Competing for Loan Informal Seniority: Theory and Evidence*

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Abstract

Using administrative data covering the universe of retail loans in Brazil, we document two facts that challenge standard models of debt dilution. First, universal default is rare: 84% of borrowers who default on one credit card continue to repay other cards. Second, borrowers systematically prioritize repayment, favoring cards with higher credit limits, lower interest rates, or bundled with other products. Motivated by these facts, we develop a model of non-exclusive lending in which lenders compete for repayment priority through contract terms and cross-selling. This competition alters equilibrium contracts and implies that equal-recovery bankruptcy policies may reduce welfare. Our back-of-the-envelope calculation implies that the credit limit one year after origination are lower by by 7% relative to the first best. Imposing equal recovery would eliminate the overprovision channel and thus lower credit limits by 2.5%.

Keywords: debt dilution, non-exclusive contracts, selective default, bankruptcy law
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1 Introduction

Individuals frequently hold multiple credit cards, student loans, mortgages, or auto loans, often financed by different lenders. On the one hand, such borrowing patterns may reflect financial flexibility: borrowers are not locked into past choices and can shop across institutions for more attractive products. On the other hand, non-exclusive lending can give rise to debt dilution: by originating new loans, lenders may impose a default externality on their competitors, as additional borrowing can affect a borrower's ability and incentives to repay existing obligations held by other institutions (e.g., Bizer and DeMarzo, 1992; Green and Liu, 2021).

Although the importance of debt dilution is well established in corporate finance theory, little is known about its empirical relevance or how it operates in the retail market. A key obstacle to studying non-exclusive lending in this context is data availability: the vast majority of credit registers for retail loans—such as, for instance, the Federal Reserve Board's FR Y-14M dataset—use a different borrower identifier for different loan types issued by different lenders. As a result, it is often impossible to use credit registers to reconstruct a customer's loan portfolio.

To the best of our knowledge, this paper is the first to analyse, both empirically and theoretically, how non-exclusive lending affects default decisions, contract terms, and welfare in the retail loan market. Our analysis leverages administrative data from the Central Bank of Brazil. Unlike the vast majority of credit registries, we observe all loans held by a given borrower across all financial institutions, including mortgages, car loans, consumer loans, and credit cards.

Using these administrative records, we reconstruct each borrower's complete loan portfolio and document new facts about repayment behavior. We first show that, contrary to what has been assumed in theoretical models developed for the corporate loans market, borrowers in financial distress do not default on all their debt. For instance, in 76% of cases, borrowers with two active credit cards default only on one of them. Second, we show that borrowers prioritize repaying loans with more favorable terms:

selective defaulters are more likely to continue repaying cards with higher available credit limits, lower interest rates, those originated by digital banks, and those issued by lenders that also provide other financial products. We refer to the loan being prioritized relative to others as having informal seniority.

Our empirical findings challenge a central assumption in theoretical models of debt dilution, namely that borrowers default universally across their obligations (e.g., Bizer and DeMarzo, 1992; Green and Liu, 2021). To study the implications of informal seniority, we develop a model with non-exclusive contracts in which lenders prioritize repaying loans with more favourable terms. In the model, lenders impose default externalities on their competitors through two distinct channels. The first operates through leverage: originating a new loan increases overall indebtedness and raises default probabilities on all outstanding loans. The second operates through repayment prioritisation: issuing a new loan affects which obligations the borrower chooses to repay. We show that distinguishing between these channels is important, as they generate different positive and normative implications.

The key insight of our model is as follows. We study an environment in which lenders can pay a cost to increase customers' continuation value from repaying credit card debt. In the baseline model, we interpret these relationship benefits as improving the quality of the mobile application or the cerdit card reward system; but our results also extend to settings in which the investment takes the form of cross-selling or offering more favourable credit card terms (credit limits and interest rates) in the future. Following the industrial organisation literature, we refer to such investments as investments in credit card quality or investment in relationship benefits.[1]

We show that there can be over- or underprovision of relationship benefits relative to the first-best due to two opposing forces. First, the standard debt dilution channel implies underprovision. Due to the default externality, lenders expect borrowers to leverage too much relative to the first-best, and thus to default too frequently.[2] Holding

[1] See, for instance, Berry and Waldfogel (2010).

[2] As in Bizer and DeMarzo (1992), a lender internalizes that originating a new loan increases the borrower's default probability on its own loan, but does not internalize the impact on the default probabilities of loans held by other lenders.

default probabilities fixed, this reduces the expected duration of the lending relationship and thus the marginal benefit of relationship benefits for the borrower, thereby weakening incentives to invest in card quality. Second, competition for repayment priority leads to overprovision. When borrowers prioritize repaying the loan with the highest continuation value, each lender has incentives to invest more than their competitors. This competition can lead to an arms race, resulting in overprovision of relationship benefits. Depending on which force dominates, the distortions in card quality implies that credit cards are either too cheap or too expensive to originate, resulting in a credit limit that is either too high or too low at origination.

In that set-up, we show that standard bankruptcy regulations can reduce welfare. For instance, by imposing the same recovery rate on non-performing loans, the regulator cancels the overprovision channel. This can reduce welfare when this channel is mild relative to the underinvestment channel. In practice, the strength of the overprovision channel depends on the default sensitivities to relationship benefits, while the underprovision channel depends on the equilibrium average default probability in the data relative to the first-best. Using our model together with our empirical estimates, a back-of-the-envelope calculation implies that the relationship benefits (in our quantification, the crtedit limit one year after origination) are lower by by 7% relative to the first best. The underprovision channel dominates and lower credit limits by 9.5%, the overprovision partially mitigates it by increasing it by 2.5%. Imposing equal recovery would eliminate the overprovision channel and thus lower credit limits by 2.5%.

We begin our empirical analysis by documenting three facts suggesting that debt dilution is a first-order force in the credit card market. First, multi-lender borrowing is pervasive: among 85 million credit card users in June 2022, 39.4 million (46.5%) maintained active cards issued by two or more institutions, collectively accounting for over 70% of the total outstanding credit card balance. Second, borrowing through credit cards is common. Approximately 20% of monthly credit card purchases are not repaid at the end of the month due to revolving balances and card-linked buy-now-pay-later

arrangements.[3] Finally, default rates are high: during the sample period, 9% of credit card borrowers default on at least one card, defined as failing to make the minimum payment for 90 days or more.

We then derive new facts about repayment behavior in the credit card market. First, we highlight that borrowers with multiple active cards rarely default on all their active cards. Indeed, among those who default on at least one card, only 16% default on all of their active cards, meaning that 84% continue to make payments on at least one card. This pattern is not driven by lenders preemptively cancelling credit cards. Defaulting on one card has little effect on the credit limits or interest rates of other cards, whereas limits and monthly usage drop to zero on cards that borrowers do not repay.

Second, we show that the likelihood of defaulting on at least one card increases with the number of cards held. For example, in a given month, 7% of individuals holding a single credit card are in default (more than 90 days past due), compared with 17% of individuals holding four or more cards. This positive correlation may reflect adverse selection, whereby *ex ante* riskier borrowers are more likely to hold multiple cards, or moral hazard, whereby holding additional cards causally increases default risk. Understanding which channel explains the correlation is central, as when recovery rates are close to zero, moral hazard is the key driver of the debt dilution problem.[4]

To estimate the causal effect of obtaining an additional card on default and to measure the extent of debt dilution, we exploit a novel, plausibly exogenous variation in the number of cards owned within a difference-in-differences framework. The variation arises when banks form partnerships with a firm. The arrangement requires employees to receive their wages through the partner bank, thereby increasing the likelihood that they obtain a card from that bank. We compare two groups of borrowers employed at the same firm around the time the partner bank changed: those who already had a relationship with the partner bank before the contract (control) and those who did not (treatment). The identification assumption is that, absent the partner bank's change,

[3] About 50% of borrowers carry a credit card balance in a given month.

[4] When recovery rates are not equal to zero, debt dilution can happen by lowering the recovery rate, even if issuing a new loan does not affect default.

the two groups of workers would have continued to follow parallel trends. Thus, the observed relative change in default probability between them can be attributed to the increased likelihood of the treatment group obtaining a new card. We find that the relative default probability of the treated borrowers one year after the treatment increases by 1.1 percentage points. Given that treated borrowers acquire, on average, 0.11 new card lenders, obtaining a new card lender increases default rates by 10 percentage points.[5]

Finally, provide suggestive evidence 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. We document this pattern by looking for each individual who is in financial trouble which card they choose to repay. Estimating regressions of default choices among selective defaulters holding multiple credit cards, we find that, on average, these borrowers default on 45% of their cards and systematically prioritize repayment of cards with higher credit limits (by 4 percentage points), those originated by digital banks (by 14 percentage points), and those issued by lenders that also provide other financial products (e.g., a 14-percentage-point higher repayment probability when the lender also holds the borrower's mortgage and a 5-percentage-point higher probability when the lender holds the borrower's auto loan).

These estimates should be interpreted with caution, as they are not recovered using quasi-experimental variation. However, the richness of our data allows us to include borrower-by-time and bank-by-time fixed effects, thereby absorbing a wide range of confounding factors. Any remaining bias in the estimated effects of contract terms would have to arise from unobserved product-level characteristics correlated with both repayment priority and contract design (e.g., rewards programs associated with premium cards, which also tend to have higher credit limits). For the digital bank effect, we aggregate bank fixed effects across digital lenders, so the estimates may partly reflect underlying institutional features such as collection technologies.

Overall, these findings indicate that default choices across lenders are not random

[5]The impact on default probability is of a similar magnitude to the one found in De Giorgi et al. (2023) for retail borrowers in Mexico.

but instead correlate with lender characteristics that are plausibly shaped by bank strategic choices, consistent with competition for repayment priority. Our empirical results also point to an additional rationale for banks to cross-sell financial products: cross-selling effectively confers implicit seniority in repayment. This mechanism differs from existing explanations for cross-selling, which emphasise account stickiness or the value of lending relationships for future business.[6]

Our empirical evidence also suggests that lenders impose a default externality on competitors through two channels. The first is the standard debt dilution effect: granting a loan increases the borrower's leverage, thereby reducing their capacity to repay existing debt (e.g., Bizer and DeMarzo, 1992). The second arises because issuing a new loan affects which loan the borrower prioritizes repaying. We refer to this as the competition for loan seniority channel.

Guided by those key features of the credit card market, we develop a model to analyse the implications of competition for loan seniority. The baseline version of the model features two decision periods. In the first period, lenders simultaneously offer loan contracts, and borrowers may accept any subset of these offers. In the second period, borrowers choose which loan to repay, subject to an income constraint.

For exposition purposes, we refer to the contract as a credit card contract. A credit card contract typically includes a credit limit for the initial period, an interest rate, and other card features that benefit the borrower in the second period. We refer to these features collectively as card quality. In practice, the quality of a card can refer to its rewards system, the growth of its credit limit, or to other features associated with the card, such as the bank's mobile application or the promise of obtaining another financial product (e.g., a mortgage). We explore each of these interpretations by extending our baseline model to multiple periods. We show that the key implications in these extensions can be derived from the baseline two-period model by examining a one-dimensional card quality variable whose value depends on the borrower's repayment behavior in the second period.

[6]See, for instance, Drucker and Puri (2005), Puri and Rocholl (2008), and Basten and Juelsrud (2023).

In our model, borrowers' card choice is driven by the following trade-off. By holding multiple cards, borrowers can increase leverage and consume more in the first period, at the cost of potentially being able to repay only a subset of their obligations. Lenders optimally cancel the credit card if the borrower does not repay their balance, and borrowers derive some utility from keeping each card in the second period. We consider that the utility is proportional to the card characteristics in the second period, and that the cost of defaulting on a card decreases with the number of active cards. The latter assumption is consistent with the data and is required for borrowers to get multiple cards in equilibrium.[7]

Lenders can choose the loan interest rate and the credit limit, and can invest to increase the borrower's perceived value of repaying the card (i.e., the card quality). When issuing a loan, lenders recognise that the borrower may also obtain credit from competing lenders and, therefore, may be able to repay only a subset of their outstanding obligations.

Due to a default externality, lenders have incentives to originate too much, as they do not internalise the cost they impose on their competitors. As a result, borrowers' default probabilities are inefficiently high, and contract terms deviate from their first-best level. The direction of this distortion is ambiguous: lenders either overinvest or underinvest in the card quality. 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 arise from lenders expecting borrowers to default more frequently due to the default externality, thereby benefiting less often from the credit card's quality.

Relative to the first-best contracts (which are achieved when contracts are exclusive in our model), non-exclusivity can also result in either higher or lower credit limits in the first period. The reason is as follows. On the one hand, non-exclusivity raises default probabilities and thereby increases lending costs, which tends to reduce loan sizes. On the other hand, potential underinvestment in card quality lowers origination

[7] Otherwise, a lender can offer a card with a credit limit such that accepting any additional loan would trigger default and thus be too costly to accept.

costs, which translates into larger loan sizes.

Due to these competing channels, standard personal bankruptcy procedures, which treat loans of the same contractual seniority equally (i.e., making them share the same recovery rate), can have unintended consequences. Indeed, by setting the same recovery rate for each loan, those regulations shut down the competition for the loan seniority channel (i.e., the overinvestment). However, this overinvestment channel can compensate for the distortions created by the underinvestment channel. As a result, in situations where the overinvestment channel is not too strong, such regulation can be welfare-decreasing.

We then combine our estimates with the model to provide a quantification of the distortions in credit limits arising from non-exclusivity. We show that, within a broad class of models, the deviation of card quality from the first best can be expressed as a weighted sum of two components: the ratio of the sensitivity of survival to contract terms, which captures the overprovision channel, and the survival probability observed in the data, which captures the underprovision channel. This sum is normalized by the survival probability in the first best. To operationalize this decomposition, we use our estimates of the sensitivity of default to credit limits together with average default rates to quantify the first two components. For the survival probability in the first best, we use our difference-in-differences estimates to construct a back-of-the-envelope measure of the average default rate among borrowers who hold two credit cards in the data but would optimally hold only one in the first best.

Related Literature

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 (e.g., Bizer and DeMarzo, 1992; Parlour and Rajan, 2001; DeMarzo and He, 2021; Green and Liu, 2021).[8] A common modelling assumption in those papers is that

[8]We focus on the debt dilution aspect of non-exclusivity. Other studies have highlighted benefits of non-exclusivity, such as the reduction of hold-up problems (e.g., Ioannidou and Ongena, 2010) and the provision of insurance against idiosyncratic shocks to lenders' liquidity (e.g., Detragiache et al., 2000).

default and recovery rates are the same for all loans with the same formal seniority. We contribute to the literature by looking at a situation in which borrowers do not universally default, and allow lenders to compete for loan informal seniority through contract terms such as credit limits or other characteristics. Previous models in the literature are thus better suited to the commercial loan market, where defaulting on one loan typically triggers a bankruptcy procedure across all other loans, whereas our model is better suited to the retail market, where such bankruptcies are often too costly for lenders to use widely.

Empirical papers on non-exclusivity in lending markets include Andersson et al. (2013), Degryse et al. (2016) and De Giorgi et al. (2023). Degryse et al. (2016) focuses on corporate loans and uses a difference-in-difference approach to show that lenders' willingness to lend decreases when a firm obtains loans from other banks. Andersson et al. (2013) use OCC data to document a pecking order in the retail loan market: borrowers tend to prioritise repaying their mortgage over their credit card debt. We complement this paper by looking at repayment priority within loans of the same formal seniority (i.e., credit cards), and show that this has implication for the way we design bankrupcy regualtions. Thanks to our granular data on contract terms and lenders, we can also dig further into the determinants of prioritisation and show that it is related to contract terms. De Giorgi et al. (2023) is closer to our paper and focuses on retail loans. They use data from a private bank and discontinuities in the bank's approval rule to show that issuing a new credit card increases the default probability on existing loans. Their estimates are of similar magnitude to those from our difference-in-differences design around changes in firm–bank relationships. We add to these empirical papers by documenting and analysing the implications of a new channel through which lenders impose a default externality on others: the competition for loan seniority channel.

We also contribute to the banking literature. Our paper is closer to the strands of the literature studying credit card borrowing, bankruptcy, and cross-selling. Recent papers on credit cards have focused on the pricing of credit cards—see, for instance, Ru and Schoar (2016), Stango and Zinman (2016), and Drechsler et al. (2025) for reduced-form

analysis, or Nelson (2025) and Galenianos and Gavazza (2022) for structural models—through a competition, behavioral, or asymmetric information angle. Our paper is closer to Ponce et al. (2017) or Gathergood et al. (2019), which shows that borrowers use the rule of thumb when repaying their debt. Our results focus on delinquent loans and suggest that when the costs are higher (i.e., losing the credit cards), the borrower behavior becomes more strategic.

The literature on delinquent loans often focuses on personal bankruptcy for household finance (see, e.g., Indarte and Kanz, 2024; Argyle et al., 2025; Ben-Ishai et al., 2026). We contribute to the literature by examining defaults outside personal bankruptcy, which constitute the vast majority of credit card defaults. A standard rationale for bankruptcy procedures is to mitigate coordination failures among creditors and to prevent inefficient collection efforts and premature liquidation of assets (e.g., Aghion et al., 1992; White, 2007). By contrast, we document a positive role for repayment competition: competition among creditors can, under certain conditions, lead to the provision of higher-quality banking services.

By showing that other loan products affect credit card repayment decisions, we also contribute to the banking literature on cross-selling (e.g., Robles-Garcia et al., 2022; Basten and Juelsrud, 2023). The existing literature has focused on account stickiness (Puri and Rocholl, 2008) or strengthening of the relationship with borrowers (Drucker and Puri, 2005). In our setting, we highlight a source of complementarity across products that arises from cross-selling, leading to repayment prioritisation. To the best of our knowledge, this source of economies of scope has not been analysed empirically and theoretically.

Finally, we also contribute to the literature on fintech lending (e.g., Berg et al., 2022). We show that fintech lenders tend to obtain more informal seniority. Therefore, while the entry of fintech companies increases competition, it may impose externalities on previous lenders through the competition for loan seniority channel.

The rest of the paper is organized as follows. Section 2 describes the institutional setting and the data. Section 3 presents the descriptive statistics and stylized facts.

Section 4 reports the difference-in-differences results. Section 5 introduces the model, while Section 6 analyzes equilibrium and welfare. Finally, Section 7 concludes.

2 Institutional Setting and Data

2.1 Data

We assemble data from different sources to construct a monthly panel data set of retail loans for all borrowers in Brazil. We focus our main analysis on 2019-2024 as we have better information on credit card operations during that period.

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 term loan, we observe outstanding loan amounts, interest rates, maturity, defaults, anonymized bank and borrower identifiers consistent across products, and the date of origination. For credit cards, we observe monthly credit card usage, revolving balances, amounts due each month, and credit limits.[9] If a borrower holds 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 also observe whether the borrower does not make the minimum payment due on their card at the end of the month.

To get information on the borrower characteristics, we supplement credit information with matched employer-employee data from the Ministry of Labor's *Relação Anual de Informações Sociais* (RAIS). These data provide information on the wage, employer, and selected sociodemographic characteristics, including age, sex, and occupation type. For informal workers, we use the lender's assessment of their income. After 2023, we also have data on the borrower's credit score.

To obtain a tractable sample size, we draw a representative sample of the borrower

[9]Credit card interest rate information is available only when the borrower maintains a revolving balance. The accuracy of credit card limit data improved sharply after May 2021. In certain specifications, we will limit the data to the period following this month.

population using a stratified sampling strategy to ensure sufficient coverage of borrowers experiencing financial distress. Within each cohort, defined at the calendar month level, we partition the population of borrowers into two groups and draw random samples. The first group comprises individuals who were current on all cards until failing to make a payment on at least one card in the cohort month. We designate these individuals, who may be transitioning into default (more than 90 days past due), as *borrowers nearing distress*. The second group comprises all remaining borrowers. Our focus on credit cards in the debt dilution analysis, and hence our sample construction, is motivated by the descriptive statistics reported in the next section (Section 2.2). We provide further details on the sampling procedure and sample characteristics in Appendix A1.

2.2 The Credit Card Industry in Brazil

In this subsection, we use aggregate, publicly available data to present descriptive statistics on the Brazilian credit card market and, where possible, compare them with those of the United States. These statistics suggest that debt dilution is a first-order force in the credit card market: individuals hold cards issued by multiple institutions and frequently borrow and default.

Prevalence of multi-lender borrowing. The credit card industry has expanded rapidly in Brazil. 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 two factors: the addition of new users and the acquisition of cards from different banks by existing users. 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 (52% of the population aged 15 years or older).[10] Over the same period, Panel A of Appendix Figure A2 shows that the share of users with active credit cards from at least two distinct financial institutions increased from 38% to 47%. Panel B shows that the

[10]We use population figures from the 2022 census.

share of outstanding credit card balances held by these users rose from 58% to 70%, consistent with higher average credit card usage among multi-lender users relative to single-lender users. Panel C shows that a substantial portion of the growth in credit card usage is associated with digital banks, which reduced the costs of applying for new cards.[11] In contrast, in the United States, 82% of consumers used a credit card in 2023, and 76.5% of consumers held two or more cards.[12]

Credit card borrowing. Borrowing with a credit card is common. In Panel A of Appendix Figure A3, we decompose the total credit card balance into three parts: non-interest-bearing purchases, revolving debt, and buy now, pay later. Non-interest-bearing purchases refer to transactions made during the billing cycle that are fully due on the next due date and incur no interest charges if paid by that date; revolving debt refers to the accumulation of debt resulting from not paying the full balance of the monthly credit card bill; and buy now, pay later debt refers to card transactions where payment is split into installments, with or without interest charges. The composition of total credit card debt has remained stable, with non-interest-bearing purchases accounting for 80% of total debt, revolving debt for 10%, and buy now, pay later for 10%. Using our micro-level data, we show that 50% of borrowers revolve at the end of the month. This number is similar to the one in the United States (see, for instance, Lee and Maxted, 2025).

