Sequential Banking: Direct and Externality Effects on Delinquency*

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Abstract

This paper examines the causal effect of additional credit on default rates using the universe of formal credit from the Mexican Credit Bureau. We make use of a regression discontinuity design over the credit score-based approval rules to generate exogenous variations in the probability of a credit card application being approved and credit expanded. In an effort to include unbanked consumers, our bank experimented with lower cutoffs. We document that moral hazard is substantial and concentrated in applicants with lower credit scores. We also document default externalities as credit by the new bank increases default of the clients in their other banks. The results suggests that moral hazard is important, that servicing lower income/score clients is hard, and that sequential banking may lead to high default equilibria.

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1 Introduction

The expansion of credit is often a goal of governments and of profit seeking banks. The former often worry that riskier and lower income segments of the population are underserved, while the latter focus on middle and high income consumers often giving several loans to the same person. Mexico is one such country where the government, and the central bank, have repeatedly complained about the low private credit to GDP ratios, while seeking ways to increase credit access.

At the same time the recent financial crisis was a painful reminder that together with a credit expansion there is a chance of default and systemic risk. Unfortunately we still know little about: i. the elasticity of default with respect to credit; ii.if and how much this elasticity varies for different consumers; and iii. the systemic effects (or default externalities) whereby the loan of one bank causes default on other credit lines potentially from different institutions. In this paper we study these three issues.

Although several recent papers have studied the credit-default elasticity (**?**, **?**, and **?**) they have reached qualitatively different conclusions as we discuss below. This may be because they study very different populations, different countries, and use different sources of variation and methods. We document that there is substantial heterogeneity in the elasticity which could potentially explain why the results may differ. Although **?** have shown theoretically that the existence of a default externality may lead to inefficient equilibria (with higher price of credit, more leverage, and more default), we provide, to the best of our knowledge, the first convincing test of such effects at the consumer level.

Our identification strategy relies upon quasi-experimental variations in the credit availability through a simple regression discontinuity design. As the probability of obtaining a new credit card is a discontinuous function of the credit score of the applicant, we are able to compare (observationally equivalent) applicants with credit scores slightly above and below of the discontinuity point. That is, we take advantage of the fact that applicants to an anonymous Bank (Bank A hereafter) credit card in the neighborhood of the discontinuity points are essentially identical, but those with credit scores above the set thresholds (unknown to the applicants) have a markedly higher probability of obtaining the new credit card and therefore larger credit. Importantly, Bank A experimented with the threshold for obtaining a new credit card, moving it from 700 to 670 and then 680 in the credit score as they were trying to go down the market and serve lower score applicants. These policy changes allow us to circumvent the local nature of RD estimation and to rigorously measure the heterogeneity of the default elasticity, as we have treatment and control comparisons at 3 levels of the score.[1] Finally, since we observe all formal loans for a given consumer, we are

[1]As in the US and other countries the credit score in Mexico measures the likelihood that a person defaults as a function of credit behavior including previous defaults; it does not measure the credit-default elasticity necessarily. The Mexican credit bureau score which Bank A uses was designed by Fair Isaac, which is meant to capture the probability of default (or 90 days delinquent) in the next 12 months. In the US the horizon is typically 24 months.

able to study whether default and delinquencies are concentrated on existing, applied for, or new loans we define the former as our main measure of externality.

The range of credit scores we study (between 640 and 730, which corresponds to about 44% of the total applicants to Bank A) map to a significant range of incomes, in particular applicants span from the second to the fourth quartile of the income distribution.[2] For example, In the US this range would move a consumer between a (marginally) poor to a good credit score.[3] That is to say the population we are studying is a relevant population for testing for the importance of asymmetric information problems and credit expansion.

Our empirical analysis first assesses the validity of the RD strategy: (a) applicants from the left and right of the thresholds are statistically 'identical' in observable characteristics, and that density of the the credit score (or running variable) is smooth, suggesting it is not manipulated by the applicants. We then show that the probability of approval increases by about 45 percentage points just to the right of the score threshold, over a basis of 3pp to the left. This jump in the probability of approval translates into an immediate 70% increase in the credit limit (on average) or about MXN 16,000 (USD 970) for those who obtained the new card. Interestingly we find that rejected applicants close to the threshold do not apply to other loans with larger probability than approved applicants afterwards, as if they were somehow discouraged by their rejection. In fact, the difference in the number of cards between our controls and treatments persists for more than two years.

Using this exogenous variation in the amount of credit, we find that the overall probability of default on a credit card increases by 6.6pp or 33% over a basis of 20pp for those who received the Bank A card. Consistently with the substantial heterogeneity in the credit score effect we find much larger increases at the lower threshold of 670, where the probability of default on a credit card increases by about 17.4pp or 84% and no effect for the 700 threshold. Note that our empirical strategy holds constant the selection of applicants (at the threshold) and gives more loans to some of them quasi-randomly. Following **?** and **?** we call "moral hazard" any increase in default caused by more credit when we hold fixed the population.[4]

There is substantial heterogeneity in terms of the number of cards: the effect of the increase in credit on default rates is larger for individuals with fewer credit cards at the moment of application. These results are fully consistent with a simple model of borrowing we present later, where we allow for unobserved heterogeneity in the type of borrowers and for agents to make a rational choice on their amount of effort (or expected probability of repayment) in a dynamic environment

[2]Although not straight-forwardly comparable, in the US about 30% of those with a credit score would have a scores between those two extremes.

[3]See https://www.creditkarma.com/faq/what-is-a-good-credit-score.

[4]In the papers cited larger debts imply less effort from the consumer as a larger part of the gains of this effort are captured by the bank because it gets paid the larger debt with larger probability. Another channel which may lead to larger default is purely mechanical –not strategic– as larger debts are less likely to be paid if income has an stochastic component. We will not separately identify these channels.

where agents can access an increasing number of credit lines overtime.

Importantly, we test for the existence of a default externality. We find that for the lowest threshold, the probability of default on an existing credit card increases by 11pp or 65% for those who get a Bank A card. Similarly the probability of default on a pre-existing credit line (not a credit card) for the same threshold increases by 16pp or 64%. To the best of our knowledge this is the first clean test of the externality effect in the credit market. And the magnitudes suggest that these externalities are large and merit careful consideration.

