The Extension of Credit with Non-Exclusive Contracts and Sequential Banking Externalities*

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Abstract

Non-exclusive sequential borrowing can increase default and impose externalities on prior lenders. We document that sequential banking is pervasive and its effects substantial. Using credit card applications from a large bank and data on the applicants' entire loan portfolios, we find that an additional credit line causes a 5.9 percentage point decline in default for high credit-score borrowers on previously existing loans. However, for low-score borrowers, it causes a 19 percentage point increase. The former use the new credit to smooth payments on preexisting loans, while the latter increase their total debt. These results have implications for "no-universal-default" regulation and financial inclusion.

Keywords: Credit cards, Sequential banking, Credit Externalities, Moral hazard, Default risk, Financial inclusion, Universal default clauses. JEL: D14, E51, G21

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1 Introduction

A standard feature of credit markets is that consumers borrow from and have non-exclusive contracts with different lenders. This generally happens over time, and hence we refer to this phenomenon as "sequential banking." Consumers build their loan portfolio over time, and most often with different lenders: A first credit card is followed by a second one, an auto loan, a personal loan, and so on. This seemingly innocuous—and pervasive—feature of credit markets can have significant implications for consumer indebtedness and default risk.

In an environment in which higher borrower debt leads to higher likelihood of default, Bizer and DeMarzo (1992) show that sequential banking introduces a time-inconsistency element to credit markets: Lenders approve loans that do not take into account the resulting devaluation of existing debt held by previous lenders, and thus impose a default externality on them. Rational pricing and perfect information do not solve the problem. Even when lenders anticipate sequential borrowing and increase interest rates to cover their losses, the resulting equilibrium involves higher interest rates, more borrowing, higher default, and more inefficiency than an equilibrium in which borrowers can commit to borrow from only one lender.

In theory, this externality could be eliminated by making contractual terms contingent on future borrowing. However, this is not how credit card and many other debt contracts are written in reality, likely because such clauses could violate competition laws, hold up the consumer, or violate other regulatory constraints. For example, the US *Credit Card Accountability, Responsibility, and Disclosure Act* of 2009 prohibits the practice of retroactively raising any annual rates, fees, or finance charges for reasons unrelated to the cardholder's behavior with their specific account.

The main research questions of this paper are: How important is sequential banking? Do subsequent loans have an impact on default in general and for preexisting loans due to the non-exclusive nature of the credit market? How big is this effect?

We provide a causal quantification of the effects on default generated by sequential banking using a quasi-experimental credit expansion to new consumers with other lines of credit (an intensive margin expansion). We find the effects on default to be economically large: For ex-ante low-credit-score borrowers, the probability of default increases by 19 and 15 percentage points for preexisting credit cards and other loans, respectively. The increase in default for low-credit-score borrowers is large. As a benchmark, we find that to compensate for it, the first lender would have to raise the interest rate by 19 percentage points—assuming an inelastic demand. An alternative view to benchmark the magnitude of the increase in default is that the effect is in the ballpark of the percentage increases in default for credit cards and loans in the US during the Great Recession. At the same time, for ex-ante high-credit-score borrowers, we find a reduction in the default probability of 5.9 percentage points for preexisting credit cards and a smaller and insignificant effect for other types of loans.

When we investigate the mechanisms behind the results, we find different behaviors between low- and high-score applicants: (i) lower-score applicants borrow more as a result of getting the additional credit card, and are therefore more leveraged ("Debt Channel"), which may explain the increase in default, and (ii) higher-score applicants use the new line to partly pay down preexisting debts ("Credit Surfing"), which could explain why they default less as a result of getting the additional card.

The paper proceeds as follows. We first document the prevalence of sequential banking. To do this, we use rich Credit Bureau data on a random sample of 1 million borrowers in Mexico, who are representative of all formal borrowers in the country (approximately 57 million). We show that the majority of borrowers hold more than one loan, with one-third having three or more loans, and that the time between getting new loans decreases sharply with the number of loans. Next, using loan application data from one of Mexico's largest banks (Bank A henceforth), together with discontinuities in the bank's approval rule, we estimate the causal effect of loan approval by Bank A on the number of loans, indebtedness, and default on all the loans the consumer has—including previously opened ones, which we observe from the Credit Bureau.[1] We are able to estimate the magnitude of the causal effects for two subpopulations. While the bank typically used a credit score of 700 as the approval threshold, during part of our sample period the bank tried to reach out to extra-marginal borrowers and adopted a 670 credit score threshold for the approval decision. Using these thresholds in a regression discontinuity (RD) design, we find that, first, the probability of approval for a new credit card increases by about 45 percentage points (pp) just to the right of the score thresholds, which translates into an immediate 47% increase in the total credit limit (on average) or about 16,000 MXN (960 USD). For those rejected, to the left of the threshold, this is not compensated for by new cards (or loans) from other lenders. The difference in the number of cards/loans between the control and treatment groups, defined as slightly below/above the thresholds, respectively, persists for 2 years.

We find that the effects of approval on default are economically substantive. For applicants close to the 670 cutoff, getting Bank A's card increases the cumulative probability of default on all credit cards (previously held and new) by 25 pp in the next 18 months compared with a control group mean of 23 pp.[2] In monetary terms, we find that an extra credit of 1,000 MXN (60 USD) causes a 1.5 pp increase in the probability of default for the lowest score group. Focusing on externalities—i.e., on credit cards and other types of loans already active at application—we estimate that for borrowers near the 670 threshold, getting approved vs rejected causes an increase in the probability of default of 19 pp and 15 pp on preexisting credit cards and other loans (e.g., auto loans, personal loans, etc.), respectively. This evidence speaks to the difficulties of financial inclusion, even at the intensive margin, in the sense that expanding the amount of credit to extra-marginal lower-score (lower-income) applicants who already have some active credit lines leads to substantial default.[3]

We find different results for applicants close to the 700 cutoff. Getting Bank A's card

[1] Bank A had no voice or veto power on the elaboration and publication of our findings. The paper was not reviewed by them.

[2] This is the local average treatment effect (LATE); the intention to treat effect is 12 pp. The cumulative probability of default is defined as the probability of being at least 3 months delinquent—as is standard in the literature—at any point between the date of application and the following 18 months.

[3] For the effects of banking expansion in a low-income setting, see Burgess and Pande (2005).

reduces the cumulative probability of default on preexisting credit cards by 5.9 pp in the next 18 months. This is consistent with Dobbie and Skiba (2013), who find that larger payday loans reduce default.

Although we cannot pin down all of the exact mechanisms for the difference in default elasticities across these two sets of applicants, we do find that lower-score borrowers appear to have larger utilization rates at application and consistently have a larger propensity to borrow on the approved Bank A's card. They accumulate twice as much debt as higher-score borrowers in response to the same increase in the credit line. We take this evidence as suggestive of binding liquidity constraints. In contrast, we find that borrowers in the 700 group engage in more debt switching across cards, paying previous outstanding debt with the newly approved credit line. This suggests that lower-score applicants have a higher need for liquidity, while higher-score applicants may apply for the card to have a line available for precautionary motives, i.e., a source of funds for rainy days.

While we show that getting an extra loan by a subsequent lender causes default on prior loans, we do not show that this behavior leads to inefficiencies. We argue that to the extent that this default cost is imposed on previous lenders, it constitutes a negative externality. The theoretical literature cited earlier shows that—even if priced and anticipated by rational lenders—sequential banking could lead to inefficiencies.

We discuss some policy actions but caution that these may come with important trade-offs. The large treatment effect heterogeneity already demonstrates that there is no single policy that can be easily applied to all borrowers. Imposing total debt/credit limit-to-income caps, while beneficial in terms of reducing the likelihood of default, will also potentially limit the scope of market competition and consumption smoothing possibilities. Similar considerations apply to any policy that renders credit contracts closer to exclusive contracts (e.g., first lender debt collection priority).

Literature Review Our paper contributes to the literature in several respects. First and foremost, given that we can observe the entire portfolio of loans for each individual, we are able to study not only the extensive margin of default, such as the probability of default, but also the intensive margin—i.e., the number or fraction of defaulted preexisting lines and the type of loans being defaulted on. This allows us to be the first to estimate default externalities in a sequential banking context. Zinman (2015) remarks on the importance of sequential banking—but, to the best of our knowledge, there is limited empirical evidence on this. While the theoretical literature has emphasized the cost of non-exclusive lender relationships (Kahn and Mookherjee, 1998), we document a potential benefit of sequential banking: Obtaining new loans from other lenders may allow for better liquidity management, which empirically translates into lower default.[4]

Second, we study a different product and elasticity of default. We focus on the credit card market and the estimation of the credit-default externality. Karlan and Zinman (2009) study how default responds to interest rate variations for a micro credit product in South Africa, focusing on the within lender/loan default. Adams et al. (2009) study how variation in the size of subprime auto loan in the US impacts within-loan delinquencies. Dobbie and Skiba (2013) study the payday lending market in the US and estimate the within-loan effect of higher loan amounts on default. Credit cards are a widespread product and "have been the locus of some of the most interesting innovations in consumer finance in the post-war period" (Zinman, 2015), and yet they are relatively understudied. Focusing on credit cards allows us to study a broad segment of the population instead of focusing on the low-income segment: Our applicants come from the 3rd to the 10th income deciles. Agarwal et al. (2017), Lieberman (2016), and Hundtofte et al. (2019) also study credit cards, but from different angles: The first paper studies the marginal propensity to lend by banks and to borrow by

[4]Another empirical literature studies non-exclusive lending from the supply side and shows that lenders anticipate future coordination problems of multi-lender lending. Hertzberg et al. (2011) show that lenders extend less credit in anticipation of other lenders' reactions to negative news about the firm. Degryse and von Schedvin (2016) show that firms that are in a one-bank relationship and get another loan from an "outside" bank are less likely to get further loans from the former bank. Arraiz et al. (2019) show that competing lenders respond to loan approvals by another institution by offering loans.

credit card holders in the US; the second paper focuses on the consumer's willingness to pay for a good credit reputation; and the third paper focuses on the (non)use of credit cards as smoothing devices.

Third, prominent papers in the literature (e.g., Karlan and Zinman, 2009; Adams et al., 2009; Dobbie and Skiba, 2013) have reached different conclusions about the existence and significance of moral hazard in consumer loan markets. Our results show that credit-default elasticities can be highly heterogeneous, even for applicants to the same bank, at the same branch, being served by the same product in the same year, and therefore provide a potential explanations of these discrepancies.

Finally, we shed light on discussions of no-universal-default clauses and other regulations that make it harder to price loans as a function of behavior with other lenders, and suggest that they can generate significant risks for the credit market by allowing sequential banking externalities to prevail.

The paper proceeds as follows. Section 2 describes the context. Section 3 describes the data and Bank A's loan approval protocol. Section 4 assesses the validity of our regression discontinuity strategy. Section 5 presents our main results, and Section 6 provides several benchmarks for the estimated effects. Section 7 discusses and presents evidence on mechanisms driving our results. Section 8 discusses policy implications and Section 9 concludes.

2 The Mexican Credit Market

Prevalence of Sequential Banking The Mexican credit card market is relatively underdeveloped compared to the US, but between 2002 and 2008 grew at 9.9% per year. This growth stemmed in no small way from banks issuing new cards to existing cardholders. In 2007 and 2008, 45% and 41%, respectively, of new cards went to customers who already had cards; between 2006 and 2008, the number of cards held by the average cardholder increased from 3.4 to 4.2 (Banxico, 2009). This increase in the number of cards in Mexico was accompanied by an increase in default rates: Whereas nonperforming card debt was 4.9% as a percentage of total credit card debt in 2002, it was 12.2% in 2012. Awarding cards or loans to borrowers who already have cards or loans is not exclusive to Mexico; it is common in the US and most other countries with a developed credit market. In the US, more than 90% of new cards go to those who already have at least one card.

Figure 1 uses a random sample of 1 million borrowers that represent the universe of all formal borrowers in Mexico to document the number of loans borrowers have and the timing between them. Conditional on having an active loan, 53% of borrowers have several loans. About 20% of borrowers have five or more loans outstanding. In terms of the timing of sequential loans, borrowers take (on average) 28 months to get a second loan, and the time window shortens significantly thereafter—for instance, to less than 9 months between the fourth and fifth loans (see Figure 1). Appendix C.1 further describes the Mexican credit card market.

Cost of Default Because collection costs are high and courts are slow and ineffective, when faced with default most banks in Mexico do not judicially pursue debts smaller than 60,000-100,000 MXN.[5] Instead, they sell the defaulted debt to collection agencies at about a 90% discount. Thus, defaults are costly for banks. Of course, this does does not mean that they internalize the cost they impose on other lenders, or that the benefit of awarding credit lines is low.

On the borrower's side, the main cost of default is a negative credit history at the Credit Bureau. Castellanos et al. (2018) have found that a loan default in Mexico subtracts close to 100 points from credit scores and makes it harder to get loans in the future. Defaulting, on the other hand, offers the benefit of not paying the principal.

Regulation Importantly, in Mexico it is illegal for banks to cancel a loan or increase the interest rate as a function of the client's behavior in servicing other loans. The author-

[5]This fact was revealed during interviews with Bank A and other banks in Mexico.

ity considers "universal default" clauses abusive.[6] The regulation states: "Abusive clauses include those that...permit the modification...of what was agreed in the contract without the consent of the user, unless it is in the benefit of the latter." Similarly, in the US, the Credit Card Act of 2009 limited "universal default" and prohibited retroactively increasing interest rates on existing balances as a function of behavior with other lenders. Moreover, limiting transactions with other banks is (generally) illegal, as competition law states that trade with other parties cannot be restrained contractually. While protecting competition, this regulation limits what banks can do to mitigate sequential banking externalities.

Pricing Mexican banks are relatively unsophisticated in their pricing; personalized pricing in credit cards is virtually non existent. Ponce et al. (2017) study the three largest banks in Mexico and write that "rewards/benefits, fees, initial credit limits, and contractual interest rates were mostly determined at the credit card-type level (e.g., classic, gold, etc.) and did not vary with the cardholder's risk profile or the cardholder's card usage." In their working paper version, they regressed the interest rate of the card against decile dummies of the bank-assessed probability of default and found insignificant coefficients.[7] In contrast, when they regress the interest rate on dummies for the type of card, these dummies are significant and have a larger predictive power (the R^2 increases from 0.12 to 0.45).

Our Bank A follows a similar pricing policy, in the sense that the interest rate is not tailored to each applicant or even correlated with the credit score. Instead, interest rates are credit-card specific (classic, gold, platinum, and infinite) and there is zero dispersion of interest rates within card type—i.e., everybody receives the same interest rate. Moreover, the contract specifies a constant interest rate, and does not make this interest rate a function of the credit score or behavior with other banks. Also, the interest rate is fairly constant across time (see Figure D.1 in the Appendix). Furthermore, Bank A has few card products. In our sample, 79% of applicants receive a gold card and 17% a classic card. The type of card

[6] See Mexican Consumer Protection Bureau-CONDUSEF for a description of the regulation.

[7] http://www.enriqueseira.com/uploads/3/1/5/9/31599787/borrowing_on_the_wrong_card.pdf.

applicants receive is not a function of the credit score; instead, it is mostly an (undisclosed) function of the applicant's income. Importantly, such a function did not change during our sample period. Thus, there is little price discrimination and, presumably, little pricing of the sequential banking externality on this margin as well.

3 Data and Approval Decision

3.1 Data

Data Sets Our empirical analysis relies on three main data sources. The first is the administrative data from Bank A that contain all credit card applications by new clients to Bank A between January 2010 and April 2012. Bank A is one of the top five largest commercial banks in Mexico, has more than 1,000 branches, and covers all 32 states. The data contain all information recorded by Bank A at the moment of application and used in the approval decision, including the applicant's credit score, annual income, credit history, etc., as well as an identification number that allows us to link application data with Credit Bureau (CB) data (see Appendix A for a description of the merging procedure). This dataset also includes the bank's approval decision, interest rate for the approved card, type of card, and credit limit awarded. We restrict the data to those applicants Bank A calls walk-ins—that is, applicants who are not former clients of Bank A. We do this because the thresholds we use in our RD methodology apply only to walk-ins. All applications in our population are demand-driven, since they are initiated by the applicant without a prompt from the bank.

The second data source is the CB dataset for our sample of applicants. Thus, our sample consists of new customers to Bank A who also appear in the CB data, which means that they must have had at least one other line of credit prior to applying to Bank A. The dataset contains the universe of loans from all formal lenders, of all types, and both active and closed loans. We have two snapshots of the CB data, one from January 2010 and the other from June 2013. The first snapshot occurs before Bank A's sample period begins and we use it to run balance tests of pre-treatment (pre-application) characteristics across the approval thresholds. We use the June 2013 snapshot to measure outcomes. For each loan, the CB dataset has its type (mortgage, personal loan, credit card, etc.); opening and closing dates; credit limit and debt at the time the snapshot was taken; current status of the credit (late payments, default, etc.); and monthly payment history for up to the last 6 years. For default we can construct a monthly panel of repayment/default status for each loan, and therefore we can measure the effects on delinquency and default 18 months after application. For the other variables, such as debt and credit limit, we only observe their levels at the time of the snapshot. Unfortunately, the CB data do not contain information on interest rates charged on the various lines.

A third source of data also comes from the Credit Bureau, but consists of a random sample of 1 million borrowers in Mexico in June 2010, and is thus representative of the whole country. We use it to compare the characteristics of Mexican borrowers vs applicants to Bank A, and to document the high prevalence of sequential banking. Table B.1 in the Appendix details all of the available variables, definitions, and data sources used in this study.

Variables Our main outcome variable is default. In keeping with the legal definition in Mexico and the literature, a card is considered to be in default if the borrower does not pay at least the stipulated minimum payment for 3 or more consecutive months. Our measures of default are defined at the applicant (not the loan) level. We measure default cumulatively from the time of application to Bank A to either 6 or 18 months after. We do this because default may lead to closing the loan, and we want to consider a loan as defaulted even if it is closed by the time of the 2013 snapshot.

We present results for two main definitions of our outcome variables for either existing loans at application to Bank A or all loans (including those opened after application): (i) the probability that any loan is in default, and (ii) the share of credit lines in default.[8] The

[8] For completeness, the Appendix includes results for 2-month delinquency as the dependent variable. We find

share is defined as the ratio of the number of credit lines in default to the total number of active lines. We include both measures to capture the effect at the extensive margin (any loan in default - probability of default) and the intensive margin (how many loans defaulted - share of loans in default). Note that the use of shares helps ease the concern about default being driven mechanically by simply having more cards to default on for those borrowers who obtain an extra line of credit. Crucially, we observe the credit score for each customer at the moment of application (which is the same score Bank A used for its approval decision), which is our running variable in the research design. Individual credit scores are held by the Credit Bureau and computed similarly to those in the US (i.e., they are calculated by Fair Isaac with a proprietary formula).

3.2 Application Process and Approval Decisions

All card applications in our sample are initiated by an individual who walks into a branch of Bank A and fills out a credit card application. Based on this application and the credit score, the bank decides whether to approve the card. We do not consider applications made by existing clients, and thus in this sense there is no targeting selection or differential marketing from Bank A.[9]

Threshold Rule Bank A's card approval policy proceeds as follows. If the walk-in applicant does not have a credit history in the Credit Bureau, he is immediately rejected. Those with a history need a credit score above a certain threshold defined by Bank A (only about 3% of cases override this rule). Applicants with a score above the threshold go to a second credit-appraisal stage, at which the application may be rejected. Our identification strategy relies on the first appraisal stage, which is based solely on the credit score threshold rule.

similar results.

[9]Bank A did not conduct any targeted marketing campaigns. Their marketing is general and on broad media: TV, street advertisements, and posters at branches. Bank A does not have contact information on non-clients, who are the sole estimation sample for this paper, so the Bank cannot send personalized advertising to them. Therefore, Bank A cannot target potential clients based on their credit score. The reason for this is that, in contrast to the US, in Mexico by law banks cannot send loan offers to non-clients without prior signed approval by the potential client (Central Bank Circular 27/2008).

We note that during the approval process, the interest rate is not tailored to applicants with different scores. Instead, interest rates are credit-card specific (classic, gold, platinum, and infinite). In our sample, the majority of applicants (79%) received the gold card and 17% the classic card. The type of card applicants receive depends on other discontinuities used later in the appraisal process (thus, neither the applicant nor the bank employee has any influence on the final outcome). Therefore, interest rates are specific to the type of credit card and homogeneous across cards at any given point in time.

Financial Inclusion Effort Bank A changed its threshold during our sample period. Bank A originally used a 700 credit score threshold in the approval decision, and most observations in our data come from periods during which this threshold was in place (January 2010 to April 2011). However, between June and November of 2011, the threshold was lowered to 670 for *all* applicants in an effort to broaden the customer base (see Figure 2). A substantial number of earlier applicants (60%) had a score below 700, which means that Bank A was rejecting most applicants under the 700 threshold rule. By lowering the threshold to 670, Bank A broadened their eligibility to an extra 18% of applicants (those with scores between 670 and 700). This new inclusion policy was enacted for all applicants in all of Bank A's branches. Precisely because Bank A wanted to ensure comparability and assess whether it should lower its approval threshold, its product offerings, pricing, and all other procedures were kept constant. Changes in the threshold policy were fully blind to both loan officers at bank branches and clients, which thus limited selection. Table 1 shows that approved applicants at the 670 and 700 thresholds had the same interest rates and very similar credit limits and approval probabilities.

Bank A intended to base the duration of the lower threshold on realized profitability, and in principle the change could have been permanent. Bank A expected these extra-marginal applicants to be profitable, but as we will see they were surprised and later reversed the policy. Bank A's expectation was reasonable; serving borrowers with scores close to 670 is not an "off-equilibrium" policy. In Figure C.1, we show that the fraction of borrowers with scores around 670 with at least one loan is 98% and the fraction with a recently obtained loan is 76%.

These two thresholds allow us to estimate treatment effects for the subpopulations with scores around each of the thresholds separately (which we call high- and low-score borrowers).

No Manipulation of Approval For our empirical design to be valid, we require that consumers are unable to manipulate their credit score with precision around the threshold. This is in fact the case, for several reasons. First, Bank A's credit score threshold policy is not communicated to either loan officers or customers. Loan officers input the loan application information into their computer terminal and receive an approval or rejection decision with no stated reason. Second, the exact formula for credit scores at the Credit Bureau is unknown to both customers and Bank A. Third, the formula uses the whole credit history, and therefore operates with a significant time lag; it may take many months to change the score significantly and/or with any precision. Keys et al. (2010) use a similar RD strategy to study mortgage securitization in the US. We will present formal evidence on the absence of manipulation of the running variable in Section 4.1.

3.3 Descriptive Statistics

Applicants at the 670 and 700 Thresholds Panels A, B, and C of Table 1 show pre-treatment summary statistics using data from Bank A collected at the moment of application and from the Credit Bureau's January 2010 snapshot. We provide statistics for the pooled sample of applicants in the [640,730] range in the first column, as well as by credit score threshold using a symmetric interval of 10 points centered around the respective threshold. In the description of the results, we refer to applicants in the [665,675] interval as the 670 score applicants, and to those in the [695,705] interval as the 700 score applicants.

A few statistics are worth pointing out, starting with monthly income as reported to the

Social Security administration. Average (monthly) income is increasing in the credit score: 11,055 MXN (about 660 USD) for 670 applicants and 14,199 MXN for 700 applicants.[10] The applicants retained in our estimation sample span a large portion of the Mexican income distribution, from the 3rd to the 10th decile, although most of the observations are concentrated between the 5th and 8th deciles (INEGI, 2012). At the same time, 670 applicants have higher debt-to-limit (leverage) ratios of 95% vs 88% for the 700, and higher probability of default at application (7% vs 4%). From the CB data on our applicants, we see that the population in the study has on average been in Credit Bureau records for almost 8 years and has an average of 3.7 loans; these include personal loans, car loans, mortgages, credit cards, etc. Finally, 700 score applicants have 39,021 MXN in total outstanding debt, while those in the 670 set have 31,310 MXN (the average credit card debt is 8,439 MXN).

How do these numbers compare with those of Mexican cardholders in general? We can compare some of these statistics with those of a random sample of Mexican cardholders in June 2010 reported by Castellanos et al. (2018). The characteristics of our sample are similar to those of their random sample in 2010, in which mean tenure in the CB is 6.5 years vs 8 in our sample; 50% are male vs 58% in our sample, with a monthly income of 14,300 MXN vs 12,910 MXN in our sample; and the number of credit cards is (on average) 1.9 vs 1.7 in our sample. The sum of all credit lines is larger for Mexican cardholders in their study, however, at 53,000 MXN vs 34,314 MXN in our sample.

