Competing for Loan Seniority: Theory and Evidence*

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Abstract

Borrowing from multiple lenders can lead to a debt dilution problem: lenders do not internalize that issuing a new loan can affect borrowers' ability and incentive to pay off loans provided by other lenders. Using data on the universe of retail loans in Brazil, we provide new evidence of the debt dilution channel in the credit card market. We show that, when unable to repay all their credit card debt, defaulters often repay a subset of their cards. They prioritize repaying the balance on their cards with the highest credit limit, cards originated by fintech companies, or cards from lenders that also sold them other financial products. Motivated by these facts, we develop a new structural model of lending with non-exclusive contracts in which lenders can use contract terms to gain loan seniority. We use the model to quantify the impact of debt dilution on contract terms and welfare.

Keywords: Credit cards, Non-exclusive contracts, Selective default
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1 Introduction

Individuals often have multiple loans, typically issued by different financial institutions. The welfare implications of non-exclusive loan contracts – that is, the ability to borrow from multiple lenders – are ambiguous. On the one hand, non-exclusivity can benefit borrowers by letting them freely shop for the best product without being locked in by previous decisions. On the other hand, the theoretical literature argues that non-exclusive contracts can generate a debt dilution problem: lenders may impose a default externality on others as originating a new loan can affect borrowers' ability and incentive to pay off existing loans (e.g., Bizer and DeMarzo 1992 or Green and Liu 2021). Green and Liu 2021).

The debt dilution problem potentially plays a more important role in the markets for unsecured household loans, where default and recovery rates are typically higher due to the absence of collateral. Moreover, since these markets lack of a formal seniority structure, lenders may seek to obtain informal seniority to increase the likelihood of repayment in the event of distress. We explore the implications of on non-exclusivity within the context of Brazil's credit card market. Borrowing form multiple lenders is common in this setting: out of 85 million credit card users in June 2022, 39.4 million (46.5%) had multiple active cards issued by two or more banks (Central Bank of Brazil 2022). These users tend to borrow more than those with a single card, accounting for over 70% of the total outstanding credit card balance.

This paper is the first to quantify the impact of debt dilution on contract terms and welfare. In particular, we show empirical evidence and analyze how lenders compete to gain informal loan seniority using contract terms. To do so, we use proprietary data from the Brazilian Central Bank to construct monthly portfolios of loans for all individuals in Brazil from 2019 to 2023. We first provide new stylized facts about default behaviour in the credit card market. Then, we construct causal estimates of the debt dilution channel using a novel plausibly exogenous variation in the probability of getting a credit card or a payroll loan from one bank. Finally, we use those reduced-form estimates and a new structural model with non-exclusive loan contracts to investigate the equilibrium implications of competition for loan seniority on contract terms and welfare.

Brazil offers an ideal setup for studying debt dilution. In contrast to other credit registers, the Central Bank of Brazil datasets allow us to link each individual to their financial products (mortgages, car loans, consumer loans, and credit cards) and associated lenders, as well as loan-specific repayment decisions. Observing the universe of financial products—and in particular, credit card portfolios—allows us to study debt dilution across all product types. This is crucial as debt dilution is likely a main concern in the credit card market: the share of credit card owners with multiple active cards originated by different financial institutions is high (46.5% in 2022); borrowing is high (30% of the population revolve their credit card balance at the end of the month); there are no formal seniority laws; and default – defined as the borrower having payments overdue for more than 90 days – is high (around 9% in 2022).

We start by providing new facts about the credit card market. We highlight that borrowers with multiple active cards rarely default on all their active cards (around 5-10% of defaulters). In addition, we show that default costs are likely low for borrowers with multiple cards. Indeed, defaulting on one card does not impact the credit limits of other cards. In contrast, limits and monthly usage levels drop to zero for the cards that defaulters did not pay.

We also show that the probability of defaulting on any card increases with the number of cards: on average 8% of individuals owning one credit card are in arrear[1] in a given month while 17% of the individuals with 4 or more cards are in arrear in at least one card. This can be explained by riskier borrowers choosing to own multiple cards (adverse selection) rather than from the causal impact of having a credit card (moral hazard).

To find the causal impact of getting a new loan on default, we use a difference-in-difference analysis. We exploit a novel, plausibly exogenous variation in the number

[1] We use the standard definition of being in arrear: Someone that used his credit card but did not make the minimum payment for 90 days.

of cards owned. The variation arises when banks form partnerships with local governments. These partnerships typically last for five years and are awarded through procurement auctions. The arrangement effectively mandates that employees receive their wages through the bank that won the auctions, increasing the likelihood that employees will obtain a card from that bank. We thus compare two groups of borrowers who worked at the same firm around the time the partner bank changed. The first group already had a relationship with the partner bank before it won (treatment), while the second did not (control). The identifying assumption is that the relative change in default probability between the two groups is due to the impact of the treatment group getting a new loan. We find that while the average number of card increased, default did not, suggesting that the correlation between default and the number of cards is due to high default borrower self-selecting into having multiple cards.[2]

Finally, we show that conditional on financial distress, borrowers' default behaviour is selective: they pay a subset of their loans and thus must choose which one to repay. We use a conservative approach to measure selective defaulters. We look at the fraction of borrowers that default on the cards that account for less than 50% of their debt; that is, they had the resources to repay these cards but chose to repay the cards that accounted for more than 50% of their debt. Using this approach, we find that at least 40% of defaulters are selective. We document that those borrowers are more likely to prioritize repaying the balance on cards with the highest credit limits (5% more likely to repay), cards issued by fintech companies (15% more likely), or cards from lenders that have also provided them with other products, such as an auto loan (5% more likely), a mortgage (10% more likely) but not a personal loan.

To mitigate endogeneity concerns, we use another difference-in-difference approach. We compare the default probabilities for credit cards issued by bank A conditional on default for two groups of borrowers. The first group works in a firm whose partner bank stayed in bank A. The second works for a firm for which the partner bank moved to bank B. WE FIND THAT...

[2]However, this fact does not imply that debt dilution is low because borrowers prioritize repaying a given set of cards.

The above results imply that debt dilution operates via two margins in the credit card market: issuing a new loan affects both the borrower's probability of default on any of their loans and which loans the borrower defaults on. The results also suggest that lenders can compete to gain loan seniority (i.e., be the bank the borrower prioritizes repaying) using contract terms and cross-selling other financial products.

Guided by those key features of the credit card market, we develop a novel model to analyze and quantify the implication of competition for loan seniority. In the model, each lender simultaneously offers a loan contract, and borrowers can choose how many contracts to accept. For exposition purposes, I refer to the contract as a credit card contract.

The borrower can use multiple cards to leverage and thus consume more at the risk of being able to repay only a subset of cards. Formally, borrowers use credit cards to consume in the first period. In the second period, the borrowers choose whether to repay the lenders subject to an income constraint. They lose the card if they do not repay its balance and derive some utility from keeping each card in the second period. I consider that the utility in the second period is proportional to each card quality. In practice, a high-quality card can refer to a card offering substantial rewards, providing a fast-growing credit limit, or being linked to the promise of getting another financial product (e.g., a mortgage).

Lenders can choose the loan interest rate, the credit limit, and can invest to increase the borrower's perceived value of repaying the card (i.e., the card quality). The key externality is that issuing a credit card reduces the borrower cost of defaulting on other cards. The reasoning is that defaulting on all card is more costly than on only a subset as the borrower needs at least one card to cater to his fundamental needs in the second period.[3] In line with what is observed in the data, lenders cannot undo this friction by designing loan contracts that are contingent on the terms of those signed with other

[3] I also consider that lenders cannot punish borrowers so much conditionally on default that they do not want to own more than one credit card. In practice, lenders can lower the borrower credit score and cancel the credit card. Those may have a limited impact if the individual does not want to borrow from that bank in the future because he owns other cards. Credit card loans are recourse, but the legal costs are so high that, in practice, recourse is not used in this market.

lenders.

When issuing a loan, lenders internalize that the borrower may get another loan from a competitor and may be able to repay only a subset of them. As a result, lenders either overinvest or underinvest in the card quality relative to the exclusive contract case. Incentives to overinvest arise because of an arms race: offering a higher quality relative to other banks increases the probability that the borrowers prioritize repaying this card. Incentives to underinvest come from lenders expecting borrowers to default more often under non-exclusivity and thus benefit less from the credit card quality.

We show that over or underinvestment in credit card quality can increase or decrease credit limits relative to the exclusive contract case. Indeed, the increase in default leads to a higher cost of lending and, thus, lower loan size. However, the potential underinvestment in card quality makes the cards cheaper to originate, which leads to lower interest rates and, thus to higher loan sizes.

The welfare impact of contract exclusivity is ambiguous. Debt dilution decreases welfare by generating too much default. However, the competition for loan seniority can increase welfare as it may reduce the markup on other financial products banks offer to gain seniority. The intuition for this result comes from interpreting the credit card quality as offering a personal loan (or any other type of loan) in the second period. In that case, the overinvestment in credit card quality can be interpreted as lowering the markup on personal credits relative to the exclusive credit card contract case. The welfare impact depends on the degree of competition in the personal loan market. When the personal credit market is perfectly competitive, competing for loan seniority forces to cross-subsidize products (i.e., making losses on personal loans and increasing credit card rates), which is not necessarily what would happen in the first best. Consequently, exclusivity (or seniority regulations) solves the debt dilution problem but can give lenders more market power in other markets.

The model also implies that, even if default and debt dilution is low in equilibrium, the threat of it existence is enough to induce large contract distortions to prevent it. For instance, let us consider a model in which the first best credit card contract would be offered absent debt dilution. To gain principality, lenders must distort credit card terms away from the first best. When a lender has a comparative advantage in implementing this distortion, he gains seniority, mitigating the debt dilution problem.

This latter point justifies the need for a structural model to simulate the off-equilibrium threat and thus assess the impact of non-exclusivity on contract terms. We use the reduced forms estimates and our model to quantify the effect of debt dilution on contract terms. WE FIND...

Litterature—We connect with several strands of the literature. First, we build on papers that study sequential and non-exclusive lending. The contributions in this field are mostly theoretical (Bizer and DeMarzo 1992, Kahn and Mookherjee 1998, Parlour and Rajan 2001, Green and Liu 2021, Attar et al. 2019, among others).[4] We contribute to the literature by allowing lenders to compete for loan seniority using contract terms instead of considering that all loans have the same seniority.

The closest empirical paper is De Giorgi et al. (2023). The paper uses a regression in discontinuity and data from a private bank in Mexico to provide causal evidence of the debt dilution for credit cards. We use data on all lenders and products so we can provide additional insights on debt dilution across products and analyze competition for loan seniority and cross-selling.[5] Furthermore, we employ a different identification strategy and develop a structural model to understand and quantify the cost of debt dilution on contract terms.