There are a number of recent papers on the issue of asymmetric information in the credit market. However, the convincing identification of the extent of asymmetric information has proven rather challenging. Since **?** called for the need of more empirical work on documenting asymmetric information, a number of papers have come to fore. Although it is fair to say that most of these papers relate to insurance markets, recent contributions by **?**, **?**, and **?** –to cite a few– study credit markets. **?** focus on microcredit costumers in South Africa and randomly vary current and future interest rates and document that a 100 basis points decrease in the promised future interest rate causes a decrease of 4% in default, but they find little effect of changes to current interest rates, suggesting low moral hazard/debt overhang. **?** are closer to us in that they focus on variation in the quantity of credit instead of price variation. They focus on subprime auto loans in the US and show that, conditional on selection, an increase of $1,000 USD in the size of auto car loans leads to a 16% higher hazard rate of default. They also look at variation in prices and in contrast to **?** they find large moral hazard effects in this dimension. Interestingly, using an RD design in the context of payday lending in the US, **?** find the opposite: that a $50 USD larger loan leads to a 17 to 33 percent *decrease* in default. They interpret this as showing that greater liquidity may allow for better debt management and timely payment.

Our paper differs from the ones mentioned above in several important dimensions. First, while all the above study the *subprime* market, we study a market for middle income individuals. Second, the percentage change in the quantity of the loan is much bigger than that used in the cited papers, which may explain our larger default elasticity estimates. We are able to look not only at the extensive margin of default, such as the probability of default, but also at the intensive margin, i.e. the number of defaulted lines as well as the amounts defaulted upon. Third, we can study heterogeneity of the response at different levels of the risk score and show that the widely different responses may explain the heterogeneity of results in the literature. Fourth, the study uses an RD methodology that gives clear variation in quantities, while **?** use randomized price variation and **?** use econometric techniques to isolate variations in loan amounts. Most importantly perhaps, we are explicitly interested not only on default on loans within a given institution, but importantly also on default externalities across *all* financial institutions. Our data allow us to study to what extent an increase in the loan supply from one bank affects default rates in *other* banks and all types of loans.

This last point is important: **?** show that default externalities may lead to inefficient equilibria and high interest rates, although so far there is little evidence on the quantitative importance of these externality effects in practice. Finally, we are able to look into long-term effects by following our borrowers for up to four years and trace out the dynamics of delinquency and default.

Methodologically our approach is similar to **?** who also use a discontinuity in loan size approval to study default on existing payday loans from the awarding institution. Our data however contains larger changes in loan amounts in different parts of the risk score.[5] **?** also use a regression discontinuity design where the running variable is the credit score, but they study moral hazard in the securitization of mortgage portfolios.[6] Further a recent paper by **?** use a design that is similar in spirit to ours to estimate the Marginal Propensity to Lend (MPL) and Borrow (MPB) in the US credit market.

The rest of the paper proceeds as follows: Section 2 describes the institutional features of the market we study and the data used in the analysis; Section 3 presents the empirical strategy; Section 4 discuss the results; Section 5 develops a simple model for the interpretation of the findings; finally, Section 6 concludes.

2 Context and Data

2.1 Some Background

A few facts on the Mexican credit card market are worth mentioning. The credit card market is relatively underdeveloped, owing perhaps to a history of nationalization, privatization and recurrent financial crises in the 1980s and 1990s, including the tequila crisis of 1994. To give a birds eye comparison, even 10 years after this crisis, in 2004, there were 0.13 credit cards per person in the country compared to 0.35 in Argentina, 0.38 in Brazil (**?**). After 2002, the number of credit cards awarded grew rapidly, close to 9.9 percent from 2002 to 2008. However, due to the financial crisis, growth stopped completely from 2008 to 2012. As of the early 2010's the coverage rate was still low: there were 30 cards per every 100 inhabitants in 2010, whereas there were about 120 credit cards for each 100 US member of the population in that same year.[7] This is not only a feature of the credit card market, in fact total credit to the private sector over GDP is close to 30% only, whereas for developed countries it is above 100%.

[5] They use $50 USD jumps in credit availability, while we use changes of about $1,000 USD (we use the 2010-2012 average MXN to USD exchange rate of .08), amounting roughly to a 70% increase in the size of their total credit lines.

[6] Two papers studying the credit card market are also related to ours. **?** examines default risk as a function of the interest rate offered and finds evidence of asymmetric information. He does not try to separately identify moral hazard and adverse selection effects while we study only moral hazard (driven by adverse selection). **?** study the elasticity of debt with respect to changes in interest rates and credit card limits using an instrumental variables strategy. They find large marginal propensities to consume out of credit line increases, however they do not look at how this affects default.

[7] See **?** and **?**.

For this paper's purpose it is important to note that this growth came in no small way from banks issuing new cards to *existing* cardholders: between 2006 and 2008 the number of cards held by the average cardholder increased from 3.4 to 4.2 (**?**). The increase in the number of cards has been accompanied by increases in default rates (although it is confounded also with the 2008 financial crisis): 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 who did not have cards before, while another part may have to do with the awarding of cards to existing cardholders who may already have substantial debt. In fact a non-negligible fraction of new cards are awarded to clients who already have cards. In 2006, 42% of new cards went to people who already had at least one card.[8] Many Mexicans have more than one card: in 2010 half the cardholders have one credit card, 20% have two cards, 11% have three, 7% have four and 12% have five or more. We suspect this is true in the US and other countries as well.

Another noteworthy fact is that credit card industry is and has been highly concentrated. The five largest banks held a steady market share of close to 90% from 2001 to 2012 in terms of the number of cards and outstanding credit card debt. The average credit card interest rate has been close 29 percent per year although there is substantial dispersion, while the government federal discount rate (TIIE) has between 5 and 7 percent.[9] Compared to the US which has thousands of credit card issuers, Mexico has only about 20. In Mexico only banks are credit card issuers. Finally we should mention that credit cards are the main financial instrument for formal financial inclusion in Mexico. **?** documents that about 70% of first loans are credit cards (not personal loans, mortgages, auto loans, etc).

Since we use the approval policies of one large bank to generate variation in total credit line sizes, one may wonder whether we are sampling from a population that is very different from the average. This turns out not to be the case. In order to compare the sample of applicants we use in the analysis to the general population within this market, we drew a random sample of of 1,000,000 cardholders from the whole market for June 2010. It turns out that the basic measures of debt are not that different from those of our RD sample.