Approval Statistics Bank A's data show that 33% of all applications within $\pm$ 5 points of the credit score threshold are approved. Average interest rates on approved cards are 37% per year, and the average approved credit limit is 15,667 MXN. Note that, given that total debt is 36,579 MXN, Bank A's card approval represents a substantial increase in borrowing opportunities.

[10] We were able to merge the applicant sample with administrative data from Social Security. However, given the prevalence of informal employment in Mexico and the quality of the matching variable, we could only match 21% of them.

4 Empirical Strategy

The rules for obtaining a credit card from Bank A allow us to use a fuzzy regression discontinuity design, with the credit score as a running variable, to estimate the causal effect of additional credit on default on all loans, and on sequentially previous loans (Thistlethwaite and Campbell, 1960; Hahn et al., 1999; Imbens and Lemieux, 2008). The identification requirements underlying this methodology are that there is a discontinuous jump at the threshold of the probability of getting the card, and that all other observed and unobserved variables are a smooth function of the running variable at this threshold. In this section, we show that in terms of observables, these requirements hold in our context. We estimate the intent-to-treat (ITT) effect by the following equation:

$$y_{it} = \alpha_k + \beta_k \mathbf{1}\left(score_i \geq \overline{score}\right) + f(score_i; \nu_k^-, \nu_k^+) + X_{it}'\xi_k + \epsilon_{it} \text{ for } k = \{670, 700\}, \quad (1)$$

where the parameter of interest β is the local, to the threshold, ITT effect. This parameter is identified by the assumption that ϵ_{it}, as well as all the possible observables $X's$, are continuous at the threshold $\overline{score}$. Following the RD literature, we accommodate potential differences away from the discontinuity point by using a polynomial in the running variable indicated by the function $f(.)$, where we allow the shape of the polynomial (but not the degree) to vary on the left (ν^-) and right (ν^+) of the discontinuity. We also allow the shape of the polynomial and coefficients of the regressors to vary for the different thresholds. For the main results we use a cubic polynomial, but provide a series of robustness checks with respect to the choice of $f(.)$ in the Appendix. In practice, since we have two discontinuities along the credit score, we estimate two ITTs, one for each threshold. The vector of controls X_{it} includes calendar month dummies as well as dummies for the number of active cards and other types of loans at the moment of application (these latter sets of dummies are included only when analyzing outcomes). Because we rely on a RD design, we use data from applicants who are within a 30 score-point range around the respective thresholds (i.e., between 640 and 730). Of the total pool of applicants to Bank A, 48% fall in this range. We note that our analysis is implemented on two samples of applicants that applied during the two different periods of time when Bank A experimented with the different thresholds. Therefore, these two samples of applicants are fully disjoint.[11]

Since our design is a "fuzzy" one (i.e., some applicants above the threshold are not approved), we also estimate a LATE effect of actually obtaining a card by instrumenting Bank A's approval of the credit card application, CR_i, with the indicator variable that is equal to one if the applicant's score is above the corresponding threshold.[12] The two-stage representation of this strategy is the following:

$$CR_i = \alpha_{1k} + \beta_{1k}\mathbf{1}\left(score_i \geq \overline{score}\right) + f(score_i; \theta_k^-, \theta_k^+) + \varepsilon_{it}, \quad (2)$$

$$y_{it} = \alpha_{2k} + \beta_{2k} CR_i + f(score_i; \gamma_k^-, \gamma_k^+) + X_{it}'\xi_k + \eta_{it}, \quad (3)$$

for $k = \{670, 700\}$. Our research design implicitly does three things: it (i) balances all characteristics (observed and unobserved) of applicants at the threshold; (ii) gives more credit to some of them quasi-randomly; and (iii) measures the effect of this additional credit on default.

[11] In cases in which an applicant applied multiple times, we only keep the latest application for each applicant. Therefore, there is no overlap across the 670 and 700 samples of applicants.

[12] As it is well known, the LATE estimates the effect of the treatment for the population of compliers, and its interpretation rests on a monotonicity assumption on how the instrument affects treatment (Imbens and Angrist (1994) and Heckman et al. (2006)). In our scenario, the monotonicity of treatment to crossing the threshold set by Bank A appears rather plausible, i.e., crossing the threshold implies a higher likelihood of being approved and receive the new credit card (see Figure 4 and Table 3, columns 1-5, where we test for the IV estimate in the number of (extra) credit cards to be equal to exactly 1). The monotonicity assumption's plausibility is also supported in our case by the close to zero probability of approval for applicants below the threshold. Further, Figure 5 shows that the gap in the number of active credit cards remains virtually constant for at least 18 months after application. We also confirm the plausibility of the monotonicity assumption with a test of first-order stochastic dominance (necessary condition for monotonicity) on the number of active credit cards, after 1, 6, and 18 months since application, for consumers just below/above the thresholds in the same spirit of Barua and Lang (2016).

4.1 Validity of the RD Design

This section presents a series of visual and formal tests of the main assumptions underlying the RD design. First, we show that the probability of obtaining a credit card is discontinuous at the thresholds; second, that the density of the credit score (the running variable) is continuous around the thresholds; and third, that an extensive set of applicant characteristics are continuous at the thresholds.

Discontinuous Treatment Probability Figure 4 shows that the approval probability does indeed have a large discontinuity at the thresholds. On average, the probability of obtaining a credit card to the left of the thresholds is virtually 0, while it sharply jumps to about 0.45 just to the right of the discontinuity. Such differential probability of receiving a credit card is fairly similar over the two score thresholds; in fact, we cannot reject the hypothesis that the jumps are statistically the same in the first column of Table 3. It is also clear that our design is a fuzzy discontinuity design, in which not everyone just above the discontinuity point gets a new credit card. The fuzziness in the design, on the right-hand side of the thresholds, arises from a set of extra conditions imposed by Bank A in terms of income, existing credit lines, and limits. However, what is crucial for identification is that the sequence of conditions imposed starts with the credit score. That is why all other applicant characteristics are balanced at the thresholds, as we show below.

Smooth Density of the Credit Score at the Thresholds Another assumption that must hold for the RD design to be valid is that applicants do not have the ability to *precisely* manipulate their credit score in order to sort themselves around the discontinuity thresholds (Lee and Lemieux, 2010). We explain above why this is a reasonable assumption in our context. Figure D.2 in the Appendix presents the empirical evidence that supports the validity of this assumption. The histograms of the standardized credit score in our pooled sample and in each subsample show that there are no noticeable discontinuities in the density at the cutoff values. A parametric McCrary (2008) test cannot reject the null hypothesis of no discontinuity, with p-values of 0.29 and 0.42 for the 670 and 700 cutoff samples, respectively.

Smoothness of Predetermined Characteristics at the Thresholds A third test of the validity of the research design is that the average characteristics of applicants on both sides of the discontinuity are statistically identical. We perform such tests on the available variables, in a regression framework in Table 2 and graphically in Figures D.3 to D.6 in the Appendix. We cannot detect any statistically significant difference across the thresholds in applicant traits or the status of loans at the time of application. Demographic variables include gender, income, amount requested, tenure at the Credit Bureau, number of credit cards 30 days before application, and total debt at the January 2010 snapshot. Note also that the economic magnitudes of the differences are small. The bottom panel of Table 2 shows balance in predetermined default and delinquency measures. These variables are defined in Table B.1.

5 Main Results

In this section we present our main results. First, we show that the approval thresholds are binding: Applicants to the right of the thresholds have more credit cards. Second, we show that this treatment is persistent. Third, we estimate the causal effects of getting a new credit card on default on all loans from all lenders, including default on sequentially prior loans.

5.1 Effect on Credit Card Availability and Persistence of Treatment

First Stage How strong is the first stage? Using CB data, Column 1 of Table 3 confirms the discontinuity in the probability of approval for the new credit card for individuals who are just above the specified credit score threshold. The probability of obtaining a new card increases by about 45 pp, while the number of credit cards owned mechanically increases by about 1 card during the first month after application for those who obtain the new card (Column 2, Panel B).[13] Panel C shows we cannot reject the hypothesis that the increase in the number of cards is equal to 1. Although we do not observe the immediate increase in credit limits and debt due to the data structure (recall that we only observe debt and limits in the two snaphots), a back-of-the-envelope calculation suggests that the ITT of the limit increase is 7,200 MXN (0.45 cards$\times$16,000 MXN approved limit), which is about a 21% ITT increase in the total limit and a 47% increase for those who are actually approved.

Persistence To establish the intensity of treatment, we show that only applicants to the right of the threshold obtain a card *in the market.* One might expect that rejected applicants would look for loans elsewhere. In fact, an important difficulty in measuring the causal effects of extra credit on delinquency is the widespread availability of credit, which allows typical control groups to access other loans. An important advantage of our paper is that we are able to measure "non-compliance" for the control group using the universe of formal loans. Columns 3-5 of Table 3 show that our treatment is present even 18 months after application—i.e., treated borrowers still have about 1 extra credit card. We also show the monthly evolution of the number of credit cards for each cutoff in Panels (b) and (c) of Figure 5.

We find that this difference is not compensated for at the intensive margin: Focusing on the credit limit for loans *active at application* and using the same RD specification, we estimate negligible differences in the credit limit of these loans for those to the right vs left of the threshold.[14] The last two columns of Table 3 present evidence for the extensive margin. If anything, for lower-score applicants, non-card loans slightly increase for those to the right of the threshold. The opposite is true for higher-score applicants. The evidence provided confirms that the treatment is persistent, and thus it allows us to look at longer-run effects. Such persistence is consistent with at least two observations: (i) borrowers get discouraged

[13]This instantaneous increase is not mechanical in the long run, as borrowers can later open or close cards.
[14]Results are available upon request.

after a rejection and do not continuously re-apply to other banks and (ii) rejected applications are recorded in the CB and might subtract points from an applicant's credit score, which could contribute to the persistence result.

5.2 Effect on Default

We now present our main results by answering three main questions. First, what is the causal effect of being awarded a new credit line on default? This cannot be settled by theory alone. On the one hand, models of moral hazard-driven default, opportunistic default, and even purely mechanical models of debt overhang suggest that more debt leads to higher default. On the other hand, one could think of a model in which higher liquidity leads to lower default, either by facilitating more productive investments or by simply providing the ability to better smooth shocks.

Second, does the credit-default elasticity vary by credit score? Again, the answer is not obvious. Scores are meant to rank-order borrowers by level of risk, not behavioral responses to policy changes. Einav et al. (2016) show, for instance, that health scores do not predict an individual's utilization response to kinks in the budget set.

The third, and arguably most interesting, question concerns sequential-banking externalities. To what extent is sequential banking a quantitatively important phenomenon, as reflected in higher default for sequentially prior lenders and non-credit-card credit lines?

5.2.1 Overall Effects: All Lines

Table 4 and Figures 5 and 6 present the effect of Bank A card approval on our measures of default following equations (1) for the ITT and (3) for the LATE. We first focus on all credit cards: those active at the moment of application to Bank A or opened afterward, including Bank A's card. Importantly, if a loan (credit card or other) was closed after the application to Bank A date but before our measurement, we still consider its default status during that period. We present results for the first 6 and 18 months after application as well as the dynamics of default in Figure 7.

670 Applicants First, what is the causal effect of being awarded a new credit line on default? The effect of an additional credit line on default is large, with default probability on any card increasing by 5 pp (11 pp) for the ITT (LATE). These are significant increases, at the 1% level, of more than 50% (120%) in the probability of default. The effects are larger 18 months after application. Columns 3 and 4 of Table 4 show an increase of 12 pp or 50% in the probability of defaulting on any credit card (ITT) and a 7.7 pp or 45% increase in the share of cards defaulted upon (intensive margin). The LATE on the probability of default, 26 pp, implies a *more than doubling* of the default probability and a 96% increase in the share of cards in default in Column 4. In monetary terms, we find that an extra credit of 1,000 MXN (60 USD) causes a 1.5 pp increase in the probability of default for the lowest score group (see Table D.13 in the Appendix).

700 Applicants Interestingly, the sharp increase in default is not present in the 700 sample; default seems to fall for this group. We find that the short-run ITT on the probability of default is -3.6 pp or a 52% fall with a LATE of -8.2 pp (120%). We also find similarly sized effects on the intensive margin; however, they are imprecisely estimated.

We also find a *reduction* in the share of cards in default in the long-run, -2.6 pp or 20% for the ITT (43% for the LATE). For the probability of default, while the effects are estimated to be negative (ITT = -2.4 pp or 12.5%, and LATE = -5.3 pp or 27.6%), they are less precise. The results for 700 applicants is consistent with Dobbie and Skiba (2013), who find a reduction in default due to larger payday loans. One potential mechanism for this is "liquidity surfing": The additional credit line allows for better liquidity management, such as paying one card's debt or minimum payment with the other card to avoid delinquency while coping with temporary shocks.

What appears clear from the analysis is that the effects on default are substantially different across the credit score distribution. In particular, a test of the equality of the coefficients for the estimated ITT (and LATE) would reject the null hypothesis of equality at least at the 2% level for the outcomes presented in Table 4 (see the bottom of the table). If we had pooled the thresholds—see Appendix Table D.14—we would have found small and insignificant effects as a result of pooling negative and positive effects on default.

5.2.2 Externality Effects: Preexisting Lines and other Types of Loans

To what extent does extra credit from Bank A trigger default on preexisting loans? Table 5 presents our main results on externalities at the 18-month horizon, while the right-most column of Figure 6 (i.e., Panels b, d, f, and h) presents them graphically. In the first two columns of Table 5, we analyze the effects on credit cards that were active at the moment of application, and therefore measure the extent of sequential banking externalities. In addition, effects can spill over to other types of loans. The four right-most columns look at spillovers to other types of non-card loans. While Columns 3 and 4 include all non-card loans active before application and those opened afterward, Columns 5 and 6 only consider non-card loans that were active at application.

670 Applicants For the 670 group, we find large and statistically significant increases in default on both preexisting cards and non-card loans. For instance, the probability of default on credit cards increases by 8.7 pp from a control comparison of 20 pp (Column 1). This is an ITT increase of 43% and a LATE of 92% for credit cards. For non-card loans, the analogous effects are smaller but still statistically and economically significant, at 22% ITT and 48% LATE for loans active at application (Column 5).

700 Applicants For the 700 group, we find once again that the extra card lowers default on preexisting cards. This holds when we measure default as the probability of defaulting on any card or the share of cards in default. Both measures exhibit a LATE close to 37% (Columns 1 and 2). Although we do estimate a negative effect for other non-card loans (Column 4), we do not consistently find spillovers to other non-card loans active at the moment of application.

The estimated ITT effects between the two thresholds are statistically different from each other at conventional levels in all cases but one. Thus, even though it appears that the negative effects on default for the 700 group are somewhat smaller and less precisely estimated, they are certainly different from the effects found for the 670 population.

It is important to note that we find no increase in credit limits for preexisting lines for either threshold, which means that the effects on default on those preexisting credit lines are due to the existence of an externality and not to the direct effect of an increase in credit limits on those lines. Thus, the effect of card approval has default consequences on other types of loans. This is an important result, since in many countries such as Mexico, reserve requirements do not account for these spillovers across loan types, and expected-losses calculations are determined at the loan level rather than at the borrower level. We will revisit this point in the policy section below.

5.2.3 Dynamics of Default

Figure 7 presents event-study graphs by plotting OLS estimates of β in the main RD specification in equation (1) for each month, starting from 12 months before and extending up to 18 months after application. The probability of default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before the date of application and a given subsequent month. Share in default is the share of cards that were in such a situation during the same period of time. In the left column, the variable was constructed including all credit cards that were active at application as well as those opened afterward, while in the right column the variable was constructed including only credit cards that were active at application. All figures show the estimated β coefficients and their 95% confidence intervals for the corresponding month. Vertical lines denote the month of the application.

The first point worth mentioning is that there are no pre-trends in default for any of the thresholds. We cannot reject the null hypothesis that the coefficients are equal to zero before application. This is a further reassurance of our identification strategy, since the populations around the thresholds appear to have similar behavior even up to 1 year before application.

The second point is that cumulative default starts to increase a few months after application for the 670 borrowers (recall that default requires 3 months of payments lower than the required minimum) and continues in an upward trajectory. On the other hand, default decreases more rapidly for the 700 borrower group and stays relatively constant afterward. We will discuss such dynamics later in the mechanisms section.

5.2.4 Robustness

Functional Form and Bandwidth We probe the robustness of our results with respect to the specification of our main estimating equations. Figure D.9 shows that our results are robust to (i) using quadratic or cubic polynomials for the function $f(\cdot)$ in equations (1 or 3); (ii) restricting the sample to applicants with scores 15 points above or below their respective cutoff; and (iii) using a non parametric estimator (local linear regression) for the $f(\cdot)$ using Imbens and Kalyanaraman (2011) bandwidths.

Credit Card Awarded A potential concern is that the different results across thresholds are driven by heterogeneous effects by type of credit card awarded to successful applicants. Since, by construction, we do not know the type of card rejected applicants would have received, we cannot estimate such heterogeneous effects. However, two facts should ease such concerns. First, the vast majority of approved applicants (79%) obtain the gold card and 17% of the remaining approved applicants received the classic card. Second, although we cannot estimate separate effects by type of card awarded, we can do so by type of card applied for; in our sample, 91% of applicants requested the gold card in their application. Tables D.9 and D.10 in the Appendix present estimates of the effects for this restricted sample of applicants. Results are similar to the baseline estimates in Tables 4 and 5.

Alternative Definition of Delinquency In Appendix D.3.1, we show that our results are robust to an alternative measure of delinquency: the probability of and the share of cards in 2-month delinquency (see Tables D.11 and D.12).

Ruling out Macro Trends Because the different thresholds operated a few months apart, one might be concerned that the heterogeneity we document is the result of different macroeconomic conditions when the 670 or 700 thresholds were in place. We argue that this is unlikely, as the time periods are not far apart and are contiguous: The 700 threshold applied from January 2010 to April 2011 and the 670 threshold immediately after that, from June 2011 to November 2011. In addition, all regressions include month fixed effects, and results are virtually unchanged when we remove them—which already suggests that the interaction of the treatment with seasonality must be small. Nonetheless, we perform several robustness checks to rule out this concern in Appendix D.4.

6 Benchmarking Effect Sizes

We benchmark the estimated effects in three ways: (i) a simple back-of-the-envelope calculation that computes the necessary change in the interest rate to keep revenues constant between a context without sequential banking (i.e., lower default probability) and one with sequential banking (i.e., higher default probability); (ii) a comparison with the effects of one of the largest financial crises and the ensuing Great Recession, and (iii) a comparison with the literature. We acknowledge that no simple benchmarking exercise is immune from skepticism, as we rely on either strong assumptions, as in (i), or a stretched comparison of different events, policy changes, populations, and outcomes.

Back-of-the-Envelope Calculation We propose a simple exercise to answer the question of how big is the increase in the probability of default for the first bank when a second bank awards a credit card to the first bank's client. We quantify this in terms of the interest rate increase that would compensate the first bank for the lost discounted revenue from the increase in default rates caused by sequential banking. To conduct this simple back-of-the-envelope calculation, we make three assumptions: that the pricing of the credit card flows is performed under risk neutrality; that the default probability and the amount of outstanding debt is invariant to changes in the interest rate (i.e. we assume an inelastic demand curve), and that the state of delinquency follows an i.i.d. Geometric distribution. We find that for the first bank to recover from sequential banking-induced losses, the annual interest rate would have to increase by 19 pp, from its current 37% to 56%. Appendix E provides the details of this back-of-the-envelope calculation.

The Great Recession and Stress Tests A second way to benchmark the effects is to compare them with the magnitudes of default observed in the financial crisis of 2008 and with results from stress tests. In the US, delinquency rates increased from 3.7% to 6.5% for credit card loans, from 2.8% to 4.7% for consumer loans, and from 1.6% to 10.9% for residential mortgages.[15] One can also benchmark default by referring to the official stress testing of the Mexican Financial Stability Committee.[16] In its 2011 report, the Committee simulates "extremely adverse scenarios" in default probabilities for the different loan segments and estimates how this would impact bank solvency. Their extremely adverse scenario corresponds closely to our estimated default externalities: Default probabilities for revolving and non-revolving consumption loans would increase by 78% and 56%, respectively. Thus, regulators believe that these are sizable effects. In fact, these increases correspond to the actual increases in default in Mexico during the financial crisis of 2008: 7.6 pp and 6.4 pp, respectively, from December 2006 to December 2008.

Previous Literature Some caution is required when relating our results to the literature, as there are substantive differences between our setup and that of the papers mentioned below. In Karlan and Zinman (2009), the largest estimated effect implies that reducing

[15]These figures were obtained from series DRCCLACBS, DRCLACBS, and DRSFRMACBS provided by FRED.
[16]See http://www.cesf.gob.mx/en/CESF/Publicaciones_e_informes.

monthly interest rates by 350 basis points in 4-month microcredit loans—and promising this low interest rate in the future for non-defaulters—leads to a 2.5 pp reduction in default (a LATE effect between 13% to 21% depending on the specification). Our effects are several times bigger. Adams et al. (2009) study subprime auto loans in the US and find that increasing auto loan size by $1,000 USD (i.e., about 15% of average loan value) increases default by 16%. Again, our results are large in comparison. In our setting, total credit line increased by less than $1,000 USD and we estimate LATE increases in default of about 90%. Dobbie and Skiba (2013) estimate that a $50 USD larger payday loan in the US (about a 20% loan size increase) *decreases* default on payday loans by 17% to 33%. This is a large effect, similar in sign and magnitude to what we find for 700 applicants.

7 Mechanisms

7.1 Conceptual Framework

We discuss below some of the potential mechanisms through which sequential borrowing could affect default on preexisting and new loans (from different lenders). The aim is to list and organize the distinct mechanisms so as help the reader interpret our results.

1. Incentive effect: Moral Hazard on Effort to Pay back the Loan In Bizer and DeMarzo (1992) consumers can ask for loans sequentially from different lenders. Banks decide whether to approve the loan based on their own profits, not those of other banks, while taking into account that the borrower will go to subsequent lenders in equilibrium. Larger debt causes the borrower to exert less effort, which leads to higher default.[17]

2. Debt Repayment Burden: Mechanical Effect A positive correlation between debt and default may occur simply by virtue of the debt being larger, without the need to appeal

[17] Lower than the socially optimal effort arises since the lender indirectly appropriates part of the borrower's effort as higher repayment, and from the borrower's limited liability constraint.

to moral hazard or adverse selection. Larger debt can give rise to strategic default (as in Einav et al., 2013), as consumers trade off the cost of defaulting vs the disutility of lower consumption due to repayment.

3. Opportunistic Default Parlour and Rajan (2001) model an unsecured credit market in which consumers have the ability to borrow from multiple lenders simultaneously. They assume that it is more beneficial to default on larger debts, since the borrower keeps a larger loan amount without having to pay it back, and that the cost of default is invariant to the amount of debt defaulted on or the number of lenders that do not get paid back. These assumptions generate a positive relationship between debt and default.

4. Option Value of Additional Lenders Defaulting on a given lender's credit card means that the card can no longer be used. However, the borrower can still use her other cards. Castellanos et al. (2018) show empirically that defaulting on a credit card in Mexico implies no longer obtaining new loans from any bank in the following years. However, they find that *previously existing* loans are not closed when default on other loans occurs. All else equal, this creates asymmetry in the cost of defaulting between borrowers who have several credit cards vis-a-vis those who only have one and are considering defaulting on their only card. The former will maintain access to formal credit if they default on one card, while the latter will not. In the context of this paper, being approved by Bank A lowers the cost of defaulting on the previous cards through this mechanism. Notice that this effect could be operational even if approval by Bank A does not cause more debt. It is likely that the marginal option-benefit of Bank A's additional card is decreasing in the number of cards a borrower has.

5. "Surfing" with the Extra Liquidity The mechanisms reviewed above suggest that having more or larger loans may cause more default. But having an extra loan may also help pay other loans and therefore avoid default. Several practitioners and academics have coined the term "surfing" for the practice of using one credit card to pay the other.[18]

Note that mechanisms 4 and 5 are more specific to a sequential-banking or multiple-lender contexts, and would not operate when a lender gives a larger loan, which is the case most of the related empirical literature focuses on. Credit-default elasticities in our context may differ from those commonly estimated by virtue of the importance of mechanisms 4 and 5. It is also likely that these five mechanisms operate simultaneously, and there is no reason to suppose they are equally strong across borrowers—which may generate the treatment effect heterogeneity we reveal.