We also contribute to the literature on credit card borrowing (See, for instance, Agarwal et al. (2015), Stango and Zinman (2016), Ponce et al. (2017), Keys and Wang (2019), Galenianos and Gavazza (2022), Nelson (2023), Berger et al. (2024), Fulford (2015), Fulford and Schuh (2024), and Matcham (2024)). We show that credit risk is bank-specific and that banks compete for priority in this market due to selective default and non-exclusivity and study equilibrium consequences and policies through the lens

[4]In some markets, banks can use collateral to exclude other lenders (e.g., Donaldson et al. 2020).

[5]Selective default has been documented in other contexts. Schiantarelli et al. (2020) show that firms default more on financially weaker banks as they perceive the value of the relationship with these banks as smaller. They also show that these effects are stronger when legal enforcement is weaker.

of a model.

By showing that other loan products affect credit card repayment decisions, we also contribute to the literature on cross-selling (e.g., Robles-Garcia et al. 2022, Basten and Juelsrud 2023). In our setting, we highlight a source of complementarity across products that emerges from a strengthening of the relationship with borrowers, which results in repayment prioritization. To the best of our knowledge, this source of economies of scope has not been analyzed empirically and theoretically.

Finally, we also contribute to the literature on fintech lending (e.g., Berg et al. 2022). We show that while the entry of fintech companies increases competition, it may impose externalities on previous lenders.

The rest of the paper is organized as follows. We first present the institutional setting and the data in section 2. Sections 3 and 4 show the descriptive statistics, stylized facts and reduced form regressions. Finally, section 5 discuss the model and the structural estimation.

2 Institutional Setting and Data

2.1 Data and Sampling

We assemble data from different sources. We obtain monthly loan-level data from the credit registry of the Central Bank of Brazil (*Sistema de Informações de Créditos*, SCR). The dataset contains the universe of bank loans – mortgages, personal credit, car loans, credit card loans, payroll-deductible loans, and others – above 200 BRL (around 35 USD). For each month, we observe loan amounts, maturities, interest rates, defaults, and anonymized bank and borrower identifiers. For credit cards, we observe the monthly credit card usage, the account balance, the interest rate, and the credit limit.[6] Credit card usage is broken down into buy now pay later amounts ("pagamento parcelado"), and regular payment ("pagamento a vista"). If a borrower holds

[6]The accuracy of credit card limit data improved after May 2021. In certain specifications, we will limit the data to the period following this month.

multiple cards with the same bank in a given month (e.g., two cards from different card networks), we observe aggregate amounts across all of their cards.

We complement credit information with data on wages and employment from the Ministry of Labor (*Relação Anual de Informações Sociais*, RAIS). We observe the income, the employer, and some sociodemographic characteristics (age, sex, type of work).

We also hand-collect data from public auctions for our difference-in-difference approach. When the employer is a government institution (e.g. city hall, estate, or federal government), banks participate in public auctions to win the right to handle the salary payments of civil servants. We are able to collect data on a large number of auctions to obtain the right to manage the payrolls of local governments. We search for these auctions on the transparency portals of local governments, and collect the auction date, the value winning bid, and the winning bank.

Our sampling procedure is described in Appendix Figure A2. For a given month t (cohort), we take a 1% random sample of individuals who were in good standing with all their credit card loans in month $t-1$ (i.e., no card with payments overdue by more than 15 days) but became more than 15 days overdue on at least one card in month t. We refer to these individuals who are transitioning into distress as treated. To reduce the total sample size, we apply this procedure every three months, starting in June 2019 and ending in December 2022 – a total of 15 cohorts. For each cohort t, we also collect credit information for the months $m \in \{t-12, t-11, ..., t-1, t, t+1, ..., t+11\}$. For each cohort, we also take a 0.025% random sample of individuals who are not part of the treated population. These include individuals who were not in good standing with all their cards at $t-1$ and individuals who were in good standing with all their cards at $t-1$ and remained in good standing at month t. We refer to these individuals as not treated or control. We apply inverse probability weighting to estimate statistics for the population of credit card users. The final data is at the cohort$\times$individual$\times$bank$\times$month level.

In Appendix Table A4, we report a total of 524,533 observations at the cohort-by-individual level, with 252,844 observations belonging to the treated group. Consistent with the growth of the credit card industry, more recent cohorts are larger than the older ones.

2.2 The Credit Card Industry in Brazil: Growth and the Extent of Multi-lender Borrowing

The credit card industry has expanded rapidly. After a stagnant period, the number of active credit cards doubled and the total amount of credit card loans grew by 73% between 2018 and 2023 (Appendix Figure A1). The growth in the number of cards was driven by the addition of new borrowers and existing borrowers acquiring cards from multiple banks. According to Central Bank of Brazil (2022), the number of credit card users increased by 31% between June 2019 and June 2022, from 65 million to 85 million (40% of the population). While in June 2019 38% of users had active cards issued by two or more banks, in June 2022 this number was 47% (Appendix Figure A2). The credit card debt of borrowers with more than one lender accounted for more than 70% of the total credit card debt in 2023.

The expansion of digital institutions was a key contributor to the growth in the number of credit card users and active credit cards (Appendix Table A1). The number of credit card users with accounts in digital banks grew from 8.9 million in June 2019 to 36.5 million in June 2022 (310% growth). The credit card loans market has experienced a drop in concentration measures (Appendix Figure A5). The Herfindahl–Hirschman index (HHI) dropped from 0.17 in 2018 to 0.11 in 2023.

In Appendix Figure, A4, we show that total credit card balance can be decomposed into non-interest bearing purchases (80%), revolving debt (10%), and buy now pay later (10%). For revolving debt, default rates exceeded 50% in 2023, while buy now, pay later default rates reached 10%. Default rates have shown an upward trend since 2018, while the composition of total credit card debt has remained stable. Appendix Figure A5 shows that credit card revolving and buy now, pay later have the highest interest rates among the main loan types, with monthly interest rates racing 10% for revolving debt.

3 Descriptive Statistics and Stylized Facts

3.1 Descriptive Statistics

In Table 2, we show how borrower characteristics are correlated with the number of active cards issued by different lenders.

Individuals with more lenders have similar average limit utilization across their cards (90 for individuals with one card and 85 for individuals with three cards). The age is also similar (40 years old).

Individuals with more card lenders have higher monthly wages (2,100 Brazilian Real for individuals with one card and 3,000 with individuals with three cards) but a higher debt service-to-income ratio (30% and 60% respectively). They also tend to have formal jobs, instead of being self-employed, entrepreneurs, or working in the informal sector (30% and 40% respectively). Individuals with more card lenders also tend to rely more on other loan types. For instance

Those facts can be explained by supply or demand factors. For instance, lenders could only be willing to offer multiple cards to individuals with high enough income. Alternatively, richer individuals live in cities that are more financially integrated and may have a higher demand for cards. Those facts are also consistent with lenders being more inclined to offer other financial products to people with more cards to gain seniority.

3.2 Stylized Facts About Default

In this section, we provide three new stylized facts about default behaviour in the credit card market. First, we show that many borrowers default on only a subset of their cards. For instance, only 10% of borrowers with three cards default on all their active cards. Second, we show that lenders do not cancel the credit limit on borrowers who defaulted on a competitor's card. Finally, we show that borrowers tend to prioritize repaying cards with better terms and cards issued by banks that offer them other financial products.

Fact 1: Many borrowers default on only a subset of their cards. To derive the first fact, we examine whether individuals who miss a payment for the first time (treated) default on all or a subset of their loans six months later. In Appendix Table A6, we show similar results for horizons different than six months. We classify a loan as in default if it is more than 90 days overdue.

In Table 3, we show that 46% of treated individuals become more than 90 days overdue on at least one card and that this number increases monotonically with the number of card lenders. This group of individuals can be decomposed into two subgroups: *universal defaulters*, who default on all cards (24%), *selective defaulters*, who default on some cards and repay others (21%).[7]

These figures include individuals who have only one card and, therefore, cannot default selectively. When we restrict the analysis to individuals with two or more cards, we find that the vast majority of defaults are selective. For example, 45% of treated individuals with two cards become more than 90 days overdue on at least one card. This figure can be broken down into 11% of universal defaulters and 34% of selective defaulters. That is, conditional on defaulting on at least one card, 75%=34/55 of borrowers repay at least one card. This proportion increases with the number of cards held by borrowers.

While the term selective default could apply to individuals who repay a subset of their credit card loans, it is possible that they default on the card for which they have insufficient resources to repay. In this case, the default is driven by a liquidity constraint rather than a deliberate choice. Since we do not have information on the liquid wealth of these borrowers to certify if they had enough resources to pay a given card or not, we create a more conservative measure of selective default. We identify borrowers who default on the cards that account for less than 50% of their total credit card debt. In this case, the default decision is necessarily a choice, since the borrower had more

[7] The two numbers add to 45% and not 46% due to rounding.

than enough resources to repay these cards.

We then show that selective defaulters (21%) are comprised of two groups: those that default on less than 50% of their credit card balance (9% of borrowers), and those that default on more than 50% of their credit card balance (12% of borrowers). That is, *at least* 43%=9/21 of selective defaulters made a deliberate repayment choice. The proportion of these borrowers also increases with the number of cards.

In Table 4, we show that selective defaulters typically hold more cards, have a greater number of bank relationships, and a higher debt service to income ratio than universal defaulters and no-defaulters. While selective defaulters have higher incomes and credit card balances compared to universal defaulters, their income and balances are lower than those of non-defaulters. Regarding other loan types, selective defaulters tend to have more outstanding loans than universal defaulters.

In Figure 3, we show that all default measures are increasing over time, potentially due to the expansion in the number of credit cards. In Appendix Figure A7, we present the same figures for individuals with at least two card lenders. In this subsample, the incidence of selective default is significantly higher, as we exclude individuals with only one card, who can only default universally. The figures confirm that the incidence of selective default is increasing over time.

Fact 2: Lenders do not cancel the credit limit on borrowers who defaulted on a competitor's card. Figure 4 provides a visual representation of the second stylized fact. We show that defaults entail the loss of the card, as the limit available and monthly card usage drop to zero. However, select defaulters keep the limit and usage amounts of the cards they repay. That is, as long as banks are the prioritized bank, they keep supplying credit to selective defaulters.

Fact 3: Borrowers prioritize repaying cards with better terms. To understand the characteristics of the bank-borrower relationship that predict default (or repayment), we use the sample selective defaulters that repay a subset of their loans and data at the borrower×cohort×bank level, that is, each observation is a bank-borrower relationship. We estimate the following regression:

$$y_{icb} = \beta X_{icb} + \alpha_{ic} + \epsilon_{icb}$$

where y_{icb} is a binary variable that takes the value one if, six months after becoming overdue for more than 30 days in any card, individual i of cohort c defaults (is more than 90 days overdue) on the credit card issued by bank b. The vector X_{ibc} contains borrower-bank characteristics measured in the month when the borrower becomes overdue for more than 30 days: limit available, limit utilization, global limit, loan balances, dummies for other active loan types, dummies for non-performance of other loan types, and dummies for bank types (digital or state-owned). We include borrower-cohort fixed effects (α_{ic}).