Credit card loans are a substantial part of households' balance sheets. In Panel B of Appendix Figure A3, we show that the participation of credit card debt in total household debt increased from 12.7% to 15% between 2018 and 2023.[13] In the United States, credit cards accounted for 6% of total household debt in 2023.[14]

Default. Using our micro-level dataset (see Appendix Table A2), we show that 7% of credit cards (approximately 11% of credit card users) are in default in a given month,

[11] Buchak et al. (2018) and Fuster et al. (2019) document faster application processes among fintech lenders in the mortgage market.

[12] Data are drawn from the *2023 Survey and Diary of Consumer Payment Choice* conducted by the Federal Reserve Bank of Atlanta. The information on the number of cards is not fully informative about multi-lender borrowing, since a consumer may hold multiple cards issued by the same financial institution.

[13] Credit cards are the most common loan contract, accounting for more than 50% of total household loan contracts.

[14] New York Fed Consumer Credit Panel.

where default is defined as failing to make the minimum payment for 90 days. Conditional on borrowing (revolving and BNPL), the number goes to 15%. In the United States, default—defined as a credit card loan being charged off in a given year—occurs at a rate of around 5% (Drechsler et al., 2025) and rises to as high as 10% among borrowers with low FICO scores.

Appendix Figure A4 shows that the share of total balances in default for revolving credit card debt exceeded 50% in 2023, while the corresponding share for *buy now, pay later* balances reached 10%. The figure also shows that, although credit cards account for about 15% of total credit, they represent more than 50% of household debt overdue by more than 15 days, a share that has been increasing since 2018.

Household debt collection. The default procedure in Brazil is broadly similar to that in the United States.[15] Following a missed credit card payment, lenders typically send internal reminders via email or phone. During this stage, the Consumer Protection Code restricts collection practices, prohibiting harassment and abusive exposure. Creditors generally wait at least 30 days before reporting the delinquency to credit bureaus. Subsequently, lenders may outsource or sell delinquent receivables to collection agencies or initiate judicial collection. In practice, few loans are recovered, as legal proceedings are costly and recovery rates are low.

3 Summary Statistics and Stylized Facts

In this section, we provide descriptive statistics and stylized facts obtained from the sample described in Section 2.1, covering the period from June 2019 to June 2022.

[15] While Brazil, like many emerging economies, does not have a personal bankruptcy law (Indarte and Kanz, 2024), this institutional difference is less consequential in practice, as the vast majority of household debt resolutions occur out of court through collections or private renegotiation rather than formal bankruptcy proceedings (Dawsey et al., 2013). Moreover, even in settings with a formal bankruptcy procedure, competition for seniority may occur prior to filing.

3.1 Summary Statistics

In Table 1, we report summary statistics for groups of individuals owning different numbers of active cards issued by different institutions. We report these statistics separately for *borrowers nearing distress* (defined in Section 2.1) and for a random sample of the overall borrower population.

While 40% of the overall population holds credit cards from more than one financial institution, the incidence is significantly higher among *borrowers nearing distress*, at 53%. Within this group, 27% hold cards from two institutions, 14% from three, 6% from four, 3% from five, and another 3% from six or more institutions. Figure 1 confirms the trend documented in Section 2.2, namely that the number of active card lenders per borrower has been increasing since 2019.

Individuals with a larger number of credit card lenders are more likely to hold formal employment, have a higher monthly income, and are more financially integrated. For example, 36% of those with a single card lender are formally employed, compared to 46% among those with three card lenders. Wages exhibit an approximately inverted U-shaped relationship with the number of card lenders. Average monthly earnings rise from 3,757 BRL among individuals with a single card to 4,171 BRL among those with three cards, and subsequently decline to 3,812 BRL for individuals with four cards. Individuals with a greater number of card lenders exhibit a higher debt-service-to-income ratio (18%, 38%, and 59% for those with one, three, and five cards, respectively), as well as higher average limit utilization across their cards (54%, 58%, and 64%). They also rely more heavily on other forms of credit. For example, 7%, 16%, and 24% of individuals with one, three, or five cards, respectively, hold an auto loan, while the corresponding figures for consumer loans are 14%, 27%, and 42%.

Individuals in the *borrowers nearing distress* group tend to have lower incomes (earning roughly 1,000 BRL less per month) and are more likely to work informally (by about 5–10 percentage points). They are also more leveraged, exhibiting higher credit card limit utilization and a greater propensity to hold other types of loans.

In Table 2, we report default rates in the month before the cohort by category of number of card lenders. We define default as not making the minimum payment on the card at the end of the month for more than 90 days. By construction, the share of borrowers with at least one card in default in the *borrower nearing distress* subsample is zero across all categories. In the general population, this share increases monotonically with the number of card lenders (from 7% among people owning one card to 15% among people owning four). However, there is no correlation between the number of credit cards and default on other loans. We interpret this as suggestive evidence that debt dilution is more substantial in the credit card market. Yet, in the *borrowers nearing distress* group, borrowers with one card lender have a higher probability of defaulting on other loans compared to borrowers with more than one card lender. The latter is consistent with the fact that this population subsample uses their credit cards to repay other loans.

3.2 Four Facts About Default in the Credit Card Market

In this section, we provide four new stylized facts about default behavior in the credit card market. First, we show that many borrowers default on only a subset of their cards. Second, we show that the default probability of *borrowers nearing distress* six months after missing a payment increases with the number of cards, even after controlling for observable determinants of default. Third, we show that lenders do not cancel the credit limits of borrowers who defaulted on a competitor's card. Finally, we show that borrowers prioritize repayment of cards with more favorable terms and of cards issued by banks with which they have other credit relationships.

Fact 1: Many borrowers default on only a subset of their cards.

To derive the first fact, we focus on the *borrowers nearing distress* group. These individuals were in good standing with all their cards in month $t-1$ and then miss a payment (overdue for more than 15 days) in time t. We investigate whether these individuals default on all or a subset of their loans six months later, defining a loan as in default

if it is more than 90 days overdue. We use this measure of default to ensure that our results are not driven by borrowers who forget to repay on time. Figure A5 shows the default incidence for alternative horizons. The results of the paper are not driven by the choice to measure default six months after the borrower first misses a payment, as the group of borrowers is relatively stable after 30 days.

In Table 3, we show that 46% of *borrowers nearing distress* become more than 90 days overdue on at least one card, and that this share 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 (for instance, $11/45 = 24\%$ of the defaulters with two card lenders and $5/47 = 11\%$ among those with three card lenders), and *selective defaulters*, who default on some cards while continuing to repay others (76% and 89%, respectively).

While the term selective default could apply to individuals who repay a subset of their credit card loans, they may default on the card for which they lack sufficient resources to repay, suggesting that the default decision is driven solely by liquidity constraints rather than a deliberate choice. In this case, selective defaulters would default on the cards that constitute the majority of their debt, implying that the distribution of the share of the total balance in default would be concentrated above the 50% threshold. However, as shown in Appendix Figure A8, the distribution does not follow this pattern. Specifically, there is a large group of selective defaulters who default on cards accounting for less than 50% of their balance, suggesting that they had sufficient resources to pay these cards but chose not to.

Motivated by this fact, 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 Table 3, we 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 A6, 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: The share of borrowers who default on at least one card increases with the number of card lenders, even after controlling for observable characteristics.

In Table 2 and Table 3, we show that default rates (at the borrower level) increase monotonically with the number of card lenders. For instance, six months after missing a payment, the probability that *borrowers nearing distress* default on at least one card is 43% for borrowers with a single card lender, 45% for those with two card lenders, and 47% for those with three card lenders. This relationship may be driven by factors such as income, liquidity, and leverage. In Table 5, we try to control for these variables and additional covariates in the subsample of formal workers, for whom salary information is available. The positive association between borrower-level defaults and the number of card lenders persists even after controlling for wage, the debt-service-to-income ratio (a proxy for liquidity), the total-debt-to-wage ratio (a proxy for leverage), and other characteristics, including age, gender, and tenure at the last job.

Fact 3: Lenders do not cancel the credit limit of borrowers who defaulted on a competitor's card.

In Figure 2, we show that defaults entail the loss of the defaulted 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. In other words, as long as banks remain the prioritized lender, they continue to supply credit to selective defaulters.

In Appendix Figure A9, we also show that defaulting on a credit card decreases the borrower's credit scores significantly. In an event study, we show that the probability of obtaining a new loan (including revolving card loans) also drops significantly after a default.

In Section 5, we rationalize lenders' behavior in our model as follows. From a lender's perspective, observing a borrower default on another card while continuing to be repaid is not necessarily bad news. Such behavior reveals informal seniority relative to competing lenders. In addition, the loss of access to the defaulted card and the deterioration in the borrower's ability to obtain new credit increase the cost of default. Taken together, these mechanisms may reduce the likelihood of default on the repaid card.[16] This view is also expressed by market participants.[17]

Fact 4: 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 of selective defaulters that repay a subset of their loans and data at the borrower-cohort-bank level. We estimate the following regression:

$$y_{icb} = \beta X_{icb} + \alpha_{ic} + \epsilon_{icb} \tag{1}$$

[16]The lender that continues to be repaid may also gain market power as the borrower's number of banking relationships declines.

[17]The former CFO of Itaú, the largest private bank in Brazil in terms of total assets, mentions in an interview with Euromoney that: "Everyone in Brazil has four credit cards, and if they don't have money to buy groceries, they use all these cards.[...] But they pay the one from the bank they have the relationship with. Banks don't care if you have a negative score if you keep paying them. So, being the main bank determines the cost of credit. People underestimate the huge relationship between being the main bank and default risk. If you are the principal relationship bank, they might default on the other banks but you will be the last one."

where y_{icb} is a binary variable that takes the value one if, six months after becoming overdue for more than 15 days on any card, individual i of cohort c defaults (i.e., 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 15 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 6. 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 7. Borrowers tend to default more on cards for which there is less limit available. In particular, default probabilities increase sharply (by 40 percentage points) 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. In the specification using data from after May 2021, when information on limits is more reliable, the results show that borrowers are 14 percentage points less likely to default on digital banks and 13 percentage points more likely to default on government-owned banks. This pattern suggests that borrowers may value their relationships with digital banks more than with other types of banks, or that digital banks have more effective debt collection infrastructure.

In general, borrowers tend to default less on banks that offer other loan products: payroll (-7 percentage points), mortgage (-14 percentage points), auto loan (-5 percentage points), and other loans (-7 percentage points). However, default is more likely if the borrower has personal loans with the bank (3 percentage points). 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 a borrower has already defaulted on other products with a given bank, the borrower is substantially more likely to default on that bank's credit card than on a credit card issued by another bank.

In Appendix Table A5, we also examine whether interest rates are a driver of default decisions. Interest rate information is available only for a subset of contracts, which reduces the sample size. We find that borrowers are 25 percentage points more likely to default on the card with the highest interest rate.

Omitted variable bias: The above results enlighten a correlation between relative contract terms and default probability. One should be cautious when interpreting the coefficients due to ommited variables. As, we look at the decision choice of which loan to default on at the individual level, the key concern comes from unobserved product characteristics.

The correlations between default probabilities and contract terms may be due to an omitted variable that varies at the product-bank level. For instance, the correlation between credit limit and default may be due to lenders offering different reward systems or having different debt collection procedures. Those concerns are partially mitigated by the use of lender fixed effects, as those features are largely fixed at the bank level. Yet it is possible that a bank offers, for instance, a higher credit limit on credit cards with a high rewards program. This would create a positive correlation between credit limits and rewards systems. Although the coefficients would not, in that case, reflect the causal impact of the credit limit, they still indicate that the lender can leverage certain contract characteristics to gain informal seniority. Similarly, the correlation between having other products and default could be due to better borrowers obtaining a card

with a higher reward and a mortgage offer, creating a correlation between unobserved credit card characteristics and getting a mortgage. It is less likely that the omitted variable is due to recollection effort, since such effort is likely to be fixed at the lender level and is thus captured by the lender fixed effects. We, however, account for that possibility in the theoretical part of the paper, in which we between investment in recollection and in credit card rewards.

While one should be cautious about interpreting the result are the causal impact of each characteristics, the results provide suggestive evidence that lender can use some characteristics to gain informal seniority. The theoretical part of the paper analyze its implication and whether the type of characterisitcs used as an impact on welfare and the way one should regulate this market.

Additional facts about the credit card limits. We also report additional facts about credit limits. The aggregate credit limit, summing all credit cards, is around 3 times the borrower's income. The average credit limit per card is 1.5 times the borrower's income, regardless of the number of cards the borrower owns. In addition, lenders do not reduce the credit limit on existing cards after the borrower gets a new card and increase the credit limit over time, provided the borrower does not default. This suggests that lenders consider the possibility of the borrower getting additional cards when setting their initial limit.

4 Difference-in-Differences

In Table 5, we show a positive relationship between the number of card lenders and default probabilities at the borrower level, even after controlling for observable default determinants. However, this relationship may arise from both unobserved borrower heterogeneity—for example, higher-risk borrowers may be more likely to obtain additional cards (adverse selection)—and the causal effect of forming new card relationships (moral hazard or burden of payment). Identifying the relative contribution of

these channels is crucial, as the latter mechanism has a direct effect on debt dilution.[18]

Using quasi-experimental variation, we show that the debt dilution channel is quantitatively important: getting a new card increases the default probability on any card one year after origination by 10 percentage points.

To determine the causal impact of obtaining a new card, we employ a difference-in-differences approach. We achieve this by leveraging certain institutional features of the Brazilian market. In particular, banks commonly form partnerships with firms to obtain the rights to process employee salary payments. The arrangement effectively mandates that employees receive their wages through the partner bank, 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 (control), while the second did not (treatment). 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 card. Appendix Figure A10 summarizes the research design.

Using the credit registry of the Central Bank of Brazil, we construct a worker-level panel around the month in which a new bank is assigned to manage a firm's payroll.[19] We retain workers who remain employed at the same firm throughout the entire window, are active credit card users, and rely exclusively on this type of loan.[20] We examine events (i.e., changes in banks managing payroll payments) occurring within the twelve months between May 2017 and April 2018.[21] Appendix Table A6 reports the

[18]When the recovery rate conditional on default is zero, debt dilution operates via the impact on loan origination on default probabilities. When the loan recovery rate is different from zero conditional on default, debt dilution can also occur even without an impact on default rates.

[19]The Central Bank uses an algorithm to identify changes in the bank managing a firm's payroll by detecting structural breaks in the volume of wage-backed payroll loans originated by each bank to the firm's employees.

[20]Restricting the sample to borrowers who rely exclusively on credit cards is not ideal, as it conditions on post-treatment borrowing choices. Nonetheless, we make this restriction to reduce concerns that the treatment alters the demand for other loan types, particularly wage-backed payroll loans. Restricting the sample to workers who remain at the same firm throughout the observation window allows us to indirectly control for changes in wages (for instance, when examining the debt-to-wage ratio) and to account for firm-by-time fixed effects.

[21]We base our sample selection on two main considerations. First, in May 2019, a change occurred in the reporting standards for credit card loans, making April 2018 the last month for which we can observe

characteristics of treated and control individuals in the month prior to the new bank assuming management of payroll. Control and treated individuals are similar in terms of the number of card lenders and debt-to-wage ratio: on average, control individuals have 1.5 card lenders and a debt-to-wage ratio of 1.5, compared to 1.2 card lenders and a debt-to-wage ratio of 1.3 among treated individuals. However, the groups differ slightly in baseline default rates: 5% of control individuals are delinquent on some card and 4% are in default on at least one card, compared to 2% and 2%, respectively, among treated individuals. Given that differences in baseline default rates may influence future borrowing trajectories, our regression specification allows for heterogeneous trends by baseline default status. The majority of individuals in our sample (80%) belong to the treatment group; only 20% already held a card from the bank that subsequently assumed management of the firm's payroll.

We estimate the following event-study regression to capture the dynamics of the effects:

$$y_{it} = \sum_{\tau=1}^{\tau=6} \beta_{-\tau} \times Treat_{i,-\tau} + \sum_{\tau=0}^{\tau=15} \beta_{\tau} \times Treat_{i,\tau} + \alpha_i + \alpha_{f(i)t} + \alpha_{d(i)t} + \epsilon_{it} \qquad (2)$$

where i indexes the individual, t the calendar month, and $f(i)$ the firm where individual i works. The variable $Treat_{i,t-\tau}$ is a dummy variable that takes the value one if individual i belongs to the treatment group and the new bank starts managing firm $f(i)$'s payroll τ months after t. The variable $Treat_{i,t+\tau}$ is a dummy variable that takes the value one if individual i belongs to the treatment group and the new bank starts managing firm $f(i)$'s payroll τ months before t. We control for time-invariant worker heterogeneity by including individual fixed effects, α_i, and we control for time-varying shocks to all workers of firm $f(i)$ by including firm-by-time fixed effects, $\alpha_{f(i)t}$. Because baseline differences in default status may shape subsequent borrowing trajectories, we interact time dummies with an indicator for whether borrower i had a default on any

a long enough post-event window (12 months) under a consistent reporting regime. Second, we focus on a period prior to the rise of digital banks as significant market players. Following their entry, the cost of obtaining a new credit card declined substantially, reducing the likelihood that our treatment would remain effective.

card in the month prior to the new bank assuming management of firm $f(i)$'s payroll, $\alpha_{d(i)t}$. We cluster standard errors at the firm level.

We also estimate the following specification at the individual-month level:

$$y_{it} = \beta_1 \times Post_Treat_{it}^{[0-6]} + \beta_2 Post_Treat_{it}^{[7-15]} + \alpha_i + \alpha_{f(i)t} + \alpha_{d(i)t} + \epsilon_{it} \qquad (3)$$

where the variable $Post_Treat_{it}^{[0-6]}$ is a dummy equal to one if individual i belongs to the treatment group and period t falls within zero to six months after the date on which a new bank assumes management of firm $f(i)$'s payroll. The variable $Post_Treat_{it}^{[7-15]}$ is a dummy equal to one if individual i belongs to the treatment group and period t falls within seven to fifteen months after the date on which a new bank assumes management of firm $f(i)$'s payroll.

Figure 3 plots the estimated coefficients from Equation 2. On average, individuals in the treated group obtain 0.11 more card lenders than those in the control group. The take-up is gradual and peaks about 10 months after a new bank begins managing salaries. The debt-to-wage ratio also increases gradually. Interestingly, the debt-to-wage ratio begins to rise before the number of cards increases, suggesting that the prospect of obtaining a new card influences the utilization of existing cards. We also observe that the delinquency (more than 15 days overdue) and default (more than 90 days overdue) rates increase. These effects start about 12 months after a new bank begins managing salaries. Across all outcomes, treated and control borrowers exhibit parallel trends in the pre-treatment period.

Table 8 reports the estimated coefficients from Equation 3 and shows similar patterns. We find that the treatment leads to an increase in the number of cards held, the total debt-to-wage ratio, and the rates of delinquency and default. On average, treated individuals increase the number of card lenders by 0.11, and their probability of default rises by 1.1 percentage points. Consequently, obtaining a new card lender raises default rates by 10 percentage points. Under the standard assumption that the distributions of unobserved borrower characteristics are similar in the treated and control groups, the treatment effect can be interpreted as the causal effect of getting a credit

card.

Appendix Table A6 shows that only a small fraction of treated borrowers use a card from the new bank at some point of the post-treatment period (163 out of 2,864, or 5.7%). We refer to these individuals as compliers. Given the small number of compliers, the overall treated-versus-control comparison is largely driven by treated borrowers who do not take up a new card (non-compliers). Therefore, Appendix Figure A11 reports results separately for compliers and non-compliers. While all three groups—compliers, non-compliers, and control individuals—exhibit parallel pre-treatment trajectories, treatment effects are substantially larger for compliers. In particular, compliers experience earlier and sharper increases in delinquency and default rates.

Validity of the research design: The identification assumption is that the relative difference in default rates between the two groups of borrowers working in the same firm is due to the causal impact of getting a new card rather than any other shock that affects the two groups differently. One potential concern is that the two groups of borrowers differ in unobservable characteristics (e.g. savings, creditworthiness). This can explain why they have different numbers of credit cards, which translates into them having different sensitivities to income shocks. Those concerns would materialise into a different parallel trend. Figures A11 show that the groups have parallel trends, making the above concerns less likely to hold in practice. Another concern is that the borrowers might be on a different borrowing trajectory, meaning that the borrowers treated would have defaulted later anyway (6 months after treatment), which drives the results. Selection into treatment: not a problem as long as the treated and control group follows parralel trend. In addition, the fact that our results align with those of confort us in thinking that this is not the case. Finally, our results recover the local average treatment effect. It is possible that those coefficients are an upper bound on the causal impact of getting a credit card. Banks that are more likely to benefit from doing the payroll are more likely to be picked, given that they are, on average, worse at screening or monitoring employees, which gives us a lower bound. Similarly, people

select into treatment (compliers); this is not an issue under the standard assumption that the unobserved characteristics are the same in the treated (compliers and non-compliers) and non-treated groups.