7.2 Empirical Evidence

It is likely that many mechanisms are present at the same time, and separating them will require data and exogenous variation we do not have. For instance, we would like to vary the stock of debt randomly to test for mechanisms 1 and 2, or vary the number of cards without changing the total credit limit to test for mechanism 3. Instead, we conduct heterogeneity analysis to shed light on the listed mechanisms. As with any heterogeneity analysis, we caution that unobserved factors might be driving the interaction effects. Therefore, we view this evidence as suggestive but not conclusive. The following results argue against mechanism 3 and provide evidence consistent with mechanisms 1, 2, 4, and 5.

Result 1a: Larger Treatment Effect for Applicants with more Initial Debt We conjecture that if debt-driven moral hazard (mechanism 1) or the debt burden (mechanism 2) operate, those lower-score borrowers with larger debt at baseline would default more when given an extra card. This is indeed what we find for applicants around the 670 threshold.

Panels (a) and (b) of Table 6 repeat our main OLS analysis from Table 4, allowing for differential effects for applicants who in January 2010 had a level of leverage (average debt-

[18] Ponce (2009) and Taylor (2003) provide evidence on surfing for Mexico and the US, while Gross and Souleles (2002) find some evidence of debt switching toward a card when its credit limit increases. Surfing can arise also from the borrower switching debt balances to the cheaper cards.

to-limit across cards) and debt in pesos above the 75th percentile; see Tables D.1 and D.3 in the Appendix for estimates of the LATE. The effects are generally larger, although not always precisely estimated, for applicants with high leverage or debt.[19] The same is true when we re-estimate the analogous Table 5 for the externality effects (see Tables D.2 and D.4), especially in the case of default spillovers to previous credit cards.

Result 1b: Debt Responses We find additional evidence on the role played by the level of debt: Applicants who are more likely to default are also those whose debt increased the most after application. Comparing across thresholds, we find that the 670 applicants—who have been shown to default more—also display larger treatment effects on total credit card debt. In Table 7, we show that the likelihood that lower-score borrowers have total credit card debt above the 25th, 50th and 75th percentiles of the distribution is 4.6, 10.7, and 5.8 pp higher relative to their control group (the values for the percentiles are 0 MXN, 10,700 MXN, and 33,000 MXN). In contrast, for high-score borrowers, we find a statistically significant and similar treatment effect at the 25th percentile of the debt distribution; whereas the estimated effect for large amounts of debt (i.e., above the 75th percentile) is virtually zero. Thus, debt increases substantially only for lower-score applicants, whose likelihood of default also increases substantially.

So far, the evidence suggests that larger debts are part of the mechanism that causes default for borrowers in the low-score threshold. These borrowers have larger propensities to borrow out of the same card approval treatment. However, differences in behavior across thresholds go further as Result 2 documents.

Result 2: High-score Borrowers Pay Debts on Previous Cards The last column of Table 7, which focuses on debt from previous loans, shows that the LATE effect of getting the card is negative: High-score borrowers pay down larger debts on previously existing

[19] The bottom of tables D.1 and D.3 report the results of the test for the equality of the effects for applicants below the 75th percentile of debt and leverage. One can note that the larger effects on default for low score consumers are not due to them having a larger debt at baseline.

cards. The effect is economically significant at a lower 8.4 pp in the likelihood of having debt above the 75th percentile.

One plausible interpretation is that the extra liquidity afforded by Bank A's card allowed the high-score borrowers to pay preexisting debt—i.e., it enables debt surfing. This behavior seems to be present on the extensive margin as well: The effect of Bank A's card for those in the high-score threshold is to reduce the number of non-card loans by repaying the outstanding debt (right-most column of Table 3). In addition, and in sharp contrast to the 670 applicants, we find that the negative effect on default among the 700 applicants becomes even more negative when they have larger debt to start with at baseline (see Table D.1). This evidence is consistent with the new card serving the purpose of surfing for those applicants who need it the most—i.e., those with larger debt and utilization at baseline.

We provide further evidence that the new card may help with the repayment of existing loans by comparing the results in Columns 3-4 of Table 4 with those in Columns 1-2 of Table 5. We see that for 700 applicants, there is almost no difference in the effect sizes on default for preexisting vs all cards. This means that the decrease in default is concentrated in preexisting cards. On the other hand, for the 670 applicants the increase in default (LATE) is 18.6 pp on preexisting cards vs 26 pp on all cards, which shows that they are defaulting on cards obtained after applying to Bank A as well as on preexisting ones.

Result 3: Outside Options Mechanism 4 postulates that once clients can rely on another card, the previous ones become less important. If this is indeed the case, then the effect of getting an additional card on default should be smaller the more cards held at baseline, all else constant. This is indeed what we show in Table 6, Panel (c), where we augment our main specification by including an interaction term between an indicator variable for having a credit score above the cutoff and the indicator variable for having more active credit cards at application than the median (which is one credit card); see Table D.5 in the Appendix for estimates of the LATE, which is more precisely estimated. We find that for low-score borrowers, the increase in default after getting Bank A's card is larger among those with fewer than two credit cards at the time of application. For low-score borrowers with two or more cards, the long run increase in default is about half the size that of those with fewer than 2 credit cards. This is consistent with the option value of an extra card decreasing in the number of cards. Finally, for high-score borrowers, we find instead that the effects are stronger for those with more cards, as if having more cards allows for better liquidity management or having more cards is associated with a larger need for debt surfing.

Result 4: Opportunistic Default Parlour and Rajan (2001) show that, conditional on defaulting, it is optimal for borrowers to max out their loans and default on all of them. However, we find that conditional on defaulting on at least one loan, borrowers typically default on only a small subset of other loans. Conditional on defaulting, only 17.3% of borrowers default on all their cards, and only 3.2% default on all their loans over a period of 3 months from the first default. Thus, default is selective. This raises a question: Which loans are borrowers more likely to default on? In Table D.8, we show that low-score borrowers default more on non-collateralized loans, those with the smallest debt, and those with the lowest credit limits. In contrast, the high-score group defaults less on loans with larger debts, with almost no difference across loans with higher vs lower limits, or based on whether they are collateralized. Moreover, the median total defaulted credit card debt-to-limit ratio is 61%, meaning that borrowers do not max out on the limit conditional on defaulting. We conclude that opportunistic default in the form modeled by Parlour and Rajan (2001) is not an important driver in our data.

The evidence presented above suggests that debt is an important driver of the effect of getting an additional card on default for the 670 group, whereas surfing appears to be especially relevant for the 700 applicants.

7.3 Understanding Differences across Thresholds

Our results show that heterogeneity along the credit score distribution is important. We can reject that the treatment response is the same for the 670 and 700 groups in the short- and long-run, with p-values below 0.05 for most outcome variables presented in Tables 4 and 5. The different default responses for 670 and 700 applicants is striking, given that these are new applicants, at the same bank, the same branches, and for the same product. Note that if we had pooled the two groups, we would have concluded that there is no effect whatsoever on default (see Table D.14 in the Appendix). This constitutes an important warning against generalizing the results of credit market policies across populations, and could explain why some papers in the literature find apparently contradicting results (e.g., Adams et al., 2009; Karlan and Zinman, 2009; Dobbie and Skiba, 2013).

Some Hypotheses on Treatment Effect Heterogeneity along the Score Distribution The heterogeneity of responses in credit markets is present in some of the seminal empirical papers in the credit literature. For example, Karlan and Zinman (2009) find strikingly different responses for men vs women. The credit score is less exogenous than gender. It depends on the borrower's previous behavior, and behavior in turn depends on preferences and opportunities that are persistent. Thus, the score itself is a valuable state variable. Below, we postulate three simple internally consistent hypotheses that clarify why treatment responses could depend on baseline score.

First, the credit score can index a borrower's type. Every borrower starts off with the same credit score. This means that lower-score applicants have behaved in riskier ways in the past, which is a signal of their propensity to default in the future. Figure 3 shows a smooth relationship between the credit score and previous default behavior. Panel (a) of the figure shows that borrowers at 670 are predictably riskier based on their credit score: Applicants with a credit score of 700 have a cumulative probability of default of around 2% in the 12 months before application, and this probability increases to about 4% for applicants with a credit score of 670. Panel (b) shows the monthly probability of default on any of their loans, conditional on not being in default in the previous month, as a function of the credit score. The probability of default is roughly twice as large for those with a score of 670, relative to those with a score of 700. Thus, the probability of default doubles in "only" 30 credit score points; it is important to note that credit scores are designed to rank consumers and do not have a cardinal interpretation.

Borrower type could be introduced in the Bizer and DeMarzo (1992) framework as a type-specific (θ) effort cost function $e_\theta(d)$, where $e'_{\theta_{700}}(d) < e'_{\theta_{670}}(d)$, meaning that the effort cost to generate income to pay debt is steeper with respect to debt for the 670 applicants. This would make them less willing to exert extra effort to avoid default for a given increase in debt, and therefore more likely to default when debt increases. This modeling strategy could simultaneously explain, why borrowers have different credit scores and why those with lower scores have larger default effects from getting an extra card.

A second source of heterogeneity is observable differences; for example, in the baseline level of debt or line utilization. Table 1 shows that the 670 applicants have lower incomes, lower total credit limits, and higher utilization rates. They are therefore mechanically more likely to default if mechanism 1 is operational. A third source of heterogeneity between applicants with different credit scores could be an unobserved dimension, such as the level of financial sophistication; 700 applicants may be more savvier regarding their finances. Sophistication can simultaneously explain why the high-score borrowers do not default when they get an additional loan, and also why they have higher credit scores in the first place.

Finally, borrowers value a good reputation and are willing to exert significant effort and resources to keep it. Even if the high-score applicants achieved their higher score by random luck, they would be less likely to default than those with lower scores, as the cost of losing a good reputation is likely larger than the cost of damaging an already bad one. This hypothesis does not rely on ex-ante differences in borrowers' types, but could still generate the heterogeneous borrower behavior we observe.

8 Discussion

8.1 Consequences of Sequential Banking

In a setting with a single lender (or exclusive contracting), the lender internalizes both the costs and benefits of providing an additional loan. In a sequential-banking setting, a new lender's loan might increase default rates on previous lenders, and therefore impose a cost on them. Thus, subsequent lenders generate an externality to the extent that they do not fully internalize the cost of their loan to prior lenders. Our findings show that sequential banking is prevalent and the existence of a negative (positive) externality for lower (higher) score applicants.

An interesting question is whether this externality leads to inefficient equilibria. Bizer and DeMarzo (1992) show that there are equilibria in which lenders fully anticipate borrowers' subsequent behavior, and therefore incur no losses in equilibrium; nonetheless, the equilibrium is inefficient compared with a "one-lender" equilibrium. They show that in all of their sequential-banking equilibria, interest rates are higher (because lenders anticipate the future cost from sequential banking) and borrowers are more indebted despite the higher interest rate. The reason is that borrowers have incentives to bank sequentially because the next lender is willing to give them a lower interest rate than the former lender for the first dollar lent, since the former does not internalize the effect an extra dollar has on default on inframarginal debt. This paper also makes the important point that inefficient allocations are consistent with equilibria in which lenders make no losses—i.e., the fact that lenders increase interest rates in anticipation of default spillovers does not correct the underlying externality.

8.2 Policy Implications

The presence of an externality might lead to inefficient outcomes and warrant market interventions. Below, we discuss the policy implications of alternative drivers of default externalities. As will become evident, there is no easy fix for the sequential-banking externality problem, with many of the policy solutions involving trade-offs that need to be quantified, which is a fruitful avenue for future research.

If the mechanical debt burden or debt-induced moral hazard mechanisms are operative, lenders might themselves limit their prevalence by decreasing the size of loans or asking for larger down payments. In our case, such debt-driven mechanisms are harder to deal with because they are influenced by the behavior of other lenders. Therefore, system-wide measures may be required. One potential policy is the establishment of *debt prioritization* that forces borrowers to repay loans in the order in which they were opened. According to Fama and Miller (1972), debt prioritization can isolate existing lenders from sequential borrowing when markets are perfect. However, under moral hazard, the sequential banking equilibrium may still be inefficient in spite of debt prioritization, since repayment is not fully guaranteed even for the first lender, and subsequent lenders affect the likelihood that the first one gets repaid. Moreover, prioritization has other costs. Mexico has recently implemented policies against prioritization in wage-collateralized loans, arguing that prioritization gave too much market power to first lenders (see Central Bank of Mexico-Circular 15/2018).

A second potential policy is *quantity regulation*—for instance, a regulation that sets a limit for a borrower's debt-to-income ratio. Such a regulation is currently being implemented in the wage-loans market in Mexico, with 40% as the established limit. Importantly, our results point to the potential benefits of policies that establish limits on a borrower's overall amount of debt across all lenders and not on a single loan. Once again, the danger is that this type of regulation restricts competition in the loan market.

If default spillovers are indeed costly, one might wonder why banks have not introduced covenants that restrict sequential-banking behavior. One potential explanation of why this does not happen is that banks are often prevented by regulators from adjusting their pricing ex-post as a function of a borrower's behavior with other lenders. In Mexico such covenants are illegal, and in the US, the 2009 Credit CARD Act outlawed universal default clauses that allowed lenders to charge higher interest rates based on default behavior with other lenders.[20] A policy recommendation is to explicitly allow banks to price risk *dynamically* as a function of behavior with other lenders. In this way, lenders can make borrowers internalize the externality they impose on others when accepting new loans.

These policies directly affect the probability that externalities across lenders occur in the first place. Alternatively, one can think of policies that ameliorate the negative consequences to the financial sector from such spillovers. It is hard to quantify the extent to which banks take sequential banking externalities into account. However, in our setting, Bank A's interest rates of approved applications do not correlate with the likelihood of the applicant getting an extra loan in the future; interest rates are constant across all customers within a given card product (e.g., classic, gold, or platinum). Such a degree of uniform pricing raises the concern that banks might also not take default externalities into account when determining their loan loss provisions and reserves. A third relevant policy is to implement *responsive reserves regulation*, according to which lenders would have to hold larger reserves for borrowers with more outstanding debt and a larger number of loans. Financial regulation in Mexico has recently moved in that direction by making banks' required reserves a function of expected losses (i.e., predicted probability of default $\times$ losses conditional on default). However, in this regulation, the predicted probability of default does not depend on the number of other loans or total indebtedness of a borrower, as we suggest, but only on the size and other characteristics of the loan under consideration.[21]

Finally, recall that the extra card from Bank A decreased the probability of default for applicants with a larger credit score, arguably because of the extra liquidity afforded by the new card (surfing). The non-exclusivity of credit contracts is also likely to lower the market power of previous lenders. Such observations do not warrant policy interventions; if anything, policies should be implemented to reduce those barriers that prevent borrowers

[20] Supporting such a ban, Larry Ausubel testified in the Senate and argued that "increases in interest rates bear no reasonable relation to default risk, i.e., these are penalty interest rates that demand regulation." https://www.ausubel.com/creditcard-papers/ausubel-testimony-12february2009.pdf.

[21] https://investors.banorte.com/es/resources/ratings-methodology.

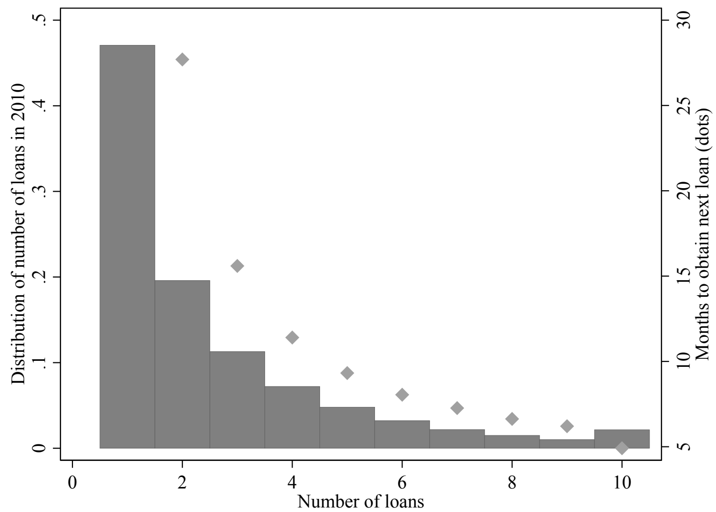
from switching banks/cards or applying to more of them. Such differences in effects across the credit score distribution demonstrate that there are no one-size-fits-all solutions. Increasing the cost of borrowing sequentially must be traded off against the costs of both an increase in the market power of prior lenders and reduced credit-smoothing opportunities. Perhaps, since these considerations seem to matter differently at different points in the credit score distribution, the more relevant lesson that can be extracted from our results is that desirable policies should take behavior heterogeneity into account (e.g., limits to overall borrowing could be made a function of a borrower's credit score).

9 Conclusion

In this paper, we document that sequential banking matters: It is prevalent, and default externalities increase default risk for lower-score consumers. Exploiting discontinuities in the credit card approval process of one of Mexico's largest banks and rich data on an applicant's full portfolio of loans, we estimate the effect of an additional card on default behavior in the short and long run and on existing and subsequent loans. On the one hand, we find that lower-credit-score applicants default *more* not only on their new card, but also on previous credit cards and other types of loans. On the other hand, higher-credit-score applicants default *less* on their preexisting cards. We provide evidence that this heterogeneity is driven by the different use of new credit by different populations. A substantive implication of such heterogeneity concerns financial inclusion efforts: The elasticity of delinquency to credit seems to be steeply decreasing in the credit score.

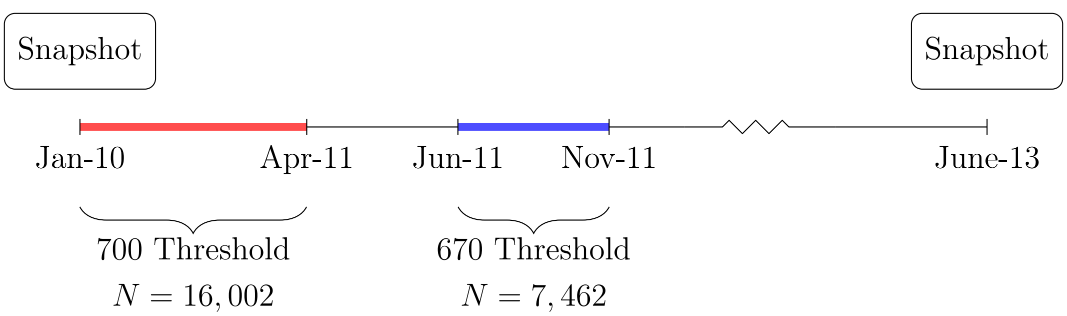
Our results indicate that allowing banks to write contracts contingent on subsequent borrowing and default behavior should be explored. However, to understand the consequences of such policies, we believe that more research will be required. Modeling bank competition in the credit card market and estimating borrower demand and default behavior would be natural steps in understanding the welfare effects of sequential banking and no-universal-default regulations. We view this analysis as an interesting avenue for future research.

Figure 1: Elapsed Time Between Loans



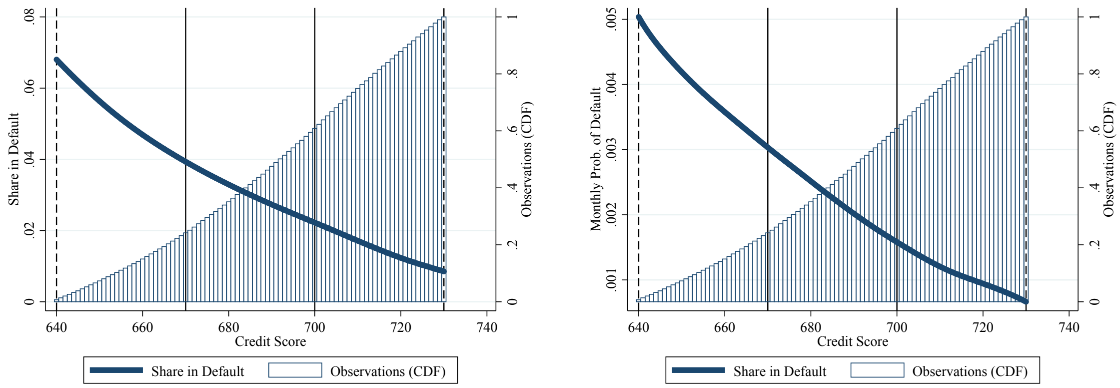
Notes: This figure plots a histogram of the number of active loans held by a random sample obtained from the universe of card holders in Mexico in 2010, as well as the average number of months between the opening dates of the 2nd and the 1st loans, the 3rd and the 2nd loans, etc. The prevalence of sequential banking manifests in the fact that starting from the 3rd loan onward, it takes a few months from sequentially getting an additional loan. Confidence intervals are not reported, since they are small enough to be confounded with the dots.

Figure 2: Timeline



Notes: This figure shows a timeline of Bank A's application process and shows the dates when different thresholds were used in the approval process. It also includes the dates of the different snapshots we received from the Credit Bureau. Bank A also increased the threshold to 680 between December 2011 and April 2012. We do not use it here, since we observe only a few months of outcomes for this subsample. However, the short-term results that we can measure lie between those of 700 and 670, as discussed below. We discard all applications made in May 2011 because Bank A was experimenting with two simultaneous cutoffs, which made the discontinuities in the probability of approval very small. We also discard a very small number of observations in which the same person applied more than once to Bank A.

Figure 3: Credit Score vs Default

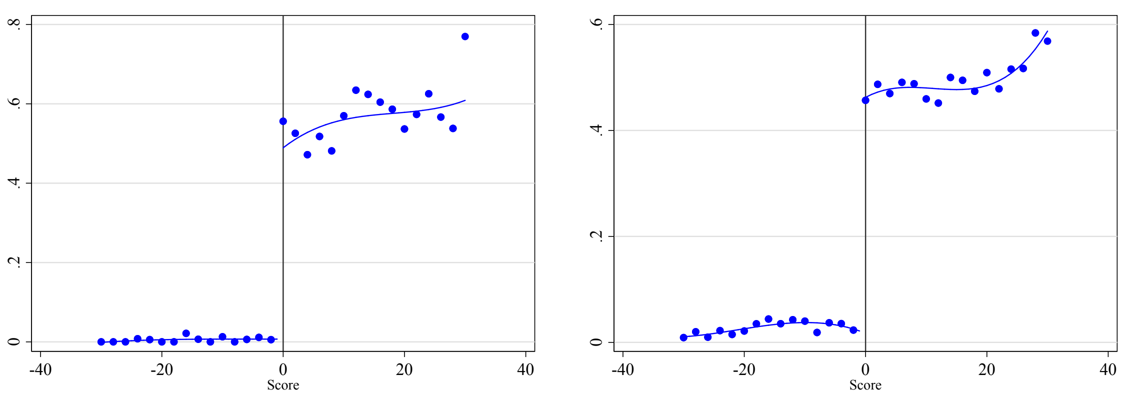


(a) Annual Cumulative Default Rates

(b) Monthly Default Rates

Notes: The figure shows the relationship between credit score (x-axis) and default (left y-axis) using data from the entire sample of applicants to Bank A's credit card. For each value of the credit score, Panel (a) plots the share of loans that were ever in default during the 12 months before the date of application. Panel (b) plots the share of loans that were not in default 12 months before the date of application, but were in default in the following month (i.e., 11 months before the date of application). The vertical right axis shows the cumulative distribution of loans in the 640-730 range of the credit score.

Figure 4: Percentage of Approved Applications by Score and Cutoff

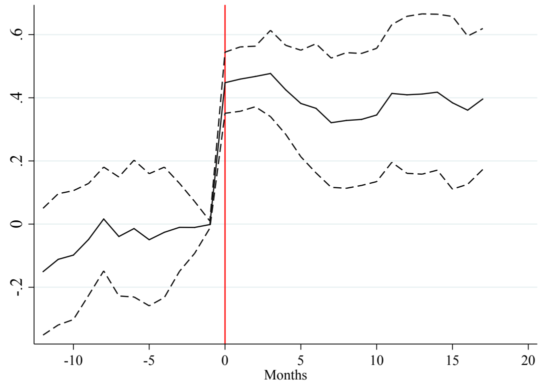


(a) 670 Sample

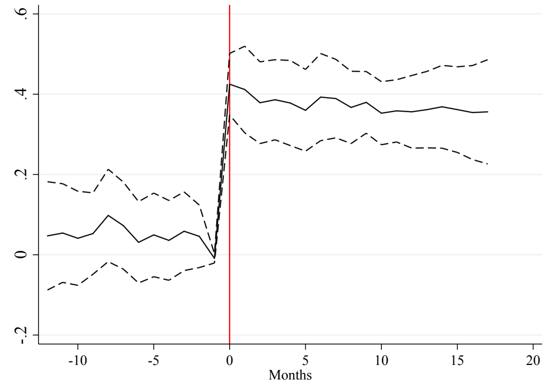
(b) 700 Sample

Notes: The figure shows the percentage of credit card applications that were approved by the bank for each pair of values of the standardized credit score between -30 and 30. It also presents a polynomial fit of degree three to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. Panels (a) and (b) show the results for the 670 and 700 samples, respectively.