We report descriptive statistics of the regression variables in Table 5. Selective defaulters default on 45% of their banks on average. In 69% of card relationships, borrowers used up all their credit card limits (100% of the limit); in 11%, more than 90% and less than 100%; in only 20% of card relationships, borrowers used less than 80% of the limit. 23% of relationships are with digital banks, 11% with state-owned banks, and the remainder (66%) with other banks. 6% of relationships contain an active payroll loan, 1% an active mortgage, 2% an auto loan, 12% a personal (consumer) loan, and 16% other loan types.

We report regression results in Table 6. Borrowers tend to default more on cards for which there is less limit available. In particular, default probabilities increase sharply (40%) on the card for which there is no limit available (100% utilization). Recalling that the mean of the dependent variable is 45%, the limit available seems to be an important driver of repayment choice.

Borrowers tend to default less on banks where they have a positive global limit, which includes limits for other loan types such as overdraft. Borrowers tend to default less on digital banks (-18%) and more on government banks (14%), meaning that borrowers may value their relationship with digital banks more than with other types of banks or that digital bank have a better debt recollection infrastructure.

In general, borrowers tend to default less on banks where they have other loan products: payroll (-6%), mortgage (-12%), auto loan (-5%), and other loans (-8%). However, default is more likely if the borrower has personal loans with the bank (4%). These results suggest that offering one loan type may increase the profitability of another, as it strengthens the bank's relationship with the borrower and improves its position in the repayment hierarchy. If the borrower already defaulted on other products from that bank, then it is also much more likely to default on the credit card from that bank rather than from another bank (15% more likely).

4 Identification strategy

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5 Model

This section is a sketch of the fuller model that will be used to bring the model to the data. The model provides intuition about the economic forces at play.

The economy is populated with two groups of agents: borrowers and lenders. There are two periods. In the first period, each lender simultaneously makes each borrower a take-it-or-leave-it offer of a loan contract. For exposition purposes, we refer to the contract as a credit card. Each borrower can accept any number of contracts. In the second period, borrowers choose the contracts they repay.

5.1 Borrowers

There is an arbitrary number of borrowers indexed by i. For exposition purposes, I drop the i index when unambiguous.

In period 1, borrower i chooses the set of cards they own. The set is denoted $\mathcal{C}$. Each credit card has a quality (e.g., rewards), a credit limit and an interest rate.

In period 2, they choose which cards to repay. This set is denoted $\mathcal{R}$. The amount the borrower repays cannot be higher than his disposable income, denoted W_i. Formally, the set of cards he repays $\mathcal{R}$ must be included in the feasible set F:

$$\mathcal{R} \subset F(\mathcal{C}) := \{f \subset \mathcal{C} : \sum_{c \in f} R_c \leq W_i\}$$

R_c is the cost of borrowing and amount L_c with card c.

The borrower chooses the set of cards to own and to repay to maximize his utility. The borrower's i utility in period 1 is the sum of its utility derived from consumption in periods 1 and 2, plus the indirect utility of owning a card at the end of period 2.

For simplicity, I consider that borrowers max out the credit limits (L_c) on each card $c \in \mathcal{C}$ to consume in period 1. This behaviour can be micro-founded with a model in which the marginal utility of consumption is higher in the first period than the marginal utility of consumption in the second period times the lender's marginal cost of lending. Formally the borrower chooses how many cards to own ($\mathcal{C}$) and which one to repay ($\mathcal{R}$), to maximize their indirect utility:

$$u(L, R) := \max_{\mathcal{C}} \overbrace{\sum_{c \in \mathcal{C}} \alpha L_c + \epsilon_{ic}}^{period\ 1} + \beta E_\epsilon[\overbrace{U(L, R, \mathcal{C})}^{period\ 2}] \tag{1}$$

$$U(L, R, \mathcal{C}) := \max_{\mathcal{R} \in F(\mathcal{C})} W_i - \sum_{r \in \mathcal{R}} [R_r + \epsilon_{ir}] + \sum_{c \in \mathcal{C}} V_c(\mathcal{R}) \tag{2}$$

$L := (L_c)_{c \in [\![i,B]\!]}$ and $(R_c)_{c \in [\![i,B]\!]}$ are vectors of loan size and payments offered in the market. $V_c(\mathcal{R})$ is the utility of repaying (i.e., $c \in \mathcal{R}$) or not (i.e., $c \notin \mathcal{R}$) card c. It can be interpreted as the continuation value of owning the card at the end of period 2. I allow the cost and benefits of repaying the card to depend on the set of cards the borrower repaid ($\mathcal{R}$). This modelling captures the fact that defaulting on card c is less costly if the borrower owns another card. To fix ideas, $V_c(\{c\})$ can be interpreted as the utility derived from the bank offering a mortgage or increasing card rewards at the end of period 2. $V_c(\{\emptyset\})$ is the cost of having a lower credit score and not being able to use any card at the end of period 2.

ϵ_{ic} and ε_{ir} are borrower card-specific parameters that affect the continuation value of owning or not (and repaying or not) the card. They are introduced to allow the demand and default functions in the next section to be continuous. Formally, ε_{ic} and ϵ_{ir} are random variables. ε_{ic} value is realized in period 1 and is observable by the borrower only. It draws its value from a continuous cumulative distribution function. ϵ_{ir} is a random variable with a continuous cumulative distribution function defined on a bounded set S. Its value is realized in period 2.

5.2 Lenders

There is an arbitrary number of lenders B.

At the beginning of period 1, lenders simultaneously offer loan contracts. They choose their credit card characteristics (i.e. credit limit and interest rate pricing schedule $r(L)$, L is the amount borrowed). Lenders also choose to invest an amount ι to increase the value of repaying the card. For simplicity of the notation, I denote $V_c(\iota) := V_c(\mathcal{R})$ when $c \in \mathcal{R}$ and normalize $V_c(\mathcal{R})$, $c \notin \mathcal{R}$ to zero. the cost of investing is paid in the first period and is denoted $c(\iota)$.

As lenders know the borrower's willingness to pay for the loan (i.e., $\frac{\alpha}{\beta}$), the equilibrium in which the lender chooses the pricing schedule and credit limit is equivalent to the one in which lenders directly choose the repayment $R := r(L)$ and the loan size L.

For each borrower i, lender b chooses the card loan size L, its repayment R and quality ι maximizes static profits conditional on their expectations about other lenders' offers and borrowers' behaviour. Formally, we have:

$$\max_{\{L_b, R_b, \iota_b\}} D_b(u)[\overbrace{\theta_b(u, \iota_b)R_b}^{Loan\ present\ Value} - \overbrace{mc_b(\theta)L_b}^{cost\ of\ lending} - \overbrace{c_b(\iota_b)}^{cost\ of\ investment}]$$

u is a shortcut notation for $u(L, R)$ defined in equation 1.

$D(u) := Pr(b \in \mathcal{C})$ is the probability that the borrower gets a card from bank b and $\theta(u, \iota) := Pr(b \in \mathcal{R})$ is the probability that the repays bank b. The probabilities are derived from the borrower problem (1), conditional on knowing the distribution of ϵ_{ir} and ε_{ic} but not their realization.

$mc(\theta)$ is the marginal cost of lending. $\theta := \frac{1}{Card(\mathcal{C}_i)} \sum_{c \in \mathcal{C}_i} \theta_c$ is the average survival probabilities of borrower i. One interpretation of this parametrization is that the marginal costs of lending increase in default probabilities through capital requirements and that lenders do not internalize the impact of their behaviour on capital requirements. The fact that the cost of lending depends on default is a way to introduce a welfare cost to the debt dilution channel: offering an additional card to a borrower may induce him to default on his previous card, which increases the cost of lending for the other lender. An alternative is to make default costly for the lender so that it destroys resources instead of just relocating borrowers' wealth across banks. The fact that lenders do not internalize the impact of default on capital requirements is made to simplify the equations.

5.3 Exclusive Contract Equilibrium

Let us now analyze the exclusive contract equilibrium. That is, borrowers can accept at most one contract.

For the equilibrium to feature no strategic default, and banks to lend, I assume that defaulting on all cards is costly and that lending yields a positive net present value. Formally:

Assumptions A1:

$$V_c(\{c\}) - \epsilon_{ir} - R > V_c(\emptyset), \ \forall R \leq W_i, \forall \epsilon_{ir} \in S \tag{3}$$

$$\alpha - mc(\theta) > 0, \ \forall \theta \tag{4}$$

With those assumptions, the equilibrium contract (R^*, L^*, ι^*) when lenders are homogeneous is:

$$R^* = W \tag{5}$$

$$L^* = \frac{W - c(\iota^*)}{mc(0)} - \overbrace{\varepsilon^{-1}}^{inverse\ demand\ semi-elasticity} \tag{6}$$

$$\iota^* := \{\iota : \frac{\beta V'(\iota)}{c'(\iota)} = \frac{\alpha}{mc}\} \tag{7}$$

Proof: See Appendix A1.

Technical considerations: To get a closed form formula for the demand semi-elasticity at equilibrium, I assume that demand has a logit form (i.e., $D_b(u) := \frac{exp(\sigma u_b)}{\sum_l exp(\sigma u_l)}$ where u_x is the borrower utility when getting a card at bank x). In a symmetric equilibrium, the semi-elasticity with respect to loan size is $\frac{1}{\alpha\sigma(1-\frac{1}{B})}$. I consider that the inverse demand semi-elasticity ε^{-1} is smaller than $\frac{W-c(\iota^*)}{mc(0)}$ so that $L > 0$.

Default is inefficient, so borrowers never strategically default $\theta = 0$.

Because of the positive net present value of lending, the borrower borrows as much as his income allows $R = W$.

The constraint on R implies a trade-off between lending and quality. Absent this trade-off, the optimal quality would be that the marginal benefit of lending equates to its costs: $\beta V'(\iota) = c'(\iota)$.Because the borrower resource is limited (W), the lender needs to select whether to offer a larger credit limit (L) or a larger quality (ι). Thus, the optimal contract is such that the marginal rate of transformation of lending equals the investment one. It implies that the optimal quality is: $\frac{mc}{\alpha}\beta V'(\iota) = c'(\iota)$.

The equilibrium loan size is the loan size if lenders were to break even $(\frac{W-c(\iota^*)}{mc(0)})$ minus a markup (ε^{-1}). The markup is the inverse demand semi-elasticity with respect to loan size. It captures the fact that lenders have some degree of market power when the demand elasticity is large and can thus charge above the marginal cost of lending.

5.4 Non-Exclusive Contract Equilibrium

For borrowers to use more than one card in equilibrium, I add the following assumption: Defaulting on all but one card is not too costly. For simplicity, I write the assumption for the case in which there are only two lenders. To make the notation unambiguous, I denote $V_c(\mathcal{R}, \mathcal{C})$ instead of $V_c(\mathcal{R})$. Formally, we have:

Assumptions A2:

$$\underbrace{1 - mc(\theta)}_{marginal\ loan\ utility} + \underbrace{V_c(\{c\}, \{c, b\}) + V_b(\{c\}, \{c, b\})}_{defaulting\ on\ one\ card\ when\ having\ 2} > \underbrace{V_b(\{b\}, \{b\})}_{not\ defaulting\ on\ 1\ card} \tag{8}$$

With this additional assumption, each borrower gets a card from each lender in equilibrium.