5 Model

Section 3.2 provides suggestive evidence that lenders can use credit card terms (e.g., credit limit) and cross-sell other products to gain informal seniority. To study the impact of competing for informal seniority on contract terms and welfare, we develop a model with non-exclusive loan contracts. Although the model is primarily intended to clarify the underlying economic mechanisms, it is formulated to serve as a foundation for a fully structural framework (see Appendix G).

In our model, the economy is populated with two groups of agents: borrowers and lenders. There is an arbitrary number of borrowers indexed by i and an arbitrary number of lenders indexed by c.

There are two periods in which agents make decisions. At the beginning of period 1, lenders simultaneously offer loan contracts and borrowers choose how many contracts to accept.[22] For each borrower i, let $\mathcal{C}_i$ denote the set of cards selected in the first period. In the second period, borrower i chooses which contracts to repay; we denote the corresponding set of repaid contracts by $\mathcal{R}_i$.

For exposition purposes, we refer to a contract as a credit card. Each credit card c has a credit limit L_c in period 1 and a gross interest rate r_c. We denote $R_c := L_c \cdot r_c$ the debt face value, due in period 2. The card also has characteristics that depend on the repayment behavior, which we denote by the vector $q_c(\mathcal{R})$. To streamline the notation, we denote q_c instead of $q_c(\mathcal{R})$ when unambiguous, and refer to q_c as the card quality.[23] In the main section, we interpret the vector q_c as benefits coming from a credit card

[22] The assumption that loans are offered simultaneously instead of sequentially is justified by the fact that being the second lender to originate does not seem to give an advantage (see fact 4). The simultaneous game assumption is more tractable and can be interpreted as a dynamic setup in which the first lender forms rational expectations about the other lender's behavior, and the second mover does not have an informational advantage.

[23] In reference to the industrial organization literature, such as Berry and Waldfogel (2010).

rewards system provided at the end of the second period if the borrower repays the credit card. We show in the appendix that our parametric assumptions are general enough so that q_c can be interpreted, in an extended three-period model, as the credit card terms (credit limit and interest rate) in the second and third periods, or as other products being offered in the second period (e.g., mortgage, or other loans).

The following subsections characterize the behavior of the borrowers (Section 5.1) and the lenders (Section 5.2).

5.1 Borrowers

This section describes borrower i's choice of cards and repayment behavior. For notational clarity, we omit the index i throughout this section.

To build intuition, we begin by providing a micro-founded version of the borrower problem (Section 5.1.1). In Section 5.1.2, we then show how to parameterise the micro-founded model to get the functional form used in the rest of the paper. Those functional forms are commonly used in empirical industrial organisation. Appendix G provides guidance on how one can bring the model to the data and perform counterfactual analysis. While the micro-foundation of Section 5.1.1 provides intuition, the reduced-form approach of Section 5.1.2 can be micro-founded by linearising any model in which the utility function is increasing in the loan size and decreasing in the debt face value.

5.1.1 Microfoundation

The borrower i gets income W_t in each period ($t \in \{1, 2\}$). In period 1, the borrower can borrow using credit cards in order to consume. Their budget constraint in the first period is denoted $c_1 p_1 = \sum_{c \in \mathcal{C}} L_c + W_1$, where $c_1 p_1$ is the consumption basket times its price and L_c is the amount borrowed in bank c. In period 2, the borrower chooses how much to consume and whether to repay credit card debt. Their budget constraint is $c_2 p_2 = W_2 - \sum_{c \in \mathcal{R}} R_c$ where R_c is the debt face value at bank c. The set of cards borrowers repay in period 2 ($\mathcal{R}$) must be feasible. That is, the amount the borrower repays ($\sum_{c \in \mathcal{R}} R_c$) cannot exceed their disposable income in the second period (W_2).

We define the feasible set $F(\mathcal{C})$ as:

$$\mathcal{R} \subset F(\mathcal{C}) := \{f \subset \mathcal{C} : \sum_{c \in f} R_c \leq W_2\} \tag{4}$$

Guided by the data, we start by making two simplifying assumptions. First, we consider that borrowers max out the credit limits on each card $c \in \mathcal{C}$ they own. This 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.[24] Second, conditional on repaying a card in period 2, the borrower repays it entirely. This behavior can be micro-founded by lenders optimally choosing to cancel the borrower's card if it is not repaid fully, thereby maximising repayment probability (see Appendix D2). Those two assumptions simplify the borrower problem: they only choose the set of cards to own and repay, rather than the amounts they borrow and repay on each card they own. This assumption is consistent with our data.[25]

The borrower's i utility in period 1 is the sum of their utility derived from consumption in periods 1 ($u(c_1, \mathcal{C})$) and 2 ($U(c_2, q, \mathcal{R})$), plus the indirect utility of owning a card at the end of period 2 (captured by q in $U(c_2, q, \mathcal{R})$). The borrower chooses consumption c_1, the set of cards to own $\mathcal{C}$, and the set to repay $\mathcal{R}$, to maximize their utility subject to their budget constraint:

$$u(L, R, q) = \max_{c_1, \mathcal{C} \in P(B)} u(c_1, \mathcal{C}) + \beta E[\max_{c_2, \mathcal{R} \in F(\mathcal{C})} U(c_2, q, \mathcal{R})] \tag{5}$$

$$s.t.\ c_1 p_1 = \sum_{c \in \mathcal{C}} L_c + W_1 \tag{6}$$

$$c_2 p_2 = W_2 - \sum_{c \in \mathcal{R}} R_c \tag{7}$$

We use the notation $L := (L_c)_{c \in B}$, $(R_c)_{c \in B}$, and $(q_c)_{c \in B}$ for the vectors of credit limits,

[24] Consumers may also place greater value on credit cards with higher limits, as these provide more readily accessible funds to address expenditure shocks.

[25] Ponce et al. (2017) finds that borrowers repay each card a bit rather than all the debt on one card. We do not find such evidence for people who default on their cards. This is likely because default decisions have higher stakes, so borrowers become more rational in that case.

interest rates, and card quality available in the market, where B is the set of cards banks offer, and $P(B)$ is the power set of B.

The fact that the utility in period 1 depends on the set of cards $\mathcal{C}$ captures the non-monetary benefits of cards (e.g., convenience as a means of payment). The card quality q and the repayment set $\mathcal{R}$ in the second period utility capture the non-monetary costs and benefits of defaulting or repaying the card.

The borrower's problem highlights that getting more cards allows the borrower to consume more in the first period, but this also increases repayment, and thus the probability of defaulting in the second period.

5.1.2 Parametrization

We now make some parametric assumptions to go from the problem defined in 5-7 to the utility function used in the theoretical analysis. These assumptions ensure the continuity of both demand and default behavior, thereby facilitating the analysis. Using the budget constraint to replace c_1 in the utility function, assuming that utilities are linear in consumption, and normalising $p_2 = 1$ and defining $p_1^{-1} = \alpha$, we get:

$$u(L, R, q) := \max_{\mathcal{C} \in P(B)} \overbrace{\sum_{c \in \mathcal{C}} \alpha L_c + \varepsilon_{ic}}^{\text{period 1}} + \beta E_{\varepsilon_{ir}} [\overbrace{U(L, R, q, \mathcal{C})}^{\text{period 2}}] \tag{8}$$

$$U(L, R, q, \mathcal{C}) := \max_{\mathcal{R} \in F(\mathcal{C})} W_i - \sum_{r \in \mathcal{R}} [R_r - \varepsilon_{ir}] + V(q, \mathcal{R}) \tag{9}$$

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

The function $V(q, \mathcal{R})$ represent the utility of repaying (when $c \in \mathcal{R}$) or not (when $c \notin \mathcal{R}$) cards. Specifying $V(q, \mathcal{R}) = \sum_{c \in \mathcal{C}} V_c(q_c, \mathcal{R})$, we can interpret $V_c(q_c, \{c\})$ as the utility derived from using the card c rewards at the end of period 2. $V_c(q_c, \{\emptyset\})$ captures

the cost of not repaying card c. Examples include having a lower credit score conditional on not repaying the card, or being unable to use the rewards because the lender canceled the card.

Appendix B discusses the micro-foundations for V_c across the three channels that allow lenders to gain seniority: by offering rewards, modifying the card terms conditional on repayments, or cross-selling products. The three channels are equivalent as they lead to a V_c function that is increasing in $q_c(\mathcal{R}) \in \mathbb{R}$.

Distinguishing between investment in recollection and in credit card rewards is important. The key reason is that higher rewards affect the borrower's utility and recovery positively, while investment in recollection is ambiguous. Recollection may not directly affect borrowers' utility (it may be a shrouded attribute or merely act as a nudge to repay a given bank). affect it positively (when being nice to the borrower is the way to get repaid), or negatively (when the bank harasses the borrower). This distinction matters for welfare and the impact of imposing the same recovery rate for all loans.[26] In interviews with market participants, they pointed out that due to consumer protection, recovery is mainly a matter of being nice to the borrower and reaching out to them once they miss a payment.

5.2 Lenders

This section describes how lender c designs their loan contract.

In period 1, lenders observe all parameters except the demand and repayment shocks (ε_{ir} and ε_{ic}). This assumption is standard in the industrial organisation literature and allows for the demand and default functions to be continuous (see, for instance, Rochet and Stole, 2002 or Taburet, 2025).

For each borrower i, lender c chooses the card credit limit L_c, the debt face value R_c, and quality q_c to maximize static profits conditional on their expectations about other

[26] Indeed, imposing the same recovery rate decreases incentives to invest in both recollection and rewards. The decrease in recollection is likely to increase welfare, as it is a pure arms race that does not affect borrowers' utility, while the decrease in rewards is likely to decrease borrowers' utility. While we do not have direct evidence of investment in recollection technology, we believe that lenders have limited heterogeneity with respect to the number of calls to the borrower, which is limited by regulation, and the impact on credit score is standardised.

lenders' offers and borrowers' behavior.[27]

The lender's profit is the probability of the borrower accepting the contract, $D_c(\cdot)$, times the net present value of the credit card contract, $NPV(\cdot)$. Investing in the card quality q_c costs $c(q_c, \theta_c(R_c, q_c))$ and increases the probability of the borrower repaying the card $\theta_c(R_c, q_c)$. Depending on the interpretation of q_c, the costs may be paid before knowing if the borrower repaid. Formally, we have:

$$\max_{\{L_c, R_c, q_c\}} D_c(u(R_c, L_c, q_c)) \left[NPV(R_c, L_c, q_c, \theta(R_c, q_c)) \right] \tag{10}$$

where the demand function $D_c(u(R_c, L_c, q_c)) := Pr(c \in \mathcal{C})$ is the probability that the borrower gets a card from bank c and $\theta(R_c, q_c) := Pr(c \in \mathcal{R})$ is the probability that they repays bank c. The probabilities are derived from the borrower's problem defined in 8-9, conditional on knowing the distribution of ε_{ir} and ε_{ic} but not their realization. Making the default probability depend on the contract terms offered by lender c as well as all its competitors is the main departure from standard models of non-exclusivity.

The expected net present value of lending, NPV, is a function of the loan present value, $\theta(R_c, q_c)R$, the cost of originating the card, $mc(\theta)L$, and the cost of quality, $c_c(q_c, \theta_c(R_c, q_c))$. Formally, we have:

$$NPV(R_c, L_c, q_c, \theta(R_c, q_c)) := \overbrace{\tau L}^{\text{profits from transacting}} + \overbrace{p^r[\theta(R, q_c)R_c - mc(\theta)L]}^{\text{profits from revolving}} - \underbrace{c_c((q_c, \theta_c(R_c, q_c))}_{\text{cost of quality}} \tag{11}$$

The quantity τL is the net profits made from fees. The borrower revolves with some exogenous probability p^r (equal to 1 in the micro-founded example of Section 5.1.1, and captured by α and β in the reduced-form specification of Section 5.1.2). In that case, the lender earns in expectation $\theta(R, q_c)R_c$ and pays the additional costs $mc(\theta)L$. Appendix C discusses micro-foundations for the function c_c for the three channels that

[27] Because lenders observe the borrower's willingness to pay for credit (i.e., α/β), the equilibrium contract terms obtained when lenders choose a pricing schedule $r(L)$—the interest rate as a function of the loan size—are identical to those obtained when lenders directly choose the repayment $R := r(L)$ and the loan size L (the credit limit).

allow lenders to gain seniority: offering rewards, modifying the card terms conditional on repayments, or cross-selling products. Until the normative analysis (Section 6.3), these distinctions are equivalent.

We consider that the marginal cost of lending $mc(\theta)$ is a function of the average survival probabilities of borrower i ($\theta := \frac{1}{|\mathcal{C}_i|}\sum_{c\in\mathcal{C}_i}\theta_c$). One interpretation of this modelling is that the marginal costs of lending increase in default probabilities through capital requirements, and that lenders do not internalize the impact of their behavior on capital requirements. In our model, the key distortion is on contract terms q_c. Those distortions are not qualitatively affected by our assumption about $mc(\theta)$. However, this modelling of $mc(\theta)$ allows to capture the standard effect of non-exclusivity on L_c: it increases the real cost of lending and thus lowers the equilibrium loan size as in Parlour and Rajan (2001). An alternative is to make default costly for the lender so that it destroys resources instead of just relocating borrowers' wealth across banks as in Parlour and Rajan (2001) for instance. The fact that lenders do not internalise the impact of default on capital requirements is made to simplify the equations.

6 Equilibrium Analysis

In this section, we analyse the properties of the model using a stripped-down parameterization to focus on building intuition about the economics at play. In particular, we consider that all borrowers revolve, lenders are symmetric and earn no transaction fees (i.e., lenders' demand and net present value functions have the same parameters with $\tau = 0$ and $p^r = 1$).

6.1 Exclusive Contract Equilibrium

To build intuition, let us first analyse the exclusive contract equilibrium. That is, the case in which borrowers can accept at most one contract. We start with this benchmark because it features no default externality and delivers the first-best contract terms under some mild assumptions. We discuss those assumptions in Section 6.3.

6.1.1 Relevant Parameters' Value

To focus on a situation in which borrowers get a credit card in equilibrium, we restrict the values the model parameters can take. Formally, the set of parameters must be such that the following conditions are satisfied:

Conditions A1:

$$\alpha - \beta mc(\theta) > 0, \ \forall \theta \tag{12}$$

$$V_c(q, \{c\}) + \epsilon_{ir} - R > V_c(q, \emptyset), \ \forall R \leq W_i, \forall \epsilon_{ir} \in S \tag{13}$$

Equation 12 ensures that lending generates social surplus (i.e., borrowing yields a positive NPV when the loan is priced at marginal cost). It asserts that the marginal utility of a loan (α) is larger than the marginal cost of lending.

Equation 13 describes the condition for borrowers to have incentives to repay their loans so that the market does not break down. The equation states that defaulting on all cards is costly enougth: the benefit of repaying the loan $(V_c(q, \{c\}))$ minus its cost $(R - \varepsilon_{ir})$ are always higher than the utility of not repaying the loan $(V_c(q, \{\emptyset\}))$. The fact that the condition 13 holds $\forall \varepsilon_{ir} \in S$ is made for simplicity of the exposition, so that defaults never happen in the exclusive contract case. This assumption can be relaxed.[28]

With those assumptions, it is optimal for the lender to cancel the cards when the borrower does not repay.[29] Without loss of generality, we thus normalise $V_c(q, \emptyset)$ to 0, set the card quality in the default state $(q_c(\emptyset))$ to zero and focus on $q_c = q_c(\{c\})$.

[28] For lending to occur, it suffices that the condition holds for some ε_{ir}.

[29] Borrower will never default, and the cost increases in the card quality in the default state.

6.1.2 Equilibrium contracts

The exclusive equilibrium contract (R^E, L^E, q^E) when lenders are homogeneous is:

$$\theta^E = 1 \tag{14}$$

$$R^E = W \tag{15}$$

$$L^E = \overbrace{\frac{W - c(q^E, \theta^E)}{mc(\theta^E)}}^{\text{lender's break-even condition}} - \overbrace{\varepsilon^{-1}}^{\text{inverse demand semi-elasticity}} \tag{16}$$

$$q^E := \{q : \underbrace{\frac{\beta V'(q)}{c'(q, \theta^E)} = \frac{\alpha}{mc}}_{\text{equalized marginal rate of transformation}} \} \tag{17}$$

Proof: See Appendix D1.

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

Equilibrium contracts: Because of assumption 13, defaulting is costly for the borrower. The contract is thus set so that borrowers never default (i.e, $\theta^E = 1$ in Equation 14).

Equation 15 states that the debt face value is equal to the borrower's income. The reason the borrower's debt capacity is maximized comes from Equation 12. Increasing W in exchange for a larger loan size is a Pareto improvement, since lending generates positive NPV.

The equilibrium loan size in Equation 16 features two elements. The first one is the loan size if lenders were to break even ($\frac{W-c(q^E)}{mc(1)}$). The second one is negative and equal to the interest rate markup ($\varepsilon^{-1} > 0$). 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 demand elasticity is large and can thus charge above the marginal cost of lending ($\frac{\varepsilon^{-1}}{L}$ per dollar lent).[30]

The fact that repayment R is bounded by income W implies a trade-off between lending L and quality q. The trade-off is captured by Equation 17. Absent this trade-off, the optimal quality would be that the marginal benefit of lending equates to its costs: $\beta V'(q) = c'(q,1)$. Because the borrower resource is limited by W, the lender needs to select whether to offer a larger credit limit (L) or a larger quality (q). Thus, the optimal contract is such that the marginal rate of transformation of lending equals the investment one (Equation 17). It implies that the optimal quality is such that $\frac{mc}{\alpha}\beta V'(q) = c'(q)$. The higher is the value of lending (i.e., $\frac{mc}{\alpha}$ low), the lower is the card quality.

6.2 Non-Exclusive Contract Equilibrium

Let us now analyse the non-exclusive contract equilibrium.

6.2.1 Relevant Parameters' Value

Depending on the parameter values, the market can either break down, be equivalent to the exclusive contract equilibrium, or feature borrowers owning multiple cards.

For instance, if the cost of defaulting is too high for borrowers, the non-exclusive equilibrium contracts and the exclusive ones are identical. The reason is the following. Consider a contract with the same characteristics as the exclusive contract (L^E, R^E, q^E) described in the previous section. The debt capacity of a borrower accepting this contract is maxed out. Thus, getting any additional contract would trigger default, which is too costly for the borrower.

To focus on the situation where the exclusive and non-exclusive cases differ, we add some curvature to the default cost function. In particular, we consider that defaulting costs are decreasing in the number of active cards the borrower owns, so that defaulting

[30]The assumption about ε_{ic} allows us to parametrise the semi-elasticity in equilibrium.

on all but one card is not too costly. The condition can be interpreted as borrowers needing at least one card to purchase the goods essential for their survival.[31] When this condition is satisfied, a borrower accepts more than one contract even if one of them has the same characteristics as the exclusive first-best contract. There can be two cases. First, the market breaks down as lenders may expect borrowers to default so often that the net present value of lending is negative. The condition $\alpha - \beta mc(\theta) > 0, \ \forall\theta$, in Equation 12 holding for all θ ensures that this situation does not happen. Second, the market does not break down, and the borrower gets multiple cards.

Let us now formally state the condition for the equilibrium to feature multiple cards. For simplicity of the exposition, we begin by stating the condition in the case where there are only two lenders and then generalise. To make the notation unambiguous, we now denote $V_c(q_c, \mathcal{R}, \mathcal{C})$ instead of $V_c(q_c, \mathcal{R})$ to distinguish between defaulting from one card when having one or when having two. Formally, the parameters must be such that:

Conditions A2:

$$\underbrace{\alpha - mc(\theta)}_{\text{marginal loan utility}} + \underbrace{V_c(q_c, \{c\}, \{c, b\}) + V_b(0, \{c\}, \{c, b\})}_{\text{defaulting on one card when having 2}} > \underbrace{V_b(q_b^*, \{b\}, \{b\})}_{\text{not defaulting on 1 card}} \tag{18}$$

To get the intuition behind the derivation of Equation 18, let us consider a borrower who has already accepted one card from lender b. The lender b offered the "exclusive" contract with a zero markup and quality q_b^E (i.e., the first-best in the exclusive contract case). The borrower now considers whether to get a new card from lender c. Appendix D2 shows that this is the key decision driving the number of cards held by borrowers in our model.