Figure 5: The Persistent Effect on Credit Card Expansion



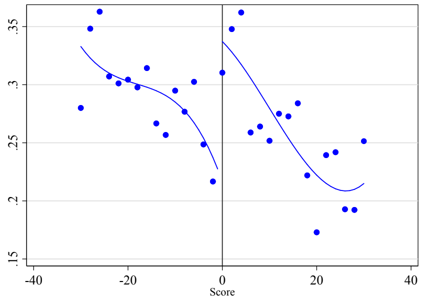
(a) CC Gap over Time (670 Sample)



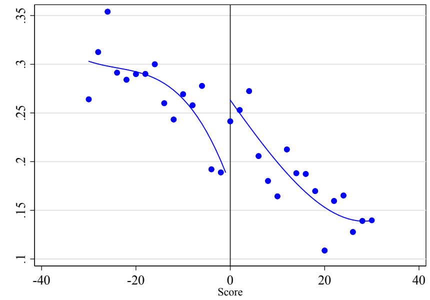
(b) CC Gap over Time (700 Sample)

Notes: These figures present OLS estimates of our main RD specification (Eq. 1) with the number of active credit cards by month (relative to the month of application) as the dependent variable. Panels (a) and (b) show results for the 670 and 700 samples, respectively. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The equation is estimated for each month separately, starting from 12 months before and extending up to 18 months after application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of application. Standard errors are clustered at the credit score level. Both figures show the β coefficients and their 95% confidence intervals for the corresponding month. Vertical lines denote the month of the application.

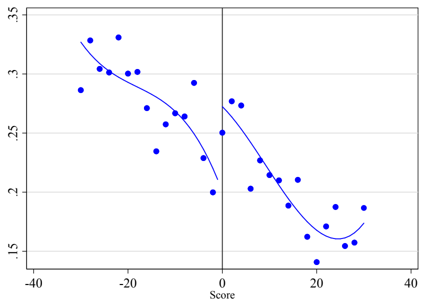
Figure 6: The Effect on Long-Run Credit Card Default



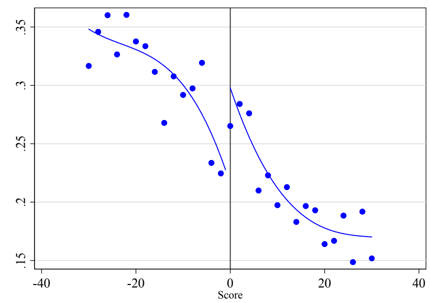
(a) Probability of Default † (670 Sample)



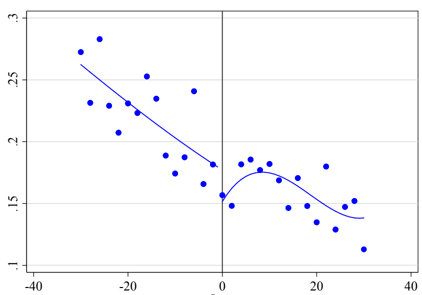
(b) Probability of Default ‡ (670 Sample)



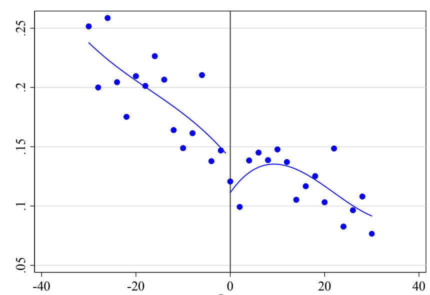
(c) Share in Default † (670 Sample)



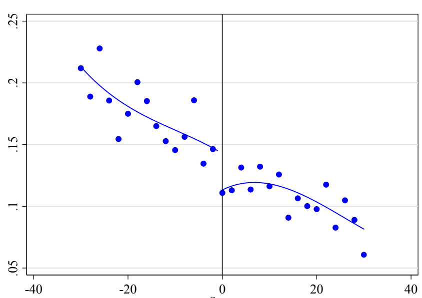
(d) Share in Default ‡ (670 Sample)



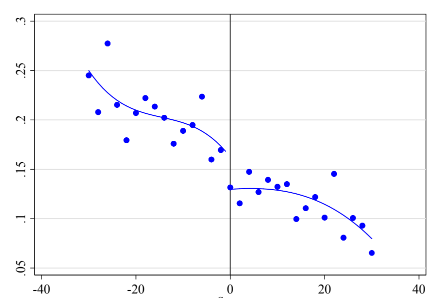
(e) Probability of Default † (700 Sample)



(f) Probability of Default ‡ (700 Sample)



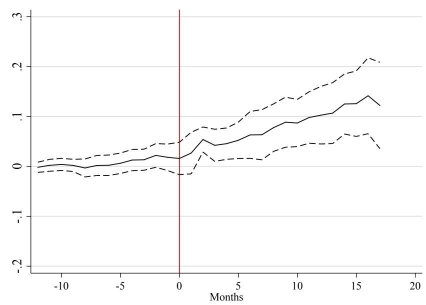
(g) Share in Default † (700 Sample)



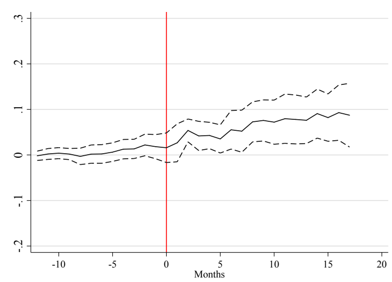
(h) Share in Default ‡ (700 Sample)

Notes: Each figure shows the mean of outcome variables regarding long-run (18 months after application) measures of default for each pair of values of the standardized credit score between -30 and 30. It also presents a polynomial fit of degree three to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 18 months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. †: the variable was constructed including all credit cards that were active at application as well as those opened afterward. ‡: the variable was constructed including only credit cards that were active at application. Panels (a)-(d) and (e)-(h) show results for the 670 and 700 samples, respectively.

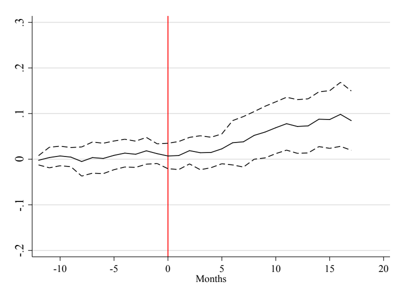
Figure 7: The Effect on Credit Card Default over Time



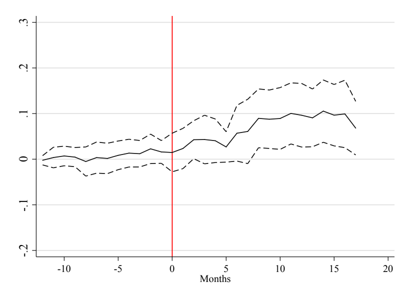
(a) Probability of Default † (670)



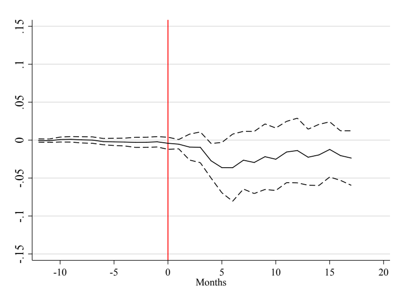
(b) Probability of Default ‡ (670)



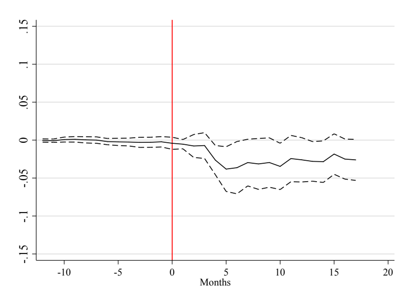
(c) Share in Default † (670)



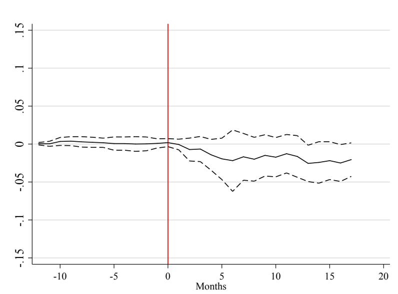
(d) Share in Default ‡ (670)



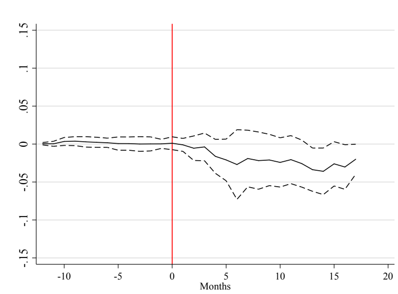
(e) Probability of Default † (700)



(f) Probability of Default ‡ (700)



(g) Share in Default † (700)



(h) Share in Default ‡ (700)

These figures present OLS estimates of our main RD specification (Eq. 1) for multiple outcome variables. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before the date of application and a given subsequent month. Share in Default is the share of cards that were in such a situation during the same period of time. †: the variable was constructed including all credit cards that were active at application as well as those opened afterward. ‡: the variable was constructed including only credit cards that were active at application. Panels (a)-(d) and (e)-(h) show results for the 670 and 700 samples, respectively. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The equation is estimated for each month separately, starting from 12 months before and extending up to 18 months after application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of application. Standard errors are clustered at the credit score level. Both figures show the β coefficients and their 95% confidence intervals for the corresponding month. Vertical lines denote the month of the application.

Table 1: Summary Statistics

	All	Score Cutoff 670	700	670 = 700
Panel A: Demographics				
Income (MXN)	12910	11055	14199	0.000
	(11162)	(10033)	(12016)	
Male	0.58	0.56	0.58	0.320
	(0.49)	(0.5)	(0.49)	
Panel B: Pre-treatment Credit Characteristics				
Tenure in Bureau (Years)	7.7	8.0	7.6	0.005
	(4.67)	(5.08)	(4.5)	
# of non-Bank A CC 30 days before	1.70	1.56	1.65	0.157
	(1.86)	(1.72)	(1.98)	
# of Active Credits 30 days before	3.70	3.95	3.56	0.000
	(2.88)	(2.92)	(2.97)	
Total Debt (MXN)	36579	31310	39021	0.001
	(61378)	(56832)	(63836)	
Total Limit (MXN)	47977	32986	44549	0.003
	(705507)	(78430)	(114272)	
# CC in Default†	0.06	0.09	0.05	0.000
	(0.28)	(0.36)	(0.24)	
Probability of CC in Default†	0.05	0.07	0.04	0.000
	(0.22)	(0.26)	(0.2)	
Share of CC in Default†	0.04	0.06	0.04	0.001
	(0.18)	(0.21)	(0.17)	
# CC in 2 Months Delinquency†	0.08	0.13	0.07	0.000
	(0.33)	(0.41)	(0.29)	
Probability of CC in 2 Months Delinquency†	0.07	0.11	0.06	0.000
	(0.25)	(0.32)	(0.23)	
Share of CC in 2 Months Delinquency†	0.06	0.10	0.05	0.000
	(0.2)	(0.26)	(0.19)	
Panel C: Applications				
Approved	0.33	0.33	0.29	0.003
	(0.47)	(0.47)	(0.45)	
Amount Requested (MXN)	20599	16196	22086	0.000
	(17926)	(17381)	(17533)	
Approved Amount (MXN)**	15667	16483	14698	0.014
	(12292)	(11594)	(12383)	
Interest Rate	36.93	37.17	36.96	0.616
	(6.84)	(4.89)	(7.68)	
N	23464	1228	3229	

Notes: This table presents summary statistics of our sample of applicants. The first column reports summary statistics for the 700 and 670 sample pooled together, including applicants who had a credit score within the +/− 30 points range around the threshold at the moment of application. The next two columns report summary statistics for each of the two samples, focusing on applicants that had a credit score within the +/− 5 points range around the threshold at the moment of application. Finally, the last column reports the p-value of the test of the null hypothesis that the means in the 700 and 670 samples are equal. Observations with a cutoff of 700 points correspond to applications made between January of 2010 and April of 2011, while observations with a cutoff of 670 correspond to applications made between June and November of 2011. Income was obtained from administrative Social Security data (with a match rate of 21%). Panel B presents measures of delinquency and default defined at the applicant level. Probability of delinquency is equal to one if the person has ever had any credit card with 60 to 90 days past due from the earliest month with available information on the card to the date of application. The probability of default is analogously defined, but defines default as delays in payment longer than 90 days. The share of delinquent credit cards is defined as the ratio of the number of cards with 2 months delinquency over the total number of cards. The share of credit cards in default is analogously defined. † signs indicate that the variable was constructed using all available past information on credit cards with opening dates earlier than the application date, i.e., for previously existing cards. ** Average credit limit approved by Bank A, conditional on approval.

Table 2: Balance Tests

	Male	Tenure (Years)	$\#CC$ 30 Days Before	Total Debt (Log)	Administrative Income (Log)	Amount Requested (Log)
			Panel A: Results By Cutoff			
Above Cutoff 670	-0.010	-0.173	0.235	0.112	-0.011	-0.093
	(0.036)	(0.473)	(0.205)	(0.152)	(0.182)	(0.257)
Above Cutoff 700	0.017	-0.423	-0.029	-0.208	-0.041	-0.092
	(0.023)	(0.245)	(0.219)	(0.161)	(0.142)	(0.104)
N	23492	23492	23492	23492	4935	23492
			Panel B: Means[-5;-1] from threshold			
670	0.58	8.18	1.45	6.30	9.02	7.34
700	0.58	7.57	1.66	7.13	9.21	9.45
			Panel C: Joint Testing (p-values)			
670 = 700	0.578	0.586	0.147	0.063	0.918	0.998
	$\#CC$ with 2M Delinq.	Prob. of CC with 2M Delinq.	Share of CC with 2M Delinq.	$\#CC$ in Default	Prob. of CC in Default	Share of CC in Default
			Panel D: Results By Cutoff			
Above Cutoff 670	-0.002	-0.006	-0.009	0.012	0.013	0.007
	(0.020)	(0.019)	(0.023)	(0.021)	(0.020)	(0.019)
Above Cutoff 700	-0.004	-0.002	0.001	-0.007	-0.004	-0.003
	(0.007)	(0.006)	(0.005)	(0.006)	(0.005)	(0.004)
			Panel E: Means [-5;-1] from thresholds			
670	0.06	0.06	0.05	0.02	0.02	0.02
700	0.02	0.02	0.01	0.01	0.01	0.01
			Panel F: Joint Testing (p-values)			
670 = 700	0.940	0.886	0.691	0.363	0.366	0.576

Notes: This table presents the results of tests of quasi-random assignment of credit cards 30 points around the cutoff. The estimates were obtained by OLS regressions of the applicant's characteristics on a third-order polynomial, allowing the intercept and the coefficients of the polynomial to differ at both sides of the cutoff. Clustered standard errors at the credit score level are reported in parentheses. We control for cyclical and seasonal variation by including indicator variables for each month during the application period. For those observations in which an applicant did not have a credit card before the application (and therefore measured delinquency is not defined), we set the variables to zero and flagged those observations with an indicator variable. In the first part of the table, Male is a dummy variable for Male applicants. Tenure is the number of years of tenure in the Credit Bureau. Number of credit cards 30 days before is the number of active credit cards the applicant had 30 days before the application date. Total debt is the logarithm of the total debt on all active credits in January 2010. Income is the applicant's income, as reported to Social Security. Amount requested measures the logarithm of the requested line in the application. In the second part of the table, the first three variables measure the number of, the probability of, and the share of cards in delinquency, which is defined as a 60- to 90-day late payment, from the earliest month with available information on the card to the application date. The last three variables are similarly constructed to capture credit card default, which is defined as late payments of 90 days or more. These variables were constructed including only credit cards that were active at the date of application. Panels A and D present the results for each cutoff sample separately. Panels B and E display the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panels C and F present the p-value of the test of the null hypothesis that the magnitude of the discontinuity is the same across samples.

Table 3: The Effect of Approval on the Number of Cards

	Probability of Approval	#*CC* 1 Month After	#*CC* 6 Months After	#*CC* 12 Months After	#*CC* 18 Months After	# Credit Lines 6 Months After Excl. CC	# Credit Lines 18 Months After Excl. CC
Panel A: OLS							
Above cutoff 670	0.472	0.448	0.382	0.414	0.396	0.234	0.254
	(0.058)	(0.049)	(0.086)	(0.111)	(0.114)	(0.098)	(0.139)
Above cutoff 700	0.444	0.425	0.360	0.358	0.356	-0.070	-0.166
	(0.015)	(0.039)	(0.052)	(0.040)	(0.066)	(0.063)	(0.078)
Panel B: IV							
Approved 670	-	0.950	0.810	0.878	0.841	0.497	0.542
	(-)	(0.048)	(0.181)	(0.247)	(0.262)	(0.228)	(0.294)
Approved 700	-	0.958	0.812	0.810	0.805	-0.158	-0.373
	(-)	(0.081)	(0.119)	(0.094)	(0.154)	(0.141)	(0.176)
Panel C: Means [-5;-1] from cutoff							
670	0.007	1.511	1.548	1.575	1.575	2.658	2.765
700	0.031	1.844	2.006	2.056	2.057	2.189	2.499
N	23492	23492	23492	23492	23492	23492	23492
Panel D: Joint Testing (p-values)							
OLS 670 = 700	0.648	0.605	0.837	0.684	0.799	0.010	0.012
IV 670 = 1	-	0.296	0.294	0.621	0.544	-	-
IV 700 = 1	-	0.606	0.115	0.042	0.205	-	-

Notes: This table reports the first-stage estimates and the RD estimates of the effect of eligibility on the number of loans at different horizons. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. In Column (1) the dependent variable is a binary variable that indicates the approval of a credit card application. In the next four columns, the dependent variable is the number of active credits cards 1, 6, 12, and 18 months after the application. In the last two columns, the dependent variable is the number of active non-credit-card loans 6 and 18 months after the application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table 4: The Effect of Approval on Credit Card Default

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
Panel A: OLS				
Above cutoff 670	0.052	0.022	0.122	0.077
	(0.019)	(0.017)	(0.044)	(0.033)
Above cutoff 700	-0.036	-0.020	-0.024	-0.026
	(0.017)	(0.014)	(0.018)	(0.011)
Panel B: IV				
Approved 670	0.111	0.046	0.260	0.166
	(0.038)	(0.035)	(0.092)	(0.067)
Approved 700	-0.082	-0.046	-0.053	-0.056
	(0.038)	(0.032)	(0.041)	(0.025)
Panel C: Means [-5;-1] from cutoff				
670	0.093	0.063	0.238	0.173
700	0.069	0.043	0.192	0.130
N	23492	23492	23492	23492
Panel D: Joint Testing (p-values)				
670 = 700	0.000	0.018	0.001	0.003

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table 5: The Effect of Approval on Long-run Default
on Preexisting Credit Cards and Other Types of Loans

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: OLS						
Above cutoff 670	0.087	0.068	0.099	0.069	0.071	0.067
	(0.036)	(0.030)	(0.034)	(0.031)	(0.031)	(0.029)
Above cutoff 700	-0.026	-0.020	-0.005	-0.019	0.016	-0.002
	(0.014)	(0.010)	(0.013)	(0.009)	(0.014)	(0.011)
Panel B: IV						
Approved 670	0.186	0.145	0.212	0.146	0.151	0.143
	(0.073)	(0.059)	(0.081)	(0.070)	(0.065)	(0.060)
Approved 700	-0.059	-0.045	-0.012	-0.043	0.036	-0.005
	(0.030)	(0.022)	(0.030)	(0.021)	(0.031)	(0.025)
Panel C: Means [-5;-1] from cutoff						
670	0.201	0.160	0.353	0.168	0.312	0.188
700	0.159	0.118	0.217	0.100	0.162	0.105
N	23492	23492	23492	23492	23492	23492
Panel D: Joint Testing (p-values)						
670 = 700	0.002	0.006	0.006	0.011	0.102	0.014

Notes: This table is analogous to Table 4, but focuses on externality effects. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table 4, but differ in terms of the types of loans they include. The first two columns consider only credit cards that were active at application (‡). The following two columns include all non-credit-card loans that were active at application as well as those opened afterward (†). The final two columns include only non-credit-card loans that were active at application (‡). All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of application. Clustered standard errors at the credit score level are reported in parentheses.

Table 6: Heterogeneous Effects of Approval on Credit Card Default

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
Panel A: Leverage				
Above cutoff 670	0.029	0.006	0.080	0.046
	(0.021)	(0.017)	(0.050)	(0.037)
Above cutoff × Above 75th perc.	0.096	0.063	0.174	0.122
	(0.064)	(0.045)	(0.093)	(0.074)
Above cutoff 700	-0.018	-0.012	0.002	-0.013
	(0.020)	(0.017)	(0.021)	(0.012)
Above cutoff × Above 75th perc.	-0.072	-0.033	-0.100	-0.048
	(0.024)	(0.019)	(0.032)	(0.022)
Panel B: Level of Debt				
Above cutoff 670	0.042	0.022	0.107	0.073
	(0.021)	(0.018)	(0.051)	(0.035)
Above cutoff × Above 75th perc.	0.040	-0.006	0.078	0.030
	(0.063)	(0.038)	(0.089)	(0.059)
Above cutoff 700	-0.020	-0.016	0.002	-0.004
	(0.018)	(0.016)	(0.018)	(0.012)
Above cutoff × Above 75th perc.	-0.060	-0.016	-0.096	-0.083
	(0.024)	(0.016)	(0.031)	(0.024)
Panel C: Number of Credit Cards				
Above cutoff 670	0.044	0.027	0.146	0.103
	(0.030)	(0.024)	(0.037)	(0.035)
Above cutoff × Above median # CC 670	0.018	-0.012	-0.055	-0.059
	(0.047)	(0.035)	(0.071)	(0.040)
Above cutoff 700	-0.016	-0.017	-0.003	-0.016
	(0.015)	(0.015)	(0.015)	(0.016)
Above cutoff × Above median # CC 700	-0.048	-0.008	-0.045	-0.022
	(0.019)	(0.016)	(0.047)	(0.039)
Panel D: Means [-5;-1] from cutoff				
670	0.093	0.063	0.238	0.173
700	0.069	0.043	0.192	0.130
N	23492	23492	23492	23492

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Panels A, B and C report the OLS estimates of an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for certain applicant's characteristics being above a given percentile. Panel A presents the heterogeneous effects for applicants with leverage (average debt-to-limit ratio across credit cards) in January 2010 above the 75th percentile of the distribution. Panel B presents the heterogeneous effects for applicants with total credit card debt in January 2010 above the 75th percentile of the distribution. Panel C presents the heterogeneous effects for applicants with active credit cards at application above the 50th percentile of the distribution. Panel D displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. In all panels, the sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table 7: The Effect of Approval on Outstanding Credit Card Debt

	Prob. Total CC Debt > 25th Prct.	Prob. Total CC Debt > 50th Prct.	Prob. Total CC Debt > 75th Prct.	Prob. Total CC Debt > 25th Prct. †	Prob. Total CC Debt > 50th Prct. †	Prob. Total CC Debt > 75th Prct. †
			Panel A: OLS			
Above cutoff 670	0.046	0.107	0.058	-0.026	-0.034	0.020
	(0.027)	(0.043)	(0.024)	(0.030)	(0.031)	(0.044)
Above cutoff 700	0.053	0.028	-0.007	-0.026	-0.017	-0.037
	(0.023)	(0.023)	(0.012)	(0.017)	(0.016)	(0.018)
			Panel B: IV			
Approved 670	0.098	0.228	0.123	-0.056	-0.073	0.043
	(0.062)	(0.094)	(0.055)	(0.060)	(0.061)	(0.093)
Approved 700	0.120	0.064	-0.015	-0.060	-0.039	-0.084
	(0.052)	(0.051)	(0.027)	(0.038)	(0.036)	(0.040)
			Panel C: Means [-5;-1] from cutoff			
670	0.670	0.391	0.172	0.525	0.518	0.249
700	0.716	0.482	0.248	0.473	0.457	0.239
N	23492	23492	23492	23492	23492	23492
			Panel D: Joint Testing (p-values)			
670 = 700	0.867	0.114	0.024	0.996	0.593	0.246

Notes: This table reports the RD estimates of the effect of eligibility on different measures of outstanding debt. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. In columns (1)-(3), the dependent variables are the probability that the applicant had a total credit card debt above the 25th, 50th and 75th percentiles of the distribution. This variable was constructed considering credit cards active at the moment of application as well as those opened afterward. In the last three columns (marked with †), the dependent variable was constructed considering only credit cards active at the moment of application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

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Online Appendix

A Merging Procedure and Sample Selection

Our merging procedure starts with data from the entire sample of applications for a Bank A credit card made between January 2010 and September 2012. Out of 604,509 original observations we keep observations with unique identifiers. Furthermore, we only keep the last application made by each individual in case the same individual applied multiple times to Bank A. After this procedure, 484,835 individuals/applications remain in the sample. We then matched this data with the CB data, achieving a 95.5% match (462,842 applicants).

