.077) | (0.064) |
| Log(Income) | | | | | 0.011*** | 0.008*** |
| | | | | | (0.008) | (0.003) |
| Employment | | | | | 0.038** | 0.041** |
| | | | | | (0.023) | (0.015) |
| Asset | | | | | 0.009* | 0.011* |
| | | | | | (0.052) | (0.087) |
| Age | | | | | 0.011 | 0.009 |
| | | | | | (0.309) | (0.318) |
| College | | | | | 0.002** | 0.007** |
| | | | | | (0.042) | (0.037) |
| Gender | | | | | 0.065*** | 0.073*** |
| | | | | | (0.001) | (0.000) |
| Married | | | | | 0.003** | 0.002** |
| | | | | | (0.017) | (0.032) |
| Liability | | | | | -0.003 | -0.002 |
| | | | | | (0.371) | (0.260) |
| Manager FEs | No | Yes | No | Yes | No | Yes |
| Branch*Time FEs | No | Yes | No | Yes | No | Yes |
| Observations | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 | 616,189 |
| R-squared | 0.092 | 0.113 | 0.101 | 0.172 | 0.184 | 0.217 |

## Table 5: 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) | (0.083) |
| Borrower Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Manager FEs | 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-squared | 0.032 | 0.162 | 0.036 | 0.104 | 0.027 | 0.135 | 0.048 | 0.179 |

## Table 6: 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 if borrowers' income is in the lowest quintile of all borrowers in the same month and High Income as reminder. 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) |
| Borrower Controls | Yes | Yes | Yes | Yes |
| Manager FEs | Yes | Yes | Yes | Yes |
| Branch*Time FEs | Yes | Yes | Yes | Yes |
| Observations | 4,019,660 | 84,984 | 84,984 | 67,080 |
| R-squared | 0.162 | 0.104 | 0.135 | 0.179 |

## Table 7: 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 credit card usage when the dependent variables are the monthly number of credit card usage (Columns 1-2), the monthly amount of credit card usage (Columns 3-4), credit card inactive likelihood (%) within six months (Columns 5-6), and credit card cancellation likelihood (%) within twelve months (Columns 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) |
| Borrower Controls | No | Yes | No | Yes | No | Yes | No | Yes |
| Manager FEs | 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-squared | 0.021 | 0.121 | 0.035 | 0.159 | 0.064 | 0.257 | 0.032 | 0.128 |

**Table 8: 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 (Columns 1-2), and the amount of investment within the bank (Columns 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) |
| Borrower Controls | No | Yes | No | Yes |
| Manager FEs | 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-squared | 0.011 | 0.042 | 0.093 | 0.161 |

## Table 9: 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 Frequency if borrowers' monthly average number of credit card usage belongs to the lowest quintile and High Frequency as reminder, and Cancellation and No Cancellation. The dependent variables are the indicator that a borrower has investment within the bank (Columns 1 and 3), and the amount of investment within the bank (Columns 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) |
| Borrower Controls | Yes | Yes | Yes | Yes |
| Manager FEs | 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-squared | 0.042 | 0.161 | 0.042 | 0.161 |

## Table 10: 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 processing time of credit card applications. We split the data sample into the approved sample (Columns 1-2) and declined sample (Columns 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 | | Declined 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) |
| Borrower Controls | No | Yes | No | Yes |
| Manager FEs | No | Yes | No | Yes |
| Branch*Time FEs | No | Yes | No | Yes |
| Observations | 350,805 | 350,805 | 265,384 | 265,384 |
| R-squared | 0.063 | 0.212 | 0.054 | 0.147 |

### Table 11: 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. We decompose the Treatment into Fast Process if borrowers' approval time is in the lowest quintile and Slow Process as reminder. 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** |
| | (0.009) | (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) |
| Borrower Controls | Yes | Yes | Yes | Yes | Yes | Yes |
| Manager FEs | 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-squared | 0.162 | 0.104 | 0.135 | 0.179 | 0.042 | 0.161 |