A new card is offered by a lender c and accepted by the borrower if it generates profits for the lender c and utility for the borrower. This condition is satisfied if (i) lender c expects the borrower will not default on card c with a positive probability, and (ii) if a new card increases the borrower's utility when priced at marginal cost for any

[31] The curvature could be put elsewhere: in the loan size or by adding some non-monetary benefits of owning multiple cards.

loan size dL. Condition (i) is satisfied thanks to the repayment shocks ε_{ir} in Equation 9. Condition (ii) is satisfied if:

$$\max_{r=\{c,b\}} [\underbrace{\alpha L_b + W + V_b(\{r\},\{c,b\})}_{\text{utility not repaying lender } b} + \underbrace{\alpha dL - mc(\theta)dL + V_c(\{r\},\{c,b\})}_{\text{utility new card}}]$$
$$> \underbrace{\alpha L_b + W - R_b + V_b(\{b\},\{b\})}_{\text{utility repaying card } b \text{ and not getting new card}} \tag{19}$$

Canceling out the terms that appear on both sides of this condition, and setting R_b to zero to maximize the right-hand side, we get the condition A2.

Appendix D2 shows that borrowers choose to repay only one card in equilibrium. Thus, although the above condition holds for the two-card case, it can be generalised to any number of lenders by adding V_e to both sides. Where V_e is the cost of defaulting on the other cards. By having the cost of defaulting increase with the number of cards in default, this equation pins down the number of cards offered in equilibrium. For simplicity, we consider that all borrowers chose the same number of cards and that this number is known by lenders.

6.2.2 Equilibrium contracts

With the parameter values satisfying conditions A_1 and A_2, each borrower gets a card from each lender in equilibrium and repays only one card. Thus, when lenders are homogeneous, each card has a default probability of $1 - \theta^{NE}$, with $\theta^{NE} = \frac{1}{|B|}$. The equilibrium contract $(R_b^{NE}, L_b^{NE}, q_b^{NE})$ for each bank b is:

$$\theta^{NE} = \frac{1}{|B|} \tag{20}$$

$$R_b^{NE} = W \tag{21}$$

$$L_b^{NE} = \theta^{NE} \frac{W - c(q_b^{NE})}{mc(\theta^{NE})} - \varepsilon^{-1} \tag{22}$$

$$q_b^{NE} := \{q : \frac{\beta V'(q)}{c'(q)} [\overbrace{\theta^{NE\prime} W \frac{c'(q)}{\beta} \frac{\alpha}{mc}}^{\text{overinvestment}} + \overbrace{\theta^{NE}}^{\text{underinvestment}}] = \frac{\alpha}{mc}\} \tag{23}$$

Proof: See Appendix D2.

Technical considerations: To get a closed-form solution for the demand semi-elasticity (ε^{-1}), We make the following assumption about the demand. We 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., $D_b(u) := \frac{exp(\sigma^d u_b)}{\sum_{l=1}^{N} exp(\sigma^d u_l)}$), the equilibrium inverse semi-elasticity is $\frac{1}{\alpha\sigma^d(1-\frac{1}{N})}$. I consider that $\varepsilon^{-1} < \frac{W-c(q_b^{NE})}{\theta^* mc(\theta^{NE})}$ so that $L_B^{NE} > 0$ to focus on the case in which there is borrowing.

Equilibrium contracts: Appendix D2 shows that it is optimal for the lender to cancel the card conditional on not repaying the loan (to maximize repayment probability), and to offer a card that maximizes the borrower's debt capacity (as in the exclusive contract case). Given those contract features, borrowers default on all but one of the cards. The expected survival probability in a symmetric equilibrium (Equation 20) is thus one over the number of cards: $\theta_b^{NE} = \frac{1}{|B|}$.

The higher default probability affects both credit limits (Equation 22) and the level of investment (Equation 23). Contrary to a model without endogenous default and card quality (e.g., Bizer and DeMarzo, 1992 or Parlour and Rajan, 2001), the implication of non-exclusivity on contract terms is ambiguous: there can be over- or under-investment with respect to the exclusive contract case.

Equation 23 highlights the two channels impacting the investment decision. The difference with the optimal level of investment (i.e., Equation 17) comes from the terms $[\theta^{NE\prime} W \frac{c'(q)}{\beta}\frac{\alpha}{mc} + \theta^{NE}] \neq 1$. For simplicity of the exposition, I assume that $\beta^{-1} = \frac{mc}{\alpha}$ in Equation 23 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 and make our results independent of this assumption.

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 increase q 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 second 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 in q.

Equation 22 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 us to compare it with the exclusive contract case:

$$L^{NE} := \sum_{b=1}^{B} L_b^{NE} = \frac{W - c(q_b^{NE}, \theta^{NE})}{mc(\theta^{NE})} - B\varepsilon^{-1} \tag{24}$$

Equation 24 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 $mc(\theta^{NE})$. 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.[32] This is the standard effect of contract non-exclusivity highlighted in, for instance, Parlour and Rajan (2001), Bizer and DeMarzo (1992) or Green and Liu (2021).

Second, exclusive contracts distort incentives to invest in q. When there is over-investment, the cost of lending increases (i.e., $c(q^{NE}) > 0$ is higher than in the non-

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

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.

6.3 Welfare Analysis

This section analyses how competition for loan seniority affects welfare and whether personal bankruptcy procedures are desirable. We focus on the non-exclusive equilibrium, and study whether it can be improved by policies that impose all loans of the same formal seniority to have the same recovery rate.

For the interested reader, we analyse in the Appendix F when the exclusive contract equilibrium is more desirable than the non-exclusive one. The key trade-off is the following. Non-exclusive contracts offer borrowers a higher product variety and the possibility to mix and match products, however, it comes at the cost of a distortion in contract terms (over- or underinvestment). There is an additional benefit to offering non-exclusive contracts when gaining seniority involves offering another loan: competition for loan seniority provides incentives to lower the markup on the product.

The random shock modelling we use is convenient for its tractability, to bring the model to the data, and to study competition (see, for instance, Rochet and Stole, 2002 for a theoretical discussion). Yet, it requires caution when making welfare statements. The reason is that random shocks affect both the default sensitivities to contract terms and the utility levels. To illustrate those two dimensions, let us consider the following parametric assumption. The repayment shocks ϵ_{ir} have the form σe_r with e_r following an extreme value distribution and σ parametrising its variance. With this parametric

assumption the borrower survival sensitivity ($\frac{\partial \theta^{NE}}{\partial q^{NE}}$) and utility ($u_i^{NE}$) are:

$$\frac{\partial \theta^{NE}}{\partial q^{NE}} = \sigma \theta^{NE}(1-\theta)V'(q^{NE}) \tag{25}$$

$$u_i^{NE} := \sum_{c \in B} \alpha L_c^{NE} + \beta ln(\sum_{c \in B} exp\{\sigma V_c(q^{NE})\}) \tag{26}$$

$$= \alpha L_c^{NE} \cdot |B| + \beta[\sigma V_c(q^{NE}) + ln(|B|)] \text{ in a symmetric equilibrium} \tag{27}$$

The above equations summarise the two channels captured by the default shocks. Equation 25 shows that the parameter σ drives the default elasticity to changes in card quality. It is thus a key parameter that affects the competition for the loan seniority channel. However, as the shocks ϵ_{ir} enter the utility function, they also capture the borrower's love for product variety (similarly to the demand elasticity parameter in CES demand). This is why σ multiplies V in Equation 27 and the utility increases with the number of products $|B|$ offered. To see that, one can compare the Equation 27 utility (u_i^{NE}) to the utility of a borrower for which the default shock enters the default decision, but not the utility (i.e. $\tilde{u}_i^{NE} = \sum_{c \in |B|} \alpha L_c^{NE} + Pr(r \in \mathcal{R}) V_c(q_c^{NE}) = \alpha L_c^{NE} \cdot |B| + \beta V_c(q^{NE})$).

To shut down the love for variety channel so that we can analyze the effect of changing the competition for loan seniority channel using changes in σ, we set $\beta = \frac{1}{\sigma}$ and consider that the utility is $\tilde{u}_i^{NE} := u_i^{NE} - \frac{\ln(|B|)}{\sigma}$. Scaling by $\frac{ln(N)}{\sigma}$ does not affect the contract terms, but it makes the utility $\tilde{u}_i$ exactly equal to the utility without the error term affecting its value.[33]

To analyse the effect of the competition for the loan seniority channel, let us take the derivative of $\tilde{u}_i^{NE}$ with respect to σ:

$$\frac{\partial \tilde{u}_i^{NE}}{\partial \sigma} = [\overbrace{-\frac{c_1(q^{NE}, \theta^{NE})}{mc(\theta^{NE})} \cdot |B|}^{\text{lower loan size}} + \overbrace{V'(q^{NE})}^{\text{higher rewards}}] \cdot \frac{\partial q^{NE}}{\partial \sigma} \tag{28}$$

$\frac{\partial q^{NE}}{\partial \sigma}$ is positive, so the sign depends on $\mathcal{W} := [-\frac{c_1(q^{NE}, \theta^{NE})}{mc(\theta^{NE})} \cdot |B| + V'(q^{NE})]$. The

[33] By still allowing the error term to enter the utility function, we ensure that borrowers' decisions are optimal so that the loss in welfare does not come from mistakes in default choices.

equation captures the following trade-off: increasing the default sensitivities incentivizes lenders to overinvest; however, this makes credit cards more expensive, which lowers the credit limit. One can estimate the c and V functions using standard industrial organisation approaches, such as Berry et al. (1995), and plug the estimates into $\mathcal{W}$.

To gain more intuition about the impact of competition on welfare, let us consider that $V(q) = \gamma q$ and $c(q) = c\frac{q^2}{2}$. In that case, we have:

$$q^{NE} = \theta^{NE}\gamma\frac{\sigma(1-\theta^{NE})W + \frac{mc}{\alpha}}{c} \tag{29}$$

$$\mathcal{W}(\sigma) = \gamma - q^{NE}[\frac{c}{mc}] \tag{30}$$

The Equation 30 implies a unique competition for loan seniority level $\varepsilon^{SB} := \frac{\partial\theta^{NE}}{\partial q^{NE}}\frac{1}{\theta^{NE}} = \sigma(1-\theta^{NE})(1-\frac{1}{|B|})$ that maximizes welfare. It is achieved for $\mathcal{W}(\sigma^{SB}) = 0$ and is equal to:[34]

$$\varepsilon^{SB} := [1 - \frac{\theta^{NE}}{\alpha}]\frac{mc}{\theta^{NE}W} \tag{31}$$

To understand Equation 31, notice that, in our model, there can be underinvestment due to default being too large, and over-investment due to competition for loan seniority. The above equation implies that, when the overinvestment channel dominates (i.e., the default elasticity in the data is higher than ε^{SB}), policies that lower the competition for loan seniority increase welfare. One candidate policy is to force borrowers to repay each lender $\frac{W}{|B|}$ in the second period. This can be interpreted as a default on any card triggering a bankruptcy procedure similar to the one for firms. The following statement and Figures **??** and **??** summarize when such a policy is likely to be desirable.

Result: *Setting a bankruptcy regulation that forces the same recovery rate (i.e., borrowers to repay all lenders $\frac{W}{|B|}$ instead of letting borrowers choose which lender to repay first) is*

[34]Indeed: $\mathcal{W}(\sigma)$ is decreasing in σ. When $\sigma = 0$, $\mathcal{W}(\sigma) := \gamma[1 - \frac{\theta^{NE}}{\alpha}] > 0$ when $\alpha > \theta^{NE}$ and $\lim_{\sigma\to\infty}\mathcal{W}(\sigma) = -\infty$.

valuable when competition for loan seniority is too high. This is more likely to be the case when the marginal costs of lending (mc)*, default* $(1\text{-}\theta)$*, and the number of lenders are low* $|B|$*, or when borrowers' debt capacity is large* W*, or value consumption in the first period is high.*

The above statement describes conditions that make competition for loan seniority detrimental to welfare, as it overcompensates the under-investment channel (as in **??**). The intuition for how it depends on the model parameters is the following (i.e., how the blue curve in **??** changes with the model parameters). When the debt capacity is large (W), it creates incentives to compete for loan seniority more aggressively because there is more money at stake. This makes it more likely that ε^{NE} is in the right region in **??**. When the number of borrowers and default are low, the underinvestment channel is likely to be small. As a result, the over-investment channel is more likely to dominate. Finally, as illustrated in Equation 28, competing for loan seniority increases rewards q at the expense of the credit limit. This tradeoff is more likely to be detrimental for borrowers when borrowing is valuable (high α) or when borrowing is cheap (low mc).

Priority rules: Moore and Hart (1995) shows that a priority rule can mitigate the debt dilution problem. However, as noted in Bizer and DeMarzo (1992), priority will have no effect if junior issuances increase the likelihood of default on senior claims due to, for instance, moral hazard.

In our model, we do not model moral hazard. Imposing a priority rule such that the "first lender to issue" should be repaid first would thus restore efficiency. While we do not explicitly model who is the first lender, we can accommodate our model as follows to include this priority rule. After the borrower accepts the credit cards, lenders learn whether they are the first cardholder (i.e., the one with priority).[35] If they have priority, lenders must commit to the contract they offered. If they do not have seniority, lenders do not have to commit. In that case, it is optimal for them to cancel the credit limit, as they would make no profit. As a result, the exclusive equilibrium contract can be

[35] In practice, this can reflect the fact that many borrowers make simultaneous credit card applications.

sustained.

Implementing such a regulation in practice might be challenging, as formal bankruptcy procedures that would guarantee priority are rarely used in the credit card context due to the significant fixed costs of litigation and the low recovery rate. An alternative would thus be to solve the problem outside of bankruptcy. For instance, by imposing a cap on the aggregate contract characteristics, such as the aggregate debt-to-income ratio (similarly to a covenant banks set for corporate loans). This regulation is costly to implement, as it may impose unnecessary restrictions if not fine-tuned to cater to borrowers' and lenders' heterogeneous needs.

Given those limitations, we limited ourselves to analysing the current regulation, under which all credit cards should have the same recovery rate in bankruptcy.

6.4 Quantification

In this subsection, we use our model together with our estimated to quantify the distortions in credit limits.

The model can be extended to feature multiple periods, a similar equation for the relationship benefits q can be written for revolvers:

$$q : \beta V'(q)\{\partial_{\beta V(q)}\theta_b(q, R, \mathcal{C})\pi + mc_L\theta_b\} = \partial_q mc(q) \tag{32}$$

The goal is to compare the relative value of these equations in the first best and in the data. Assuming that $V(q)$ is separable in credit limits $V(q) = V(L) + \tilde{V}(q\{L\})$, $V(L) = \alpha log(\sum_c L_c)$ and linear costs, we have that the aggregate credit limit q^{Data} relative to the first best credit limit should be:

$$\frac{mc_L\theta_b^{FB}}{\partial_q\theta_b\pi + mc_L\theta_b^{Data}} = \frac{q^{FB}}{q^{Data}} \tag{33}$$

We thus need to find the survival probabilities per period in the first-best (θ_b^{FB})

and in the data (θ_b^{Data}). The profits per period π conditional on survival, the survival sensitivities to contract terms $\partial_q \theta_b$ and the marginal cost of lending mc_L.

We estimated that $\partial_q \theta_b \approx 1.5 \times 10^{-5}$. With log utilities, this implies a coefficient of $\partial_{V(q)} \theta_b 1.5 \times 10^{-5} * \frac{q^{Data}}{\beta\alpha} = \frac{1.5}{1.13} \times 10^{-5}$. $\frac{q^{Data}}{\beta\alpha}$ is the borrower's willingness to pay for an additional real, which we assume is around 1.13 given the interest rate in brazil.

We have $\pi = r \cdot L$ with the net profitability conditional on survival per year being 17%, using estimates from Drechsler et al. (2025)[36] and the average borrowing amount is 10000 reais per card as in our data. We get that $\partial_q \theta_b(q, R, \mathcal{C})\pi$ is around $0.17 * 10000 * 1.5 \cdot 10^{-5} = 2.5\%$ in the data. We assume that only repayment R matters for aggregate default, so $\partial_q \theta_b(q, R, \mathcal{C})$ is equal to zero in the first best.

θ_b is the survival rate, which is around 10% for borrowers with two cards and around 1% for the same borrowers with one card only, according to our difference-in-differences estimates. Considering that the marginal cost of lending is about the return on deposits (i.e., 1+13%), we get that $mc_L \theta_b$ is 0.96 in the data and 1.06 in the first-best.

The relative credit credit limit is $\frac{L^{data}}{L^{FB}} = \frac{0.96+0.025}{1.06} \approx 0.93$ so the aggregate credit limit are 7% lower than in the first best. Imposing a regulation requiring equal recovery would further reduce the credit limit by 2.5%.

7 Conclusion

In this paper, we use a rich administrative dataset of household credit in Brazil to document new facts about the credit card market. We show that it is common for borrowers to hold multiple active cards issued by different lenders. We find that default rates rise with the number of lenders, and that, when facing financial distress, borrowers tend to prioritize repaying certain banks over others. Furthermore, we show that prioritized banks keep supplying credit to individuals even after they default on other banks.

While borrowing from multiple lenders may reflect increased competition and greater access to differentiated loan products and services, it also presents challenges,

[36]The net returns are 6.7% to which we add the net credit loss rate of 10%.

as externalities between lenders can lead to inefficiencies. Banks may respond to it by competing for repayment priority. We study these market inefficiencies through the lens of a model featuring non-exclusivity and repayment decisions.

Although our focus is on the credit card market, the idea of lenders endogenously competing for seniority applies more broadly to contexts in which claimants compete for scarce resources that are not allocated according to rules set by regulation (e.g., bankruptcy law) or contractual agreements. In many countries, the lack of formal household debt resolution mechanisms means that providers of unsecured loan products, beyond just credit cards, also compete for repayment priority. Similarly, before filing for bankruptcy, both firms and individuals may strategically select which creditors to prioritize. Consequently, our framework provides valuable insights into the implications of non-exclusivity in a variety of other contexts.

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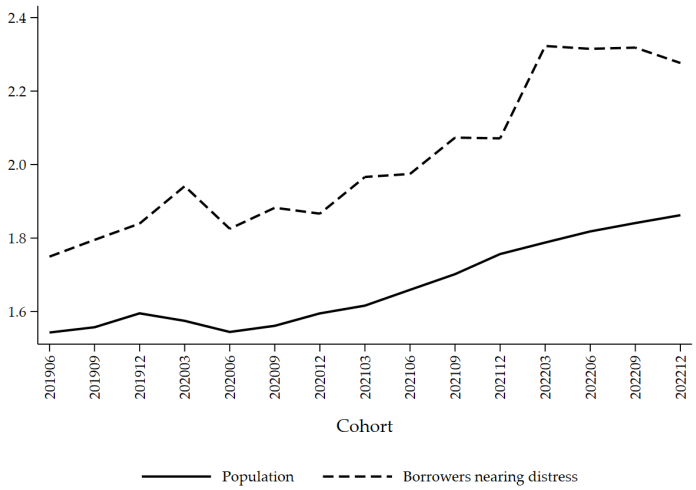
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Figures

Figure 1: Evolution of borrowing from multiple card lenders



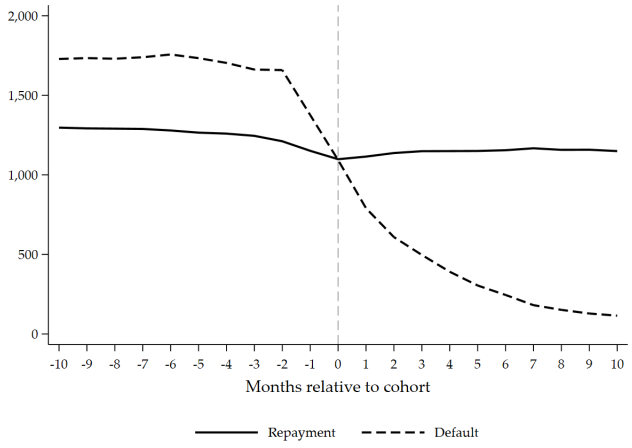
(**a**) Average number of credit card lenders



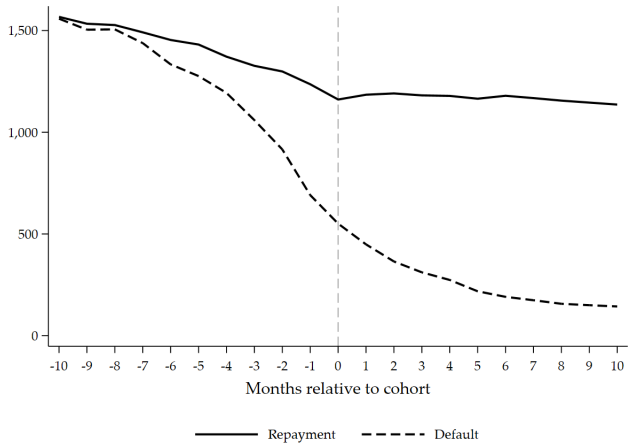
(**b**) Share of card borrowers with two or more credit card lenders

Notes: The unit of observation is the borrower–cohort. Panel (a) shows the evolution of the average number of credit card lenders per borrower. Panel (b) shows the evolution of the share of borrowers with two or more credit card lenders. Population statistics are computed using inverse probability weighting.