The equilibrium contract for each bank b $(R_b^*, L_b^*, \iota_b^*)$ when lenders are homogeneous is:

$$R_b^* = W \tag{9}$$

$$L_b^* = \frac{W - c(\iota_b^*)}{\theta^* mc(\theta^*)} - \varepsilon^{-1} \tag{10}$$

$$\iota_b^* := \{\iota : \frac{\beta V'(\iota)}{c'(\iota)}[\overbrace{\theta' W \frac{c'(\iota)}{\beta}}^{over\ investment} + \overbrace{\theta}^{under\ investment}] = \frac{\alpha}{mc}\} \tag{11}$$

Proof: See appendix A2.

Technical considerations: To get a closed-form solution for the demand semi-elasticity (ε^{-1}), I make the following assumption about the demand. I consider that there are B types of lenders indexed by x. Within each type x, there is an arbitrary number of lenders N that compete for the x^{th} credit card of the borrower. That way the semi-elasticity is (i.e., $D_b(u) := \frac{exp(\sigma u_b)}{\sum_{l=1}^{N} exp(\sigma u_l)}$), the equilibrium semi-elasticity is $\frac{1}{\alpha\sigma(1-\frac{1}{N})}$. I consider that $\varepsilon^{-1} < \frac{W-c(\iota_b^*)}{\theta^* mc(\theta^*)}$ so that $L_B^* > 0$ to focus on the case in which there is borrowing.

The first difference with the exclusive contract case is that borrowers default on all but one card. The expected survival probability in equilibrium is thus: $\theta_b^* = \frac{1}{N}$.

The higher default probability affects both credit limits (equation 10) and the level of investment (equation 11). While the normative effect of higher default is unambiguous, the positive implications are.

There can be over or under-investment with respect to the exclusive contract case. For simplicity of the exposition, I assume that $\beta^{-1} = \frac{mc}{\alpha}$ in equation 11 when discussing the different channels at play below. When doing the comparative static with respect to the exclusive contract case, this shuts down the fact that when the marginal cost goes up, the relative cost of lending versus investing goes up, so lenders substitute lending with investment.

Equation 11 highlights the two channels impacting the investment decision. The difference with the optimal level of investment (i.e., equation 7 when $\beta^{-1} = \frac{mc}{\alpha}$) comes from the terms $[\theta' W + \theta] \neq 1$.

The terms $\theta' W$ is potentially larger than one. It can lead to over-investment due to an arms race channel: Lenders have incentives to invest to gain seniority, yet in equilibrium, other lenders also invest. In practice, this investment can represent too many rewards offered in the second period or the promise to make a loan below the break-even rate in the future. Interpreting the model as secured lending instead of credit cards, the overinvestment could represent asking for too much collateral to gain seniority.

The term θ is smaller than one and leads to underinvestment. The reason is that borrowers are less likely to benefit from the continuation value of the card as they are likely to default, so lenders have fewer incentives to invest.

Equation 10 shows the effect of non-exclusive contracts, and thus higher default on credit limits. As borrowers get a number of cards equal to the number of lenders, I calculate the borrower i total amount of lending. This allows me to compare it with the exclusive contract case:

$$L^* := \sum_{b=1}^{B} L_b^* = \frac{W - c(\iota_b^*)}{mc(\theta^*)} - B\varepsilon^{-1} \tag{12}$$

Equation (12) highlights the three channels that are affecting the loan size relative to the exclusive contract case.

First, with exclusive contracts, the cost of lending increases $mc(\theta^*)$. This effect tends to increase the break-even rate and thus decrease the equilibrium loan size. This is the first source of inefficiency: Because the default is not too costly for borrowers when they own multiple cards, there is debt dilution in equilibrium, leading to too much default.[8]

Second, exclusive contracts distort incentives to invest. When there is overinvestment, the cost of lending increases (i.e., $c(\iota^*) > 0$ is higher than in the non-exclusive case), pushing the credit limit down. When there is underinvestment, the opposite happens. These results imply that looking only at the impact on credit limits to draw conclusions about welfare can be misleading.

Third, lenders set a markup ε^{-1} for each additional card, lowering the loan size of each card. This effect adds up to the number of cards. Imperfect competition thus becomes even more costly under non-exclusive contracts.

6 Conclusion

Access to credit has been growing, particularly in emerging economies, with credit cards playing a key role in this expansion. In this paper, we highlight that these contracts are non-exclusive and that borrowers tend to prioritize certain banks over others. While borrowing from multiple lenders may reflect increased competition and greater access to loan products, it also presents challenges, as externalities between lenders can lead to inefficiencies. Banks may respond to it by competing for priority. We study these market inefficiencies through the lens of a model and discuss policies that could mitigate them.

[8]The assumption that $\alpha > mc(\theta^*)$ ensures that lending is still positive NPV. This allows the equilibrium to exist for an arbitrary number of lenders.

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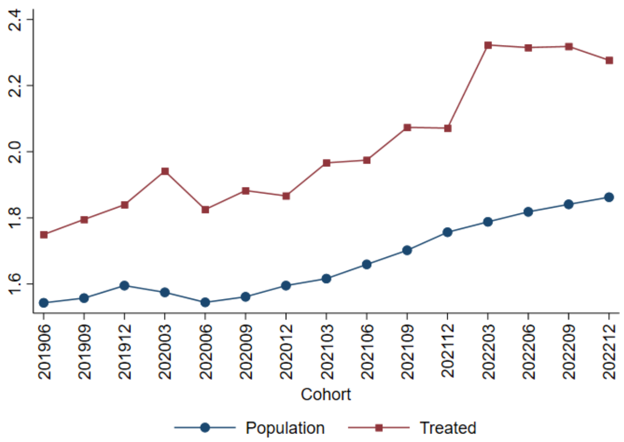
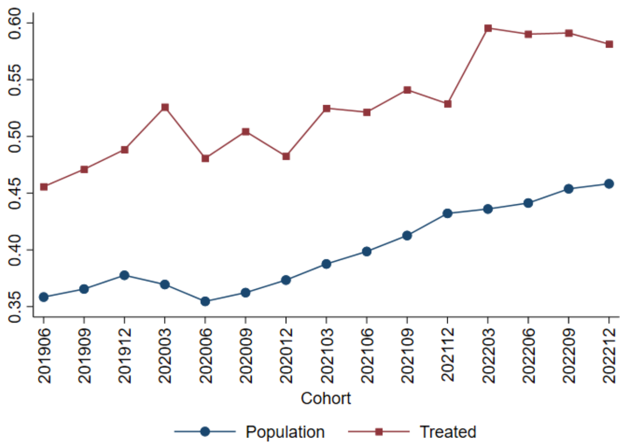
Figures

Figure 1: Evolution of borrowing from multiple card lenders



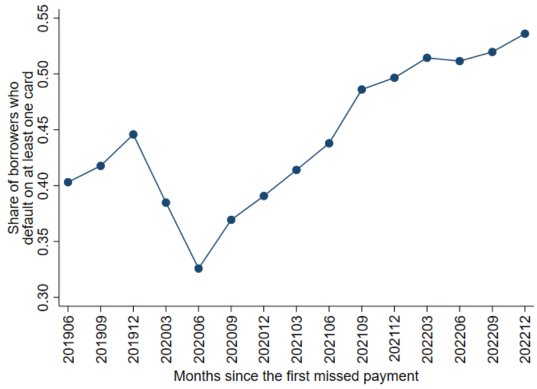
(**a**) Average number of credit card lenders



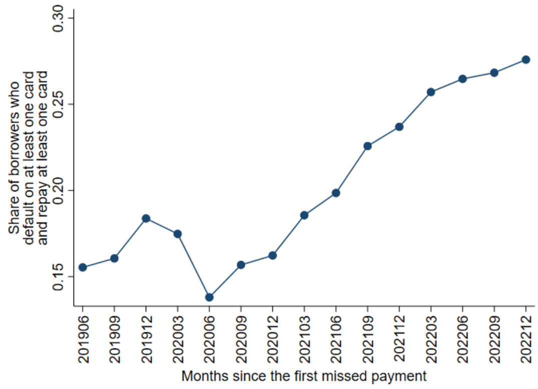
(**b**) Share of card borrowers with two or more credit card lenders

Notes: Data at the borrower-cohort level. We compute population averages using inverse probability weighting.

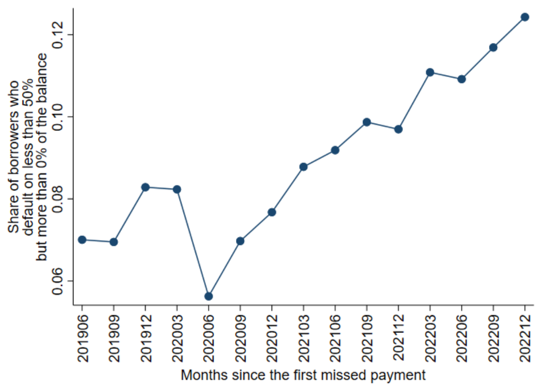
Figure 2: Default and selective default evolution



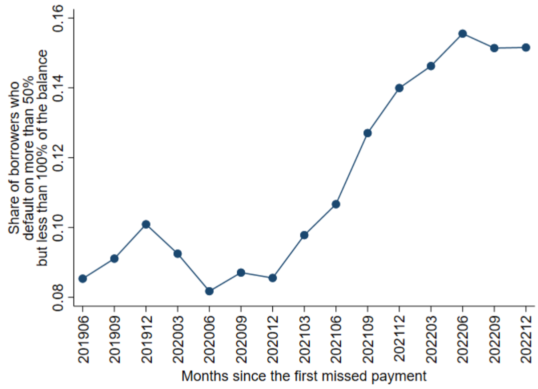
(**a**) Share of treated borrowers with at least one card 90+ days overdue



(**b**) Share of treated borrowers with at least one card 90+ days overdue and at least one in good standing



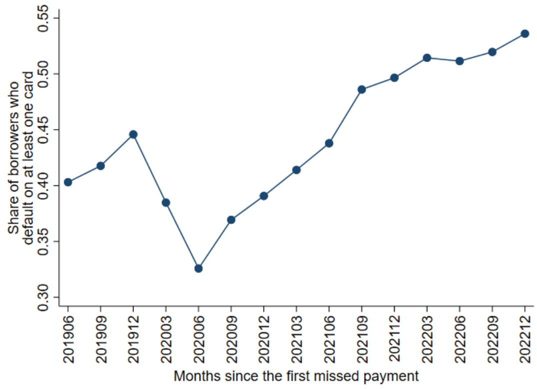
(**c**) Share of treated borrowers with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance



(**d**) Percentage of treated borrowers with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample is comprised of individuals in the treated group who have one or more cards. We classify a card as in default if there is balance overdue for more than 90 days six months after the borrower becomes more than 30 days overdue.