2.2 Data

We rely on two main data sources. The first one comes from all the credit card applications made to Bank A between March 2010 and April 2012 from applicants that were not already clients of Bank

[8] This number was 45%, 41%, 25%, and 20% respectively in 2007, 2008, 2009, and 2010.

[9] See the Reports by the Bank of Mexico (2014) Reporte sobre las condiciones de competencia en el mercado de emision de tarjetas de credito.

A.[10] The data contain all the information recorded by Bank A at the moment of the application and used during the approval decision, including information on applicants' credit score, date of application, self-reported annual income (which we are now verifying with social security data), gender, client status, and type of credit card applied for, some credit bureau information as well as an id number that allowed us to merge it with the the credit bureau data. The data also include the bank's approval decision, type of card, and credit limit awarded in case of approval.

A crucial variable in our analysis is the applicant's credit score at the moment of application, as we will exploit such variable as our running variable in the research design. The credit score is computed by the the credit bureau and sold to Bank A. We use exactly the same score that Bank A used for its approval decision. The calculation of the score is similar to the ones in the US (in fact the scoring method was designed by Fair Isaac, the leading credit scoring company in the US), using the individual's credit history, types and number of credits in use, and amount of outstanding debt, among others. It does not use any information about the individual's occupation, income, employment history, gender, age, or geographic location. The range of the credit score observed in our sample goes from 400 to 800. As it will be shown later, the bank's approval policy has a large discontinuity for some specific values within this range. More importantly, Bank A changed the threshold twice during our sample period, so that ultimately we have 3 thresholds which will allow the identification of our parameters of interest in multiple parts of the credit score distribution. Observations with a cutoff of 700 points correspond to applications made in 2010, and between January and April of 2011. Observations with a cuff of 670 correspond to applications made between June and November of 2011, and observations with a cutoff of 680 correspond to applications made between December 2011 and April 2012.[11]

We merge this Bank A data with a second dataset coming from the Credit Bureau that contains the universe of loans for all these individuals. In this second dataset an observation corresponds to a single loan, and for each loan we observe its type (mortgage, personal credit, credit card, etc.), opening and closing date, the credit limit and debt at the time the snapshot is taken, the current status of the credit (late payments, default, etc.) and the monthly payment history up to the last 7 years. Such a data setting allows us to precisely measure all possible delinquencies in for every month.[12] While for variables on quantities such as current limit and debt we rely on up to 6 snapshots. This merging step only drops 4.5% of the original sample of applicants for which a

[10]The reason for excluding existing Bank A clients is that the bank's approval rules with respect to applications from its existing clients is less strict and thus no discontinuity in the approval decision can be exploited. We further restrict the sample by dropping applicants with credit cards from other two banks. The problem with these banks is that they seem to be following a similar approval policy to the one used by the anonymous bank, creating a discontinuity in the predetermined characteristics of our applicants. In particular, they generate a discontinuity in the number of active credit cards just before the application at Bank A.

[11]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 small set of observations where the same person applied more than once to Bank A.

[12]A card is delinquent one month if the minimum payment corresponding to that month was not paid. In keeping with the legal definition in Mexico and with most papers in the literature, a card is in default if it is delinquent for 3 consecutive months or more.

match could not be found.[13]

Data on dates of opening and closing, and on the history of delinquency, which are our main outcomes of interest are very precisely measured. The variables related to credit limits and debt are a bit more problematic for several reasons. First, we do not observe monthly information for these variables, just snapshots of the months when the credit bureau data was extracted. Since card applications fall in different months, for each snapshot a different number of months elapsed for different applicants.[14] Second, the authorities (and banks) are very concerned with the amount of on time payments in part because reserve requirements depend on this; they are less concerned with the amount of debt partly because lacking a reliable measure of income no regulation depends on leverage. Third, borrowers can legally complain about false positives in the case of default which they see in their credit report, but the credit report does not show debt. Finally, debt is a variable with unbounded support that tends to have high variance. This variance is exacerbated for revolving loans like credit cards which can have different debt in different days, and the bank report the balance on the day it uploads the information to the credit bureau, there is no legally determined reporting date. We do report credit limits and debt as outcome variables subject to these concerns. To reduce to some extent the variance of the outcomes, and to alleviate the measurement error, we also report results for threshold dummy variables.

Originally we obtained two snapshots of information from the credit bureau in January of 2010, before the thresholds we use were set, we use this snapshot to asses balance across the threshold(s). i.e. across treatment and control groups, and December of 2012 to measure outcomes. These are our main periods of study. We later obtained other snapshots from June 2012, June and December 2013, and finally April 2014, which we use in the later sections of the paper to asses longer term impacts.[15]

2.3 Descriptive Statistics

The working sample we use is described in Table 1. Our sample comprises all applicants to Bank A credit card who applied for a card between January 2010 and April 2012. Panels A and B show pre-treatment summary statistics using data from Bank A, collected at the moment of application and from the banking commission obtained for the January 2010 financial statement of the applicant. We provide statistics on the pooled sample of applicants as well as by credit score thresholds (in each column we include applicants with credit scores in the +-5 points range around the threshold).

It is important to point out that the sample we consider for our analysis, i.e. all the applicants

[13] This occurs mostly because of typos in the registration of the applicant id number.

[14] In all regressions we control for elapsed time since application.

[15] Using data several years after credit origination has a cost however. By law the credit bureau has to delete defaulted loans in at most 6 years after default happens, but it can be as early as 2 years after default depending on the size of the amount defaulted. This means that looking beyond two years may generate some attrition issues in our data.

to the credit card of Bank A with scores between 640 and 730, is not a small fraction of the entire sample of applicants and in fact is quite heterogeneous in many respects, most importantly in credit worthiness. It is also important to note that the distribution of the credit scores in the overall sample of applicants is the following: 37% below 640, 55% below 670 (lowest cutoff), 59% below 680 (middle cutoff), 69% below 700 (highest cutoff) and 83% below 730.