Figure 2: Evolution of credit card limits and usage among selective defaulters: paid versus unpaid cards



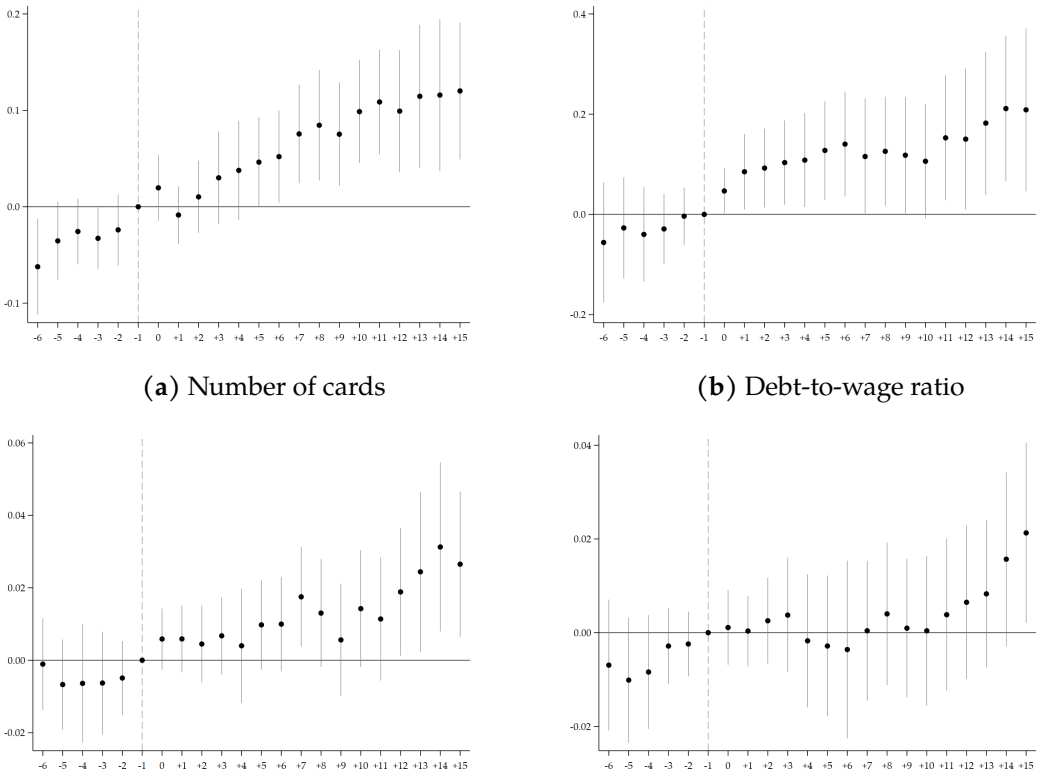
(**a**) Selective defaulters' monthly card usage: paid versus unpaid cards



(**b**) Selective defaulters' limit available: paid versus unpaid cards

Notes: The sample consists of *borrowers nearing distress* who are selective defaulters—individuals repaying at least one card while defaulting on another (payments over 90 days past due). Month 0 is defined as the month in which a borrower becomes more than 15 days overdue on any card.

Figure 3: Difference-in-Differences



(**a**) Number of cards

(**b**) Debt-to-wage ratio

(**c**) Delinquency rate

(**d**) Default rate

Notes: The figures present the results from estimating Equation 2. We report 95% confidence intervals calculated using standard errors clustered at the firm level. Delinquency (default) is a dummy variable equal to one if the individual has any debt payment overdue by more than 15 (90) days.

Figure 4: $(\varepsilon^{SB}, \varepsilon^{NE}, \varepsilon^{BR})$ **are the optimal, current and under regulation semi-elasticities**

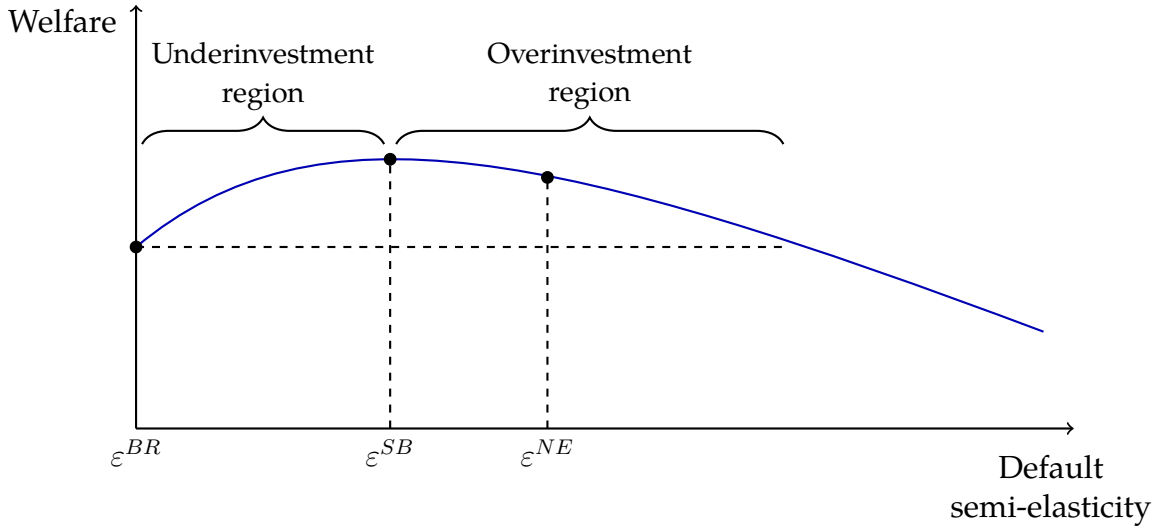
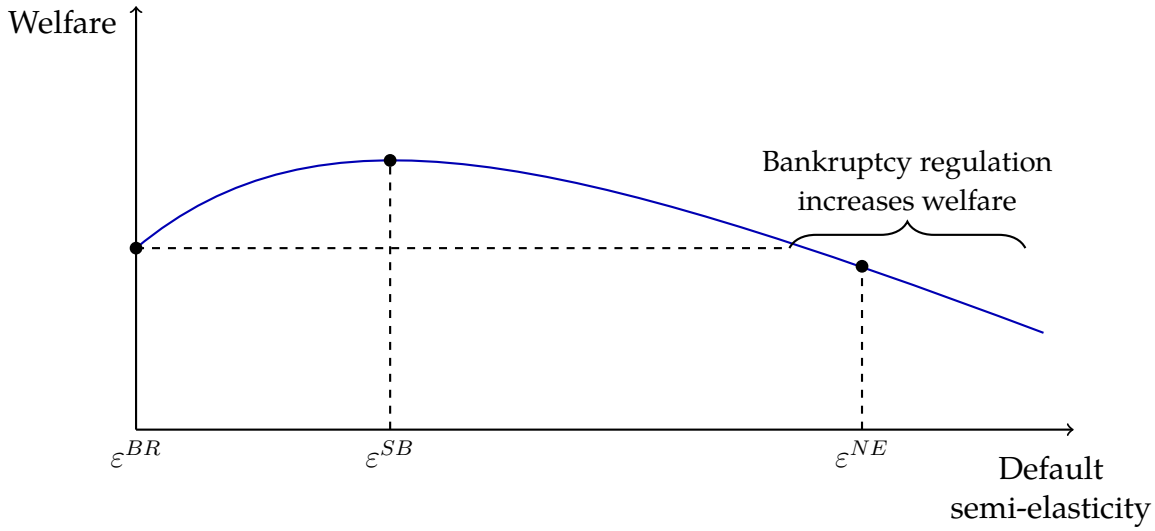


Figure 5: Example where the bankruptcy regulation is welfare increasing



Tables

Table 1: 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
Fraction of borrowers	60%	24%	9%	4%	2%	1%
Panel B: Borrowers nearing distress						
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
Fraction of borrowers	47%	27%	14%	6%	3%	3%

Notes: The unit of observation is the borrower–cohort. In Panel A, we compute population averages using inverse probability weighting. In Panel B, we compute sample means for the group of *borrowers nearing distress*. *Wage* (*formal*) refers to wages recorded in administrative data (RAIS) and are only available for workers employed in formal jobs. *Wage* (*reported*) refers to wages reported by banks. *Formal sector* is a dummy variable that takes the value one if the individual has a formal job. *Debt service to income* is the ratio of debt payments to income. All monetary values are in Brazilian reais (BRL).

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

	Number of card lenders					
	1	2	3	4	5	6+
Panel A: Random sample						
Default payroll loan	0.04	0.04	0.03	0.03	0.03	0.02
Default mortagage	0.01	0.01	0.01	0.01	0.01	0.02
Default auto loan	0.04	0.03	0.03	0.02	0.03	0.04
Default personal loan	0.11	0.10	0.10	0.10	0.11	0.13
Default other loans	0.10	0.08	0.09	0.09	0.09	0.11
Default credit card	0.07	0.10	0.13	0.15	0.17	0.21
Panel B: Borrowers nearing distress						
Default payroll loan	0.07	0.04	0.03	0.03	0.02	0.03
Default mortagage	0.05	0.02	0.01	0.01	0.00	0.01
Default auto loan	0.09	0.05	0.03	0.03	0.02	0.02
Default personal loan	0.09	0.08	0.06	0.05	0.05	0.05
Default other loans	0.11	0.07	0.05	0.04	0.04	0.07
Default credit card	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The unit of observation is the borrower–cohort in the month before the cohort. In Panel A, we compute population averages using inverse probability weighting. In Panel B, we compute sample means for the group of *borrowers nearing distress*.

Table 3: Default rates by number of cards of *borrowers nearing distress*

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

Notes: The unit of observation is the borrower–cohort for the sample of individuals classified as *borrowers nearing distress*. Columns (1) and (2) partition this group into borrowers who repay all credit cards six months after the cohort month and those who default on at least one card six months after the cohort month, respectively. Columns (3) and (4) further classify borrowers who default on at least one card into those who default on all cards (*universal defaulters*) and those who default on at least one card while continuing to repay at least one other card (*selective defaulters*), respectively. Columns (5) and (6) further split the latter group—*selective defaulters*—into borrowers who default on cards accounting for more than 50 percent and less than 50 percent of their total credit card balance, respectively, measured in the month of the missed payment.

Table 4: Mean of selected variables by default category of *borrowers nearing distress*

	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: The unit of observation is the borrower–cohort for the sample of individuals in the *borrowers nearing distress* group 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 values are in Brazilian reais (BRL).

Table 5: Default rates by number of cards: controlling for observables

	(1)	(2)	(3)	(4)	(5)	(6)
2 card lenders	0.03***	0.04***	0.04***	0.03***	0.04***	0.03***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
3 card lenders	0.06***	0.07***	0.08***	0.06***	0.07***	0.05***
	(0.011)	(0.011)	(0.011)	(0.009)	(0.011)	(0.009)
4 card lenders	0.09***	0.10***	0.12***	0.09***	0.10***	0.08***
	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)
5 card lenders	0.12***	0.14***	0.15***	0.11***	0.13***	0.10***
	(0.017)	(0.015)	(0.015)	(0.014)	(0.016)	(0.014)
6+ card lenders	0.22***	0.23***	0.24***	0.19***	0.21***	0.17***
	(0.017)	(0.017)	(0.016)	(0.016)	(0.018)	(0.016)
Age		-0.004***	-0.003***	-0.003***	-0.003***	-0.003***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female		-0.038***	-0.042***	-0.044***	-0.042***	-0.043***
		(0.003)	(0.004)	(0.004)	(0.003)	(0.004)
Wage			-0.008***	-0.008***	-0.008***	-0.008***
			(0.001)	(0.001)	(0.001)	(0.001)
Tenure			-0.000**	-0.000***	-0.000***	-0.000***
			(0.000)	(0.000)	(0.000)	(0.000)
Debt service to income				0.083***		0.076***
				(0.012)		(0.012)
Total debt to income					0.002***	0.001***
					(0.000)	(0.000)
Constant	0.460***	0.609***	0.604***	0.594***	0.603***	0.595***
	-0.005	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)
Observations	74,468	74,448	74,448	73,792	74,448	73,792
R-squared	0.153	0.161	0.164	0.174	0.167	0.175

Notes: The sample consists of *borrowers nearing distress* with a formal job. The dependent variable is an indicator equal to one if the borrower defaults on any card six months after the cohort month. All independent variables are measured at the cohort month. *Age* is measured in years, and *female* is a dummy variable equal to one if the worker is female. We only include borrowers with a formal job in the cohort month. *Tenure* refers to the length of time (in months) the worker has been in the job, and *wage* is the monthly salary (in thousands of BRL). *Debt service to income* is defined as total monthly debt payments divided by wage, while *total debt to income* refers to total outstanding debt divided by wage. The data are at the borrower–cohort level. All regressions include cohort and county fixed effects. Standard errors, reported in parentheses, are clustered at the cohort level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Descriptive statistics of regression variables

	(1)	(2)	(3)	(4)	(5)	(6)
	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 *borrowers nearing distress* with two or more card lenders and that default on a subset of their cards. All variables are binary and measured in the cohort month. We report the mean in column (1), the standard deviation in column (2), the 25th percentile in column (3), the median in column (4), the 75th percentile in column (5), and the number of observations in column (6).

Table 7: Predictors of selective default

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Unrestricted sample				Sample with interest rate information			
	All cohorts		Post May 2021		All cohorts		Post May 2021	
Positive global limit	-0.31***	-0.30***	-0.11***	-0.18***	-0.26***	-0.27***	-0.13***	-0.17***
	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.02)
Digital bank	-0.19***		-0.16***		-0.15***		-0.12***	
	(0.00)		(0.00)		(0.01)		(0.01)	
State-owned bank	0.17***		0.17***		0.23***		0.25***	
	(0.01)		(0.01)		(0.01)		(0.01)	
Payroll loan	-0.09***	-0.12***	-0.13***	-0.14***	-0.07***	-0.12***	-0.11***	-0.14***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Mortgage	-0.15***	-0.15***	-0.22***	-0.20***	-0.10**	-0.13***	-0.18***	-0.18***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)	(0.05)
Mortgage x state-owned bank	0.32***	0.20***	0.30***	0.19***	0.15***	0.14***	0.14**	0.14**
	(0.04)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)	(0.06)
Auto loan	-0.06***	-0.04***	-0.08***	-0.06***	-0.07***	-0.05***	-0.10***	-0.08***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)
Personal loan	0.04***	0.02***	0.04***	0.02***	0.02***	0.02***	0.01*	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Other loans	-0.11***	-0.06***	-0.12***	-0.04***	-0.07***	-0.06***	-0.08***	-0.05***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Default payroll	0.16***	0.16***	0.29***	0.26***	0.25***	0.22***	0.32***	0.28***
	(0.05)	(0.05)	(0.07)	(0.06)	(0.06)	(0.06)	(0.08)	(0.07)
Default mortgage	-0.08	-0.05	-0.05	-0.00	-0.04	-0.01	0.19	0.21
	(0.18)	(0.18)	(0.24)	(0.25)	(0.20)	(0.20)	(0.27)	(0.28)
Default auto loan	0.17***	0.20***	0.21***	0.26***	0.12	0.15**	0.20**	0.22**
	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)	(0.07)	(0.09)	(0.09)
Default personal loan	0.18***	0.17***	0.19***	0.19***	0.14***	0.14***	0.16***	0.17***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Default other loans	0.18***	0.15***	0.15***	0.13***	0.23***	0.18***	0.22***	0.17***
	(0.02)	(0.02)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)
Card with the largest contractual limit	-0.04***	-0.04***	-0.06***	-0.06***	-0.03***	-0.04***	-0.05***	-0.06***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Card with the largest balance	0.19***	0.18***	0.21***	0.19***	0.21***	0.19***	0.21***	0.19***
	(0.00)	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Card with the largest interest rate					0.29***	0.25***	0.32***	0.27***
					(0.00)	(0.00)	(0.00)	(0.00)
Constant	0.50***	0.47***	0.46***	0.43***	0.37***	0.39***	0.33***	0.35***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	174,078	174,031	119,827	119,785	101,989	101,950	68,905	68,869
R-squared	0.213	0.292	0.201	0.287	0.290	0.357	0.290	0.358
Borrower FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: The table reports coefficient estimates from Equation 1. The sample is comprised of *borrowers nearing distress* 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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Difference-in-differences approach

	(1)	(2)	(3)	(4)
	Number of cards	Card debt to income	Delinquency	Default
$Post_Treat^{[0-6]}$	0.05***	0.092***	0.009**	0.007
	(0.02)	(0.033)	(0.004)	(0.005)
$Post_Treat^{[7-15]}$	0.11***	0.137**	0.019**	0.011*
	(0.03)	(0.053)	(0.008)	(0.006)
Constant	1.3***	1.3***	0.029***	0.025***
	(0.03)	(0.05)	(0.010)	(0.009)
Observations	67,132	67,132	67,132	67,132
R-squared	0.775	0.841	0.648	0.651

Notes: The table reports results from the estimation of Equation 3. Delinquency (default) is a dummy variable equal to one if the individual has any debt payment overdue by more than 15 (90) days. In all regressions, we include individual fixed effects, firm-by-month fixed effects, and baseline default status interacted with time dummies. Standard errors, reported in parentheses, are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

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A Empirical part

A1 Sampling

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 potentially transitioning into default (i.e., more than 90 days overdue) as *borrowers nearing distress*. 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 individual in 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 *borrowers nearing distress*. These individuals include those who were not in good standing with all their cards at $t-1$ and those 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 *all other borrowers*. The sampling procedure is described in Appendix Table A1. We apply inverse probability weighting to estimate statistics for the population of credit card users. The final data is at the cohort-individual-bank-month level.

In Appendix Table A2, we report the default and delinquency rates for both groups in the month preceding the cohort. For the *all other borrowers* group, 7% of individuals have at least one card with payments overdue by more than 90 days (default), and 10.3% of borrowers have at least one card with payments overdue by more than 15 days (delinquent). By design, both the delinquency and default rates for the *borrowers nearing distress* group are zero. In Appendix Table A3, we report a total of 524,533 observations at the cohort-by-individual level, with 252,844 observations belonging to the *borrowers nearing distress* group. Consistent with the growth of the credit card industry, more recent cohorts are larger than the older ones.

Table A1: Sampling procedure for cohort t

	Repayment Standing at t-1	Repayment Standing at t	Share sampled
Borrowers nearing distress	Good	Bad	1%
All other borrowers	Good	Good	
All other borrowers	Bad	Good	0.025%
All other borrowers	Bad	Bas	

Notes: The table describes our sampling procedure. A borrower is classified as being in good repayment standing if all active cards exhibit payment delays of no more than 15 days. Conversely, an individual is classified as being in bad repayment standing if at least one active card has a payment overdue by 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 A2: Default and delinquency incidence at $t-1$ (month before the cohort)

	Borrowers nearing distress		All other borrowers	
	Card level	Borrower level	Card level	Borrower level
Panel A: All card users				
Delinquency rate	0	0	10.3	13.2
Default rate	0	0	7.0	9.2
Panel B: Card users with 2+ cards				
Delinquency rate	0	0	10.4	17.6
Default rate	0	0	7.0	12.2

Notes: A credit card loan is classified as delinquent if its payments are more than 15 days overdue and as in default if its payments are more than 90 days overdue. A borrower is considered delinquent (in default) if at least one of their credit cards has payments that are more than 15 (90) days overdue.

Table A3: Sample evolution

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

Notes: The table shows the evolution of the number of unique card users per cohort and group classification.

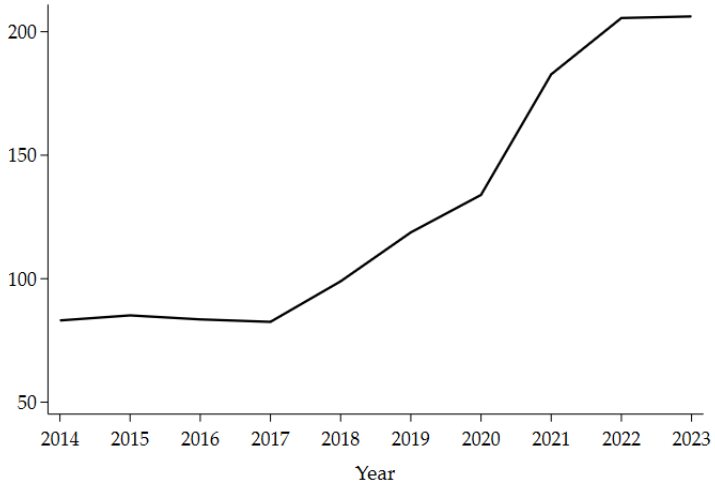
Table A4: Size of groups based on the number of credit card lenders

	Frequency			Shares	
Number of card lenders	Borrowers nearing distress	All other borrowers	Total	Borrowers nearing distress	All other borrowers
1	117,788	163,114	280,902	47%	60%
2	68,462	65,961	134,423	27%	24%
3	34,509	25,363	59,872	14%	9%
4	16,432	9,908	26,340	6%	4%
5	7,793	4,033	11,826	3%	1%
6+	7,860	3,310	11,170	3%	1%
Total	252,844	271,689	524,533	100%	100%

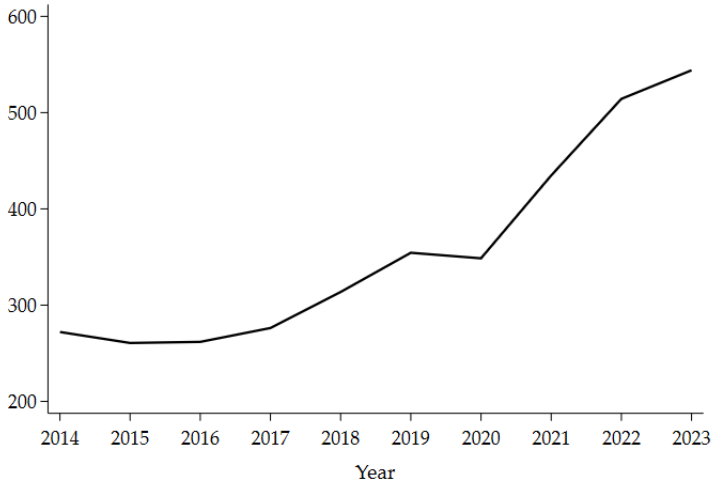
Notes: Borrowers are categorized based on the number of credit card lenders. The data are at the borrower-cohort level.