Figure 3: Default and selective default evolution



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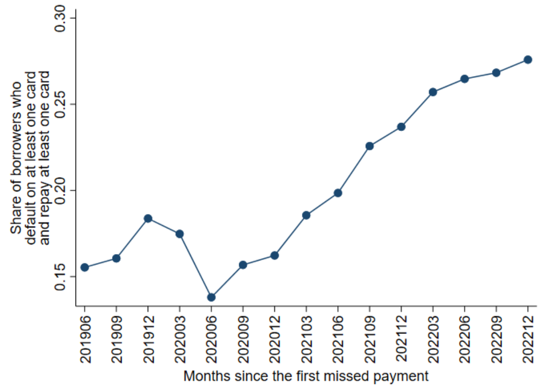
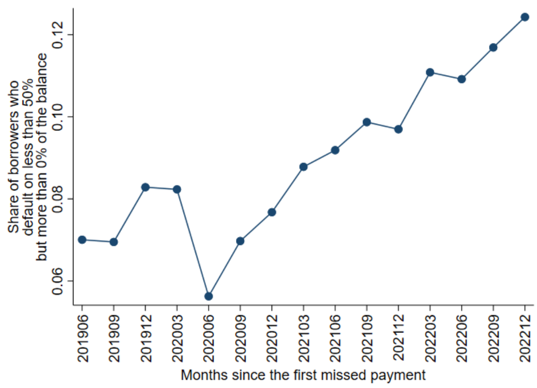
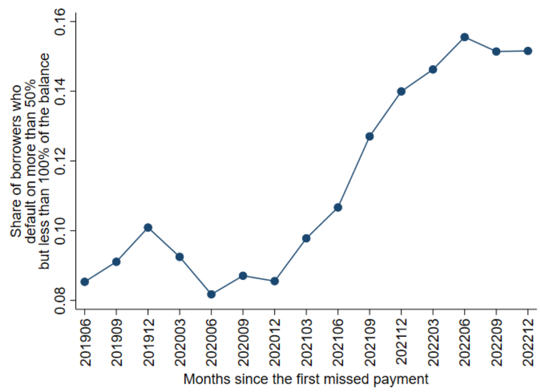


(**b**) Share of treated borrowers with at least one card 90+ days overdue and at least one in good standing



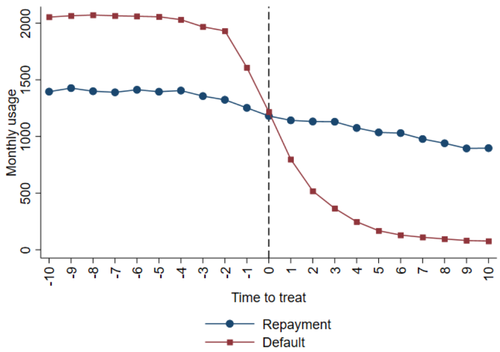
(**c**) Share of treated borrowers with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance



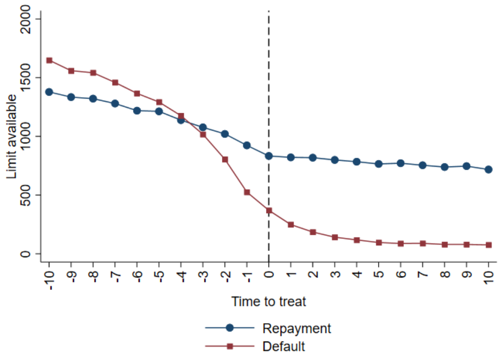
(**d**) Percentage of treated borrowers with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample is comprised of individuals in the treated group who have one or more cards. We classify a card as in default if there is balance overdue for more than 90 days six months after the borrower becomes more than 30 days overdue.

Figure 4: Evolution of the limit and card usage, cards repaid versus not repaid of selective defaulters



(**a**) Card monthly usage, card pair versus not repaid of selective defaulters



(**b**) Limit available, card pair versus not repaid of selective defaulters

Notes: The sample is comprised of individuals in the treated group who repay at least one card and default on at least one. Month 0 is the month when borrowers first miss a payment.

Tables

Table 1: Average number of relationships

	Number of credit relationships				Dummy
	Banks	Cards	Digital banks	State-owned banks	2+ cards
201906	2.61	1.54	0.14	0.46	0.36
201909	2.63	1.56	0.17	0.46	0.37
201912	2.67	1.60	0.18	0.46	0.38
202003	2.65	1.57	0.18	0.46	0.37
202006	2.64	1.54	0.20	0.47	0.35
202009	2.64	1.56	0.22	0.47	0.36
202012	2.69	1.60	0.26	0.47	0.37
202103	2.74	1.62	0.30	0.47	0.39
202106	2.79	1.66	0.40	0.46	0.4
202109	2.84	1.70	0.47	0.47	0.41
202112	2.90	1.76	0.52	0.48	0.43
202203	2.99	1.79	0.62	0.48	0.44
202206	3.04	1.82	0.67	0.51	0.44
202209	3.10	1.84	0.73	0.53	0.45
202212	3.14	1.86	0.79	0.54	0.46

Notes: Data at the borrower-cohort level. We compute population averages using inverse probability weighting. Bank relationships refer to relationships with an active loan. Card relationships refer to the number of active credit card lenders. Digital banks refer to banks that operate without physical branches or agents. State-woned banks refer to banks owned by the federal or state governments.

Table 2: Mean of selected variables by number of credit card lenders

	Number of card lenders					
	1	2	3	4	5	6+
Panel A: Random sample (population)						
Wage (formal)	3,757	4,124	4,171	3,812	3,841	3,920
Wage (reported)	3,214	3,704	3,766	3,607	3,737	3,663
Debt service to income	0.18	0.27	0.38	0.48	0.59	0.85
Formal sector	0.36	0.43	0.46	0.46	0.47	0.47
Age	45	44	44	44	43	41
Total balance card	2,631	5,386	7,985	10,300	13,335	20,069
Average limit utilization (%)	54	55	58	61	64	69
Share cards 100% utilization	0.22	0.22	0.24	0.26	0.29	0.34
Total card limit available	5,129	9,247	11,206	11,793	12,688	13,086
Dummy auto loan	0.07	0.12	0.16	0.20	0.24	0.26
Dummy mortgage	0.06	0.09	0.10	0.11	0.11	0.11
Dummy other loans	0.27	0.35	0.43	0.48	0.53	0.60
Dummy payroll loan	0.17	0.21	0.23	0.26	0.26	0.25
Dummy personal loan	0.14	0.20	0.27	0.34	0.42	0.53
Panel B: Treated sample						
Wage (formal)	2,151	2,943	3,320	3,399	3,548	3,396
Wage (reported)	2,121	2,778	3,054	3,159	3,272	3,374
Debt service ratio	0.26	0.41	0.54	0.65	0.77	1.00
Formal sector	0.29	0.38	0.42	0.44	0.44	0.45
Age	39	42	42	42	42	41
Total balance card	1,558	4,234	6,950	9,702	12,621	19,724
Average limit utilization (%)	83	77	75	76	76	78
Share cards 100% utilization	0.74	0.53	0.47	0.45	0.44	0.45
Total card limit available	548	2,431	3,901	4,639	5,233	6,271
Dummy auto loan	0.06	0.11	0.16	0.20	0.22	0.24
Dummy mortgage	0.03	0.06	0.08	0.09	0.10	0.11
Dummy other loans	0.35	0.45	0.52	0.57	0.63	0.69
Dummy payroll loan	0.12	0.22	0.25	0.26	0.28	0.26
Dummy personal loan	0.21	0.30	0.36	0.43	0.48	0.59

Notes: Data at the borrower-cohort level. In Panel A, we compute population averages using inverse probability weighting. In Panel B, we compute sample means for the treated group. Wage (formal) refers to wages recorded in administrative data (RAIS) and only available for workers employed in formal jobs. Wage (reported) refers to wages reported by banks. Formal sector is a dummy that takes the value 1 if the individual has a formal job. Debt service to income is the ratio of debt payments to income. All monetary amounts are in Brazilian reais (BRL).

Table 3: Default rates by number of cards, treated sample

Number of card lenders	Shares					
	Repay all cards	Default on at least one card	Default on all cards	Selective: Borrower defaults on card with		
				Largest balance	Smallest balance	Total
1	0.57	0.43	0.43	-	-	-
2	0.55	0.45	0.11	0.20	0.13	0.34
3	0.53	0.47	0.05	0.22	0.19	0.41
4	0.51	0.49	0.04	0.23	0.22	0.45
5	0.46	0.54	0.03	0.25	0.26	0.51
6+	0.36	0.64	0.02	0.35	0.27	0.62
Total	0.54	0.46	0.24	0.12	0.09	0.21

Notes: Data at the borrower-cohort level. Selective means that the borrower defaults on at least one card while repaying at least one other card. Selective largest balance means that borrowers defaulted on the cards that accounted for more than 50% of their total card balance measured in the month when they missed a payment. Selective smallest balance means that borrowers defaulted on the cards that accounted for less than 50% of their total card balance measured in the month when they missed a payment.

Table 4: Mean of selected variables by default category

	No	Selective		Universal
	default	Largest balance	Smallest balance	default
Number of banks	4.1	4.6	4.8	3.6
Number of card lenders	2.9	3.2	3.3	2.4
Number of digital banks	0.6	1.0	0.9	0.7
Share card balance digital banks	0.15	0.15	0.17	0.16
Number of state-owned banks	0.6	0.7	0.7	0.6
Wage (formal)	3,559	2,735	3,083	2,245
Wage (reported)	3,203	2,719	2,855	2,365
Debt service to income	0.46	0.68	0.56	0.48
Formal job	0.42	0.40	0.41	0.29
Age	43	39	42	36
Dummy payroll loan	0.25	0.20	0.29	0.12
Dummy mortgage	0.08	0.07	0.08	0.05
Dummy auto loan	0.15	0.15	0.14	0.10
Dummy personal loan	0.31	0.42	0.41	0.36
Dummy other loan types	0.50	0.55	0.53	0.46
Dummy default payroll loan	0.01	0.01	0.01	0.01
Dummy default mortgage	0.00	0.00	0.00	0.00
Dummy default auto loan	0.00	0.01	0.01	0.01
Dummy personal loan default	0.02	0.03	0.04	0.03
Dummy other loan types	0.03	0.05	0.04	0.04
Total card balance	6,432	9,166	7,279	5,295
Total credit balance	38,455	35,735	37,930	20,201
Age bank relationship (years)	8.1	6.2	6.8	4.8

Notes: Data at the borrower-cohort level for the sample of treated individuals with two or more card lenders. Selective means that the borrower defaults on at least one card while repaying at least one other card. Selective largest balance means that borrowers defaulted on the cards that accounted for more than 50% of their total card balance measured in the month when they missed a payment. Selective smallest balance means that borrowers defaulted on the cards that accounted for less than 50% of their total card balance measured in the month when they missed a payment. Wage (formal) refers to wages recorded in administrative data (RAIS) and only available for workers employed in formal jobs. Wage (reported) refers to wages reported by banks. Formal sector is a dummy that takes the value 1 if the individual has a formal job. Debt service to income is the ratio of debt payments to income. All monetary amounts are in Brazilian reais (BRL).