After this match we applied the following criteria. First, since Bank A has a much laxer approval policy with their existing clients (those who have a bank account at the moment of application), no discontinuity in the probability of approval could be exploited. Therefore, to use the RD methodology we were forced to keep only applications from individuals that did not have a bank account in Bank A at the moment of application. Second, during certain months within the sample period Bank A ran several experiments with the credit score threshold that determines eligibility of a new credit card. Thus, in some months there were multiple close credit score thresholds that made the discontinuities in the probability of approval not as strong as those exploited throughout this paper. We drop all applications made within those sub periods. After this selection process, we are left with 106,444 applications, which have credit scores ranging between 400 and 800. Finally, given the local nature of the RD design, we narrowed our final sample to applicants with a credit score (measured at the moment of application) that is within the ± 30 points bounds around the credit score threshold used by Bank A in the approval policy at the relevant threshold regime period.

B Variable Construction

Table B.1 presents the list of variable analyzed throughout the paper, their description, and the source of the data used in their construction. The variables constructed using data from Bank A and the Social Security Administration in Mexico are measured at a specific point in time (at the month of the credit card application and in the closest month available relative to the application, respectively). The variables obtained from the Credit Bureau are constructed using data from two snapshots of the credit reports of each applicant, one from January 2010 and the other from June 2013. All the variables from the Credit Bureau, with the exception of those related to default, are measured at those two dates. For variables related to default behavior, we can construct variables at other points in time since each credit report includes data on monthly default status from the date of the report back to the last 6 years.

Table B.1: List of Variables

Variable	Description	Source
Credit Score	Credit score computed by the Credit Bureau at the moment of application	Bank A
Income (MXN)	Monthly income	Social Security Admin.
Male	1 = Male; 0 = Female	Bank A
Tenure in Bureau (Years)	Number of years since entrance into Bureau's records	Credit Bureau
# of non-Bank A CC 30 days before	Number of non-bank A credit cards that are active 30 days before bank A made the approval decision	Credit Bureau
# of Active Credits 30 days before	Number of total credits and loans that are active 30 days before bank A made the approval decision	Credit Bureau
Total Debt (MXN)	Total outstanding debt in January 2010 in active credits that were not in default	Credit Bureau
Total Limit (MXN)	Total credit limit in January 2010 in active credits that were not in default	Credit Bureau
# CC in Default†	Number of credit cards in default before bank A's decision. Default is measured as a late payment beyond 90 days, partial or total debt not recovered, fraud committed by the client	Credit Bureau
Probability of CC in Default†	Indicator that the number of credit cards in default before bank A's decision is positive	Credit Bureau
Share of CC in Default†	Number of credit cards in default before bank A's decision as a fraction of number of credit cards that were active at some point before the decision	Credit Bureau

Variable	Description	Source
# CC in 2 Months Delinquency†	Number of credit cards with 2-months late payments before bank A's decision	Credit Bureau
Probability of CC in 2 Months Delinquency†	Indicator that the number of credit cards with 2-months late payments before bank A's decision is positive	Credit Bureau
Share of CC in 2 Months Delinquency†	Number of credit cards with 2-months late payments before bank A's decision as a fraction of number of credit cards that were active at some point before the decision	Credit Bureau
Approved	Indicator that bank A approved the application and granted a new credit card	Bank A
Amount Requested (MXN)	Amount requested by the applicant to be the credit limit of the potentially new credit card	Bank A
Approved Amount (MXN)**	Amount requested by the applicant to be the credit limit of the potentially new credit card, conditional on being approved	Bank A
$\#CC$ 1 Month After	# of Active credit cards 1 month after the application	Credit Bureau
$\#CC$ 6 Months After	# of Active credit cards 6 months after the application	Credit Bureau
$\#CC$ 12 Months After	# of Active credit cards 12 months after the application	Credit Bureau
$\#CC$ 18 Months After	# of Active credit cards 18 months after the application	Credit Bureau
# Credit Lines 6 Months After (Excl. CC)	# of Active credits (excluding credit cards) 6 months after the application	Credit Bureau
# Credit Lines 18 Months After (Excl. CC)	# of Active credits (excluding credit cards) 18 months after the application	Credit Bureau
Prob. of CC with 2M Delinq. (6 and 18 months)	Indicator that client had a 2-months late payment in any credit card within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Share of CC with 2M Delinq. (6 and 18 months)	Number of credit cards with 2-months late payment as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Prob. of CC in Default (6 and 18 months)	Indicator that client defaulted on any credit card within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Share of CC in Default (6 and 18 months)	Number of credit cards in default as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Prob. of CC with 2M Delinq. ‡ (18 months)	Indicator that client had a 2-months late payment in any credit card within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Share of CC with 2M Delinq. ‡ (18 months)	Number of credit cards with 2-months late payment as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Prob. of CC in Default ‡ (18 months)	Indicator that client defaulted on any credit card within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Share of CC in Default ‡ (18 months)	Number of credit cards in default as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Prob. Of Credit Lines in Default Excl. CC † (18 months)	Indicator that client defaulted on any credit (excluding credit cards) within the first 18 months after the application (it includes credits active at application or opened later)	Credit Bureau

Variable	Description	Source
Share of Credit Lines in Default Excl. CC † (18 months)	Number of credits (excluding credit cards) in default as a fraction of the number of credits (excluding credit cards) within the first 18 months after the application (it includes credits active at application or opened later)	Credit Bureau
Prob. Of Credit Lines in Default Excl. CC ‡ (18 months)	Indicator that client defaulted on any credit (excluding credit cards) within the first 18 months after the application (it includes only credits active at application)	Credit Bureau
Share of Credit Lines in Default Excl. CC ‡ (18 months)	Number of credits (excluding credit cards) in default as a fraction of the number of credits (excluding credit cards) within the first 18 months after the application (it includes only credits active at application)	Credit Bureau
Prob. Total CC Debt>25th perc.	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 25th percentile (it includes credit cards active at application or opened later)	Credit Bureau
Prob. Total CC Debt>50th perc.	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 50th percentile (it includes credit cards active at application or opened later)	Credit Bureau
Prob. Total CC Debt>75th perc.	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 75th percentile (it includes credit cards active at application or opened later)	Credit Bureau
Prob. Total CC Debt>25th perc. †	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 25th percentile (it includes only credit cards active at application)	Credit Bureau
Prob. Total CC Debt>50th perc. †	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 50th percentile (it includes only credit cards active at application)	Credit Bureau
Prob. Total CC Debt>75th perc. †	Indicator that the total outstanding debt in all active credit cards in June 2013 is above the 75th percentile (it includes only credit cards active at application)	Credit Bureau
Prob. of Default Largest Debt	Indicator that client defaulted on the credit with the largest outstanding debt (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Smallest Debt	Indicator that client defaulted on the credit with the smallest outstanding debt (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Largest Limit	Indicator that client defaulted on the credit with the largest credit limit (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Smallest Limit	Indicator that client defaulted on the credit with the smallest credit limit (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Oldest Credit	Indicator that client defaulted on the oldest credit (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Youngest Credit	Indicator that client defaulted on the credit opened most recently (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Coll. Credit	Indicator that client defaulted on collateralized credits (it includes credits active at application or opened later)	Credit Bureau
Prob. of Default Non-Coll. Credit	Indicator that client defaulted on non-collateralized credits (it includes credits active at application or opened later)	Credit Bureau

C Context and Summary Statistics

C.1 The Mexican Credit Card Market

The Mexican credit card market is relatively underdeveloped and concentrated. The five largest banks held a steady market share of close to 90% for the last 20 years in terms of the number of cards. Mexico has only about 20 card issuers (only banks can issue cards), with average credit card interest rates around 29 percent per year, while the government federal discount rate (TIIE) has remained between 5 and 7 percent (Banxico, 2013). Mexico also has a relatively low penetration of cards, owing perhaps to a history of nationalization, privatization and recurrent financial crises in the 1980s and 1990s, including the Tequila crisis of 1994. Even in 2004, ten years after this crisis, there were 0.13 credit cards per person in the country compared to 0.35 in Argentina and 0.38 in Brazil (US, 2008). As of the early 2010s, the coverage rate was still low: There are close to 30 cards per every 100 inhabitants, whereas the analogous number for the US is 120.[22] Low penetration is not only a feature of the credit card market in Mexico, in fact total credit to the private sector over GDP is close to 30% only, whereas for developed countries it is often above 100%.

Between 2002 and 2008 the number of cards awarded grew at a rate of 9.9 percent per year. For the purpose of this paper it is important to note that this growth came in no small way from banks issuing new cards to *existing* cardholders. In 2007 and 2008, 45% and 41% of new cards went to people who already had cards. In fact, between 2006 and 2008 the number of cards held by the average cardholder increased from 3.4 to 4.2 (Banxico, 2009). This is reflected in the distribution of the stock of cards in the economy: in 2010 half the cardholders had one credit card, while 20%, 11% , 7%, 12% had two, three, four and five or more credit cards.[23]

The increase in the number of cards in Mexico was accompanied –although we do not claim causality here– by increases in default rates: while the non-performing card debt was 4.9% as a percentage of total credit card debt in 2002, it was 12.2% in 2012. Part of the increase may be due to the incorporation of riskier marginal borrowers, while another part to awarding cards to borrowers that already had cards and substantial debt.

C.2 Cost of Default and No-Universal Default Regulation

After a default episode, Bank A and most banks in Mexico do not go after debts smaller than 60,000-100,000 MXN, as collection costs are high and courts slow and ineffective. When faced with credit card default, banks in Mexico sell the defaulted debt to collection agencies

[22]See Comision Nacional Bancaria y de Valores (2013) and Federal Reserve Bank of New York (2010).

[23]Awarding cards or loans to borrowers that already have cards or loans is even more common in the US, in particular above 90% of new cards go to people who already have at least 1 card.

at about 90% discount. Thus, defaults are highly costly for banks. On the other hand, the main cost of default a borrower faces is a negative credit history at the Credit Bureau. Castellanos et al. (2018) have found that a loan default in Mexico subtracts close to 100 points from credit scores and makes it much harder to get loans in the future.

Interestingly, in Mexico it is illegal for banks to cancel a loan or increase its interest rate as a function of the client's behavior in servicing *other* loans. The authority considers "universal default" clauses abusive.[24] The regulation states that "Abusive clauses include those that... (g) permit the modification...of what was agreed in the contract without the consent of the user, unless it is in the benefit of the latter." [25] In the US the Credit Card Act of 2009 limited "universal default" and prohibited retroactively increasing interest rates on existing balances as a function of behavior with other lenders. This limits what banks can do to mitigate sequential banking externalities.[26]

C.3 Descriptive Statistics

Panels A, B and C of Table 1 show pre-treatment summary statistics using data from Bank A collected at the moment of application and from the Credit Bureau's January 2010 snapshot. We provide statistics for the pooled sample of applicants, as well as by credit score threshold using a symmetric interval of 10 points centered around the respective threshold. In the description of the table, we refer to applicants in the [665,675] interval as the 670 score applicants, and to those in the [695,705] interval as the 700 score applicants.

We want to highlight a subset of statistics, starting with monthly income as reported to the Social Security administration. Income varies with the score: It is 11,055 MXN (about 660 USD) for the 670 applicants and 14,199 MXN for the 700 applicants. This means that when we talk about going after extra-marginal borrowers by offering loans to lower credit score applicants, it also means giving loans to lower income applicants.[27] This level of income would place our applicants' sample in the third quarter of the household income distribution in Mexico (INEGI (2012)). However, given the large variation in income, applicants kept in our estimation sample span a large portion of the Mexican income distribution, with most of the observations concentrated between the 5th to 8th higher deciles. From the CB data, we see that the population in the study has on average been in the Credit Bureau

[24]See http://e-portalif.condusef.gob.mx/reca/manual/DCG_cla_abu.pdf

[25]Central bank regulators told us in correspondence that they do not know of any credit contract in Mexico that allows default in one contract to affect the conditions of another, in compliance with the regulation.

[26]On the other hand the regulation may have benefits. http://www.ausubel.com/creditcard-papers/ausubel-testimony-12february2009.pdf argues that penalties for default in other banks were much higher than the increased risk this represented.

[27]We were able to merge the applicants sample with administrative data from the Social Security. Although given the high degree of informal jobs and the quality of the matching variable, we could only match 21% of them. We also observe self reported income of all applicants filed with the application, but we do not use it here as the bank does not verify it and we think is over-reported and noisy; it tended to be higher than the income reported by employers to the Social Security for the applicants we could match. On average it was 27,350 MXN (about 1,640 USD) per month (unreported in Table).

records for almost 8 years and has an average of 3.7 loans – these include personal loans, car loans, mortgages, credit cards, etc. Applicants in the 700 group have 39,021 MXN pesos in total outstanding debt, while those in the 670 set have 31,310 MXN. This means that our applicants use loans other than cards since the average credit card debt is 8,439 MXN (about 505 USD, not reported), about a quarter of total debt.

Our measures of delinquency and default are defined at the applicant (not the credit) level. For Table 1 (pre-treatment) we define the probability of delinquency in credit cards as equal to one if the person has had *any* credit card with 60 to 90 days past due *at any point in time* from the earliest month with available information of the card to the date of application to Bank A.[28] Note that we are using a cumulative measure of delinquency and not measuring delinquency at a specific point in time. We do this because default may lead to the closing of the loan, and we want to consider a loan as defaulted even if it is closed by the 2013 snapshot.[29] The probability of default is analogously defined, but considering loans that were 90 days or more past due. This corresponds to the standard definition of default used by the Mexican authorities (and has legal consequences in Mexico in terms of the ability to sue the client and in terms of reserve requirements). We also present results for the share of credit cards in default, defined as the ratio of the number of cards in default over the total number of active cards. Measuring default as a share of cards helps easing concerns about default being driven mechanically just by the simple fact of having more cards to default upon for those above the threshold. In the analysis, we show that all results go in the same direction. The risk measures we use in Panel B include credit cards that are active at application as well as those that were closed within 12 months before application, but not cards opened after application to Bank A. It turns out that the environment we study is risky: On average 5% of applicants had defaulted in some card before they applied for the new card. The share of cards in default is 4%. Columns 2 and 3 show that these realized risk measures are inversely related to the credit scores, as would be expected. In the last column, we report tests of equality of means across subsamples and find that these differences are statistically significant.

Finally, Panel C displays some of the variables related to the application process. Bank A's data shows that around 30% of all applications in this more restricted range were approved. It also shows that applicants request larger lines than are approved. While on average applicants requested 20,599 MXN, approved applications received on average a credit limit

[28] In Section 5.2 we will measure cumulative default from the time of application instead.

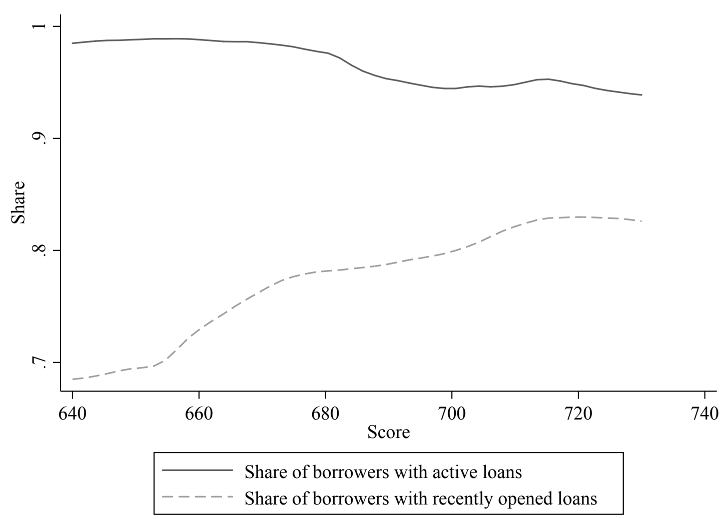
[29] A separate issue is that the CB by law has to delete defaulted loans from their dataset after some years as a function of default severity. If the defaulted debt is less than 113 MXN the bad credit history is deleted within a year, if it is between 113 and 2,260 MXN it is deleted after 2 years, those between 2,260 and 4,520 MXN within 4 years, and those above 4,520 MXN within 6 years. However this is unlikely to be an issue for our study for two reasons: (i) Conditional on default the average debt defaulted on in our sample is 15,635 MXN; (ii) we can compute the default episodes for each individual and if that were to be an issue we should see a downward trend in the number of defaults per individual, this is clearly not the case in our data.

of 15,667 MXN (940 USD). The fact that people are applying, that they get 25% lower limits than requested, and that they accept interest rates of 37% per year (this number does not include fees, APRs are higher, not in table) may suggest that they are liquidity constrained. Note also that given that total debt is 36,579 (and the limit of credit lines is 47,977 MXN), card approval represents a substantial increase in borrowing opportunities.

How do these numbers compare to those of Mexican cardholders in general? We can compare some of these statistics to those of a random sample of Mexican cardholders in June 2010 displayed in Castellanos et al. (2018). It turns out that the characteristics of our sample are similar to the characteristics of their random sample in 2010. Mean tenure in the CB is 6.5 years vs 8 in our sample, 50% are male vs 58% in our sample, people have an income of 14,300 pesos per month vs 12,910 in our sample, and the number of credit cards is 1.9 on average vs 1.7 in our sample. The sum of all credit lines is larger for Mexican cardholders however, at 53,000 pesos vs 47,977 in our sample.

C.4 Loans are frequently awarded below 670

Figure C.1: Fraction of borrowers with loans or recent loans by credit score

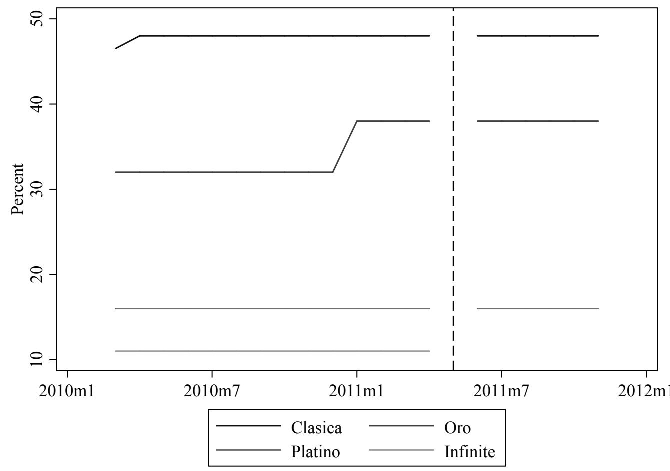


Notes: This figure plots the fraction of borrowers who have at least one active loan at the time of application (solid line)—i.e. a loan that is reported as open by the lender—and the fraction of borrowers with loans that were originated within 6 months of the application date (dashed line), as a function of the credit score observed at the time of application.

D Additional Tables and Figures

D.1 Characteristics of Bank A's Credit Card

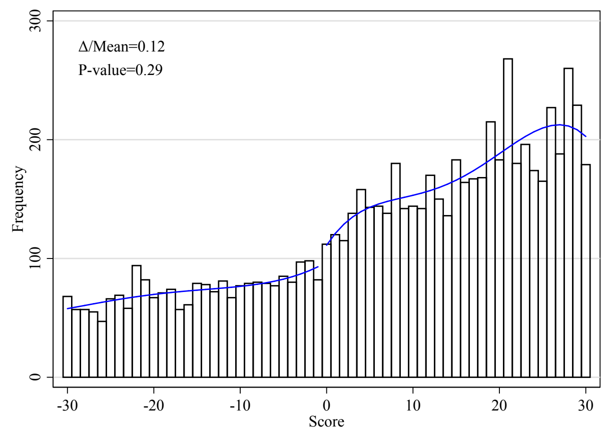
Figure D.1: Average Interest Rate over Time



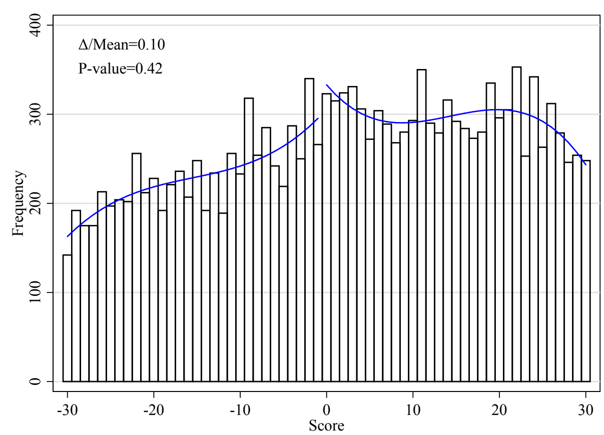
Notes: This figure shows the average interest rate charged by each type of credit card that Bank A offered to approved applicants. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The vertical line denotes the period when Bank A changed the approval policy.

D.2 Smoothness tests

Figure D.2: The Distribution of Credit Scores



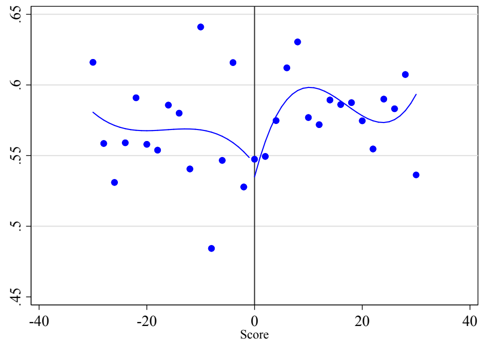
(a) 670 Sample



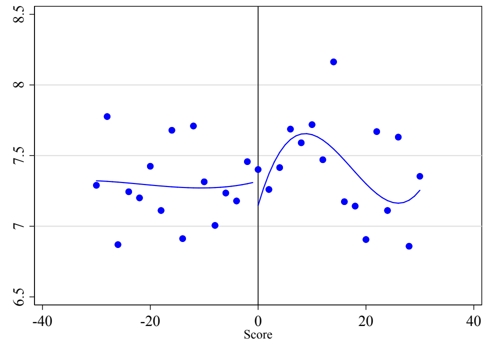
(b) 700 Sample

Notes: The figure shows the frequency distribution of credit scores in the population of applicants. The size of each bin corresponds to one point of the credit score. Panels (a) and (b) show the histogram of the score for the 670 and 700 samples, respectively. The score is standardized so that 0 equals the threshold score for each sample. The blue lines represent two approximating third-order polynomials at each side of the threshold (for the 670 sample we included a fourth order term). We also report the value of the discontinuity at the threshold as a percentage of the mean frequency, and the *p*-value of the test of the null hypothesis that there is no discontinuity at 0.