A2 Institutional setting: additional details from aggregate data

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



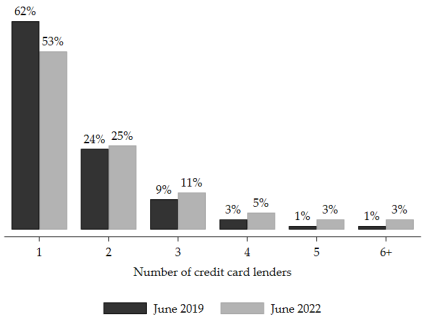
(**a**) Total number of active credit cards (in millions)



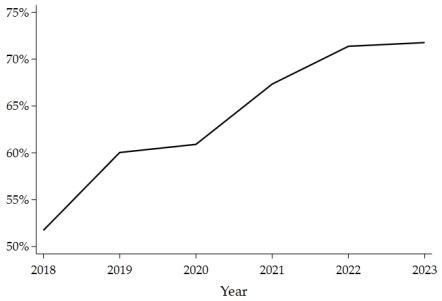
(**b**) Total credit card loans (inflation-adjusted values in billions BRL)

Notes: The figure reports the total number of active credit cards and credit cards outstanding balance per year. Monetary values are expressed in constant 2023 Brazilian reais and adjusted by the consumer price index (*Índice Nacional de Preços ao Consumidor Amplo,* IPCA). Source: Central Bank of Brazil (*Estatísticas de Meios de Pagamentos* and IF.data).

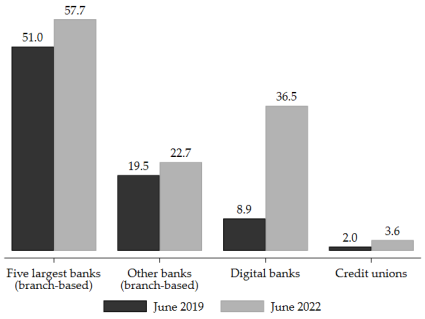
Figure A2: Evolution of borrowers with more than one card lender and growth of digital banks



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



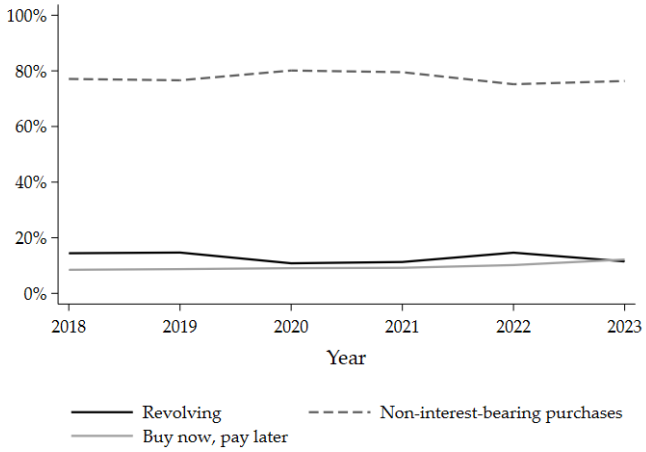
(**b**) Share of total credit card balance held by borrowers with two or more card lenders



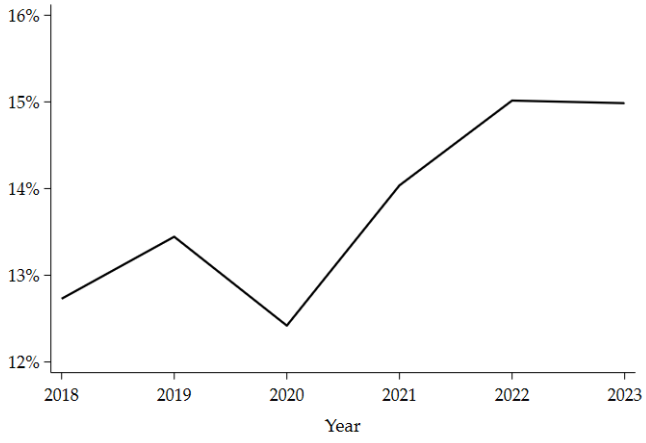
(**c**) Number of credit card users by bank type category, 2019 and 2022

Notes: Panel (a) shows the distribution of credit card users by the number of card lenders in 2019 and 2022. Panel (b) reports the share of total outstanding credit card balances held by users with two or more card issuers. Panel (c) presents the evolution of the number of credit card users per bank type category. All statistics are computed using data from Central Bank of Brazil (2022).

Figure A3: Composition of credit card balance and participation of credit card debt in total household debt



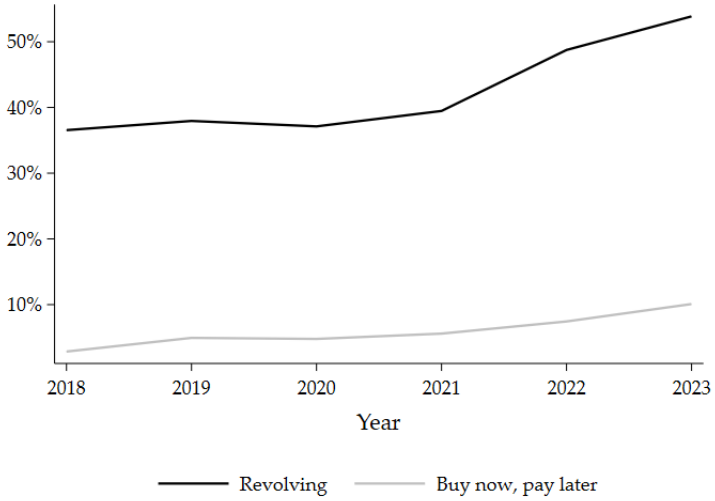
(**a**) Composition of credit card balance



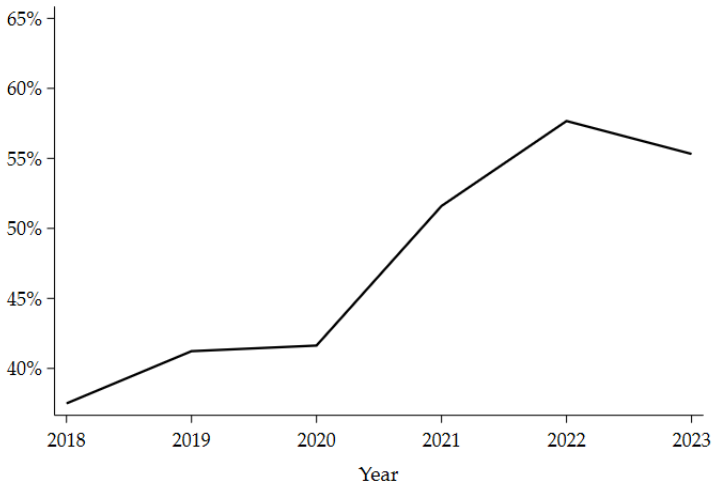
(**b**) Participation in total household debt

Notes: Panel (a) shows the composition of credit card balances. *Revolving* balances arise when cardholders do not pay the full statement balance by the due date and therefore accumulate interest-bearing debt. *Non-interest-bearing purchases* are transactions made during the billing cycle that are fully due on the next payment date and incur no interest if paid on time. *Buy now, pay later* (BNPL) balances correspond to credit card transactions repaid in installments, with or without interest. Panel (b) shows the participation of credit card debt in total household debt. The data are from the Central Bank of Brazil's SCR.data and Time Series Management System.

Figure A4: Participation of credit card debt in total household debt default



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

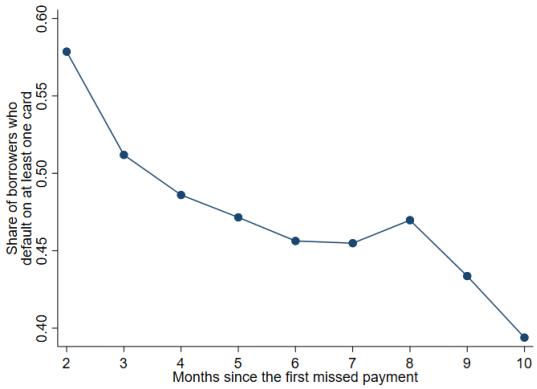


(**b**) Participation in total amount overdue for more than 15 days

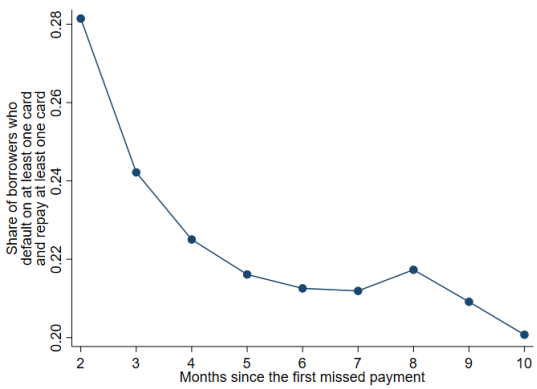
Notes: Panel (a) shows the share of balances in default for the *revolving* and *buy now, pay later* categories. Default is defined as payments more than 90 days past due. Panel (b) shows the share of credit card debt overdue by more than 15 days in total household debt overdue by more than 15 days. We use data from the Central Bank of Brazil's SCR.data and Time Series Management System.

A3 Default and selective default evolution t months after becoming 15+ days overdue

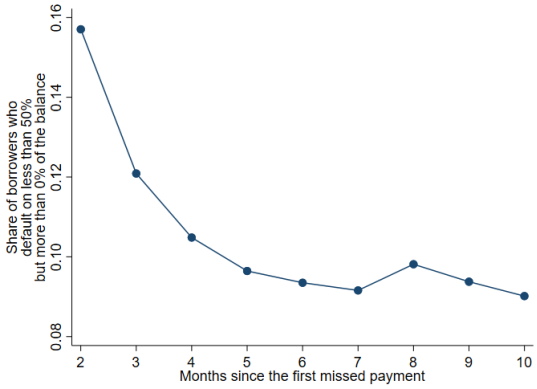
Figure A5: Default and selective default evolution t months after becoming 15+ day overdue



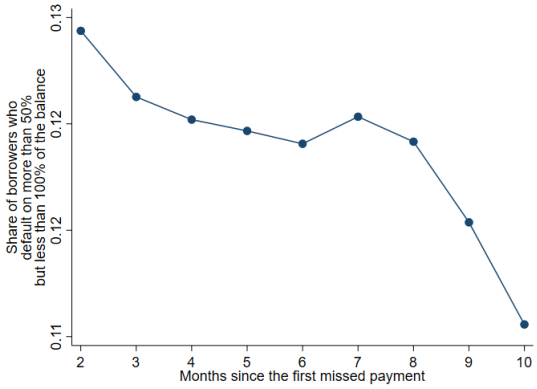
(**a**) Share of *borrowers nearing distress* with at least one card 90+ days overdue



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

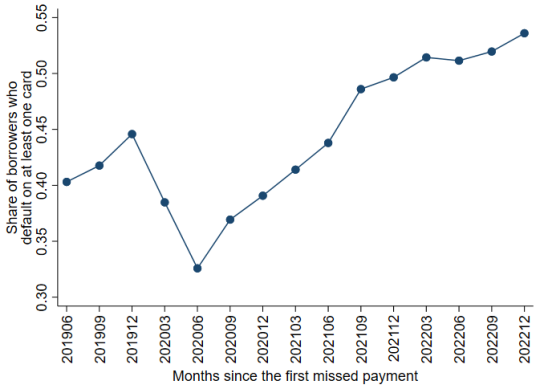


(**c**) Share of *borrowers nearing distress* with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance

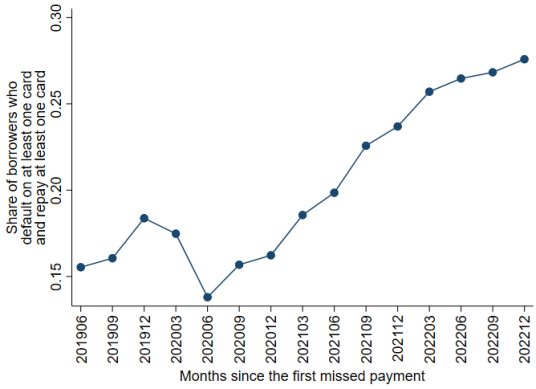


(**d**) Percentage of *borrowers nearing distress* with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

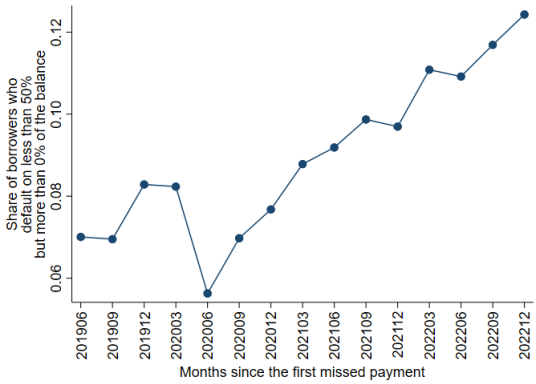
Figure A6: Default and selective default evolution



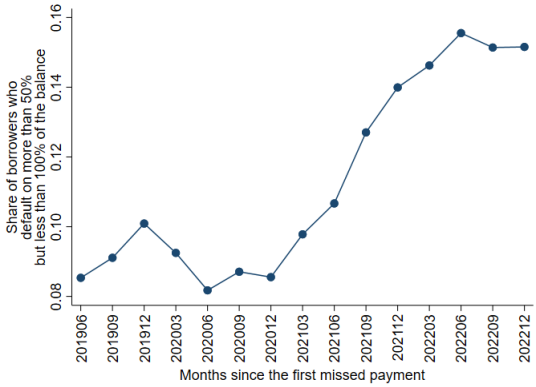
(**a**) Share of *borrowers nearing distress* with at least one card 90+ days overdue



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



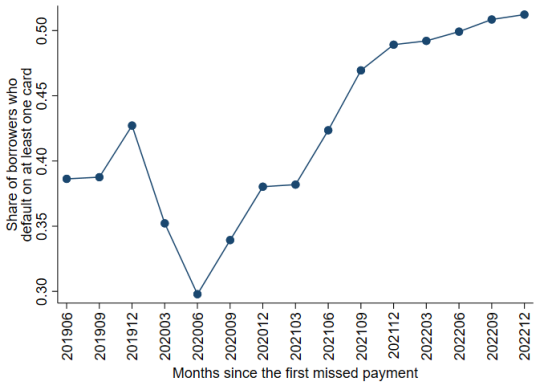
(**c**) Share of *borrowers nearing distress* with at least one card 90+ days overdue, at least one in good standing, and default on less than 50% of the total card balance



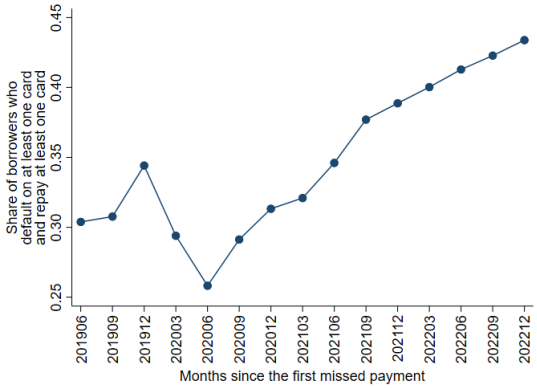
(**d**) Percentage of *borrowers nearing distress* with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample comprises *borrowers nearing distress* 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 15 days overdue.

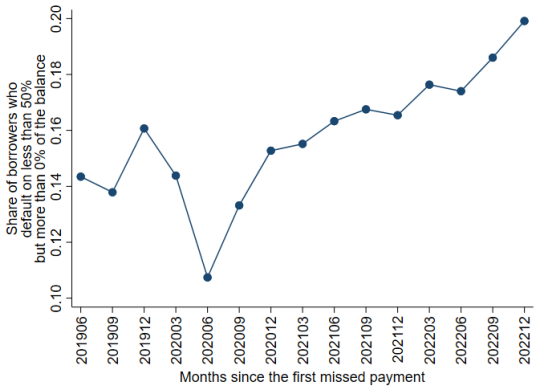
Figure A7: Default and selective default evolution, borrowers with at least two cards



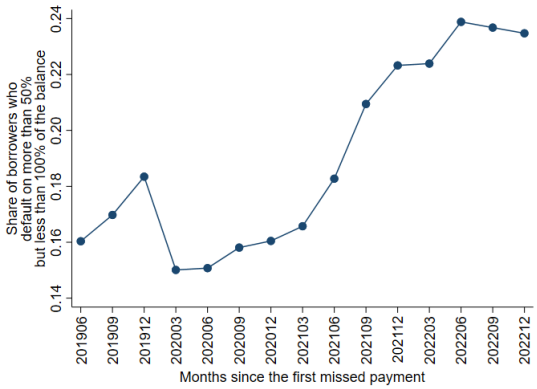
(**a**) Share of *borrowers nearing distress* with at least one card 90+ days overdue



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



(**c**) Share of *borrowers nearing distress* 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

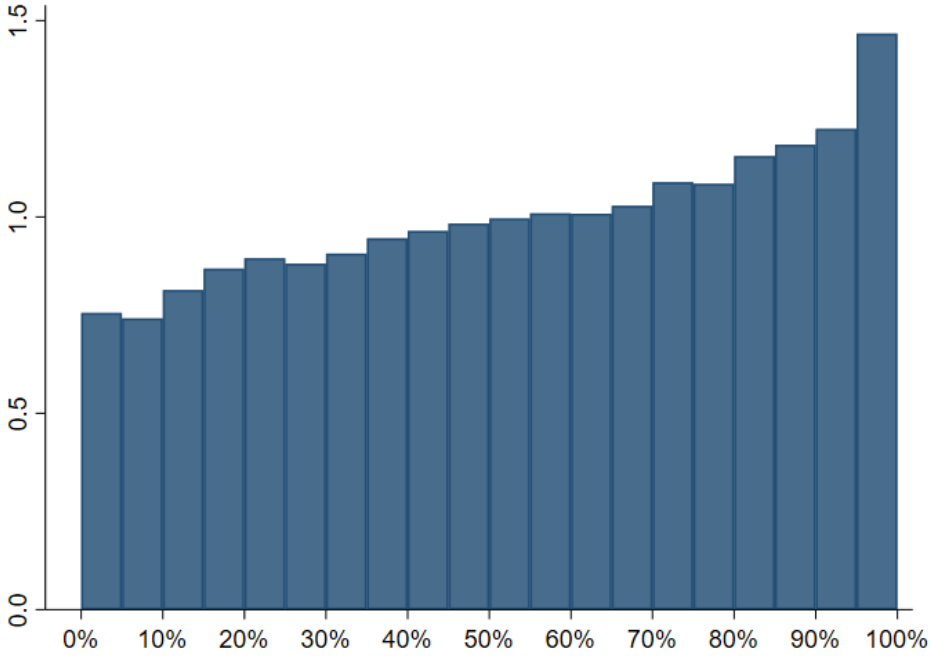


(**d**) Percentage of *borrowers nearing distress* with at least one card more than 90 days overdue and at least one card in good standing, and default on more than 50% of the total card balance

Notes: The sample comprises *borrowers nearing distress* who have two or more cards. We classify a card as in default if there is a 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

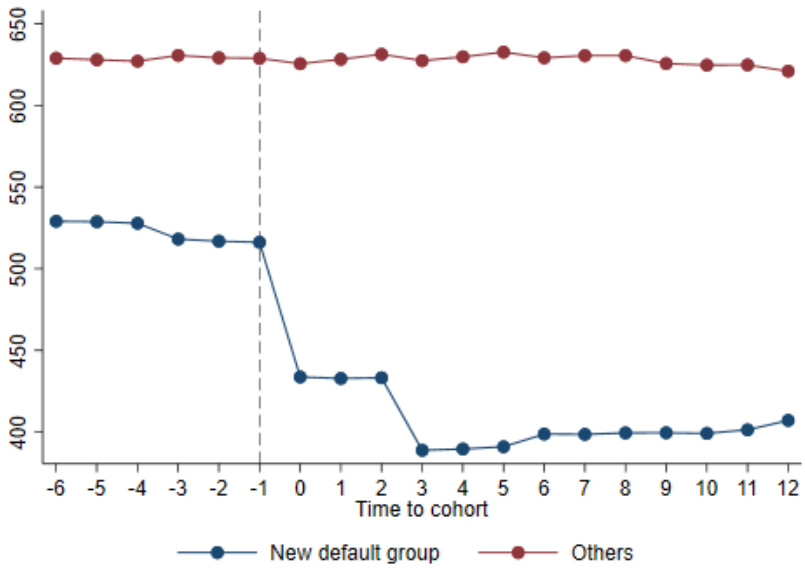
Figure A8: Share of balance in default



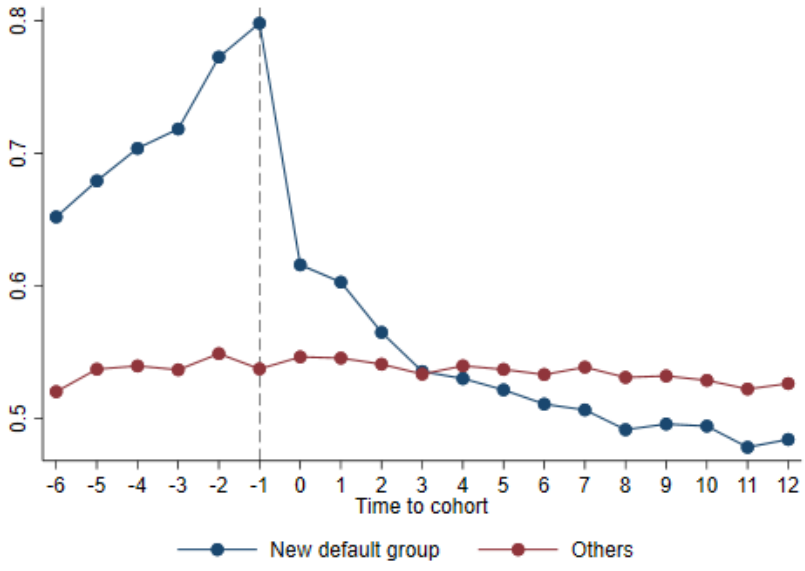
Notes: This figure plots the distribution of the share of total balance in default among selective defaulters. We measure default as payment more than 90 days past due six months after the cohort month. We compute the shares using the balances at the cohort month.