Table 5: Descriptive statistics of regression variables

	Mean	SD	p25	p50	p75	N
Default	0.45	0.5	0	0	1	174,893
Positive global limit available	0.16	0.37	0	0	0	174,893
Limit utilization 50% - 60%	0.02	0.15	0	0	0	174,893
Limit utilization 60% - 70%	0.02	0.15	0	0	0	174,893
Limit utilization 70% - 80%	0.03	0.17	0	0	0	174,893
Limit utilization 80% - 90%	0.03	0.18	0	0	0	174,893
Limit utilization 90% - 100%	0.11	0.31	0	0	0	174,893
Limit utilization 100%	0.69	0.46	0	1	1	174,893
Digital bank	0.23	0.42	0	0	0	174,893
State-owned bank	0.11	0.31	0	0	0	174,893
Payroll loan	0.06	0.23	0	0	0	174,893
Mortgage	0.01	0.1	0	0	0	174,893
Auto loan	0.02	0.14	0	0	0	174,893
Personal loan	0.12	0.32	0	0	0	174,893
Other loan types	0.16	0.37	0	0	0	174,893
Default payroll loan	0	0.03	0	0	0	174,893
Default mortgage	0	0.01	0	0	0	174,893
Default auto loan	0	0.03	0	0	0	174,893
Default personal loan	0.01	0.07	0	0	0	174,893
Default other loan types	0.01	0.08	0	0	0	174,893
Positive card limit	0.31	0.46	0	0	1	174,893
Largest positive card limit available	0.16	0.36	0	0	0	174,893
Largest card balance	0.31	0.46	0	0	1	174,893
2nd largest positive card limit available	0.08	0.28	0	0	0	174,893
2nd largest card balance	0.31	0.46	0	0	1	174,893

Notes: Data at the borrower-bank-cohort level for the sample of treated individuals with two or more card lenders and that default on a subset of their cards. All variables are binary.

Table 6: Predictors of selective default

	(1)	(2)	(3)	(4)	(5)	(6)
	Selective		Selective: less than 50%		Selective: more than 50%	
	All cohorts	Post May 2021	All cohorts	Post May 2021	All cohorts	Post May 2021
Limit utilization 50% - 60%	0.06***	0.06***	0.02	0.02	0.10***	0.11***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Limit utilization 60% - 70%	0.06***	0.06***	0.02	0.02	0.12***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Limit utilization 70% - 80%	0.07***	0.08***	0.03**	0.03**	0.12***	0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Limit utilization 80% - 90%	0.11***	0.12***	0.04***	0.04***	0.17***	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Limit utilization 90% - 100%	0.13***	0.13***	0.07***	0.06***	0.16***	0.18***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Limit utilization 100%	0.40***	0.41***	0.35***	0.34***	0.34***	0.37***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Positive global limit	-0.33***	-0.24***	-0.23***	-0.18***	-0.18***	-0.16***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Digital bank	-0.18***	-0.14***	-0.12***	-0.08***	-0.15***	-0.14***
	(0.00)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)
State-owned bank	0.14***	0.13***	0.13***	0.11***	0.05***	0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Payroll loan	-0.06***	-0.07***	-0.04***	-0.05***	-0.04***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mortgage	-0.12***	-0.14***	-0.09**	-0.10*	0.02	0.01
	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.05)
Mortgage x state-owned bank	0.29***	0.24***	0.25***	0.22***	0.07	0.03
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)	(0.05)
Auto loan	-0.05***	-0.05***	-0.04***	-0.05***	-0.06***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)
Personal loan	0.04***	0.03***	0.00	-0.01	0.04***	0.04***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Other loans	-0.08***	-0.07***	-0.04***	-0.04***	-0.09***	-0.09***
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)
Default payroll	0.17***	0.17***	0.23***	0.23***	0.04	0.09
	(0.05)	(0.06)	(0.06)	(0.08)	(0.05)	(0.06)
Default mortgage	0.12	0.21	0.21	0.39	0.10	0.66***
	(0.20)	(0.32)	(0.22)	(0.26)	(0.23)	(0.07)
Default auto loan	0.12*	0.07	0.13	0.05	0.12**	0.11
	(0.06)	(0.08)	(0.08)	(0.10)	(0.05)	(0.07)
Default personal loan	0.21***	0.21***	0.20***	0.21***	0.05**	0.06**
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.03)
Default other loans	0.12***	0.06**	0.13***	0.10**	0.03	0.01
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)	(0.02)
Largest limit available	-0.05***	-0.04***	0.03***	0.03***	0.02**	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
2nd largest limit available	-0.02***	-0.02**	-0.00	-0.00	0.01	0.01
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Largest card balance	0.16***	0.15***	-0.33***	-0.32***	0.62***	0.57***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.01)
2nd largest card balance	0.06***	0.06***	0.20***	0.19***	-0.01***	-0.01**
	(0.00)	(0.00)	(0.01)	(0.01)	(0.00)	(0.00)
Constant	0.18***	0.19***	0.20***	0.21***	0.14***	0.16***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Observations	174,893	120,962	78,021	52,594	96,872	68,368
R-squared	0.277	0.290	0.376	0.359	0.564	0.531

Notes: The sample is comprised of treated borrowers who have two or more credit card lenders, default on at least one card, and repay at least one card. The data are at the borrower-cohort-bank level. All variables are binary. All regressions include borrower-cohort fixed effects. Robust standard errors are reported in parentheses. Selective less than 50% means that borrowers defaulted on the cards that accounted for less than 50% of their total card balance measured in the month when they missed a payment. Selective more than 50% means that borrowers defaulted on the cards that accounted for more than 50% of their total card balance measured in the month when they missed a payment.

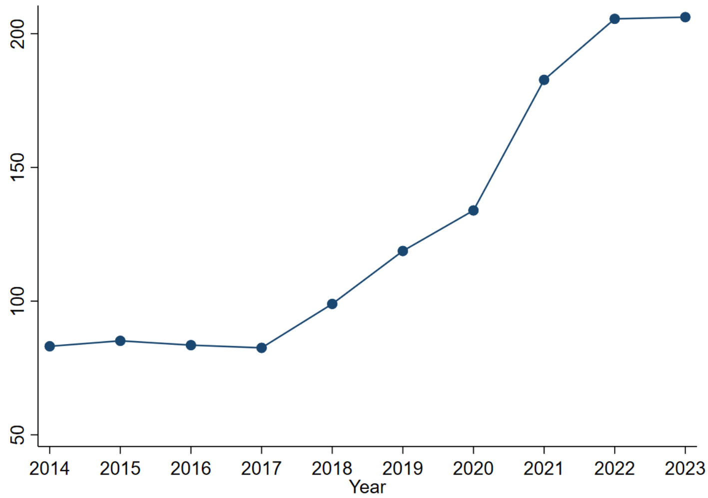
Online Appendix

Contents

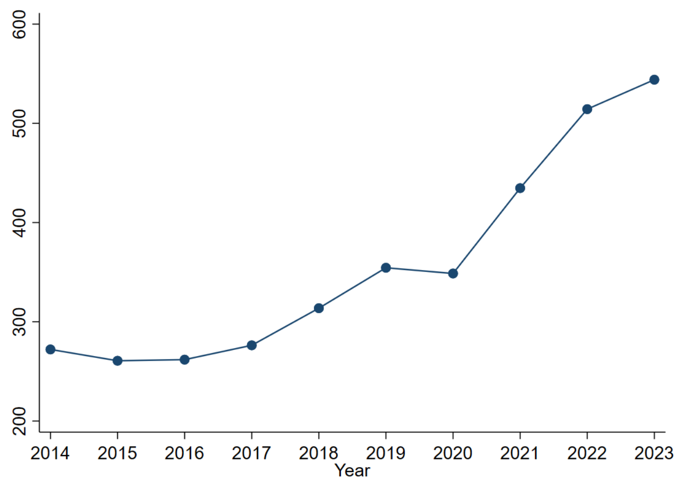
A Empirical part

A1 Institutional setting: additional details from aggregate data

Figure A1: Evolution of number of credit cards and credit card balance



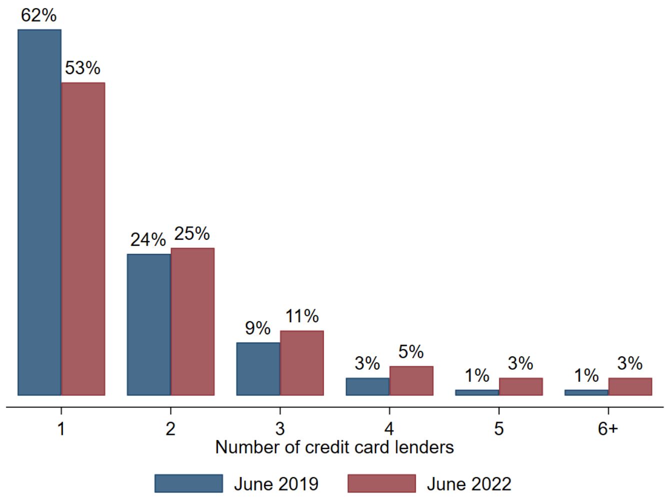
(**a**) Total number of active credit cards (in millions)



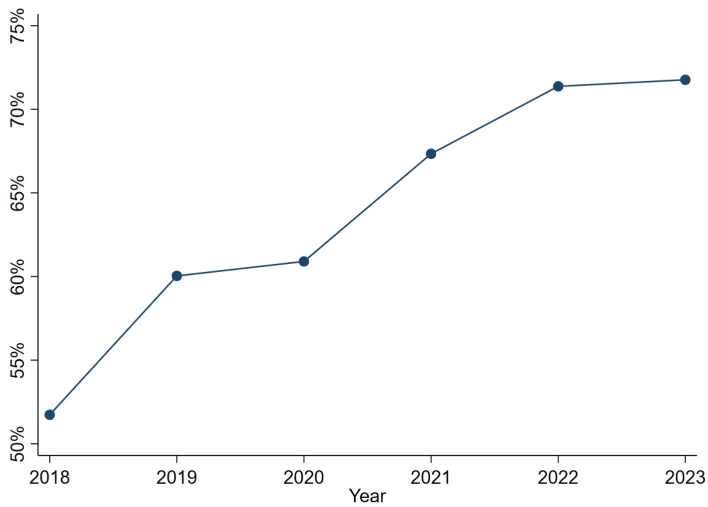
(**b**) Total credit card loans (inflation-adjusted values in billions BRL)

Notes: Total number of active cards and credit cards outstanding balance per year. Monetary quantities are in 2023 values, adjusted by the consumer price index (IPCA). Source: Central Bank of Brazil (*Estatísticas de Meios de Pagamentos* and IF.data).