The average self reported income of applicants is MXN 27,350 (about USD 2,200) per month (unreported in Table), we will be using administrative data on income in later drafts. This level of income would place our applicants' sample in the top second decile of the overall Mexican income distribution (**?**). However, given the large variation, the income distribution of applicants kept in our estimation sample spans a large chunk of the Mexican income distribution, with most of the observations concentrated in the 6th or higher deciles. The majority of the applicants are males (57%). The population in the study has on average been in the credit bureau records for almost 8 years. The average applicant has debt of $34,732 MXN, which is higher for the 700 threshold, and on average has 1.5 credit cards from different banks other than Bank A and 3.5 credit lines (these include personal loans, car loans, mortgages, etc.) from all banks. The average credit card debt is $7,949 MXN (about $600 USD). These applicants have access to other sources of credit since credit card debt only represents 25% of total debt.

One of our main outcomes –and a proxy for moral hazard in many models– is default, which is measured as a late payment past due for more than 90 days. We choose this measure since it is 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) and in the literature (**?**). However in the paper we also present results for payments that are between 30 and 60 days past due, which we call delinquency. Both definitions will show results in the same direction.

The risk measures we use in Panel A consider default and delinquency in the 12 months before application for each applicant, regardless of whether the card was still open at the moment of application. On average 6% of applicants have defaulted in the year before they applied for the new card, and on average 0.07 credit cards were in default in the same period. We also calculate the share of cards in delinquency or default to be 5%. Measuring default as a share of cards will help ease concerns about default being driven mechanically just by having more cards to default upon for those above the threshold(s). The downside of using shares is that we might care about the number, and probability of cards in default rather than the shares. These risk measure are inversely related to the credit scores which is an indication that the credit score is a "sensible" screening mechanism.[16] If we focus only on credit cards that were active at the moment of application, in

[16] In order to avoid overlaps in observations across thresholds (columns) we only use observations that are at most a distance of 5 points from the respective cutoff in this Table.

Panel B, we see that only 1% of them were in default in January 2010. If we focus on a less severe measure of delinquency we see that 2% credit cards were delinquent.

In Panel C we show some descriptive statistics which apply to approved cards. Bank A's data shows that around 30% of all applications were approved with an average credit limit of $15,502 MXN ($1,400 USD). This change in credit limit is substantial as it represents about 65% of the sum of the limit in all cards 30 days before application. We view this large shock as an advantage of the paper over previously cited literature and a possible reason why we are finding large effects on default. Two things suggest that applicants are credit constrained, beyond the fact that they applied for loans. First, interest rates are high at 37% per year[17]. Second, on average people are getting about 20% lower amounts of credit than what they actually requested.

3 Empirical Strategy and Methodology

The wealth of data and the clear rules for obtaining a Bank A credit card give us the opportunity to apply a simple (fuzzy) regression discontinuity design approach for the identification of the moral hazard problem in the credit market, and to document the risk of furthering financial inclusion and expanding credit. (**?**, **?** and **?**).

The probability of obtaining an extra credit card, i.e. an extra line of credit, changes discontinuously at a Bank A established threshold. Interestingly that threshold has been modified twice by the bank so that we have in fact 3 thresholds with heterogeneous populations, starting from the more credit-worthy (score 700) to the less credit worthy (score 670). The reason for this is that Bank A tried to serve costumers in these lower scores only to find out that it was not a profitable strategy. These different thresholds allow us to analyze whether the effects of extra credit are heterogenous across the credit score distribution. In fact, there are good reasons to expect the default and delinquency rates to be differential across the score distribution, since the scope of the credit score is to reflect credit worthiness. This point will be made more formally with the aid of a simple model in section 5. Note however that there is no necessary connection between the level of predicted default and the treatment response to more credit (a cross-partial derivative basically).

In the empirical analysis we proceed with the typical RD estimating equation:

$$y_{it} = \alpha + \beta \mathbf{1} \left(score_{it} \geq \overline{score}_t \right) + f(score_{it}; \nu^-, \nu^+) + X'\xi + \epsilon_{it}, \tag{1}$$

where the parameter of interest is β. This is the estimate of the local Intent-to-Treat (ITT) effect, which is identified by the fact that ϵ_{it}, as well as all the possible observables $X's$, are

[17] This is above the interbank rate (TIIE) which is about 4 percent; it does not include fees as in APR in the US.

continuous at the threshold $\overline{score}_t$. In order to accommodate potential differences away from the discontinuity point, we control for a third order 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 will later provide a series of robustness checks with respect to the $f(.,.,.)$ function. In practice, since we have multiple discontinuities along the credit score, we estimate 3 different $ITT's$, one for each threshold. In the baseline estimations we allow for a different cubic polynomial for each of the thresholds.

As our design is a "fuzzy" one, i.e. not all applicants above the thresholds are given a card[18]. Since we are also interested in estimating the effect of actually obtaining a card (i.e. in the local ATT), we instrument the endogenous variable (i.e. Bank A's approval of the credit card application) with an indicator variable that is equal to one if the applicant's score is above the corresponding threshold. The two-stage representation of this strategy is the following:

$$CR_{it} = \alpha_1 + \beta_1 \mathbf{1}\left(score_{it} \geq \overline{score}_t\right) + f(score_{it}, \theta^-, \theta^+) + \epsilon_{it}, \tag{2}$$

$$Y_{it} = \alpha_2 + \beta_2 CR_{it} + f(score_{it}, \gamma^-, \gamma^+) + \eta_{it}. \tag{3}$$

We will discuss the parameters of interest as we go along with the analysis. At this point we just want to mention that although the analysis presented in the main tables is performed through parametric regressions where we control for third-order polynomials on both side of the discontinuity, the Appendix D shows a battery of robustness checks with respect to bandwidth selection, including the optimal "IK" bandwidth (**?**), nonparametric estimation, and different functional forms for $f(.,.,.)$, as well as adding a set of controls. The results show substantial robustness.

3.1 Validity of the Design

We present a series of visual, and formal, tests of the three 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 applicants' characteristics (the $X's$) are continuous at the thresholds.[19]

[18]Bank A told us that after passing the credit score threshold they take into account other variables in the decision.

[19]We provide a similar analysis by number of credit cards held at the moment of application, as part of our analysis of heterogeneous effects, in Appendix C.

3.1.1 Discontinuous Probability

As one can see in Figure 1 the discontinuity in the approval probability is quite stark at the thresholds. When we pool all of them together, we see that 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 three different score thresholds, in fact we cannot reject that the jumps are statistically the same, as can be seen in the first column of Table 4. Essentially the probability of getting a new line of credit is about 45pp higher for someone who has a score just above the threshold rather than just below the threshold. It is also clear that our design is a fuzzy discontinuity design where not everyone just above the discontinuity point gets a new credit card, therefore one can estimate either the local ITT or the local ATT by IV. We produce both sets of estimates in the sections below.