A5 Default and credit scores

Figure A9: Evolution of credit scores around default events



(**a**) Credit score



(**b**) Probability of obtaining a new loan

Notes: This figure plots the average credit score and probability of obtaining a new loan for borrowers who experience a new default in a given month (the cohort) relative to borrowers who do not experience a default in the same month.

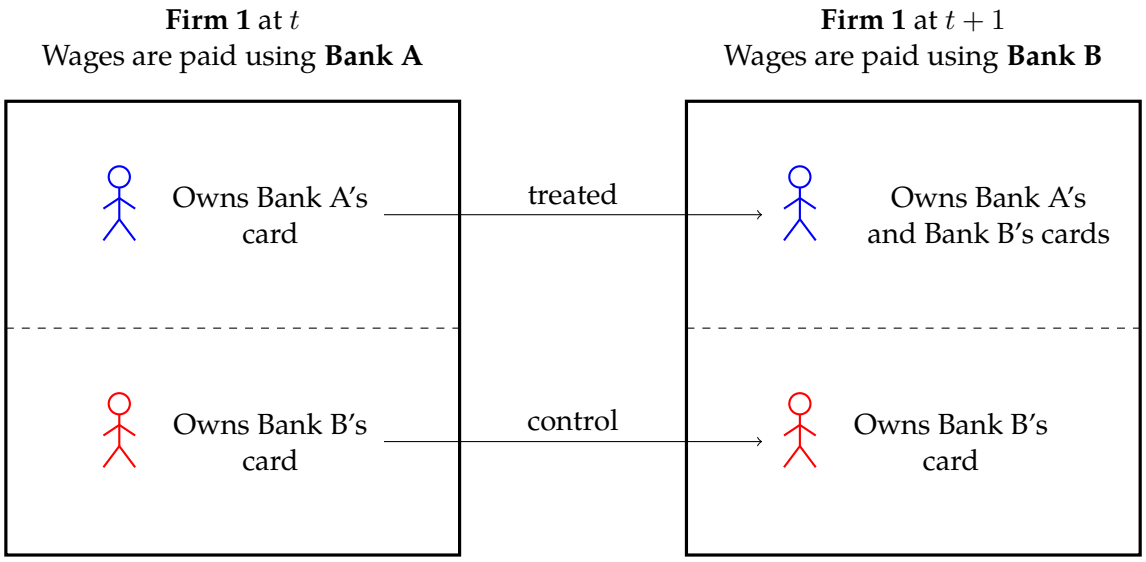
Table A5: Predictors of selective default

	(1)	(2)
	All cohorts	Post May 2021
Limit utilization 50% - 60%	0.11***	0.11***
	(0.01)	(0.01)
Limit utilization 60% - 70%	0.12***	0.12***
	(0.01)	(0.01)
Limit utilization 70% - 80%	0.13***	0.14***
	(0.01)	(0.01)
Limit utilization 80% - 90%	0.20***	0.21***
	(0.01)	(0.01)
Limit utilization 90% - 100%	0.23***	0.23***
	(0.01)	(0.01)
Limit utilization 100%	0.46***	0.47***
	(0.01)	(0.01)
Positive global limit	-0.28***	-0.26***
	(0.01)	(0.02)
Digital bank	-0.19***	-0.15***
	(0.00)	(0.01)
State-owned bank	0.20***	0.20***
	(0.01)	(0.01)
Payroll loan	-0.03***	-0.07***
	(0.01)	(0.01)
Mortgage	-0.06	-0.11**
	(0.05)	(0.05)
Mortgage x state-owned bank	0.10**	0.08
	(0.05)	(0.06)
Auto loan	-0.05***	-0.07***
	(0.01)	(0.02)
Personal loan	0.05***	0.04***
	(0.01)	(0.01)
Other loans	-0.03***	-0.03***
	(0.01)	(0.01)
Default payroll	0.20***	0.25***
	(0.06)	(0.07)
Default mortgage	0.15	0.14
	(0.18)	(0.23)
Default auto loan	0.12	0.15
	(0.08)	(0.09)
Default personal loan	0.15***	0.14***
	(0.03)	(0.03)
Default other loans	0.24***	0.21***
	(0.03)	(0.04)
Largest limit available	0.03***	0.03***
	(0.01)	(0.01)
2nd largest limit available	0.02**	0.02***
	(0.01)	(0.01)
Highest interest rate	0.25***	0.25***
	(0.00)	(0.00)
Constant	0.09***	0.09***
	(0.01)	(0.01)
Observations	102,632	69,257
R-squared	0.321	0.344

Notes: The table reports coefficient estimates from Equation 1. The sample consists of *borrowers nearing distress* 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. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

A6 Difference-in-differences analysis

Figure A10: Identification strategy



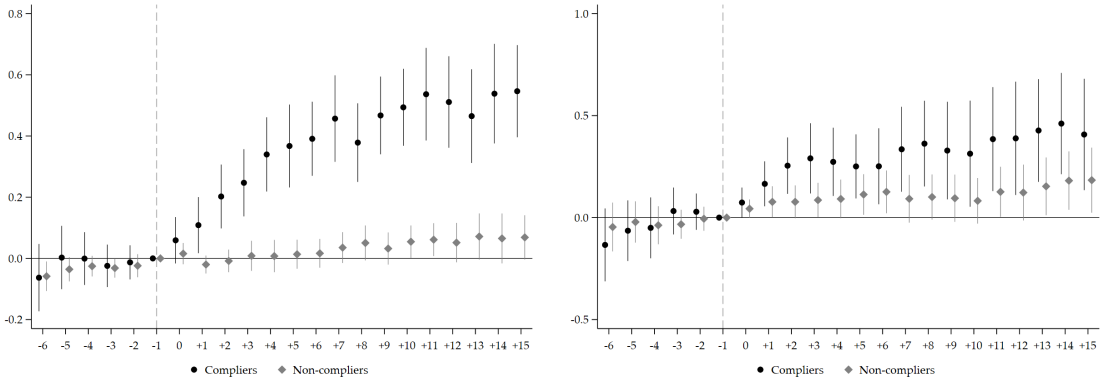
Notes: We compare the relative number of cards and default probability of the blue (treated) and red (control) groups of borrowers before and after the change in the bank that manages the payroll.

Table A6: Descriptive statistics

		Treated		
	Control	Complier	Non-complier	All
Number of card lenders	1.5	1.3	1.2	1.2
Debt-to-wage ratio	1.5	1.0	1.3	1.3
Delinquency rate	0.05	0.02	0.02	0.02
Default rate	0.04	0.01	0.02	0.02
Number of individuals	702	163	2,701	2,864

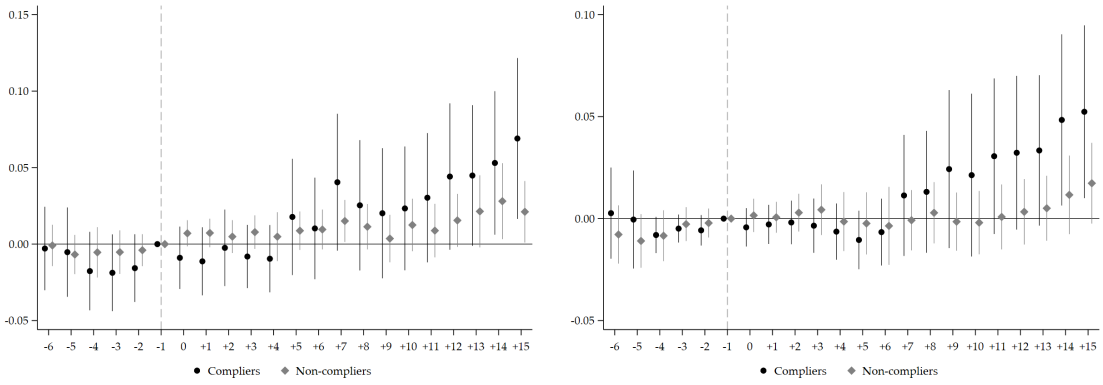
Notes: We report means of selected variables in the month prior to the new bank assuming management of payroll. Means are reported separately for three groups: individuals in the control group, compliers (treated borrowers who use a card from the new bank at some point after treatment), and non-compliers (treated borrowers who never use a card from the new bank in any month of the post-treatment period). Delinquency (default) is defined as a dummy variable equal to one if the individual has any debt payment overdue by more than 15 (90) days

Figure A11: Difference-in-Differences: Compliers versus Non-compliers



(**a**) Number of cards

(**b**) Debt-to-wage ratio



(**c**) Delinquency rate

(**d**) Default rate

Notes: The figures show the results from estimating Equation 2 with the following modification: treatment dummies are interacted with post-treatment take-up status—compliers (treated borrowers who use a card from the new bank at some point after treatment) and non-compliers (reated borrowers who never use a card from the new bank in any month of the post-treatment period). We report 95% confidence intervals calculated using standard errors clustered at the firm level. Delinquency (default) is defined as a dummy variable equal to one if the individual has any debt payment overdue by more than 15 (90) days

B Examples of micro-foundations for V_c

Let us now discuss different functional forms for V_c that can capture the stylized facts presented in Section 3.2. The empirical section suggests that three main channels can affect repayment behavior. First, the lenders can invest in an app or a reward system that the borrower values, making the threat of cancelling the card upon default more costly. Second, the lender can change the credit limit on the card depending on the repayment behavior. Third, the lender can offer another loan product in the second period if the borrower does not default on the card.

Those three channels can be captured using the following parametrization of V_c:

$$\text{App or reward system: } V_c(q_c, \mathcal{R}) = q_c(\mathcal{R}) \tag{34}$$

$$\text{Credit limit: } V_c(\tilde{L}_c, \tilde{R}_c, \mathcal{R}) = \tilde{L}_c(\mathcal{R}) - \beta \tilde{R}_c(\mathcal{R}) \tag{35}$$

$$\text{Other Loan product: } \sum_c V_c(\underbrace{\tilde{L}_c, \tilde{R}_c}_{q_c}, \mathcal{R}) = E_{\varepsilon_b}[\max_b \{\tilde{L}_b(\mathcal{R}) - \beta \tilde{R}_b(\mathcal{R}) + \varepsilon_b\}] \tag{36}$$

In Equation 34, q_c can be interpreted as the app quality or the generosity of the reward system. In Equations 35 and 36, $\tilde{L}_c$ and $\tilde{R}_c$ are the loan size and the debt face value for the credit card and the other loan product, respectively. The variables q_c, $\tilde{L}_c$ and $\tilde{R}_c$ are functions of $\mathcal{R}$. That is, lenders can condition their value based on the borrower's repayment behavior, potentially canceling access to the bank app or the rewards if the borrower does not repay the credit card.

The timing assumption behind Equations 35 and 36 is the following, and requires adding one period to the model. After seeing the repayment in period 2, the lender changes the credit card contract to offer a new loan product. The repayment $\tilde{R}$ of the new contract happens at the end of a third period. The benefit of borrowing $\tilde{L}$ happens in the second period. For simplicity, we assume that the borrower cannot get a new credit card contract in period 2 (for Equation 35), or that the other loan contracts are exclusive in the second period (for Equation 36). This assumption is in line with the empirical evidence that other contracts offered are mortgages or car loans, for which

borrowers typically only get one. The fact that the borrower does not get a new card (for Equation 35) can be micro-founded by a model in which the repayment shocks in the third period are perfectly correlated with those in the second period. In that case, since the next section shows that the borrower repays only one contract in the second period, the lender learns that if they have seniority in the third period, and are thus the only lender.

The following section 6.1 shows that when lending generate a positive net present value, there exist an equilibrium in which it is optimal to exclude borrowers in the second period (i.e., set $q_c = L_c = R_c = 0$ if $c \notin \mathcal{R}$) if they did not repay their debt, and to set $\tilde{R} = \tilde{W}$ if they repays, where $\tilde{W}$ is the borrower wage in the third period. In that case, all three equations are equivalent: They are all increasing functions of one variable (q_c or $\tilde{L}_c$) conditional on repayment. V_c can be normalized to zero conditional on defaulting on card c. This justifies the general approach used in Equation 9.

C Examples of Micro-foundations for c_c

Using the three micro-foundations discussed in Section 5.1, potential functional forms for the cost function are:

$$\text{Rewards: } c_c(q_c, \theta_c(R_c, q_c)) := c_c(max\{q_c(\mathcal{R})\}) \text{ positive convex and increasing} \quad (37)$$

$$\text{Credit limit: } c_c(R, \tilde{R}, \tilde{L}, \theta_c(R, \tilde{R}, \tilde{L})) = -\theta_c(R, \tilde{R}, \tilde{L})\{\tilde{R} - mc\tilde{L}\} \quad (38)$$

$$\text{Other Loan: } c_c(R, \tilde{R}, \tilde{L}, \theta_c(R, \tilde{R}, \tilde{L})) = -\theta_c(R, \tilde{R}, \tilde{L})\tilde{D}(\tilde{R}, \tilde{L})\{\tilde{R} - mc\tilde{L}\} \quad (39)$$

In Equation 37, we consider that setting a generous reward system requires the lender to set aside some money in the first period $c(max\{q_c(\mathcal{R})\})$. The operator $max\{q_c(\mathcal{R})\}$ captures the fact that the bank pays the cost in the first period and should ensure to have invested enough to provide the maximum reward it committed to.

In equations 38 and 39, the costs are paid in the second period, after the repayment $\mathcal{R}$ is observed. We drop the $\mathcal{R}$ from the variables $(R, \tilde{R}, \tilde{L})$ to simplify the notation. The cost function can be positive or negative depending on the markup the lender sets for

the other product, sold in the second period. In Equation 39, $D(\tilde{R}, \tilde{L})$ is the probability of choosing bank c in the second period. It is derived from Equation 36.

As in section 5.1, when lending is a positive NPV, it is optimal to set $\tilde{R} = \tilde{W}$, where $\tilde{W}$ is the borrower's income in the second period. All the equations are thus functions of one variable (q or $\tilde{L}$).

D Proofs

D1 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 $R = \alpha L - u + V_c(q)$, and allow the lender to choose (u, L, q). The first-order condition with respect to L is always positive, so we must be at a corner solution.

More formally, let us denote u the borrower utility and $q := (\bar{q}, \underline{q})$ where $\bar{q}$ is the card quality conditional on repaying the card $\underline{q} \geq 0$ is the reward conditional on default:

$$u := \alpha L + \int_{-\infty}^{\bar{\epsilon}} V(\bar{q}) - R - \epsilon dF(\epsilon) + \int_{\bar{\epsilon}}^{\infty} V(q) dF(\epsilon) \tag{40}$$

With $\bar{\epsilon} := V(\bar{q}) - V(\underline{q}) - R$. $\bar{\epsilon}$ is the threshold above which the borrower chooses to default.

The lender problem is:

$$\max_{\bar{q}, q, R, L} D(u)[\int_{-\infty}^{\bar{\epsilon}} R dF(\epsilon) - mcL - c(\bar{q}, \underline{q})] \tag{41}$$

Using the change of variable $L = \frac{1}{\alpha}[u - (\int_{-\infty}^{\bar{\epsilon}} V(\bar{q}) - R - \epsilon dF(\epsilon) + \int_{\bar{\epsilon}}^{\infty} V(q) dF(\epsilon))]$,

the lender problem becomes:

$$\max_{\bar{q}\geq 0, \underline{q}\geq 0, W\geq R\geq 0, u} D(u)\{\int_{-\infty}^{\bar{\epsilon}} RdF(\epsilon) - \frac{mc}{\alpha}[u - \int_{-\infty}^{\bar{\epsilon}} V(\bar{q}) - R - \epsilon dF(\epsilon) - \int_{\bar{\epsilon}}^{\infty} V(q)dF(\epsilon)] - c(\bar{q}, \underline{q})\} \tag{42}$$

This setup is general enough to capture the credit limit and new loan cases by letting: $c(q) = \int_{-\infty}^{\bar{\epsilon}} \tilde{c}(\bar{q})dF(\epsilon) + \int_{\bar{\epsilon}}^{\infty} \tilde{c}(\underline{q})dF(\epsilon)$.

The derivative with respect to $\underline{q}$ yields:

$$A := -V'(\underline{q})Rf(\bar{\epsilon}) + \frac{mc}{\alpha}V'(\underline{q})[1 - F(\bar{\epsilon})] - c_2(\bar{q}, \underline{q}) \tag{43}$$

$$A < 0 \; \forall q, R > 0, \bar{\epsilon} \implies \underline{q} = 0 \tag{44}$$

The derivative with respect to $\bar{q}$ yields:

$$V'(\bar{q})Rf(\bar{\epsilon}) + \frac{mc}{\alpha}V'(\bar{q})[F(\bar{\epsilon})] - c_1(\bar{q}, \underline{q}) \tag{45}$$

The derivative with respect to R yields:

$$B := F[1 - \frac{mc}{\alpha}] - Rf(\bar{\epsilon}) \tag{46}$$

$$B > 0 \; \forall R, \bar{\epsilon} \implies R = W \tag{47}$$

The derivative with respect to u yields:

$$\pi := [\int_{-\infty}^{\bar{\epsilon}} RdF(\epsilon) - mcL - c(q, \bar{q})] = \frac{D}{D'}\frac{mc}{\alpha} \tag{48}$$

The condition $\alpha - mc(\theta) > 0, \; \forall\theta$ implies that $F[1 - \frac{mc}{\alpha}] > 0$ in Equation 46. Using the first order conditions with respect to q, we have $\bar{q} > \underline{q}$. Together with the conditions $V_c(q, \{c\}) - \epsilon_{ir} - R > V_c(q, \emptyset), \; \forall R \leq W_i, \forall\epsilon_{ir} \in S$, we have $f(\bar{\epsilon}) = 0$ if $R < W$. Equation 47 is satisfied so that $R = W$.

The same conditions imply that Equation 44 is satisfied as well ($[1 - F(\bar{\epsilon})] = 0$ and $f(\bar{\epsilon}) = 0$, $c' > 0$ so that $B < 0$) so that the card is canceled conditional on not repaying.

Rearranging the first order conditions with respect to u (Equation 48) and $\bar{q}$ (Equation 45) using the fact that $F = 1$ and $f = 0$, $\frac{D}{D'} = \varepsilon^{-1}$ gives us the L^* and q^* conditions.

D2 Proof non-exclusive contracts equilibrium

We start by describing the behavior of borrowers and lenders when borrowers own multiple cards. Then, we show that in equilibrium, borrowers indeed use multiple cards.

The proof proceeds in four steps. We first show that lenders cancel the card when the borrower does not repay the debt entirely. Then, we prove that the borrower chooses to repay only one card. Third, we demonstrate that the borrower uses multiple credit cards in equilibrium. Finally, we derive the equilibrium contract characteristics.

Step 1: *Lenders cancel the card conditional on not repaying the debt fully*

We show that the lender cancels the credit card if the borrower does not repay the full debt face value. As in proof D1, I denote $q = (\bar{q}, \underline{q})$, where $\underline{q}$ is the card quality conditional on default. We show that lenders optimally set $\underline{q} = 0$ if the borrowers repay less than the debt face value.