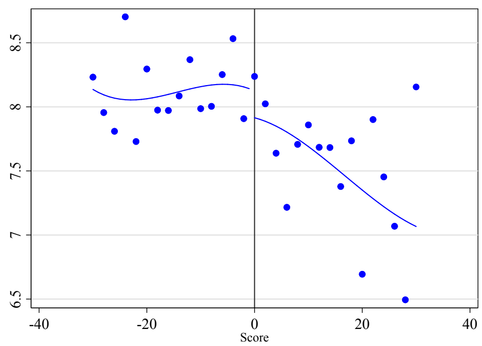
Figure D.3: Pre-Treatment Characteristics – 670 Sample



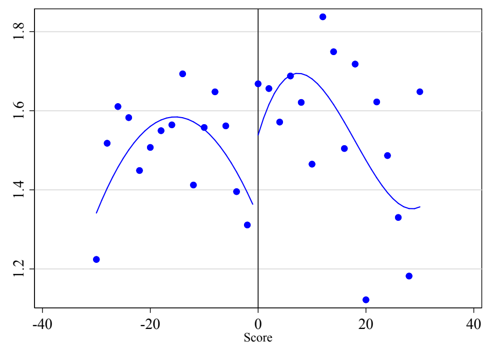
(a) % Male



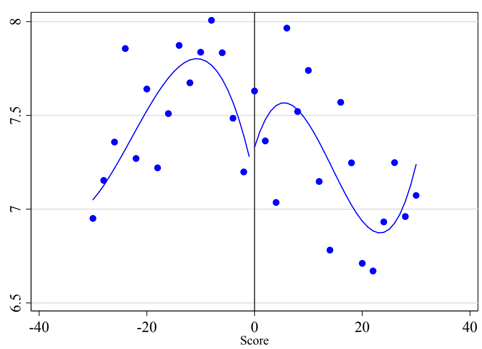
(b) Amount requested (Log)



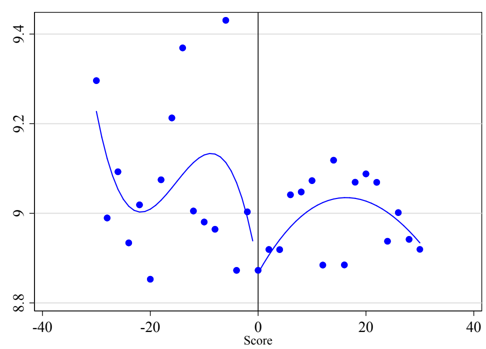
(c) Tenure in Bureau



(d) # CC 30 days before



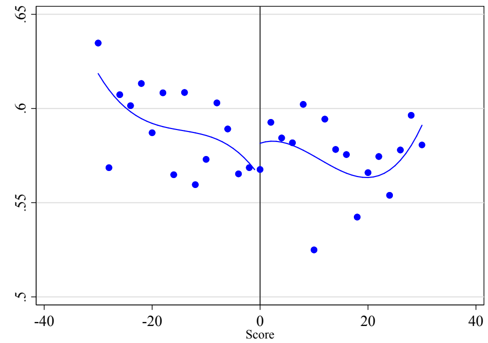
(e) Total debt (Log)



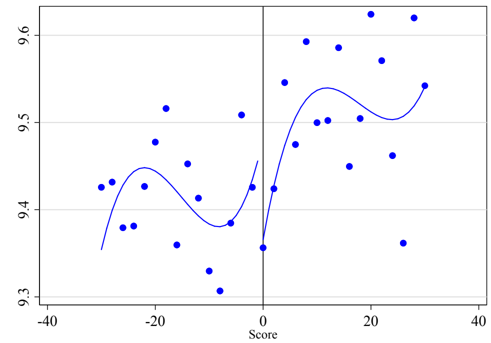
(f) Income (Log)

Notes: Each figure shows the mean of predetermined characteristics for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. The sample is restricted to applicants that faced a cutoff of 670 during the application process. Panel (a) refers to the percentage of males in each score bin, Panel (b) to the credit limit requested at the application in logs, Panel (c) to the years each person has been in the Credit Bureau, Panel (d) to the number of active credit cards applicants had 30 days before the application, Panel (e) to total Debt in 2010 and panel in logs and Panel (f) to the applicant's administrative income in logs.

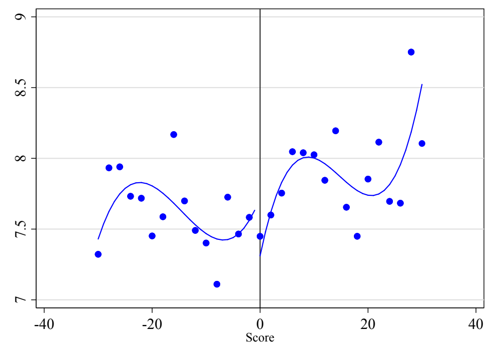
Figure D.4: Pre-Treatment Characteristics – 700 Sample



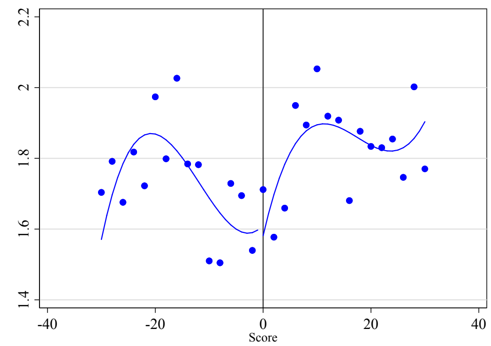
(a) % Male



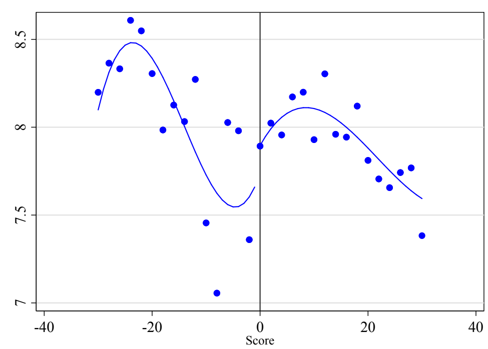
(b) Amount requested (Log)



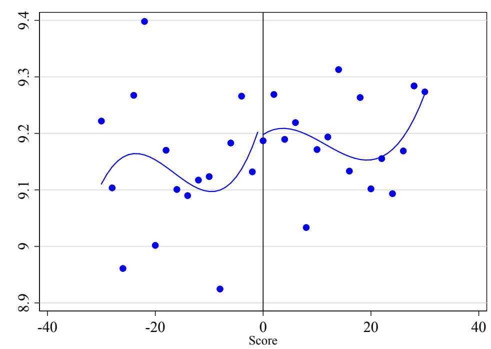
(c) Tenure in Bureau



(d) # CC 30 days before



(e) Total debt (Log)

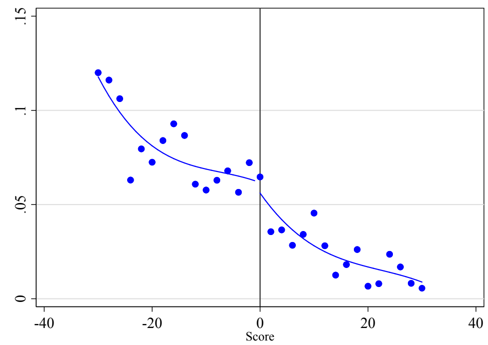


(f) Income (Log)

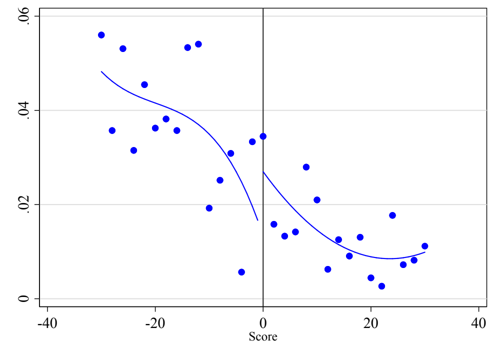
Notes: Each figure shows the mean of predetermined characteristics for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. The sample is restricted to applicants that faced a cutoff of 700 during the application process. Panel (a) refers to the percentage of males in each score bin, Panel (b) to the credit limit requested at the application in logs, Panel (c) to the years each person has been in the Credit Bureau, Panel (d) to the number of active credit cards applicants had 30 days before the application, Panel (e) to total Debt in 2010 and panel in logs and Panel (f) to the applicant's administrative income in logs.

Figure D.5: Pre-Approval Outcome Variables – 670 Sample

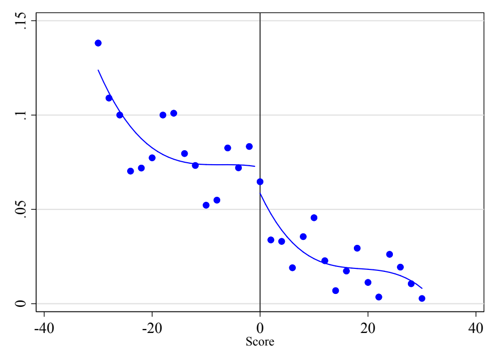
v



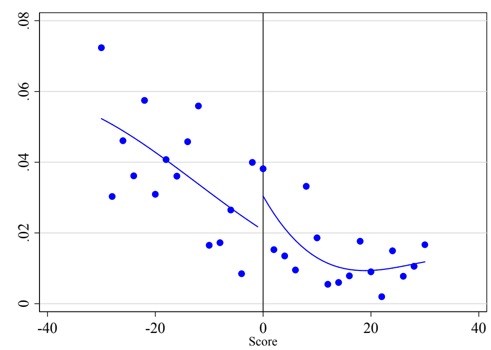
(a) Prob. of CC with 2M Delinq.



(b) Prob. of CC in Default



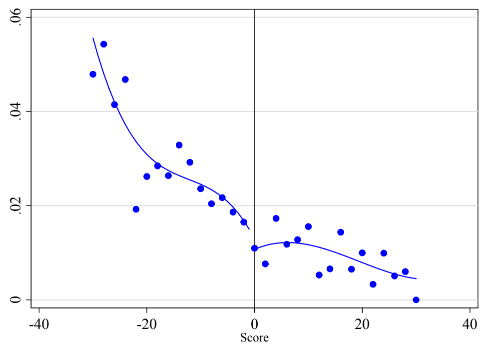
(c) Share of CC with 2M Delinq.



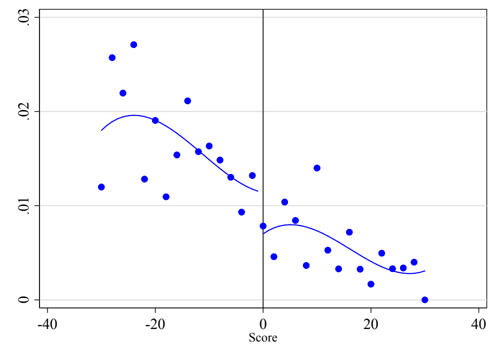
(d) Share of CC in Default

Notes: Each figure shows the mean of predetermined characteristics for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. The sample is restricted to applicants that faced a cutoff of 670 during the application process. Panel (a) refers to the probability of a delinquency, which is defined as an indicator variable that is equal to one if the applicant has had any credit card with 60 to 90 days past due from the earliest month with available information of the card to the application date, and Panel (c) to ratio of the number of cards in delinquency over the total number of cards. Panels (b), (d) are analogous but focus on default, which is defined as late payments of 90 days or more. These variables were constructed including only credit cards that were active at the date of application.

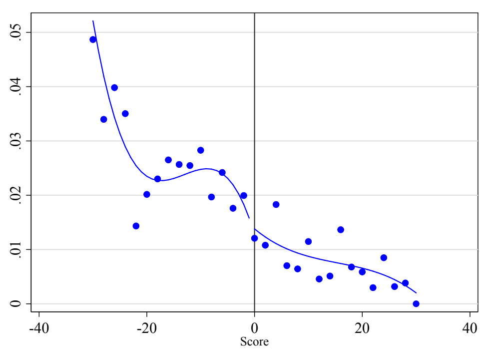
Figure D.6: Pre-Approval Outcome Variables – 700 Sample



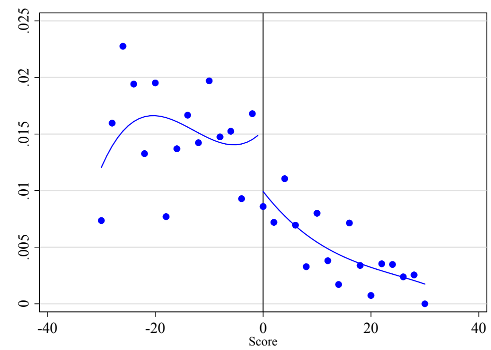
(a) Prob. of CC with 2M Delinq.



(b) Prob. of CC in Default



(c) Share of CC with 2M Delinq.

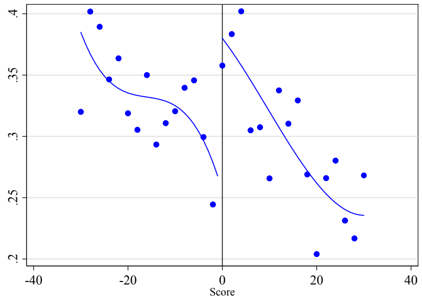


(d) Share of CC in Default

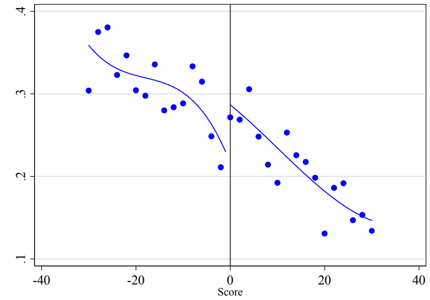
Notes: Each figure shows the mean of predetermined characteristics for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. The sample is restricted to applicants that faced a cutoff of 700 during the application process. Panel (a) refers to the probability of a delinquency, which is defined as an indicator variable that is equal to one if the applicant has had any credit card with 60 to 90 days past due from the earliest month with available information of the card to the application date, and Panel (c) to ratio of the number of cards in delinquency over the total number of cards. Panels (b), (d) are analogous but focus on default, which is defined as late payments of 90 days or more. These variables were constructed including only credit cards that were active at the date of application.

D.3 Outcome variables

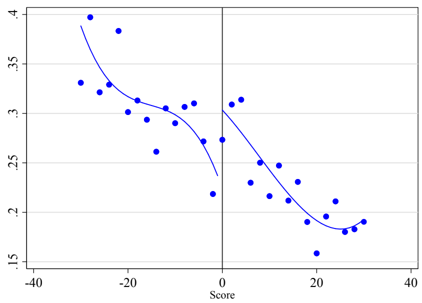
Figure D.7: The Effect on Long-Run Credit Card Delinquency



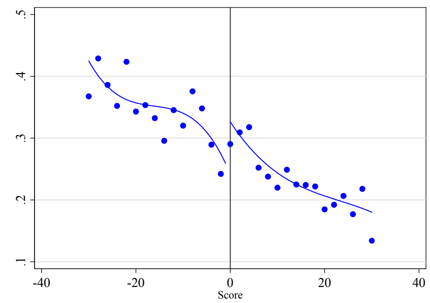
(a) Prob. of 2M Delinq. † (670 Sample)



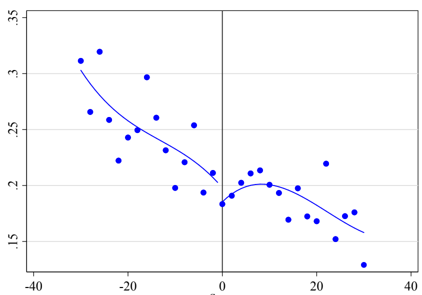
(b) Prob. of 2M Delinq. ‡ (670 Sample)



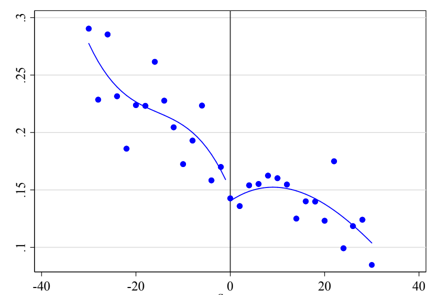
(c) Share in 2M Delinq. † (670 Sample)



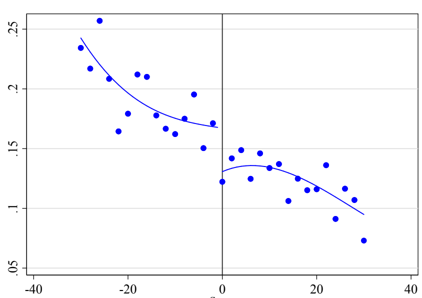
(d) Share in 2M Delinq. ‡ (670 Sample)



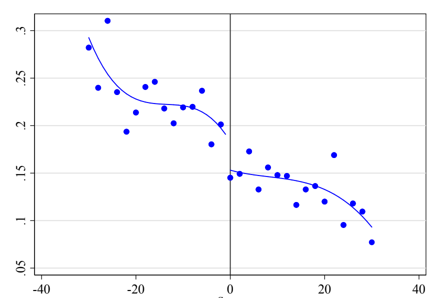
(e) Prob. of 2M Delinq. † (700 Sample)



(f) Prob. of 2M Delinq. ‡ (700 Sample)



(g) Share in 2M Delinq. † (700 Sample)



(h) Share in 2M Delinq. ‡ (700 Sample)

Notes: Each figure shows the mean of outcome variables regarding long-run (18 months after application) measures of delinquency for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process. Probability of 2M Delinquency is an indicator variable that is equal to one if the applicant has had at least one delinquency episode, which is defined as a 60 to 90-day late payment, between 12 months before and 18 months after the date of application. Share in 2M Delinquency is the share of cards that were in such a situation during the same period of time. †: the variable was constructed including all credit cards that were active at application as well as those opened afterward. ‡ The variable was constructed including only credit cards that were active at application. Panels (a)-(d) and (e)-(h) show results for the 670 and 700 samples, respectively.

Table D.1: The Effect of Approval on Credit Card Default:
Heterogeneity by Level of Debt

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
	Panel A: OLS			
Above cutoff 670	0.042	0.022	0.107	0.073
	(0.021)	(0.018)	(0.051)	(0.035)
Above cutoff × Above 75th perc.	0.040	-0.006	0.078	0.030
	(0.063)	(0.038)	(0.089)	(0.059)
Above cutoff 700	-0.020	-0.016	0.002	-0.004
	(0.018)	(0.016)	(0.018)	(0.012)
Above cutoff × Above 75th perc.	-0.060	-0.016	-0.096	-0.083
	(0.024)	(0.016)	(0.031)	(0.024)
	Panel B: IV			
Approved 670	0.097	0.052	0.245	0.170
	(0.046)	(0.041)	(0.117)	(0.078)
Approved × Above 75th perc.	0.036	-0.026	0.051	-0.006
	(0.113)	(0.069)	(0.175)	(0.114)
Approved 700	-0.053	-0.042	0.005	-0.007
	(0.048)	(0.042)	(0.046)	(0.031)
Approved × Above 75th perc.	-0.078	-0.010	-0.158	-0.133
	(0.045)	(0.037)	(0.054)	(0.042)
	Panel C: Means [-5;-1] from cutoff			
670	0.093	0.063	0.238	0.173
700	0.069	0.043	0.192	0.130
N	23492	23492	23492	23492
	Panel D: Joint Testing (p-values)			
670 = 700	0.001	0.010	0.024	0.026

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with total credit card debt in January 2010 above the 75th percentile of the distribution. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.2: The Effect of Approval on Long-run Default on Preexisting Credit Cards and Other Types of Loans: Heterogeneity by Level of Debt

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: OLS						
Above cutoff 670	0.070	0.060	0.137	0.102	0.099	0.099
	(0.043)	(0.032)	(0.042)	(0.032)	(0.033)	(0.027)
Above cutoff × Above 75th perc.	0.084	0.045	-0.157	-0.145	-0.117	-0.142
	(0.086)	(0.066)	(0.104)	(0.045)	(0.107)	(0.056)
Above cutoff 700	0.003	0.003	0.008	-0.018	0.037	0.004
	(0.013)	(0.011)	(0.024)	(0.014)	(0.014)	(0.010)
Above cutoff × Above 75th perc.	-0.110	-0.088	-0.052	-0.004	-0.079	-0.023
	(0.033)	(0.026)	(0.061)	(0.031)	(0.036)	(0.023)
Panel B: IV						
Approved 670	0.162	0.138	0.313	0.233	0.226	0.228
	(0.096)	(0.069)	(0.111)	(0.085)	(0.081)	(0.068)
Approved × Above 75th perc.	0.086	0.031	-0.350	-0.306	-0.259	-0.299
	(0.164)	(0.122)	(0.189)	(0.092)	(0.186)	(0.100)
Approved 700	0.008	0.008	0.022	-0.048	0.096	0.010
	(0.033)	(0.028)	(0.061)	(0.036)	(0.036)	(0.025)
Approved × Above 75th perc.	-0.182	-0.146	-0.094	0.012	-0.166	-0.041
	(0.052)	(0.043)	(0.116)	(0.059)	(0.062)	(0.038)
Panel C: Means [-5;-1] from cutoff						
670	0.201	0.160	0.353	0.168	0.312	0.188
700	0.159	0.118	0.217	0.100	0.162	0.105
N	23492	23492	23492	23492	23492	23492
Panel D: Joint Testing (p-values)						
670 = 700	0.105	0.077	0.001	0.001	0.074	0.001

Notes: This table is analogous to Table D.1, but focuses on externality effects. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with total credit card debt in January 2010 above the 75th percentile of the distribution. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table D.1, but differ in terms of the types of loans they include. The first two columns consider only credit cards that were active at application. The following two columns include all non-credit-card loans that were active at application as well as those opened afterward. The final two columns include only non-credit-card loans that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.3: The Effect of Approval on Credit Card Default:
Heterogeneity by Leverage

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
	Panel A: OLS			
Above cutoff 670	0.029	0.006	0.080	0.046
	(0.021)	(0.017)	(0.050)	(0.037)
Above cutoff × Above 75th perc.	0.096	0.063	0.174	0.122
	(0.064)	(0.045)	(0.093)	(0.074)
Above cutoff 700	-0.018	-0.012	0.002	-0.013
	(0.020)	(0.017)	(0.021)	(0.012)
Above cutoff × Above 75th perc.	-0.072	-0.033	-0.100	-0.048
	(0.024)	(0.019)	(0.032)	(0.022)
	Panel B: IV			
Approved 670	0.070	0.014	0.189	0.111
	(0.051)	(0.040)	(0.119)	(0.088)
Approved × Above 75th perc.	0.134	0.099	0.219	0.161
	(0.118)	(0.080)	(0.187)	(0.144)
Approved 700	-0.046	-0.031	0.006	-0.031
	(0.051)	(0.044)	(0.052)	(0.033)
Approved × Above 75th perc.	-0.105	-0.044	-0.171	-0.071
	(0.057)	(0.049)	(0.067)	(0.049)
	Panel C: Means [-5;-1] from cutoff			
670	0.093	0.063	0.238	0.173
700	0.069	0.043	0.192	0.130
N	23492	23492	23492	23492
	Panel D: Joint Testing (p-values)			
670 = 700	0.055	0.327	0.111	0.096

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with leverage (average debt-to-limit ratio across credit cards) in January 2010 above the 75th percentile of the distribution. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.4: The Effect of Approval on Long-run Default on Preexisting Credit Cards and Other Types of Loans: Heterogeneity by Leverage

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: OLS						
Above cutoff 670	0.048	0.029	0.094	0.076	0.067	0.082
	(0.043)	(0.033)	(0.043)	(0.033)	(0.037)	(0.029)
Above cutoff × Above 75th perc.	0.157	0.155	0.021	-0.029	0.014	-0.063
	(0.088)	(0.069)	(0.069)	(0.035)	(0.097)	(0.048)
Above cutoff 700	0.003	-0.002	0.008	-0.014	0.028	0.005
	(0.016)	(0.011)	(0.015)	(0.010)	(0.019)	(0.013)
Above cutoff × Above 75th perc.	-0.117	-0.073	-0.048	-0.018	-0.043	-0.024
	(0.033)	(0.021)	(0.040)	(0.022)	(0.045)	(0.025)
Panel B: IV						
Approved 670	0.115	0.069	0.222	0.179	0.158	0.193
	(0.100)	(0.074)	(0.115)	(0.087)	(0.096)	(0.077)
Approved × Above 75th perc.	0.218	0.231	-0.043	-0.109	-0.033	-0.170
	(0.173)	(0.129)	(0.150)	(0.083)	(0.185)	(0.101)
Approved 700	0.008	-0.004	0.020	-0.035	0.071	0.012
	(0.039)	(0.027)	(0.039)	(0.026)	(0.048)	(0.033)
Approved × Above 75th perc.	-0.201	-0.122	-0.089	-0.018	-0.099	-0.044
	(0.066)	(0.042)	(0.076)	(0.043)	(0.089)	(0.050)
Panel C: Means [-5;-1] from cutoff						
670	0.201	0.160	0.353	0.168	0.312	0.188
700	0.159	0.118	0.217	0.100	0.162	0.105
N	23492	23492	23492	23492	23492	23492
Panel D: Joint Testing (p-values)						
670 = 700	0.313	0.360	0.061	0.009	0.387	0.008

Notes: This table is analogous to Table D.3, but focuses on externality effects. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with leverage (average debt-to-limit ratio across credit cards) in January 2010 above the 75th percentile of the distribution. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table D.3, but differ in terms of the types of loans they include. The first two columns consider only credit cards that were active at application. The following two columns include all non-credit-card loans that were active at application as well as those opened afterward. The final two columns include only non-credit-card loans that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.5: The Effect of Approval on Credit Card Default: Heterogeneity by Number of Credit Cards