Figure A2: Evolution of borrowers with more than one card lender



(**a**) Share of card users by number of credit card lenders, 2019 and 2022



(**b**) Share of total credit card balance held by borrowers with multiple card lenders

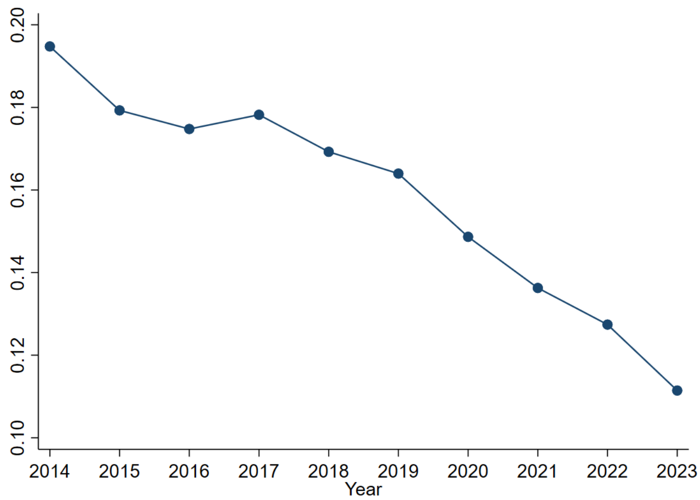
Notes: Computed based on figures from Central Bank of Brazil (2022).

Table A1: Number of credit card users per institution type

	June 2019	June 2022	Growth
Five largest banks (branch-based)	51.0	57.7	13%
Other banks and retailers	19.5	22.7	16%
Digital banks	8.9	36.5	310%
Credit unions	2.0	3.6	80%
Total	81.4	120.5	

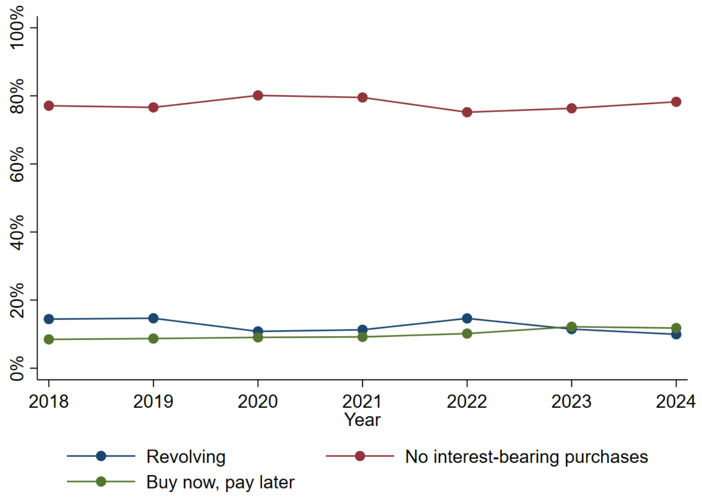
Note: Categories are not mutually exclusive. One individual can have accounts in more than one institution type. Source: Central Bank of Brazil (2022).

Figure A3: Herfindahl–Hirschman index: credit card loans

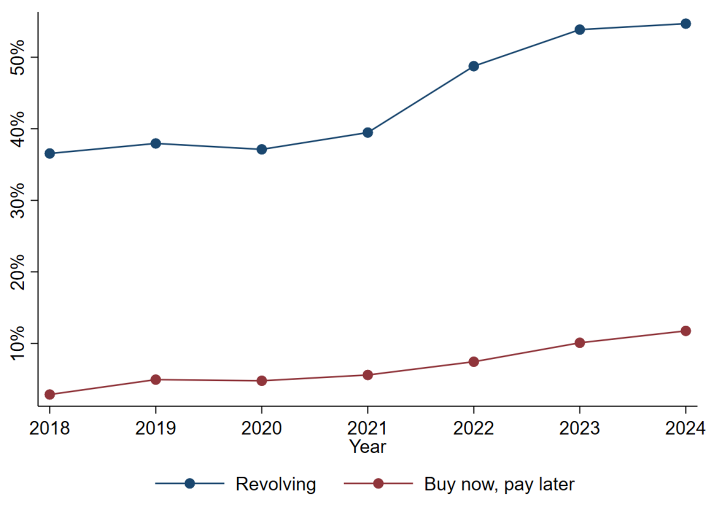


Notes: We calculate the Herfindahl–Hirschman Index (HHI) for the Brazilian banking sector based on the shares of each bank in the credit card loan market. Source: Central Bank of Brazil (IF.data).

Figure A4: Composition of credit card balance



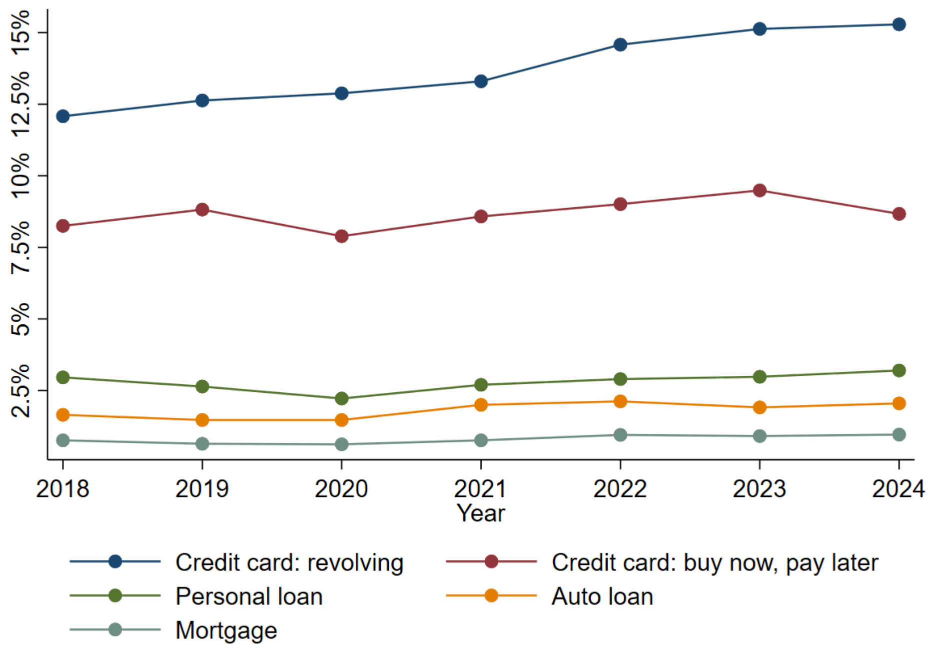
(**a**) Composition of credit card balance



(**b**) Share of total balance in default

Notes: Balance in default refers to payments that are more than 90 days overdue. Source: Central Bank of Brazil, Time Series Management System.

Figure A5: Monthly interest rate of different household loan types



Notes: Data from the Central Bank of Brazil, Time Series Management System.

A2 Sample characteristics

Table A2: Sampling procedure for cohort t

	Repayment standing at $t-1$	Repayment standing at t	Share sampled
Treated	Good	Bad	1%
Control	Good	Good	0.025%
Control	Bad	Good	
Control	Bad	Bad	

Notes: Good repayment standing means that all cards are with a maximum delay of 15 days. Bad repayment standing means that at least one card is overdue for more than 15 days. The sample is taken at time t at the individual level, conditional on the individual having at least one active card.

Table A3: Default and delinquency incidence at $t-1$ (month before the cohort)

	Control		Treated	
	Card level	Borrower level	Card level	Borrower level
Panel A: All card users				
Delinquency rate	10.3	13.2	0	0
Default rate	7.0	9.2	0	0
Panel B: Card users with 2+ cards				
Delinquency rate	10.4	17.6	0	0
Default rate	7.0	12.2	0	0

Notes: A credit card loan is delinquent (in default) if it is more than 15 (90) days overdue. A borrower is delinquent (in default) if at least one card is more than 15 (90) days overdue.

Table A4: Sample evolution

Cohort	Treated 0	Treated 1	Total
201906	15,799	15,186	30,985
201909	16,186	15,435	31,621
201912	16,476	13,348	29,824
202003	16,469	18,293	34,762
202006	16,390	10,128	26,518
202009	16,514	10,323	26,837
202012	16,931	11,281	28,212
202103	17,047	17,696	34,743
202106	18,025	15,804	33,829
202109	18,726	17,780	36,506
202112	19,668	22,750	42,418
202203	20,130	22,817	42,947
202206	20,667	20,407	41,074
202209	21,125	21,499	42,624
202212	21,536	20,097	41,633
Total	271,689	252,844	524,533

Notes: Number of cohort-individual observations per cohort and treatment status.

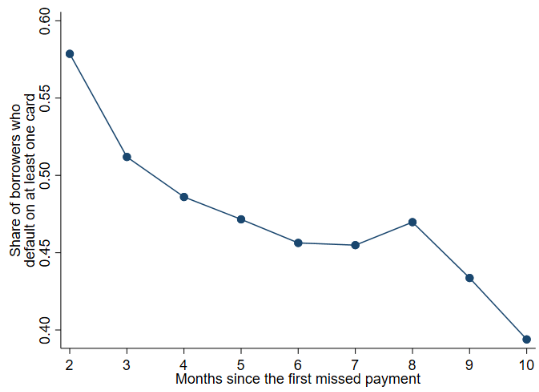
Table A5: Size of groups based on the number of credit card lenders

	Treated		
	0	1	Total
Panel A: Number of card lenders			
1	163,114	117,788	280,902
2	65,961	68,462	134,423
3	25,363	34,509	59,872
4	9,908	16,432	26,340
5	4,033	7,793	11,826
6+	3,310	7,860	11,170
Total	271,689	252,844	524,533
Panel B: Number of lenders (any credit product)			
1	67,315	50,114	117,429
2	76,590	61,671	138,261
3	54,925	50,677	105,602
4	32,640	35,274	67,914
5	18,417	22,121	40,538
6+	21,802	32,987	54,789
Total	271,689	252,844	524,533

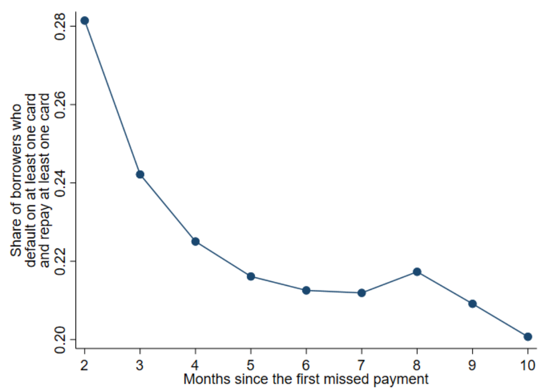
Notes: Borrowers are categorized based on the number of credit card lenders and the total number of lenders (across all products). Data at the borrower-cohort level.