## Table 12: 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), distance to headquarters (Panel C), and past performance (Panel D). 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 | Delinquency | Time to Delinquency | Reinstatement | Time to Reinstatement | Dummy = 1 if Amount>0 | Investment Amount |
|---|---|---|---|---|---|---|---|---|---|---|
| | (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) | (0.131) |
| 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) | (0.085) | (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) | (0.009) | (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) | (0.041) | (0.114) | (0.036) | (0.071) | (0.042) | (0.085) |
| Panel D: Manager's past performance | | | | | | | | | | |
| Above Median | -0.658*** | -532.8*** | 2.145*** | 2.251*** | 0.471*** | -0.611*** | -9.325** | 0.691*** | -0.020*** | -1032.7*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.001) | (0.003) | (0.011) | (0.001) | (0.000) | (0.000) |
| Below Median | -0.366* | -243.8 | 1.644** | 1.277* | 0.223* | -0.478* | -6.908** | 0.342** | -0.018* | -664.8* |
| | (0.072) | (0.115) | (0.039) | (0.054) | (0.075) | (0.064) | (0.027) | (0.019) | (0.077) | (0.083) |
| Borrower Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Manager FEs | 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 |

## Table 13: Nonlinear incentive and bank profit

In this table, we report the estimation results for the difference-in-differences regressions that investigate the impact of the nonlinear incentives on bank profit. The dependent variables are interest charge of average daily balance (%) (Column 1), interchange income of average daily balance (Column 2), total fees of average daily balance (%) (Column 3), total cost of average daily balance (%) (Column 4) and realized profit of average daily balance (%) (Column 5). Variables are defined in Appendix A. After is a dummy variable that equals to one if the bank introduced nonlinear incentive scheme. 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.

| | Interest Charge | Interchange Income | Total Fees | Total Cost | Realized Profit |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| After | 0.311** | -0.247* | -0.226** | 0.153** | -0.268** |
| | (0.017) | (0.068) | (0.021) | (0.019) | (0.032) |
| Branch FEs | Yes | Yes | Yes | Yes | Yes |
| Manager FEs | Yes | Yes | Yes | Yes | Yes |
| Mean (Dep.var) | 16.37 | 3.72 | 8.05 | 26.31 | 1.83 |
| Observations | 1,008 | 1,008 | 1,008 | 1,008 | 1,008 |
| R-squared | 0.275 | 0.347 | 0.218 | 0.332 | 0.459 |

# 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).

Average daily balance is the arithmetic mean of account-level end-of-day balances over the billing cycle aggregated at branch day level.

Interest charge is the account-level interest expenses over the billing cycle as an annualized percentage of average daily balance aggregated at branch day level.

Interchange income is the account-level interchange fee revenue from merchants as an annualized percentage of average daily balance aggregated at branch day level.

Total fees is the account-level sum of card related fees, including annual fee, cash advance, debt suspension, late fee, and other fees as an annualized percentage of average daily balance aggregated at branch day level.

Total cost is the account-level sum of net charge-offs, cost of funds, rewards and fraud expenses, and operational costs as an annualized percentage of average daily balance aggregated at branch day level.

Realized profit is the account-level difference between total revenue (sum of interest charges, interchange income, and total fees) and total cost as an annualized percentage of average daily balance aggregated at branch day level.

## 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 investigating the relationship between the reduced usage of bank 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 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 investments than their counterparts. 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]

Our results are robust to the measure of borrowers' hard information, including borrowers' personal assets and employment status. 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 assets in Table B1 and by borrower's employment status in Table B2. As shown, our results are robust to the hard information for borrowers. The alternative explanation for negative consequences of gaming behaviors, i.e., customers with more vulnerability that drive lower investments because their financial circumstances are negatively affected by credit cards is not supported.

[TABLE B1 ABOUT HERE]

[TABLE 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.