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
	Panel A: OLS			
Above cutoff 670	0.044	0.027	0.146	0.103
	(0.030)	(0.024)	(0.037)	(0.035)
Above cutoff × Above median # CC 670	0.018	-0.012	-0.055	-0.059
	(0.047)	(0.035)	(0.071)	(0.040)
Above cutoff 700	-0.016	-0.017	-0.003	-0.016
	(0.015)	(0.015)	(0.015)	(0.016)
Above cutoff × Above median # CC 700	-0.048	-0.008	-0.045	-0.022
	(0.019)	(0.016)	(0.047)	(0.039)
	Panel B: IV			
Approved 670	0.112	0.071	0.375	0.274
	(0.070)	(0.061)	(0.084)	(0.082)
Approved × Above median # CC 670	-0.012	-0.046	-0.230	-0.204
	(0.097)	(0.075)	(0.118)	(0.078)
Approved 700	-0.044	-0.047	-0.008	-0.037
	(0.043)	(0.042)	(0.042)	(0.044)
Approved × Above median # CC 700	-0.068	0.002	-0.077	-0.028
	(0.037)	(0.039)	(0.088)	(0.080)
	Panel C: Means [-5;-1] from cutoff			
670	0.093	0.063	0.238	0.173
700	0.069	0.043	0.192	0.130
N	23492	23492	23492	23492
	Panel D: Joint Testing (p-values)			
670 = 700	0.063	0.040	0.001	0.005

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with active credit cards at application above the 50th percentile of the distribution. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.6: The Effect of Approval on Long-run Default
on Preexisting Credit Cards and Other Types of Loans: Heterogeneity by Number of Credit Cards

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: OLS						
Above cutoff 670	0.088	0.088	0.123	0.106	0.108	0.102
	(0.034)	(0.034)	(0.039)	(0.039)	(0.032)	(0.033)
Above cutoff × Above median # CC 670	-0.000	-0.043	-0.044	-0.084	-0.084	-0.079
	(0.066)	(0.050)	(0.060)	(0.047)	(0.066)	(0.054)
Above cutoff 700	-0.001	-0.001	-0.012	-0.022	0.006	-0.015
	(0.018)	(0.018)	(0.021)	(0.012)	(0.016)	(0.013)
Above cutoff × Above median # CC 700	-0.056	-0.043	0.017	0.008	0.025	0.031
	(0.049)	(0.044)	(0.041)	(0.020)	(0.043)	(0.031)
Panel B: IV						
Approved 670	0.225	0.226	0.318	0.273	0.280	0.263
	(0.079)	(0.079)	(0.119)	(0.114)	(0.093)	(0.091)
Approved × Above median # CC 670	-0.084	-0.155	-0.191	-0.239	-0.243	-0.227
	(0.122)	(0.099)	(0.130)	(0.116)	(0.136)	(0.112)
Approved 700	-0.003	-0.002	-0.034	-0.062	0.016	-0.042
	(0.049)	(0.049)	(0.058)	(0.034)	(0.045)	(0.035)
Approved × Above median # CC 700	-0.097	-0.075	0.042	0.036	0.038	0.070
	(0.099)	(0.091)	(0.089)	(0.043)	(0.088)	(0.063)
Panel C: Means [-5;-1] from cutoff						
670	0.201	0.160	0.353	0.168	0.312	0.188
700	0.159	0.118	0.217	0.100	0.162	0.105
N	23492	23492	23492	23492	23492	23492
Panel D: Joint Testing (p-values)						
670 = 700	0.021	0.023	0.000	0.002	0.002	0.002

Notes: This table is analogous to Table D.5, but focuses on externality effects. Heterogeneous effects are obtained by estimating an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for applicants with active credit cards at application above the 50th percentile of the distribution. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the baseline effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table D.5, but differ in terms of the types of loans they include. The first two columns consider only credit cards that were active at application. The following two columns include all non-credit-card loans that were active at application as well as those opened afterward. The final two columns include only non-credit-card loans that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.7: Heterogeneous Effects of Approval on Long-run Default on Preexisting Credit Cards and Other Types of Loans

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: Leverage						
Above cutoff 670	0.048	0.029	0.094	0.076	0.067	0.082
	(0.043)	(0.033)	(0.043)	(0.033)	(0.037)	(0.029)
Above cutoff × Above 75th perc.	0.157	0.155	0.021	-0.029	0.014	-0.063
	(0.088)	(0.069)	(0.069)	(0.035)	(0.097)	(0.048)
Above cutoff 700	0.003	-0.002	0.008	-0.014	0.028	0.005
	(0.016)	(0.011)	(0.015)	(0.010)	(0.019)	(0.013)
Above cutoff × Above 75th perc.	-0.117	-0.073	-0.048	-0.018	-0.043	-0.024
	(0.033)	(0.021)	(0.040)	(0.022)	(0.045)	(0.025)
Panel B: Level of Debt						
Above cutoff 670	0.070	0.060	0.137	0.102	0.099	0.099
	(0.043)	(0.032)	(0.042)	(0.032)	(0.033)	(0.027)
Above cutoff × Above 75th perc.	0.084	0.045	-0.157	-0.145	-0.117	-0.142
	(0.086)	(0.066)	(0.104)	(0.045)	(0.107)	(0.056)
Above cutoff 700	0.003	0.003	0.008	-0.018	0.037	0.004
	(0.013)	(0.011)	(0.024)	(0.014)	(0.014)	(0.010)
Above cutoff × Above 75th perc.	-0.110	-0.088	-0.052	-0.004	-0.079	-0.023
	(0.033)	(0.026)	(0.061)	(0.031)	(0.036)	(0.023)
Panel C: Number of Credit Cards						
Above cutoff 670	0.088	0.088	0.123	0.106	0.108	0.102
	(0.034)	(0.034)	(0.039)	(0.039)	(0.032)	(0.033)
Above cutoff × Above median # CC 670	-0.000	-0.043	-0.044	-0.084	-0.084	-0.079
	(0.066)	(0.050)	(0.060)	(0.047)	(0.066)	(0.054)
Above cutoff 700	-0.001	-0.001	-0.012	-0.022	0.006	-0.015
	(0.018)	(0.018)	(0.021)	(0.012)	(0.016)	(0.013)
Above cutoff × Above median # CC 700	-0.056	-0.043	0.017	0.008	0.025	0.031
	(0.049)	(0.044)	(0.041)	(0.020)	(0.043)	(0.031)
Panel D: Means [-5;-1] from cutoff						
670	0.201	0.160	0.353	0.168	0.312	0.188
700	0.159	0.118	0.217	0.100	0.162	0.105
N	23492	23492	23492	23492	23492	23492

Notes: This table is analogous to Table 6, but focuses on externality effects. Panels A, B and C report the OLS estimates of an augmented specification that includes the interaction between the polynomials on both sides of the discontinuity with an indicator variable for certain applicant's characteristics being above a given percentile. Panel A presents the heterogeneous effects for applicants with leverage (average debt-to-limit ratio across credit cards) in January 2010 above the 75th percentile of the distribution. Panel B presents the heterogeneous effects for applicants with total credit card debt in January 2010 above the 75th percentile of the distribution. Panel C presents the heterogeneous effects for applicants with active credit cards at application above the 50th percentile of the distribution. Panel D displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. In all panels, the sample consists of all applicants with standardized credit score at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table 6, but differ in terms of the types of loans they include. The first two columns consider only credit cards that were active at application. The following two columns include all non-credit-card loans that were active at application as well as those opened afterward. The final two columns include only non-credit-card loans that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

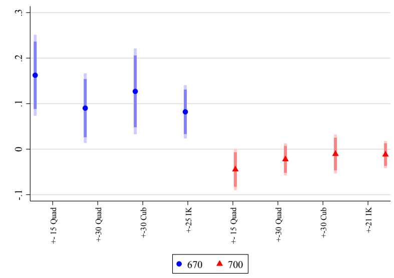
Table D.8: The Allocation of Long-run Default

	Prob. of Default Largest Debt	Prob. of Default Smallest Debt	Prob. of Default Largest Limit	Prob. of Default Smallest Limit	Prob. of Default Oldest Credit	Prob. of Default Youngest Credit	Prob. of Default Coll. Credit	Prob. of Default Non-Coll. Credit
				Panel A: OLS				
Above cutoff 670	0.090	0.078	0.016	0.127	0.071	0.064	0.027	0.140
	(0.058)	(0.032)	(0.050)	(0.045)	(0.034)	(0.052)	(0.019)	(0.041)
Above cutoff 700	-0.056	-0.017	-0.045	-0.032	-0.040	-0.028	-0.020	-0.015
	(0.015)	(0.020)	(0.014)	(0.014)	(0.019)	(0.011)	(0.017)	(0.020)
				Panel B: IV				
Approved 670	0.192	0.166	0.035	0.271	0.152	0.137	0.058	0.299
	(0.118)	(0.074)	(0.104)	(0.110)	(0.067)	(0.108)	(0.041)	(0.088)
Approved 700	-0.126	-0.037	-0.101	-0.071	-0.090	-0.063	-0.045	-0.034
	(0.033)	(0.045)	(0.030)	(0.030)	(0.043)	(0.025)	(0.039)	(0.045)
				Panel C: Means [-5;-1] from cutoff				
670	0.244	0.233	0.249	0.215	0.240	0.165	0.061	0.421
700	0.176	0.182	0.163	0.160	0.156	0.089	0.049	0.287
N	23492	23492	23492	23492	23492	23492	23492	23492
				Panel D: Joint Testing (p-values)				
670 = 700	0.013	0.030	0.209	0.002	0.002	0.087	0.058	0.001

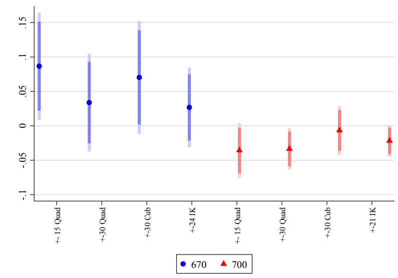
Notes: This table reports the RD estimates on default during the 18 months after the application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The dependent variables were constructed using information from all types of credits that were active at application as well as those opened afterward. In the first two columns, the dependent variable is an indicator variable that is equal to one if the applicant has had at least one default episode between 12 months before and 18 months after the date of application in the credit with the largest and smallest debt. In the following two columns, the dependent variable is similarly defined but focuses on the credits with the largest and smallest credit limit. In the following two columns, we analyze default on the oldest and youngest credit. In the last two columns, we analyze default on collateralized and non-collateralized loans. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

D.3.1 Robustness

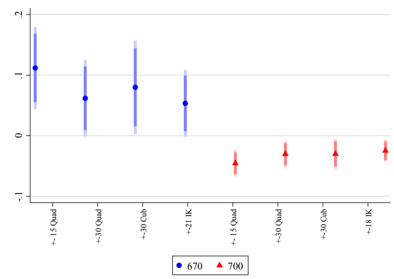
Figure D.8: Robustness of ITT Long-run Results



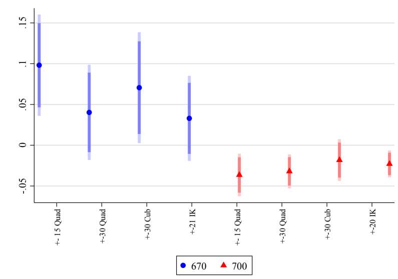
(a) Prob. of CC with 2M Delinq. †



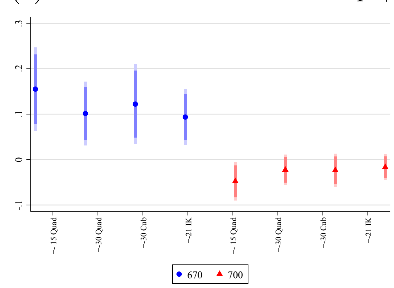
(b) Prob. of CC with 2M Delinq. ‡



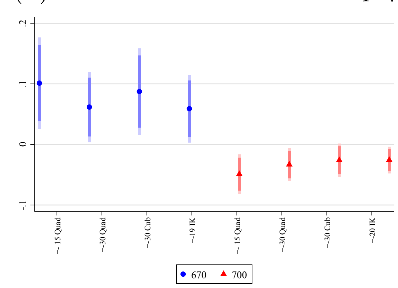
(c) Share of CC with 2M Delinq. †



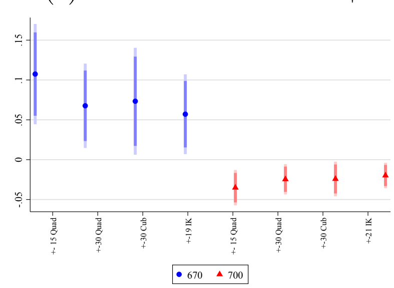
(d) Share of CC with 2M Delinq. ‡



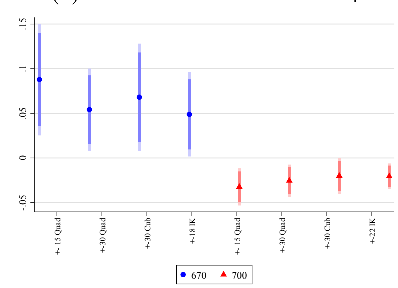
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



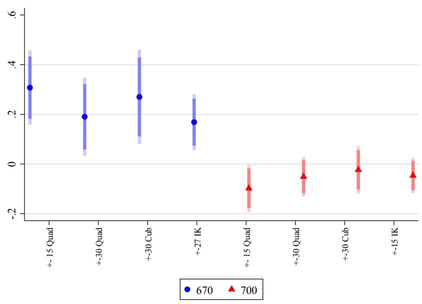
(g) Share of CC in Default †



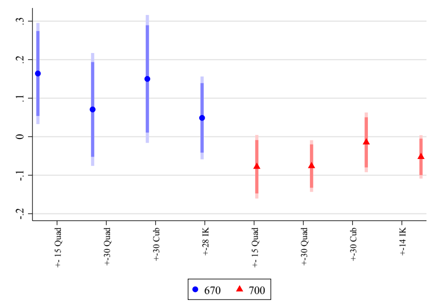
(h) Share of CC in Default ‡

Notes: The figures present the robustness of the estimated ITT effect on different measures of delinquency and default, using different polynomials (quadratic and cubic), different ranges above the cutoff (15 and 30) and those obtained from a local linear regression with optimal bandwidths provided by Imbens and Kalyanaraman (2011). Vertical bars denote 90% and 95% confidence intervals (standard errors were clustered at the credit score level). Each color represents a different cutoff. Delinquency and default are measured cumulatively from the moment of application up to 18 months after. † The variable was constructed including all loans that were active at application as well as those opened afterward. ‡ The variable was constructed including only loans that were active at application.

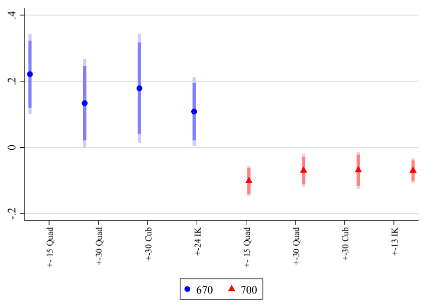
Figure D.9: Robustness of LATE Long-run Results



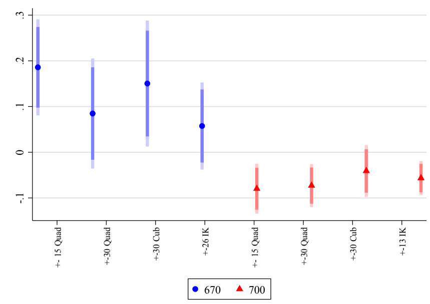
(a) Prob. of CC with 2M Delinq. †



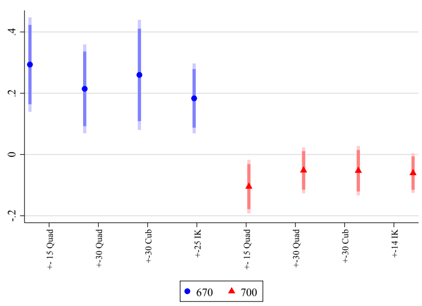
(b) Prob. of CC with 2M Delinq. ‡



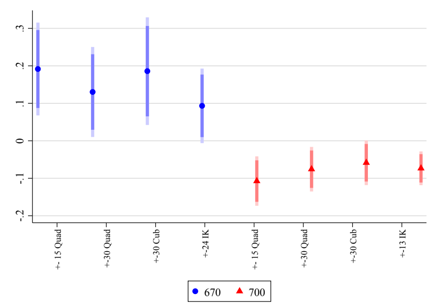
(c) Share of CC with 2M Delinq. †



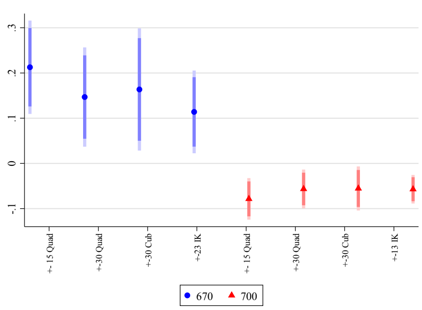
(d) Share of CC with 2M Delinq. ‡



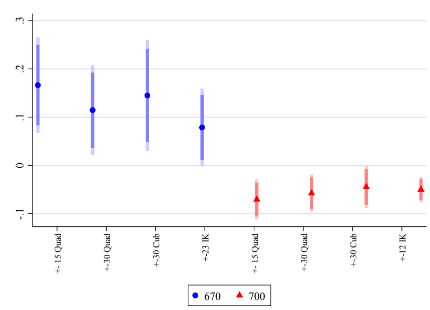
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



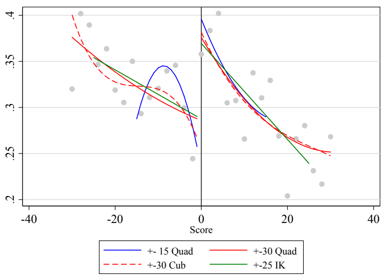
(g) Share of CC in Default †



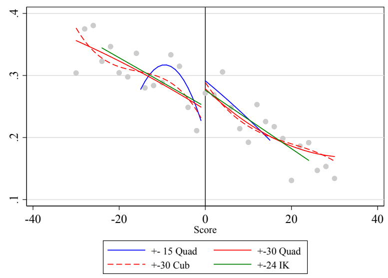
(h) Share of CC in Default ‡

Notes: The figures present the robustness of the estimated LATE effect of the application being approved on different measures of delinquency and default, using different polynomials (quadratic and cubic), different ranges above the cutoff (15 and 30) and those obtained from a local linear regression with optimal bandwidths provided by Imbens and Kalyanaraman (2011). Vertical bars denote 90% and 95% confidence intervals (standard errors were clustered at the credit score level). Each color represents a different cutoff. Delinquency and default are measured cumulatively from the moment of application up to 18 months after. † The variable was constructed including all loans that were active at application as well as those opened afterward. ‡ The variable was constructed including only loans that were active at application.

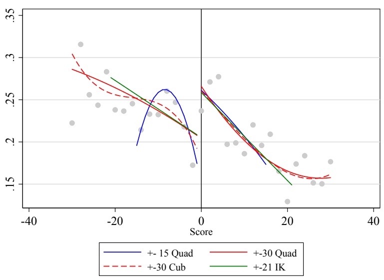
Figure D.10: Robustness of ITT Long-run Results



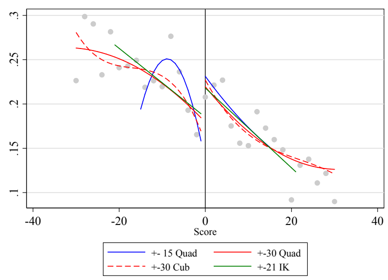
(a) Prob. of CC with 2M Delinq. †



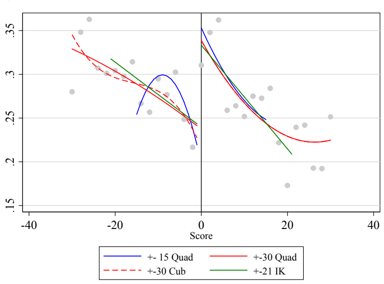
(b) Prob. of CC with 2M Delinq. ‡



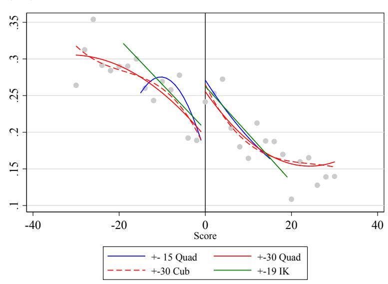
(c) Share of CC with 2M Delinq. †



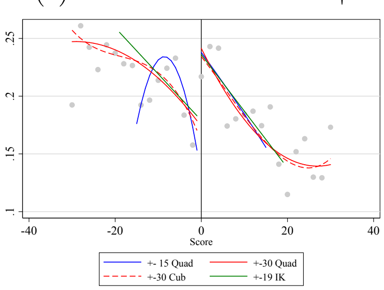
(d) Share of CC with 2M Delinq. ‡



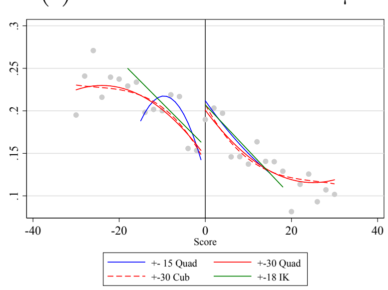
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



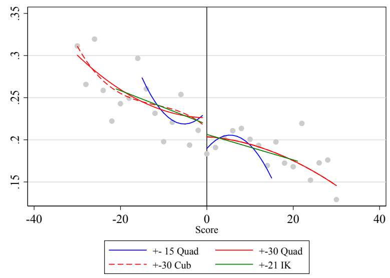
(g) Share of CC in Default †



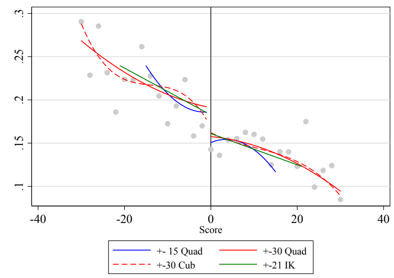
(h) Share of CC in Default ‡

Notes: Each figure shows, for the 670 sample, the mean of outcome variables for each pair of values of the standardized credit score between -30 and 30. It also presents the fit of the specifications behind the point estimates shown in Figure D.8. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

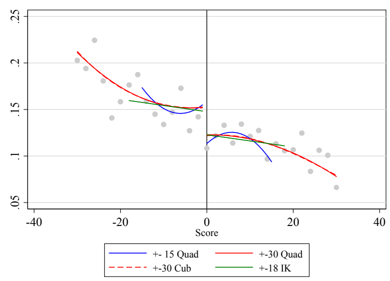
Figure D.11: Robustness of ITT Long-run Results



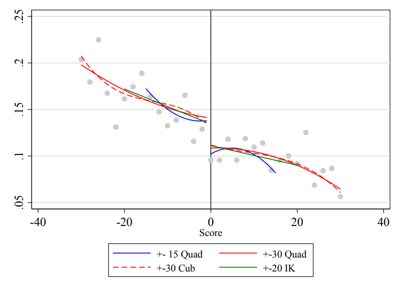
(a) Prob. of CC with 2M Delinq. †



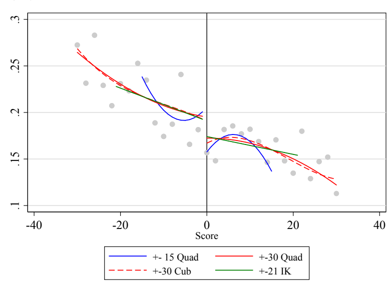
(b) Prob. of CC with 2M Delinq. ‡



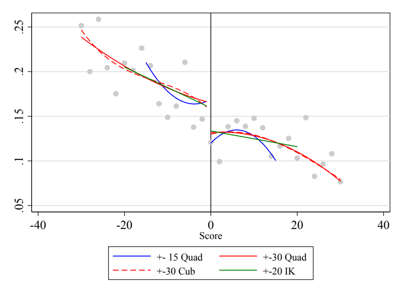
(c) Share of CC with 2M Delinq. †



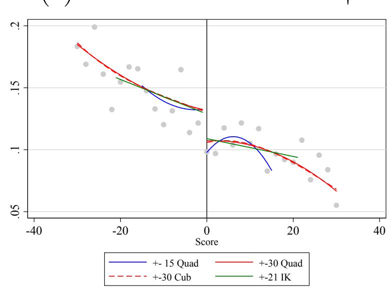
(d) Share of CC with 2M Delinq. ‡



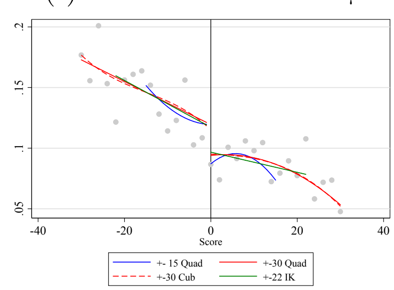
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