The fuzziness in the design, on the right hand side of the thresholds, arises from a set of rules imposed by Bank A. In particular some extra criteria in terms of observable characteristics such as income, existing credit lines, and limits play a role in the approval process. We are not at liberty to disclose or use the exact criteria employed by Bank A in determining approval to the right hand side of the thresholds. However, what is crucial for identification is that even controlling for all those criteria the discontinuities are essentially the same as the sequence of conditions imposed starts off with the credit score. That is why all other applicants' characteristics are balanced at the thresholds as we show below.

3.1.2 Applications' Density

Another assumption that needs to 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 *precisely* sort themselves around the discontinuity thresholds (**?**). Figure 2 shows the histograms of the standardized credit score in our pooled sample and in each subsample. The figures include the results of a parametric version of the test presented by **?**, in which we formally test whether there is a discontinuity in the density of the credit score at the cutoff values. As it can be seen, there are no noticeable discontinuities in the density at the three cutoff values. For example the McCray's test, which tests the null hypothesis is of no discontinuity, has a p-value of 0.34 for the pooled sample. The same statistics equals 0.36, 0.66, and 0.4 for the 670, 680, and 700 thresholds, respectively.

3.1.3 Balance of Applicants' Characteristics

A third test of the validity of the research design is that the characteristics of the applicants on both side of the discontinuity are statistically identical. We perform such tests on the available variables, graphically in Figure 3, and in a regression framework in Table 2. For brevity we present in the main text only the figures for the pooled sample, while the tables produces the relevant statistics for both the pooled sample and the different thresholds. The corresponding figures for the different thresholds can be found in the Appendix B.1. As can be seen in the Figures and Tables we cannot detect any statistically significant difference between applicants's traits (at the time of application) to the left and right of the discontinuity point, for the pooled sample, on income, gender, tenure in the credit bureau, number of credit cards, number of credit lines (including loans) and amount of credit available. Such results are essentially confirmed when we split the sample according to the different thresholds, aside from two marginally significant differences at the 10% level for the share of male for the 680 threshold, and tenure in the bureau of about less than half-a-year for the 700 threshold.

Further, we test for differences in those variables that will be our main outcomes of interest in the analysis to follow, i.e. several measures of delinquency and default. The picture presented in Figure 4 and in Table 3 is that overall individuals to the left and right of the thresholds do not appear to be different in terms of delinquency and default. Only the number of cards and probability of 2 months delinquencies appear marginally (at the 10 percent level) statistically different at the threshold for the pooled sample, while no differences are detected for the 3 thresholds separately.

Overall, we take these results as consistent with the identifying assumptions, i.e. quasi-random assignment at the threshold, where a few points difference in the credit score do not reflect almost any differences in observables. This results leads us to conclude that individuals in the neighborhood of the threshold are essentially identical, while the probability of obtaining a new credit card for those to the right of the threshold is about 45pp larger.

4 Main Results

4.1 Effect on Credit Card Availability, Credit Limit and Debt

The previous section gives us confidence in the ability to identify potential informational frictions in the credit market. We are able to investigate their relevance for the financial inclusion of the middle class as well their externality effects on the pre-existing credit lines, a crucial issue for the credit sector.

We first show the probability of approval, and number of credit cards 30 days after application. We will then consider the impact on the available credit and debt on all the cards before application and acquired after by December 2012, the first ex-post snapshot of data where we can look into both credit limits and debt balances. Further, in order to easy the concerns on measurement we also show the probability of credit and debt being above median. We note, as already mentioned, that for the monetary quantities of credit and debt we need to rely on the different snapshots available to us, while for the measures of default and delinquency we have continuous time information as we will show later in section 4.2 where we look into the dynamics of delinquency and default.

The first two columns of Table 4, as well as Figure B1.4, confirm the discontinuity in the probability of approval for the new credit card for individuals who are just above the specified threshold in terms of credit score. The probability of obtaining a new card increases by about 45pp for the pooled sample, while the number of credit cards owned mechanically increases by about 1 for those who obtain the new card and given that 45% of the applicants get a new card that essentially translate into the .45 effect of column two of Table 4 and Panel (a) of Figure B1.4. This also suggests that the thresholds set by Bank A are not crucial for obtaining (once applied for) other cards, otherwise the number of new cards on average would be "substantially" larger than .45. While confirming the validity of the design those results are not unexpected as they are almost mechanical.

As we do not observe the immediate increase in credit limits and debt, due to the data structure, we can easily apply a back of the envelop calculation on the increase in credit limit as we know from the results in column 1 and 2 of Table 4 that applicants to the right of the discontinuity will have a 45pp increase in the probability of obtaining the new credit line from bank A. This means that we can compute the average ITT for credit limit by simply multiplying the probability by the amount of the credit limit which we observe in our data from Bank A: from Table 1 we have that the approved credit limit is about 16,000MXN (1,300 USD) therefore the immediate increase in credit limit is ITT(credit limit)$= .45 * 16,000 = 7,200$MXN or about a 30% increase over the existing total credit availability. Obviously, the increase in the credit limit for those who are actually approved is exactly 16,000MXN or about a 70% increase over the existing limits. This is to say that the increase in credit limit is actually a substantial increase.

Similarly, we find a sustained increase in the credit limit if we look at all the active cards by December 2012 for the lowest threshold but not for the others. In general we see a substantial and significant increase in credit limits and debt for the lowest threshold either if we look at different measure of credit availability and debt as we do in Table 4.

It is also interesting to notice that on existing cards before application it seems that the control group somewhat obtaing slightly larger credit limits (column 7).

4.2 Effect on Delinquency and Default

Baseline Results

4.2.1 Effect on Delinquency and Default: All Lines

In Figure 7 below we show the effects on default and delinquency for either those applicants with score (slightly) above the thresholds (ITT) or those who actually get a new card (ATT). In particular we can see a pretty clear increase in the number of cards ever 2 months delinquent for the two lowest thresholds as well as for the pooled sample. The effects are decreasing over the score distribution, i.e. the effects are largest for the applicants around the 670 threshold. The relative ITT effects with respect to applicants whose scores are zero to five point below the thresholds (the means for the dependent variables are found at the bottom of the table) vary from 40% (.084/.381) for the pooled sample to about 57% (.188/.331) for the lowest threshold. The corresponding ATT are clearly larger in magnitude, as the ATT is essentially the ITT/Probability of a new card (roughly in order to get at the magnitude of the $ATT's$ we should just multiply the $ITT's$ by $1/.44 \simeq 2$).