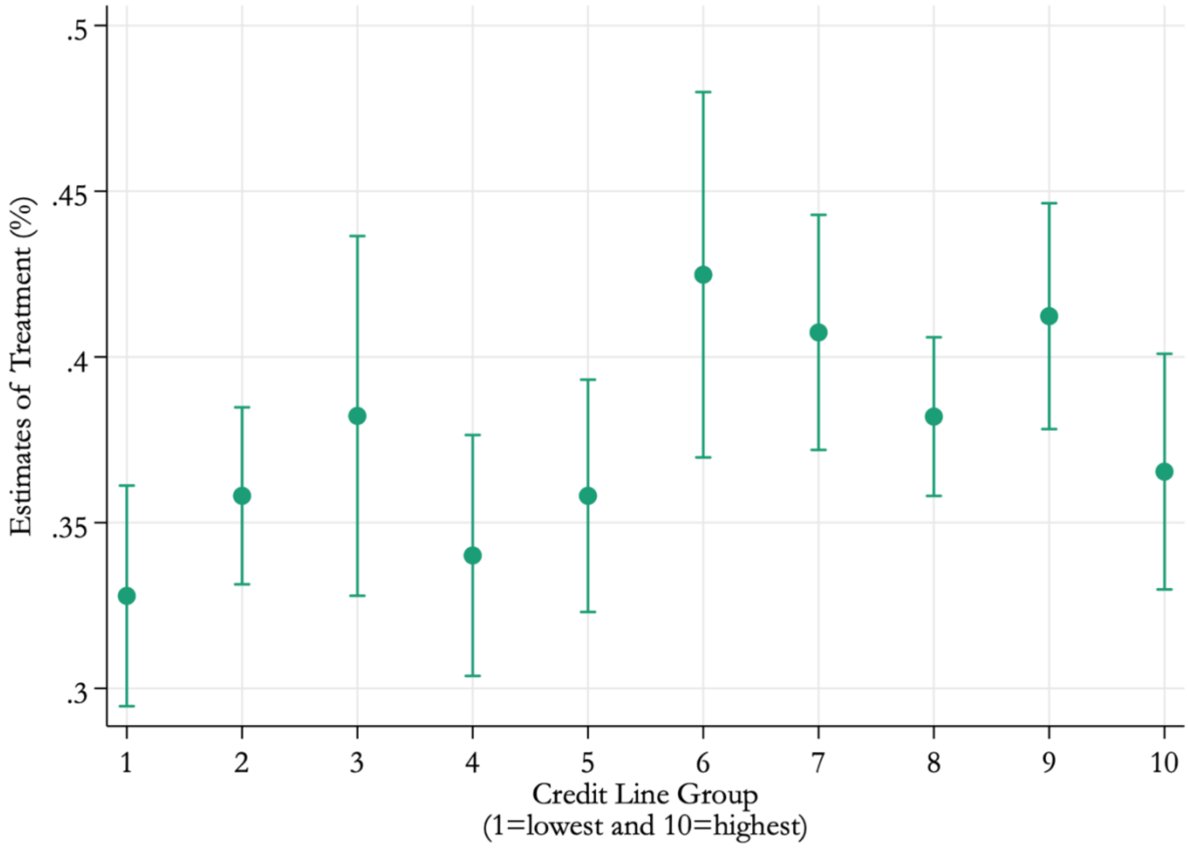
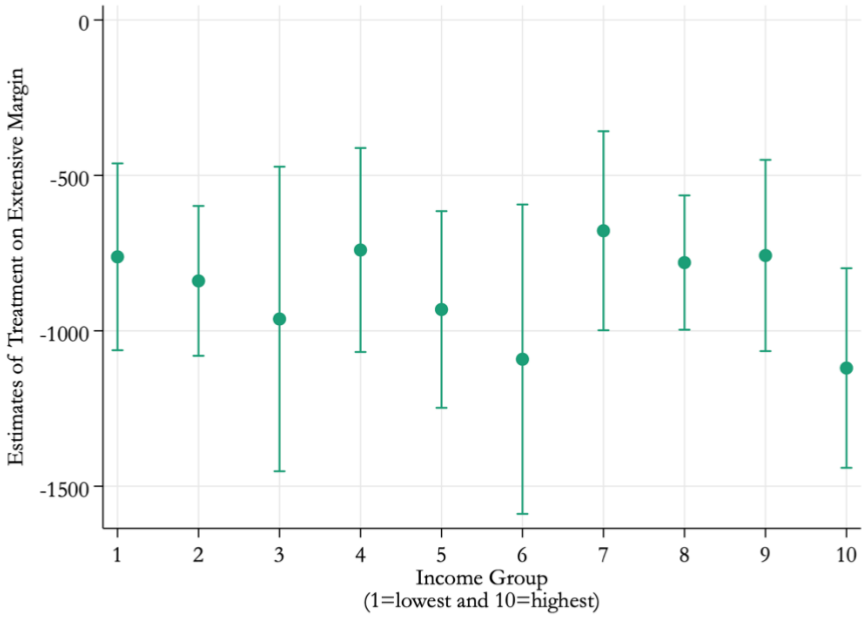