(g) Share of CC in Default †



(h) Share of CC in Default ‡

Notes: Each figure shows, for the 700 sample, the mean of outcome variables for each pair of values of the standardized credit score between -30 and 30. It also presents the fit of the specifications behind the point estimates shown in Figure D.8. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Table D.9: The Effect of Approval on Credit Card Default: Applicants to Gold Card

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
	Panel A: OLS			
Above cutoff 670	0.048	0.015	0.131	0.078
	(0.018)	(0.017)	(0.043)	(0.032)
Above cutoff 700	-0.035	-0.018	-0.025	-0.023
	(0.018)	(0.013)	(0.019)	(0.011)
	Panel B: IV			
Approved 670	0.103	0.032	0.282	0.169
	(0.039)	(0.036)	(0.094)	(0.068)
Approved 700	-0.082	-0.041	-0.058	-0.054
	(0.042)	(0.032)	(0.044)	(0.026)
	Panel C: Means [-5;-1] from cutoff			
670	0.096	0.065	0.239	0.174
700	0.071	0.044	0.200	0.136
N	21486	21486	21486	21486
	Panel D: Joint Testing (p-values)			
670 = 700	0.001	0.062	0.000	0.002

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Estimates are obtained for the sample of applicants that requested Bank A's Gold credit card in their application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.10: The Effect of Approval on Long-run Default
on Preexisting Credit Cards and Other Types of Loans: Applicants to Gold Card

	Prob. of CC in Default ‡	Share of CC in Default ‡	Prob. of Credit Lines in Default Excl. CC †	Share of Credit Lines in Default Excl. CC †	Prob. of Credit Lines in Default Excl. CC ‡	Share of Credit Lines in Default Excl. CC ‡
Panel A: OLS						
Above cutoff 670	0.088	0.065	0.110	0.075	0.079	0.078
	(0.034)	(0.029)	(0.036)	(0.030)	(0.030)	(0.025)
Above cutoff 700	-0.024	-0.015	-0.002	-0.018	0.021	0.003
	(0.013)	(0.010)	(0.016)	(0.009)	(0.012)	(0.009)
Panel B: IV						
Approved 670	0.188	0.139	0.237	0.161	0.170	0.168
	(0.074)	(0.059)	(0.088)	(0.068)	(0.067)	(0.054)
Approved 700	-0.056	-0.034	-0.005	-0.043	0.049	0.007
	(0.031)	(0.024)	(0.037)	(0.022)	(0.028)	(0.021)
Panel C: Means [-5;-1] from cutoff						
670	0.203	0.162	0.356	0.171	0.316	0.188
700	0.165	0.123	0.220	0.103	0.163	0.107
N	21486	21486	21486	21486	21486	21486
Panel D: Joint Testing (p-values)						
670 = 700	0.002	0.012	0.004	0.005	0.081	0.006

Notes: This table is analogous to Table D.9, but focuses on externality effects. Estimates are obtained for the sample of applicants that requested Bank A's Gold credit card in their application. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Measures of default are defined in the same way as the variables presented in Table D.9, but differ in terms of the types of loans they include. The first four columns include variables constructed including only credit cards that were active at application. The following two columns include all non-credit card loans that were active at application as well as those opened afterward. The final two columns include only non-credit card loans that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.11: The Effect of Approval on Short-run Credit Card Delinquency

	Prob. of CC with 2M Delinq.	Share of CC with 2M Delinq.	Prob. of CC with 2M Delinq. ‡	Share of CC with 2M Delinq. ‡
		Panel A: OLS		
Above cutoff 670	0.053	0.019	0.037	0.027
	(0.019)	(0.018)	(0.022)	(0.019)
Above cutoff 700	-0.038	-0.025	-0.039	-0.023
	(0.027)	(0.019)	(0.022)	(0.018)
		Panel B: IV		
Approved 670	0.113	0.040	0.079	0.057
	(0.044)	(0.039)	(0.051)	(0.042)
Approved 700	-0.086	-0.057	-0.088	-0.052
	(0.060)	(0.044)	(0.049)	(0.040)
		Panel C: Means [-5;-1] from cutoff		
670	0.133	0.093	0.127	0.093
700	0.096	0.059	0.090	0.060
N	23492	23492	23492	23492
		Panel D: Joint Testing (p-values)		
670 = 700	0.010	0.074	0.036	0.084

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 months after the application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. In the first two columns, dependent variables were constructed using information from all credit cards that were active at application as well as those opened afterward. In the last two columns (‡), the dependent variables were constructed including only credit cards that were active at application. Probability of 2M Delinquency is an indicator variable that is equal to one if the applicant has had at least one delinquency episode, which is defined as a 60 to 90-day late payment, between 12 months before and 6 months after the date of application. Share in 2M Delinquency is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.12: The Effect of Approval on Long-run Credit Card Delinquency

	Prob. of CC with 2M Delinq.	Share of CC with 2M Delinq.	Prob. of CC with 2M Delinq. ‡	Share of CC with 2M Delinq. ‡
	Panel A: OLS			
Above cutoff 670	0.127	0.084	0.070	0.071
	(0.047)	(0.039)	(0.041)	(0.034)
Above cutoff 700	-0.011	-0.032	-0.007	-0.018
	(0.021)	(0.013)	(0.018)	(0.013)
	Panel B: IV			
Approved 670	0.270	0.181	0.150	0.150
	(0.097)	(0.082)	(0.085)	(0.070)
Approved 700	-0.024	-0.070	-0.015	-0.041
	(0.048)	(0.029)	(0.040)	(0.029)
	Panel C: Means [-5;-1] from cutoff			
670	0.283	0.201	0.244	0.186
700	0.218	0.146	0.179	0.133
N	23492	23492	23492	23492
	Panel D: Joint Testing (p-values)			
670 = 700	0.006	0.006	0.081	0.016

Notes: This table reports the RD estimates on different measures of cumulative default during the first 18 months after the application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. In the first two columns, dependent variables were constructed using information from all credit cards that were active at application as well as those opened afterward. In the last two columns (‡), the dependent variables were constructed including only credit cards that were active at application. Probability of 2M Delinquency is an indicator variable that is equal to one if the applicant has had at least one delinquency episode, which is defined as a 60 to 90-day late payment, between 12 months before and 18 months after the date of application. Share in 2M Delinquency is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.13: The Effect of Additional Credit Limit on Long-Run Credit Card Default

	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default †	Share of CC in Default †
	Panel A: IV			
Approved Amount 670	0.015	0.010	0.011	0.008
	(0.006)	(0.004)	(0.004)	(0.004)
Approved Amount 700	-0.004	-0.004	-0.004	-0.003
	(0.003)	(0.002)	(0.002)	(0.002)
	Panel B: Means [-5;-1] from cutoff			
670	0.238	0.173	0.201	0.160
700	0.192	0.130	0.159	0.118
N	23492	23492	23492	23492
	Panel C: Joint Testing (p-values)			
670 = 700	0.000	0.001	0.001	0.003

Notes: This table presents OLS estimates of the RD specification $y_{it} = \alpha + \beta\gamma ApprovedAmount_i + f(score_{it}, \nu^-, \nu^+) + X'\xi + \nu_{it}$, where $ApprovedAmount_i$ is instrumented with the threshold dummy $\mathbf{1}\left(score_{it} \geq \overline{score}_t\right)$. Panel A presents the IV results for each subsample. Panels B displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel C presents the p-value of the test of the null hypothesis that the OLS estimate of the magnitude of the effect is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The first two columns include all credit cards that were active at application as well as those opened afterward. The last two columns include only credit cards that were active at application. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

Table D.14: The Effect of Approval on Credit Card Default: Pooled Results

	Short run (6 Months)		Long run (18 Months)	
	Prob. of CC in Default	Share of CC in Default	Prob. of CC in Default	Share of CC in Default
	Panel A: OLS			
Above pooled cutoffs	-0.013	-0.010	0.014	0.000
	(0.015)	(0.013)	(0.021)	(0.013)
	Panel B: IV			
Approved pooled cutoffs	-0.029	-0.022	0.031	0.000
	(0.033)	(0.029)	(0.045)	(0.029)
	Panel C: Means [-5;-1] from cutoff			
Pooled cutoffs	0.075	0.048	0.203	0.140
N	23492	23492	23492	23492

Notes: This table reports the RD estimates on different measures of cumulative default during the first 6 and 18 months after the application. Estimates are pooled across the 670 and 700 samples. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores 5 points below the cutoff. Finally, Panel D presents the p-value of the test of the null hypothesis that the magnitude of the discontinuity is the same across samples. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. Dependent variables were constructed using information on all credit cards that were active at application as well as those opened afterward. Probability of Default is an indicator variable equal to one if the applicant has had at least one default episode, which is defined as late payments of 90 days or more, between 12 months before and 6 (or 18) months after the date of application. Share in Default is the share of cards that were in such a situation during the same period of time. All regressions control for a third-order polynomial, allowing for a discontinuity of the standardized score at the value of 0. Regressions also include as control variables a set of month fixed effects and a sample-specific set of indicator variables for each number of credit cards and other types of loans active at the moment of the application. Clustered standard errors at the credit score level are reported in parentheses.

D.4 Comparing across thresholds

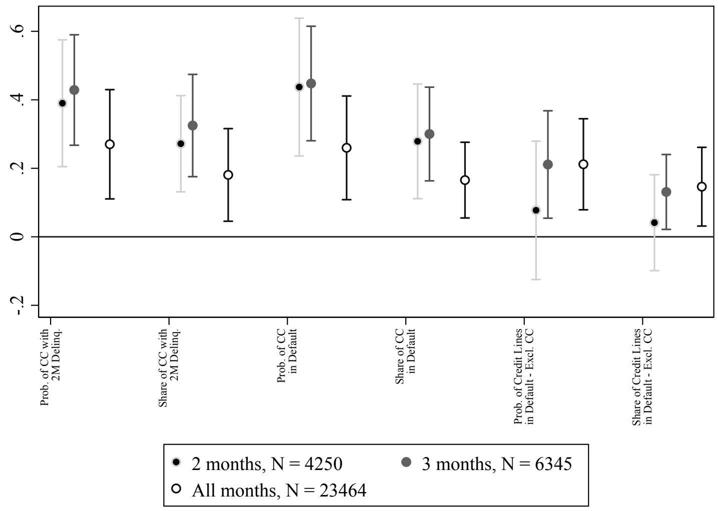
As a first test, Figures D.12 and D.13 in the Appendix plot estimates obtained using a 3-month (or 2-month) sample of contiguous months containing data on applications made in February, March, and April 2011 (or March and April 2011, respectively) for the estimates at the 700 threshold, and from June, July, and August 2011 (or June and July 2011) for the 670 estimates.[30] Although this reduces our sample size by two-thirds (or three-quarters), the estimated effects are similar to those we presented in the baseline estimations.

A second piece of evidence comes from the fact that applicants' characteristics are rather similar across the two periods. Figure D.14 in the Appendix plots the monthly averages of applicants' (i) credit score, (ii) self-reported income, (iii) age, and (iv) gender. We normalize each variable to 100 in the first month of the sample. The vertical line in the figure indicates the start of the 670 period. There are no pronounced trends in any of these variables, indicating that the selection of applicants is similar across time.

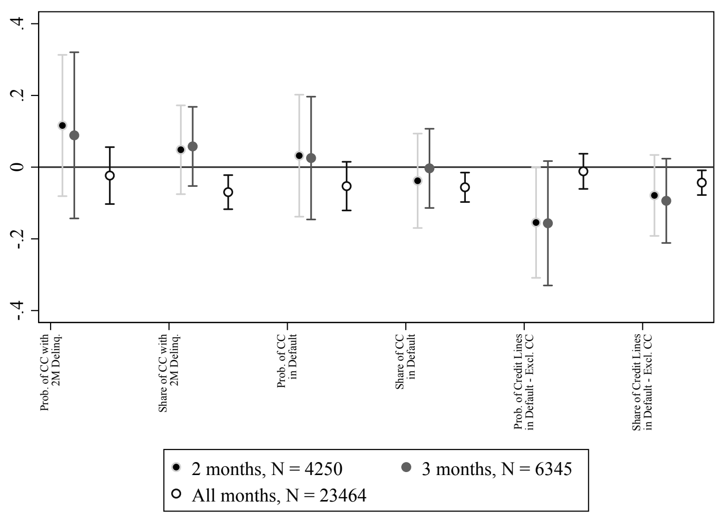
Figure D.15 in the Appendix presents a third check. It compares default rates for applicants who are "always-controls" regardless of the threshold regime—i.e., those with a score in the [640,660] range. We do this in order to not confound a differential treatment effect with a differential time trend effect. If propensities to default were different across months in the 700 threshold regime versus the 670 threshold regime, such differences would likely show up in different default levels for the always-control group at those different periods. Figure D.15 shows that this is not the case. It presents the regression-estimated difference in cumulative default between applicants with scores in the [640,660] range in the 700 regime and applicants with scores in the [640,660] range in the 670 regime. We find no difference in cumulative default rates for the always-control group in the two threshold regimes.

[30]We exclude May 2011, since it was a transition month and part of it used both thresholds simultaneously.

Figure D.12: The Effect on Long-Run Delinquency
by Number of Months around Change in Cutoff



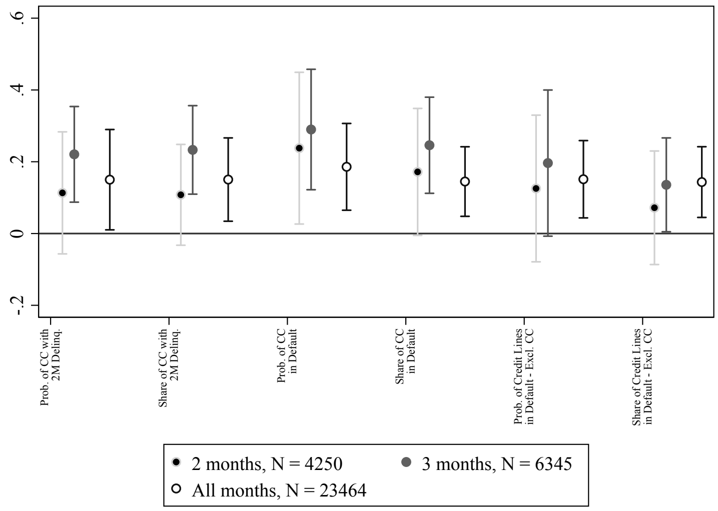
(a) 670 Cutoff



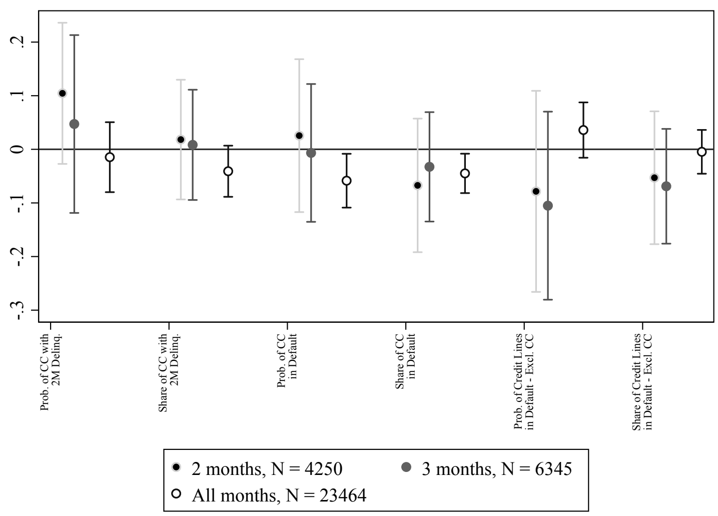
(b) 700 Cutoff

Notes: These figures present the estimated LATE effects for different populations of the 670 and 700 samples. The dependent variables were constructed including credit cards that were active at application as well as those opened afterward. Panel (a) presents the effects for the 670 sample, while Panel (b) presents them for the 700 sample. On the horizontal axis both graphs have several measures of default. Delinquency and default are measured cumulatively from 12 months before application up to 18 months after. For each cutoff and variable, the figure compares the main LATE results (hollow dots) against estimates obtained using the 3-month (or 2-month) sample, which uses data from applications made in February, March and April 2011 (or March, April 2011, respectively) for the estimates for the 700 group, while it uses data from June, July and August 2011 (or June and July 2011) for the 670 group. Vertical lines denote 90% confidence intervals (standard errors were clustered at the credit score level).

Figure D.13: The Effect on Long-Run Delinquency on Credit Cards Active at the Moment of Application by Number of Months around Change in Cutoff



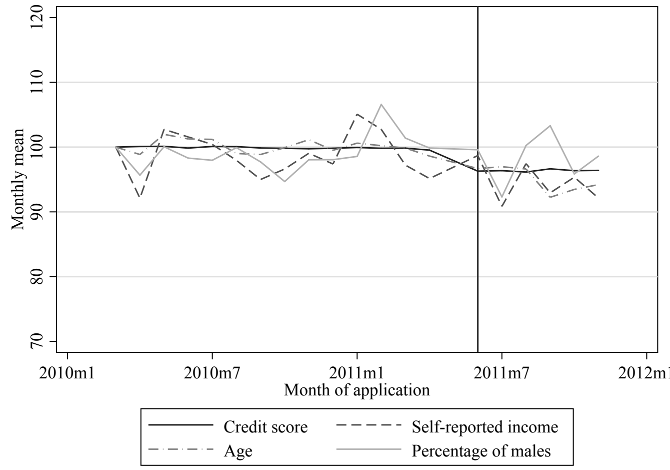
(a) 670 Cutoff



(b) 700 Cutoff

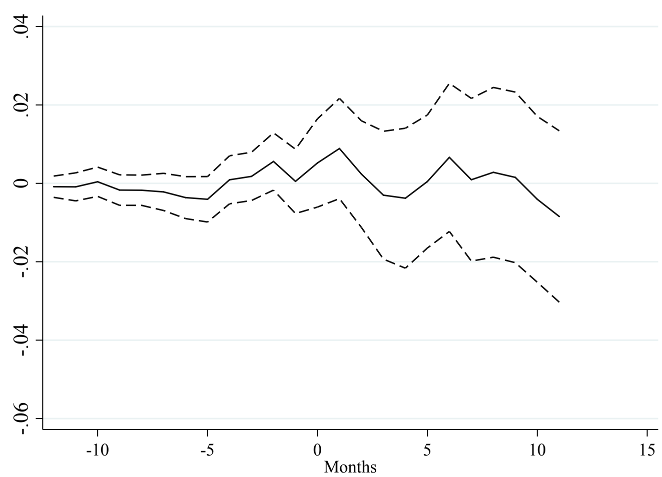
Notes: These figures present the estimated LATE effects for different populations of the 670 and 700 samples. The dependent variables were constructed including only credit cards that were active at application. Panel (a) presents the effects for the 670 sample, while Panel (b) presents them for the 700 sample. On the horizontal axis both graphs have several measures of default. Delinquency and default are measured cumulatively from 12 months before application up to 18 months after. For each sample and variable, the figure compares the baseline LATE results (hollow dots) against estimates obtained using the 3-month (or 2-month) sample, which uses data from applications made in February, March and April 2011 (or March, April 2011, respectively) for the estimates for the 700 group, while it uses data from June, July and August 2011 (or June and July 2011) for the 670 group. Vertical lines denote 90% confidence intervals (standard errors were clustered at the credit score level).

Figure D.14: Evolution of Average Applicants' Characteristics



Notes: This figure shows the evolution of the average applicants' characteristics. Each series has been normalized to its corresponding values as of the first month available in our applications data. The vertical line marks the month in which Bank A started using 670 as the threshold value in the approval process.

Figure D.15: Comparison of Default Rates between Applicants with Scores below the Threshold across Experiments



Notes: This figure plots the coefficient of the regression $y_{it} = \alpha_t + \beta_t Cutoff_i^{670} + \chi_{it}$, where the dependent variable is an indicator variable that is equal to one if the applicant has had at least one default episode between 12 months before the date of application and a given subsequent month t (normalized as months-after-application), and $Cutoff_i^{670}$ indicates whether applicant i applied during the 670-threshold regime. The dependent variable was constructed including all credit cards that were active at application as well as those opened afterward. β_t captures the cumulative probability of being in default t months before/after application for applicants that applied during the 670-regime relative to those that applied during the 700-regime. The sample consists of applicants that had a score between 640 and 660 (this restriction yields 4,315 observations). The figure reports the estimates obtained by running the regression for each t, together with the 90% confidence interval. Standard errors are clustered at the credit score level.

E Back of the Envelope Calculation

We propose a simple exercise to answer the question of how big is the increase in the probability of default for the first bank when a second bank awards a credit card to the first bank's client. We perform this exercise in terms of what interest rate increase would compensate the first bank for the lost discounted revenue from the increase in default rates caused by sequential banking. To conduct this simple back-of-the-envelope calculation, we make three assumptions: that the pricing of the credit card flows is performed under risk neutrality; that the default probability and the amount of outstanding debt is invariant to changes in the interest rate (i.e. we assume an inelastic demand curve), and that the state of delinquency follows an i.i.d. Geometric distribution with a per period probability p. Equation (4) equalizes the discounted present values of revenues under two scenarios.

$$\begin{aligned}
&\sum_{t=3}^{\infty}(1-p)^{t-3}p\underbrace{\left(\frac{1-\beta^t}{1-\beta}Debt*r+\beta^{t+5}\lambda\left(Debt+6*Fee\right)\right)}_{\text{Discounted revenues of credit card that defaults in } t} \qquad (4)\\
&\quad=\sum_{t=3}^{27}(1-p)^{t-3}p\left(\frac{1-\beta^t}{1-\beta}Debt*r^*+\beta^{t+5}\lambda\left(Debt+6*Fee\right)\right)\\
&\quad+\sum_{t=28}^{\infty}(1-p)^{25}(1-p^*)^{t-28}p^*\left(\frac{1-\beta^t}{1-\beta}Debt*r^*+\beta^{t+5}\lambda\left(Debt+6*Fee\right)\right).
\end{aligned}$$

In the first scenario on the left-hand side, we are computing the expected discounted revenues of a card issued by the first (and only) bank from the time of issuance ($t=0$). Since to be legally considered in default the card has to be delinquent for at least 3 periods, the probability of default occurring in period $t \geq 3$ is $(1-p)^{t-3}p$. In terms of revenues, the bank receives interest income until the card is defaulted on (i.e., a discounted amount of $\frac{1-\beta^t}{1-\beta}Debt*r$, where β is the discount factor). From then onward, the bank accumulates late fees of $Fee = 200MXN$ for 6 months, at which point it sells the debt at a discount of 90% ($\lambda = 0.1$), which is consistent with industry standards in Mexico. The term in parentheses corresponds to the discounted revenues when default occurs in period t; then, we take the expectation with respect to the time t when default happens.

The right-hand side of the equation represents the second scenario, in which a second bank approves a new credit line to the borrower. We allow the first bank to be the only source of financing for 28 months, which is the average time it takes to obtain a second card in Mexico (see Figure 2). At $t = 28$ as a result of the new loan, the probability of default changes from p, the probability when the contract is exclusive, to p^*, the probability when the card from Bank A is available. Other than the change in probability of default and the card's interest rate, the remaining parameters are kept constant.

We assume a discount factor of $\beta \approx 0.9959$ (monthly equivalent of a yearly discount factor of $0.9524 \approx \frac{1}{1+0.05}$) to match a standard long-term yearly rate of 5%. The monthly interest rate is set to $r = (1+0.37)^{1/12} - 1 = 0.0266$ (see Table 1). The probabilities of default are set to $p = 0.02$ (the converted probability of cumulative default for control applicants with one card at application) and $p^* = 0.047$ (the converted probability of default that we estimate for applicants with one card at application—see Column 1 of Table D.6).[31] Finally, we set $Debt = 8,400 MXN$ to the average credit card debt in January 2010. This exercise delivers a counterfactual annual interest rate of 56%, which is larger than the current interest rate of 37%. That is, to compensate for the increase in the default rate, the interest rate on the first Bank's card would have to increase by 19 pp.

[31] To construct monthly probabilities of default from our estimates, we assume that the state of default follows an i.i.d. Geometric distribution with probability p. Then, $p = 1 - (1 - p^{cum})^{1/18}$, where p^{cum} is the cumulative probability of being in default 18 months after application.