A3 Default and selective default evolution t months after becoming 30+ day overdue

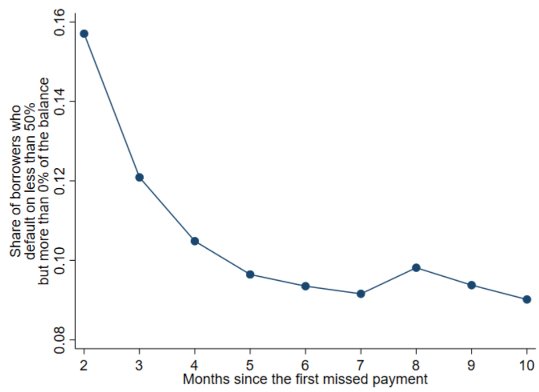
Figure A6: Default and selective default evolution t months after becoming 30+ day overdue



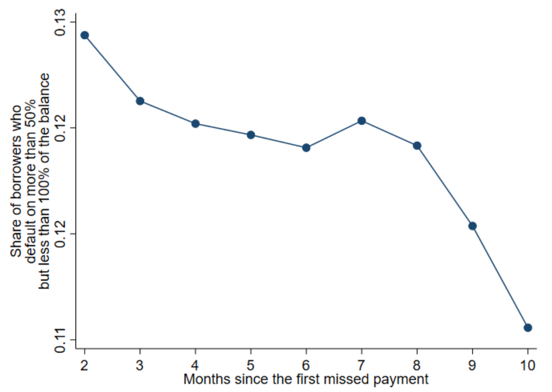
(**a**) Share of treated borrowers with at least one card 90+ days overdue



(**b**) Share of treated borrowers with at least one card 90+ days overdue and at least one in good standing

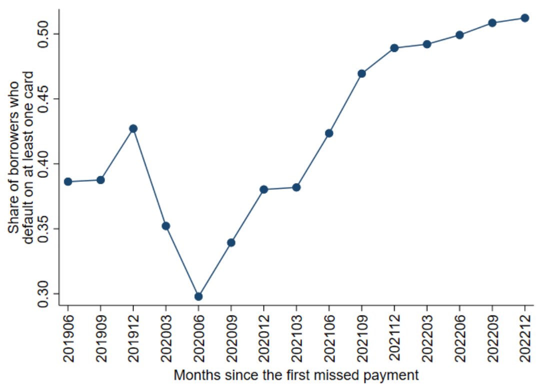


(**c**) Share of treated borrowers with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance

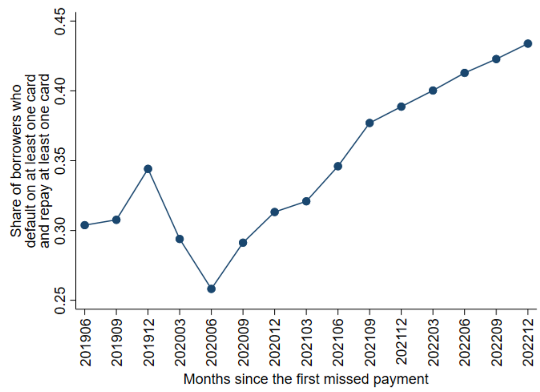


(**d**) Percentage of treated borrowers with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

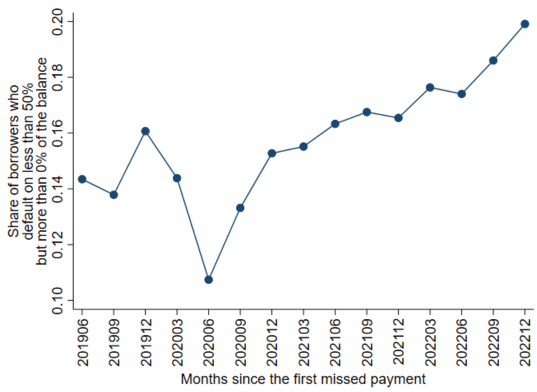
Figure A7: Default and selective default evolution, borrowers with at least two cards



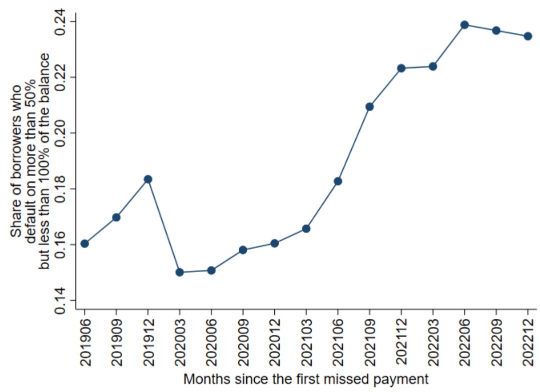
(**a**) Share of treated borrowers with at least one card 90+ days overdue



(**b**) Share of treated borrowers with at least one card 90+ days overdue and at least one in good standing



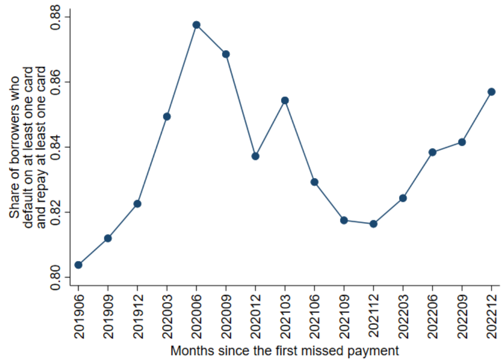
(**c**) Share of treated borrowers with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance



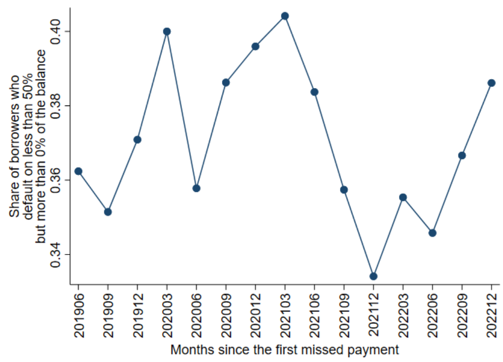
(**d**) Percentage of treated borrowers with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample is comprised of individuals in the treated group who have two or more cards. We classify a card as in default if there is balance overdue for more than 90 days six months after the borrower becomes more than 30 days overdue.

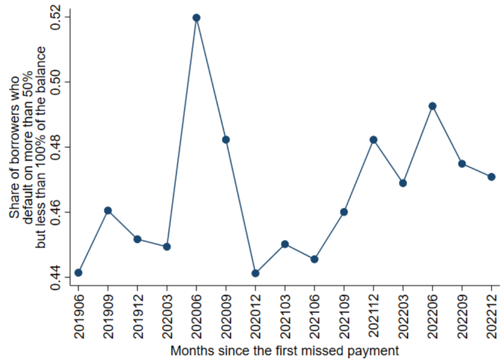
Figure A8: Default and selective default evolution, borrowers with at least two cards, conditional on defaulting on at least one card



(**a**) Share of treated borrowers with at least one card 90+ days overdue and at least one in good standing



(**b**) Share of treated borrowers with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance



(**c**) Percentage of treated borrowers with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample is comprised of individuals in the treated group who have two or more cards and that default on at least one card. We classify a card as in default if there is balance overdue for more than 90 days six months after the borrower becomes more than 30 days overdue.

A4 Share of balance in default among selective defaulters

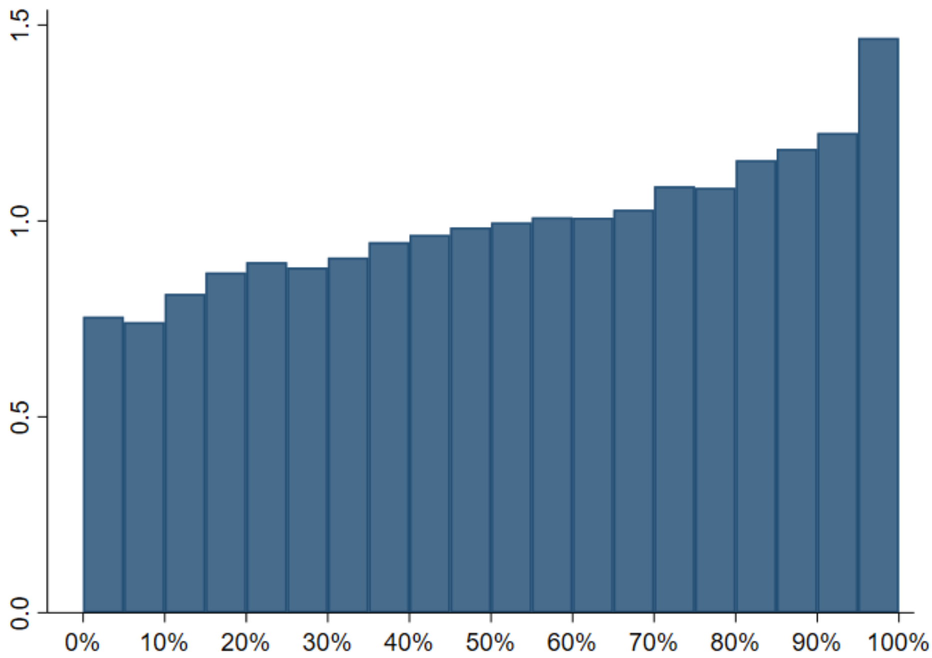


Figure A9: Share of balance in default

Notes: This figure plots the distribution of the share of total balance in default among selective defaulters. We measure default as payment more than 90 days overdue six months after the cohort month. We compute the shares using the balances at the cohort month.

B Proofs

A1 Proof exclusive contracts equilibrium

With assumption A1, default is not optimal. In addition, A1 also implies that it is optimal to max out the borrower's borrowing capacity (i.e., $R = W$). To see this, one can use the change of variable $R = \alpha L - u + V_c(\iota)$, and allow the lender to choose (u, L, ι). The first-order condition with respect to L is always positive, so we must be at a corner solution.

Using the change of variable $L = \frac{u - V_c(\iota)}{\alpha}$ where u is the borrower utility, the lender problem is:

$$\max_{u,\iota} D(u)[W - \frac{mc}{\alpha}[u - \beta V_c(\iota)]] - c(\iota)] \tag{13}$$

The first-order conditions with respect to u and ι yield the equations 6 and 7.

A2 Proof non-exclusive contracts equilibrium

With assumption A2, the borrower chooses to repay only one card. The borrower's utility is thus:

$$u := \sum_c L_c + \beta \sum_c \theta_c(V(\iota))[W - R_c + V_c(c) - E[\varepsilon_{ir}|\mathcal{R} = c]] \tag{14}$$

Where $V(\iota) := (V_c(\iota_c))_c$.

As in proof A1, we have $R = W$. The maximization problem is thus:

$$\max_{u,\iota} D(u)[\theta_c(V(\iota))W - \frac{mc}{\alpha}[u - \beta \sum_d \theta_d((V(\iota))V_d(\iota_d)]] - c(\iota)] \tag{15}$$

The first order conditions with respect to ι yield:

$$V_c(\iota_c)'\theta_c'(V(\iota))W + \frac{mc\beta}{\alpha}\theta_c V_c'(\iota_c) = c'(\iota) \tag{16}$$

I used the fact that $\sum_d \theta'_d[V_d + E[\varepsilon]] = 0$ in a symmetric equilibrium.

For simplicity, I also assumed that lenders do not internalize the effect of ι on capital requirements. The rationale is that the government sets capital requirements, and those are taken as given by the lender.