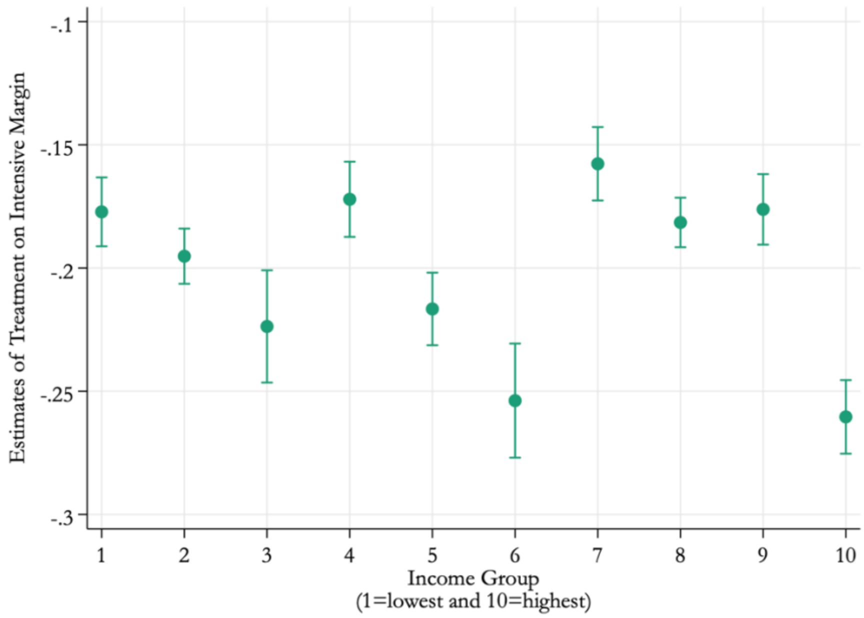
**Figure B2: Investment difference between last-week and non-last-week borrowers**

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**



## Table B1: Credit outcomes by the personal assets 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 assets. We decompose the Treatment into Less Assets if borrowers' assets are in the lowest quintile of all borrowers in the same month and More Assets as reminder. 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) |
| Less Asset | 0.518*** | -0.723*** | -10.945*** | 0.736*** |
| | (0.003) | (0.001) | (0.004) | (0.002) |
| More Asset | 0.290* | -0.486 | -7.173 | 0.325* |
| | (0.058) | (0.115) | (0.139) | (0.091) |
| LastWeek | -0.169* | 0.129 | 2.597 | -0.177** |
| | (0.064) | (0.477) | (0.160) | (0.043) |
| Borrower Controls | Yes | Yes | Yes | Yes |
| Manager FEs | Yes | Yes | Yes | Yes |
| Branch*Time FEs | Yes | Yes | Yes | Yes |
| Observations | 4,019,660 | 84,984 | 84,984 | 67,080 |
| R-squared | 0.162 | 0.104 | 0.135 | 0.179 |

**Table B2: Credit outcomes by the employment status 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 borrower's employment status on the credit outcome. We decompose the Treatment into Employed and Unemployed. 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) |
| Employed | 0.242* | -0.457 | -7.102* | 0.277* |
| | (0.086) | (0.173) | (0.063) | (0.089) |
| Unemployed | 0.561*** | -0.723*** | -10.174*** | 0.735*** |
| | (0.001) | (0.000) | (0.003) | (0.002) |
| LastWeek | -0.169* | 0.129 | 2.597 | -0.177** |
| | (0.054) | (0.218) | (0.107) | (0.047) |
| Borrower Controls | Yes | Yes | Yes | Yes |
| Manager FEs | Yes | Yes | Yes | Yes |
| Branch*Time FEs | Yes | Yes | Yes | Yes |
| Observations | 4,019,660 | 84,984 | 84,984 | 67,080 |
| R-squared | 0.162 | 0.104 | 0.135 | 0.179 |