A similar picture emerges if we look at the extensive margin: the probability of having a card being 2 months delinquent. The average ITT effect is .0415 (or an increase of 20%) and again the effect is largest for the 670 threshold: .107 over a basis of .217 for the just below 670 (or about 50% increase). Once again, the $ATT's$ are about double the $ITT's$. Importantly, we find that the effects for the 700 threshold are smaller and insignificant, reflecting the importance of the heterogeneity in types along the distribution of scores.

As mentioned before, the prior two measures of delinquency (and similar measures for default) are plagued by some potential mechanical effects as the number of cards (or credit lines) increases differentially across the thresholds. We therefore present also a measure of delinquency and default which is immune from such mechanical effects: the share of cards or credit lines that exhibit the delinquent behavior. If we turn to such a measure as in the next column of Table 5, we get the same heterogenous effects where the increase in delinquency is largest for the 670 threshold. For that sample, we estimate an increase in the share of delinquent cards of .072 over a counterfactual mean of .158 (a 45% increase). At the same time we do not detect any significant effect for the pooled sample, and for the 700 threshold we detect a smaller but significant fall in the share of delinquent cards. We have similar effect if we look at our measure of default.

Importantly, in the last 3 columns of Table 5 we start to analyze the externality effects of an additional credit line. There, we analyze the behavior of different credit lines, not credit cards, and therefore not the new line offered by Bank A. We find that the probability of default for credit lines that are not credit cards (and therefore not the Bank A new card) increases substantially for the 670 threshold by more than 25% for the ITT and therefore more than 50% for the ATT. We will dig deeper into the externality effects in Table 6, where we analyze the impacts on existing credit cards and credit lines at the moment of application. These latter results are quite important and provide a first empirical test of the externality in sequential banking in the presence of asymmetric information.

4.2.2 Effect on Delinquency and Default: Externality Effects on Existing Lines

We devote this section to the study of the externality effects of an increase in credit limit on pre-existing credit lines. First, we can show that the there is no differential increase in credit availability on existing lines at the moment of application nor by December 2012, so that if we see any effect on those pre-existing credit lines it will entirely be due to the existence of the externality and not to the direct effect of an increase in credit limit on those lines nor to a price effect. Table 6 follows a similar ordering of outcome variables as Table 5, but focuses on the default of credit cards that were active at the moment of the application. What emerges from a look through the different measures of delinquency and default is a substantial increase in the likelihood of being delinquent as well as defaulting on other credit cards or credit lines already open at application. In particular, our most robust measures, based on the shares of CC delinquent, CC defaulted, and other than credit lines defaulted, all show a substantial positive effect (more delinquency and default) for the lowest credit score. This result is consistent with a substantial degree of heterogeneity along the distribution of the credit score, with worse types the lower the credit score. Focusing on those measures, we see an increase in the share of credit card delinquent for the 670 threshold by .063 or about 40% for the ITT, which translate into a increase in the share of delinquent cards for those who actually obtain a new card of about 84%.

Interestingly such result is confirmed for a harsher measure of behavior, i.e. share of credit card in default (for existing card) increases by about 5.84pp or 40% for the 670 threshold for the ITT, and by 12.4pp or more than 80% for the ATT. No significant effect is found for higher thresholds. Not only the externality effect appears on credit cards but also on all credit line open at time of application. For example, if one looks at the effect on the share of defaulted credit lines (not credit cards) that shows an increase by 6.3pp or 35% for the 670 sample. Overall these set of results show a very significant and robust externality effect of an increase in credit limit given by other financial institutions on existing credit lines. To our knowledge this paper provides the first convincing test of the existence of such externality which clearly is not fully internalized by the financial institutions as the results on delinquency and default in Table 6 show.

4.3 Heterogeneous Effects by Number of Credit Cards at Baseline

Our conceptual framework which we will discuss in detail in Section 5 is based on potential borrowers of different types, not fully observable, who have differential costs of repayment for any given level of debt. These borrowers face in each period the decision to repay their debt and improve their likelihood of obtaining extra credit, which contributes to their consumption. This set-up leads directly to at least two interconnected testable implications on default and delinquencies: decrease of delinquent behavior i. in the credit score, and ii. in the number of credit cards (or lines). In practice a well behaved borrower, which typically is a good type, will repay with higher likelihood and as such have a larger number of cards (in turn, this will also imply higher credit score for better types who are also more likely to repay). In the previous sections we tested for the first of these two implications, i.e. delinquencies decrease with credit score, below we tackle the second implication.

4.3.1 Effects on Credit Availability and Debt by Number of Credit Cards

We first present the distribution of credit cards held in our population in Figure 8. At the moment of application, consumers hold 1.5 credit cards on average. However, about 30% of consumers hold no credit card at the application date, about 25% hold 1, 18% hold 2, 12% hold 3, 5% hold 4, and about 5% hold 5 or more credit cards. We describe the characteristics of the sample based on credit cards held at time of application in Table C.1. The number of credit cards held increases with income, and tenure in the credit bureau. At the same time, total credit (debt) also increases with the number of credit cards, while consistent with our theoretical framework default and delinquency fall with the number of cards. This is consistent with the fact that financial institutions are able to discriminate across consumers also based on their credit score, which increases with credit cards held. Also consistently with a sensible credit market and screening mechanisms, the limit approved and interest rates charges fall with number of credit cards.

We proceed by interacting our parameters of interest with a quadratic polynomial in the number of credit cards at baseline. The reason for proceeding in this fashion, rather than with a fully non parametric specification, is that we would have no statistical power left if we were to cut the data by number of credit cards and score (we would have more than 40 cells, 3 scores by 15 possible credit cards). Obviously some of the cells would be sparsely populated, in fact slightly above 10% of the overall sample has 4 or more credit cards. The IV results are presented in Tables F.1 (for all credit cards) and F.2 (for credit cards active at the moment of application only), and Figures F.1 (for all credit cards) and F.2 (for credit cards active at the moment of application only).