We prove the result here for the credit reward case (i.e., the cost is paid in the first period as in Equation 37). Appendix D3 show that this result also holds for the situation in which the borrower also uses the credit card in period 2 (as in equations 38 and 39).

We now describe the timing in the lender problem 10 for the credit reward case. In period 2, the lenders can choose the card quality function $0 \leq q(R_c) \leq q^*$ at no cost. q^* is the maximum card quality, determined by the investment in the first period. R_c^* is the debt face value determined in period 1, R_c is the amount of debt c the borrower chooses to repay in the second period.

The lender maximisation problem 10, conditional on having originated a card, and

having already invested in the card maximum quality (q^*) can be rewritten:

$$\max_{q(R_b)} \; E[R_b] \tag{49}$$

$$s.t.\ Borrower\ behavior:\ \{R_b : \max_{R_c} \sum_c V_c(q_c(R_c)) - R_c,\ s.t. \sum_c R_c \leq W\} \tag{50}$$

$$Repayment\ lower\ than\ debt\ face\ value:\ R_b \leq R_b^* \tag{51}$$

$$Quality\ cannot\ be\ negative:\ q(R_b) \geq 0 \tag{52}$$

$$Maximum\ quality\ is\ bounded\ by\ period\ 1\ investment:\ q(R_b) \leq \bar{q} \tag{53}$$

To maximize the probability of repayment, the lender sets: $q_c(R_c) = \bar{q}$ for $R_c = R_b^*$ and $q_c(R_c) = 0$ otherwise. This is because they want to maximize $V_c'(q_c(R_c))q_c'(R_c)$. One way to do this is to set $q_c(R_c) = q^*$ when repaying fully and $q_c(R_c) = 0$ otherwise. This is the best response when other lenders also follow this strategy. This equilibrium may not be unique. However, this implementation prevents borrowers from repaying each credit card a bit, which is consistent with the data.

Step 2: *The borrower repays only one card when they borrow from multiple lenders*

Assumption A1 ensures that lenders set $R^* = W$ as long as $F[1 - \frac{mc}{\alpha}] - Rf(\bar{\epsilon}) > 0$ and that borrowers do not default on all their cards (see appendix D1).

Given that $R_c^* = W$ for all cards c, and the step 1 results, the borrower chooses to default on all but one card.

Step 3: *Borrowers get multiple credit cards*

Assumption A2 ensures that the borrower gets more than one card. To see that, let us show that borrowers using only one contract cannot be an equilibrium.

We show in steps 2 and 3 that the borrower chooses to repay one card at most. Indexing by b the lender from which the borrower got their first card and c any other

lender, the borrower can benefit from getting a new card from c with a loan size dL if:

$$\underbrace{\alpha L_b + W + V_b(\{c\},\{c,b\})}_{utility\ not\ repaying\ lender\ b} + \underbrace{\alpha dL - mc(\theta)dL + V_c(\{c\},\{c,b\})}_{utility\ new\ card} > \underbrace{\alpha L_b + W - R_b + V_b(\{b\},\{b\})}_{utility\ repaying\ card\ b\ and\ not\ getting\ new\ card} \tag{54}$$

Let us now consider that lender b offers the first-best contract so that the right-hand side of Equation 54 is maximized,[37] which makes getting a new card less likely.

Lender b is unwilling to increase the loan size as this would trigger default, which increases the cost of lending and lowers the borrower's utility (see proof D1).

Yet, the borrower has incentives to get a new card from another lender. This happens because the new contract benefits both the borrower and the new lender, thanks to assumption A2 which makes Equation 54 hold.

Indeed, the new contract offers the borrower the possibility to default on the first credit card while still having access to a second credit card at the end of the second period. A2 ensure that this possibility is valuable to the borrower so that the second lender can generate some profits by originating a new card: Formally, the marginal surplus generated by a dollar lent $(\alpha L_b + \alpha + W - mc(\theta))$ plus the cost of defaulting on one card only $(V_c(\{c\},\{c,b\}) + V_b(\{c\},\{c,b\}))$ is strictly greater than the utility of having only the first best contract $(\alpha L_b + W - R_b + V_b(\{b\},\{b\}))$.

The second lender offers a new contract if they expect the borrower to repay them with some strictly positive probability. In that case, there exists a repayment $(R = \frac{mcL+\epsilon}{\theta},\ \epsilon > 0)$ and loan size such that profits is positive $(D(u)[\theta R - mcL] > 0)$ and borrower utility increases when taking an additional card. Step 4 shows that such θ exists in a symmetric equilibrium.

Step 4: *Deriving the optimal loan size and quality*

[37] The same argument holds for any other contract offered. If $R < W$, then a competitor can make profits.

The borrower utility net of the card specific shocks ϵ_{ic} is denoted:

$$u := \sum_c L_c + \beta \sum_c \{\theta_c(V(q))[W - R_c + V_c(q,c) - E[\varepsilon_{ir}|\mathcal{R} = c] \tag{55}$$

$$+[1 - \theta_c(V(q))]V_c(0, \mathcal{R} \neq c)\} \tag{56}$$

Where $V(q) := (V_c(q_c))_c$.

We normalize $V_c(c, \mathcal{R} \neq c)$ to zero. The maximization problem is thus:

$$\max_{u,q} D(u)[\theta_c(V(q))W - \frac{mc}{\alpha}[u - \beta \sum_d \{\theta_d((V(q))V_d(q_d) - E[\varepsilon_{ir}|\mathcal{R} = c]\}] - c(q)] \tag{57}$$

The first-order conditions with respect to q yield:

$$V_c'(q_c)\theta_c'(V(q))W + \frac{mc\beta}{\alpha}\theta_c V_c'(q_c) = c'(q) \tag{58}$$

I used the fact that $\sum_d \theta_d'[V_d + E[\varepsilon|\mathcal{R} = c]] = 0$.

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

D3 Repayment with other contracts in the second period

The section shows that it is optimal for the lender to cancel the card, conditional on the borrower not repaying the full debt face value. We focus on the case in which the card quality is interpreted as offering a loan in the second period as in equations 38 and 39.

Formally, let us look at the lender problem in period 2 before the borrower makes his repayment choice. Lender b conditions the credit card offer in the second period on repayment r_b made by the borrower. Denoting the credit card offer $(L(r_b), R(r_b))$, the

lender objective function is:

$$\max_{L(r_b),R(r_b)} \int r_b + [R_b(r_b)\theta((r_c)_c) - mcL(r_b)]dF(r_b) \tag{59}$$

$$s.t. F(r_b)\ defined\ by\ problem\ 61 \tag{60}$$

Let us assume that the borrower repayment shocks ϵ are persistent for the first and second contract, so that lender b expects to lose seniority with probability one with the new loan contract if they lost it with the old one, that is, $\theta((r_c)_c)$ is zero if they repaid the other lender. This simplifies the exposition by making the second contract "exclusive" in the second period, as only one lender is willing to lend.

The borrower in the second period chose which card to repay. Their maximization problem is:

$$\max_{r:=(r_c)_c} W + \sum_c \alpha L_c(r_c) - R_c(r_c) - r_c + \epsilon_c \tag{61}$$

$$s.t. \sum r_c \leq W$$

$$0 \leq r_c \leq W$$

Suppose the other lenders offer $\bar{L}_c$, $R(r_b) = W$ if the borrower repays the debt in full and zero otherwise. We now show that doing this is the best response for lender b. The maximisation problem implies that the borrower repays only one card.

Using the borrower problem 61, the probability of lender b being repaid is thus: $Pr(\alpha\bar{L}_c + \epsilon_c \leq max_{r_b \leq W} W - \alpha L(r_b) - r_b + \epsilon_b)$. For the lender, the problem is then equivalent to choosing r_b and L instead of the pricing schedule. Lender utility is maximized at $r_b = W$ as $\alpha > mc$. One way to implement the optimal contract is by offering $\bar{L}_c$, $R(r_b) = W$ if the borrower repays the debt in full and zero otherwise. The lender's problem is thus to choose the loan size conditional on repayment L_b. This problem is thus similar to the one analyzed in appendix D2. Formally, the lender problem is:

$$\max_{L_b} \overbrace{Pr(\alpha L_b + \epsilon_b \geq \alpha L_c + \epsilon_c \; \forall c)}^{\theta(L_b)} [W_1 + W_2 - mcL_b] \tag{62}$$

W_1 is the repayment from the first loan and W_2 from the second. The first order conditions give the optimal L_b.

E Cross-Selling

For the case in which a product is sold in the second period, we have:

$$c' := D'\pi + D[\sigma\tilde{W} - \tilde{m}\tilde{L} - \tilde{m}] \tag{63}$$

Plugging it into Equation 17 , we have:

$$\frac{\beta}{\alpha} mc = D[\sigma(W - \tilde{m}L) - \tilde{m}] \tag{64}$$

$$\iff \tilde{L}^* = \frac{\tilde{W}}{\tilde{m}} - [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{1}{\sigma} \tag{65}$$

$\frac{1}{\sigma}$ is the markup absent cross subsidy. $\frac{\beta}{\alpha}\frac{mc}{\tilde{m}}\frac{1}{\sigma}$ is the cross-subsidy incentives: Having a credit card puts the lender in the borrower consideration set to get another loan.

Using Equation 16, and the fact that $c(q^*)) = [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{D^*}{\sigma}$

$$L^* = \overbrace{\frac{W - c(q^*)}{mc}}^{Lender\ break\ even\ condition} - \overbrace{\varepsilon^{-1}}^{inverse\ demand\ semi-elasticity} \tag{66}$$

The borrower utility is thus:

$$u^* = L^* + \beta\tilde{L}^* = \alpha[\frac{W + [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{D^*}{\sigma}}{mc} - \varepsilon^{-1}] + \beta[]\frac{\tilde{W}}{\tilde{m}} - [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{1}{\sigma}] \tag{67}$$

$$\Longleftarrow u^* = \alpha[\frac{W + [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{D^*}{\sigma}}{mc} - \varepsilon^{-1}] + \beta[\frac{\tilde{W}}{\tilde{m}} - [1 + \frac{\beta}{\alpha}\frac{mc}{\tilde{m}}]\frac{1}{\sigma}] \tag{68}$$

The impact of cross-subsidy is:

$$\frac{\alpha}{mc}\frac{1}{N}\frac{1}{\sigma}+\frac{\beta}{\tilde{m}}\frac{1}{\sigma}[\frac{1}{N}-\frac{mc}{\alpha}] \tag{69}$$

Cross-subsidy can be a way to attract the borrower to make them on your choice set, which is bad for welfare. On the other hand, this can allow the borrower to get more credit card loans as this provides incentives to lower the markup to attract borrowers.

F Exclusive versus non-exclusive

Let us interpret q^{NE} as an additional loan contract taken in period 2 and use the extreme value random shocks as in Section 6.3.

F1 Exclusive case

The borrower's utility in the exclusive case is:

$$u_i^E = \alpha L+\beta E[W-R+\{\max_c V(q)+\tilde{\sigma}\epsilon_c\}] \tag{70}$$

$$= \alpha L+\beta[W-R+ln(\sum_c exp(\tilde{\sigma}V(q_c))) \tag{71}$$

Assuming that lending a card in the first period puts the borrower in the consideration set for the second product, the profits are:

$$\max_{R,L,q} D(u)[R-\frac{mc}{\alpha}L+\tilde{D}(q)[W-mcq]] \tag{72}$$

$$\max_{u,q} D(u)[W-\frac{mc}{\alpha}(u-\beta ln(\sum_c exp(\tilde{\sigma}V(q_c))))+\tilde{D}(q)[W-mcq]] \tag{73}$$

The first-order condition with respect to q yields:

$$\frac{mc}{\alpha}\beta\tilde{\sigma}V'(q_c)\tilde{D}(q)+\tilde{D}'[W-mcq]]-\tilde{D}(q)mc=0 \tag{74}$$

$$\iff q^E=\frac{W}{mc}-\tilde{\varepsilon}^{-1}[1-\frac{mc}{\alpha}\beta\tilde{\sigma}V'(q_c)] \tag{75}$$

The relevant functions at equilibrium are (when denoting N the number of lenders in the consideration set in the second period):

$$c(q) = -\frac{1}{N}[W - mcq] \tag{76}$$

$$V(q) := \gamma q - W - \tilde{R} = \gamma q \tag{77}$$

$$L^E = \frac{W - c(q^E)}{mc} - \epsilon^{-1} \tag{78}$$

$$q^E = \frac{W}{mc} - \tilde{\varepsilon}^{-1}[1 - \frac{mc}{\alpha}\beta\tilde{\sigma}\gamma] \tag{79}$$

$$u_i^E = \alpha L + \beta[\sigma V(q_c)) + ln(N)] \text{ in a symmetric equilibrium} \tag{80}$$

F2 Non-exclusive case

$$u_i^{NE} := \sum_{c\in B} \alpha L_c^{NE} + \beta E[\max_c \{\overbrace{E[\max_d V(q|c) + \tilde{\sigma}\epsilon_d]}^{V_c}] + \varepsilon_c\}] \tag{81}$$

$$= \sum_{c\in B} \alpha L_c^{NE} + \beta[ln(\sum_d exp(V(c)))] \tag{82}$$

The lender problem is:

$$\max_{R,L,q} D(u)[\theta R - \frac{mc}{\alpha}L + \theta_c\tilde{D}(q)[W - mcq]] \tag{83}$$

$$\max_{u,q} D(u)[\theta W - \frac{mc}{\alpha}(u - \beta[ln(\sum_d exp(V(c)))]) + \tilde{\theta}_c D(q)[W - mcq]] \tag{84}$$

Taking the first order condition with respect to q:

$$\theta' W + \frac{mc}{\alpha}\beta\tilde{\sigma}V'(q_c)\theta_c\tilde{D}(q) + [\theta(q)\tilde{D}'(q) + \theta'(q)\tilde{D}(q)][W - mcq]] - \theta(q)\tilde{D}(q)mc = 0 \tag{85}$$

$$\iff q^{NE} = \frac{W}{mc} \overbrace{-\tilde{\varepsilon}_{NE}^{-1}}^{lower\ markup} + \overbrace{\varepsilon_{NE}^{-1}\frac{mc}{\alpha}\beta\tilde{\sigma}V'(q_c)]}^{under-investment} + \overbrace{\frac{\theta'}{\delta}W}^{over-invesment} \tag{86}$$

with $\delta := \theta(q)\tilde{D}'(q) + \theta'(q)\tilde{D}(q)$.

The markup tends to be lower because of the competition for loan seniority.

The relevant functions are now:

$$c(q) = -\theta \frac{1}{N}[W - mcq] \tag{87}$$

$$V(q) := \gamma q \tag{88}$$

$$L^{NE} = \frac{\theta W - c(q^E)}{mc} - \epsilon^{-1} \tag{89}$$

$$q^{NE} = \frac{W}{mc} - \tilde{\varepsilon}_{NE}^{-1}[1 - \frac{mc}{\alpha}\beta\tilde{\sigma}\gamma] \tag{90}$$

$$u_i^E = \sum_c \alpha L_c + \beta[\sigma V(q_c)) + ln(N) + ln(|B|)] \text{ in a symmetric equilibrium} \tag{91}$$

F3 Comparison exclusive versus non exclusive

We have:

$$u_i^{NE} = \alpha L_c^{NE} \cdot |B| + \beta[\tilde{\sigma} V_c(q^{NE}) + ln(|B|)] \tag{92}$$

$$u_i^E := \alpha L_c^E + \beta\tilde{\sigma} V_c(q^E) \tag{93}$$

The welfare impact of non-exclusive contract are ambiguous. Non-exclusive contract benefits the borrower due to their love for variety (captured by $ln(|B|)$). It also decreases the markup for the loan market in the second period due to the competition for loan seniority ($\varepsilon_{NE}^{-1} < \varepsilon^{-1}$). However, a non-exclusive contract creates a debt dilution problem, which can create distortions (i.e., the over-investment channel $\frac{\theta'}{\delta}W$).

G Identification of supply parameters and counterfactual

The key challenge with this type of model is tractability. This section presents some modelling assumptions that allow us to achieve tractability and uniqueness of the equilibrium.

G1 Borrowers

The borrower chose the number of cards, the card in their portfolio and which card to default on.

The choice of how many cards to own is:

$$Pr(\mathcal{C}_i, \mathcal{R}_i) = Pr(Card(\mathcal{C}_i)) \cdot Pr(\mathcal{C}_i|Card(\mathcal{C}_i)) \cdot Pr(\mathcal{R}_i|\mathcal{C}_i, Card(\mathcal{C}_i)) \tag{94}$$

$\mathcal{C}_i$ is the choice of credit cards the borrower gets. $\mathcal{R}_i$ is the set of cards the borrower repays.

Borrower problem: The borrower's choice of $\mathcal{C}_i$ and $\mathcal{R}_i$ is driven by the following problem:

$$\max_{C_i} U_{iC_i} + \varepsilon_{iC} + E[\max_{r \in P(\mathcal{C}_i)} V_r + \epsilon_{ir}] \tag{95}$$

with $V_r := \sum_{c \in \mathcal{R}_i} v_{ic_j}$, and $U_{iC} := \sum_{c \in C} u_{ic_j}$

Assuming the shocks are extreme value distributed, we have closed-form expressions. Indeed, when ϵ_{ic_j} is extreme value distributed, we have $E[\max_{\mathcal{R}_i \in P(\mathcal{C}_i)} V_r] := I(\mathcal{C}_i) := ln(\sum_{r \in P(\mathcal{C}_i)} exp(\frac{V_r}{\lambda}))$. In that case, the probability of seeing the set of cards $\mathcal{C}_i$ is:

$$Pr(\mathcal{C}_i|Card(\mathcal{C}_i)) = \frac{exp(U_{iC} + \lambda I(C))}{\sum_{m \in M(n)} exp(U_{im} + \lambda I(m))} \tag{96}$$

$M(n)$ is the set of all combinations of cards the borrower can choose from that have n cards.

G1.1 Default

The utility of borrower i of not defaulting on the card c_j offered by bank j is:

$$u_{ic_j} = \beta_i X_{c_j} + \xi_{c_j} + \epsilon_{ic_j} \tag{97}$$

X_{c_j} are card characteristics and β_i is a function of borrower observable characteristics. ξ_{c_j} is a card bank fixed effect.

With probability $d(\mathcal{C}_i)$ they enter the default state. Conditional on default, they universally default with probability $1-\lambda$, the lender j survival probability for borrower is thus:

$$\theta_{ic_j}(\mathcal{C}_i) = (1 - d(\mathcal{C}_i)) + d(\mathcal{C}_i)\lambda_i Pr(u_{ic_j} \geq u_{ic_h}, \forall h | \mathcal{C}_i) \tag{98}$$

G2 Lender

Lender maximizes static profits. We allow lenders to invest in marketing (ξ) at the cost $(mc^m(\xi))$ to increase their demand. This approach is used for tractability so that the model can be solved using a contraction mapping. This assumption is consistent with the empirical findings of Drechsler et al. (2025), which shows that marketing is a big component of the cost of credit cards. The lender problem is:

$$\max_{X,\xi} D(f(X) + \xi) \overbrace{[\tau + p_r \cdot [\theta(X)r - mc]L - mc^m(\xi)]}^{\pi(X,u)} \tag{99}$$

$D(f(X) + \xi)$ is the probability that the borrower chooses the bank, conditional on the number of cards he has.

τ is the profits coming from fees, p_r is the probability of revolving.

$\theta(X)$ is the probability of repaying the loan, given the borrower's card choice set.

Using the change of variable $U = f(X) + \xi$, we have:

$$\max_{X,U} D(U) \overbrace{[\tau + p_r \cdot [\theta(X)r - mc]L + mc^m(U - \beta X)]}^{\pi(X)} \tag{100}$$

The first-order condition with respect to X yields (assuming $mc(d, U - \beta X)$ linear):

$$rL: \; p_r \cdot [\theta + \theta' r L] = mc^m \beta^r \tag{101}$$

$$L: \tau - p_r mc + L\theta' r + mc^m \beta^L = 0 \tag{102}$$

Those two equations allow us to recover the marginal costs conditional on having default elasticities and revolving probabilities (mc^m for Equation 101 and $\tau - p_r mc$ for Equation 102).

Let us now look at how to solve for counterfactuals.

Using Equation 102, we can express $L\theta' r$ as a function of parameters. Let's denote this γ. Plugging it into the Equation 101 and using the fact that $\theta' = \sigma\theta(1 - \theta)$, we can solve for R for each bank b. Using the formula for $\frac{\theta_b}{\theta_c}$, we can then recover L_c as a function of L_b. Using the θ_b we can then solve for L_b.

Let us consider that we can solve for R and L. In that case, the maximization problem is of the form:

$$\max_U D(U)[A - mcU] \tag{103}$$

Where A is a constant (derived below). The first-order condition yields:

$$D'(U)[A - mcU] = Dmc \tag{104}$$

When D has a logit form, we have:

$$[A - mcU] = D[A - mcU] + mc \tag{105}$$

Indeed, the function $F(A - mcU) := D(U)[A - mcU] + mc$ is a contraction mapping as $D(U) < 1$.