The effects can be summarized in the following statement: default and delinquency increase substantially (and significantly) for those with lower scores and with fewer existing credit cards at the moment of application. However, for customers with higher scores and larger number of cards it appears that the effects are negative and significant on default and delinquencies. These latter consumers seem better able to buffer shocks and possibly transfer balances across cards.

4.4 Elasticity of Defaults to Credit Availability

TO BE WRITTEN TABLE 7 AND 8.

5 A Simple Theoretical Framework

The previous sections showed that the effects of an additional credit card on default rates are heterogeneous in two aspects: the credit score threshold used by the bank and the number of credit cards the applicant had at the moment of application. That is, the moral hazard effect was found to be stronger for applicant's with lower credit score thresholds and with fewer number of credit cards at the moment of application. In this section, we present a stylized model that combines both results in a unified framework.

We present a very simple model in a dynamic setting with multiple credit lines overtime. This is a partial equilibrium model in which banks play no direct role. An infinitely-lived consumer tries to get access to credit in each period in order to be able to fund a project. At the beginning of each period a consumer enjoys a utility that depends on the number of (identical) credit cards available from the previous period. At the end of the period, he makes a repayment decision by choosing the an effort level p, which is equivalent to the probability of repayment. The repayment choice is simplified to two options: repay all cards or default at most one card. Repayment is costly and the cost of repayment is given by a cost function $v(p;\theta)$, which satisfies $v_p' > 0$, $v_p'' > 0$ and $v_{p,\theta}' > 0$. The parameter θ can be interpreted as the type of the consumer, with higher θ representing a higher cost of repayment for a given level of p.

The banking sector works in the following way. After the consumer made a repayment decision, he goes to the credit card market to apply for a new card. New applications are not always approved. Banks approve new applications with probability ϕ, which is a function of the consumer's repayment behavior in the last period. If the consumer repaid his previous debt the application is approved with probability ϕ_h, and with probability $\phi_l < \phi_h$ otherwise. The difference in these probabilities mimics the role of the credit score, which is a function of past behavior but not of *types*. This assumption is not unreasonable, given the way actual credit scores are computed. The difference in approval probabilities could also capture the relationship between the credit score of the applicants and the approval policies of banks for different values of the score.

The value of a consumer in possession of n credit cards in period t is given by

$$
\begin{aligned}
V_t(n) = \max_p u(n) - v(p;\theta) + \beta \left[p \left(\phi_h V_{t+1}(n+1) + (1-\phi_h) V_{t+1}(n) - Rn \right) \right. \\
\left. + (1-p) \left(\phi_l V_{t+1}(n) + (1-\phi_l) V_{t+1}(n-1) - R(n-1) \right) \right]
\end{aligned}
$$

where β is a discount factor, R is the gross interest rate payed on credit cards and $u(n)$ is the flow utilities of having n credit cards, satisfying $u' > 0$ and $u'' < 0$.[20] In order to induce a strictly

[20] This is a way to represent the value of credit cards in a reduced form. One could microfound this preference in a simple

positive holding of credit cards we assume that $u'(0) = \infty$ and $v'(0;\theta) = 0$. With probability p the credit gets repaid and with a probability ϕ_h the application gets approved, so the future value of the consumer goes from $V_{t+1}(n)$ to $V_{t+1}(n+1)$. Similarly, with probability $1-p$ the loan is not repaid and a credit card is lost, but with probability ϕ_l the consumer gets a new credit card and the value goes from $V_{t+1}(n-1)$ to $V_{t+1}(n)$. The first order condition of the repayment problem is given by

$$\begin{aligned}\frac{\partial v\left(p^{*};\theta\right)}{\partial p} \leq\ & \beta\left(V_{t+1}\left(n\right) - Rn + \phi_h\left(V_{t+1}\left(n+1\right) - \left(V_{t+1}\left(n\right)\right)\right)\right. \\ & \left. - \left(V_{t+1}\left(n-1\right) - R(n-1) + \phi_l\left(V_{t+1}\left(n\right) - V_{t+1}\left(n-1\right)\right)\right)\right)\end{aligned}$$

The consumer will increase the probability of repayment until the marginal cost equals the marginal benefit, given by the difference of the value of repayment and keeping n credit cards with the value of not repaying and loosing a card. Given our assumptions, the comparative statics with respect to θ are straightforward. Since the right hand side of the FOC does not depend on p, we have:

$$\frac{\partial p(\theta)}{\partial \theta} = -\frac{\partial^2 v\left(p;\theta\right)}{\partial p \partial \theta} / \frac{\partial^2 v\left(p;\theta\right)}{\partial^2 p} < 0$$

Thus, consumers with higher cost of repayment will choose lower probability of repayment (i.e., will default more often), which will in turn imply lower holdings of credit cards on average by the effect of a lower credit score on the probability of approval of new credits. Our empirical results can be interpreted within the implications of this simple model. Even though for a given bank-chosen threshold in the credit score the total population is similar across the threshold value, there is variability in the average characteristics of individuals (or types) across thresholds, with applicants near the 670 threshold having higher type (θ in the model) than those near the 680 and 700 thresholds. Thus, differences in types are responsible for the heterogeneous effects across the three thresholds. Our model also predicts that individuals with higher cost of effort also have a lower number of cards (on average) due to the impact of default decisions on the applicant's credit score. This would explain the negative correlation between the number of credit cards and the moral hazard effect.

6 Conclusions

This paper studies the effects of credit expansion and inclusion to the Mexican middle class using a set plausibly exogenous shocks to the credit availability of borrowers. Those shocks are large in

Aiyagari economy **?**, in which the borrowing limit is defined as the number of credit cards available from the last period. Then, $u\left(n\right)$ would represent the indirect utility as a function of the borrowing limit.

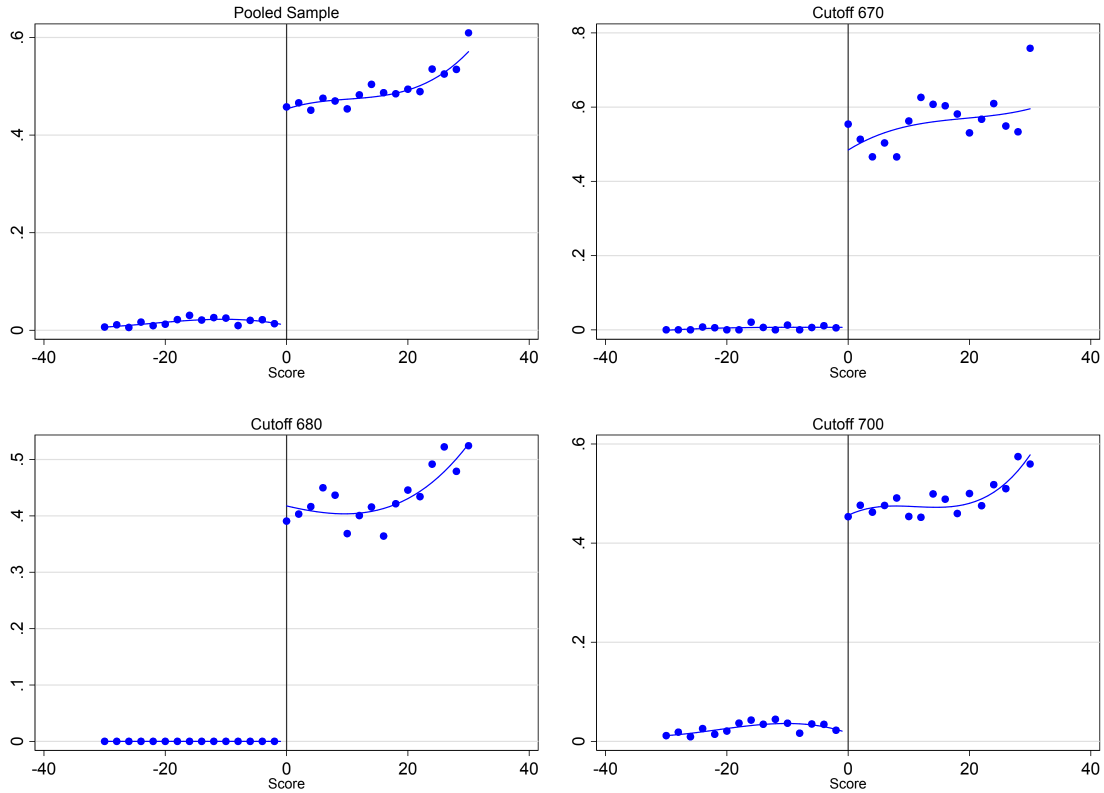
magnitude, i.e. about 1,000USD of extra credit or 70% increase over the existing limits. Exploiting those variations we are able to find support for a simple model of adverse selection driven moral where borrowers differ in type and repayment actions, we show that worse types of borrowers will end up with a lower number of credit lines and default more often than good borrowers. The effects in terms of default are quite large and could explain why there is a substantial amount of rationing in the credit market just below certain levels of credit worthiness, in a similar vein to **?** and **?**. In fact the behavior of Bank A is totally consistent with our findings, as default increases noticeably for the 670 threshold over the 680, the Bank decided to raise the threshold to 680, while 700 seemed too high of a threshold given that from the very start there was no evidence of differential default.

Table 1: Summary Statistics

		Score Cutoff			P-value		
	All	670	680	700	670=680	670=700	680=700
Panel A: Pre-treatment Credit Characteristics							
Credit Score	689	671	680	700	0.000	0.000	0.000
	(13)	(3)	(3)	(3)			
Tenure in Bureau (Years)	7.7	8.0	7.8	7.6	0.304	0.009	0.142
	(4.75)	(5.06)	(4.99)	(4.5)			
# of non-Bank A CC 30 days before	1.53	1.48	1.47	1.58	0.876	0.095	0.043
	(1.75)	(1.64)	(1.5)	(1.89)			
# ofActive Credits 30 days before	3.62	3.85	3.71	3.49	0.181	0.000	0.010
	(2.8)	(2.84)	(2.62)	(2.86)			
CC Debt (MXN)	7949	7242	6052	8861	0.042	0.004	0.000
	(14720)	(14276)	(12652)	(15464)			
Total Debt (MXN)	34732	30865	27623	38542	0.164	0.001	0.000
	(59141)	(55087)	(52066)	(62409)			
Total CC Limit	24278	22306	22374	25930	0.959	0.006	0.003
	(38645)	(35860)	(34423)	(41392)			
# CC in Default† 6 months before	0.03	0.03	0.03	0.02	0.383	0.043	0.330
	(0.18)	(0.21)	(0.19)	(0.16)			
Probability of CC Default† 6 months before	0.02	0.03	0.02	0.02	0.406	0.089	0.447
	(0.15)	(0.17)	(0.15)	(0.14)			
Share of CC in Default† 6 months before	0.02	0.03	0.02	0.02	0.246	0.157	0.971
	(0.13)	(0.15)	(0.13)	(0.13)			
# CC in 2 months delinquency† 6 months before	0.02	0.03	0.01	0.01	0.071	0.002	0.280
	(0.11)	(0.15)	(0.1)	(0.09)			
Probability of CC 2 months delinquency† 6 months before	0.02	0.03	0.02	0.01	0.074	0.000	0.144
	(0.13)	(0.17)	(0.14)	(0.12)			
Share of CC in 2 months delinquency† 6 months before	0.02	0.03	0.02	0.02	0.035	0.002	0.484
	(0.15)	(0.19)	(0.14)	(0.14)			
Panel B: Active cards at the moment of application							
# CC in Default‡	0.02	0.02	0.02	0.01	0.461	0.008	0
	(0.13)	(0.14)	(0.17)	(0.1)			
Probability of CC Default‡	0.01	0.02	0.02	0.01	0.546	0.005	0
	(0.12)	(0.14)	(0.15)	(0.09)			
Share of CC in Default‡	0.02	0.02	0.02	0.01	0.861	0.019	0.019
	(0.11)	(0.13)	(0.12)	(0.09)			
# CC in 2 months delinquency‡	0.03	0.05	0.04	0.02	0.523	0	0
	(0.19)	(0.22)	(0.23)	(0.14)			
Probability of CC 2 months delinquency‡	0.03	0.05	0.04	0.02	0.207	0	0
	(0.17)	(0.22)	(0.2)	(0.12)			
Share of CC in 2 months delinquency‡	0.03	0.05	0.04	0.02	0.062	0	0
	(0.16)	(0.21)	(0.17)	(0.12)			
Panel B: Applications							
Approved	0.28	0.33	0.24	0.28	0.000	0.002	0.003
	(0.45)	(0.47)	(0.43)	(0.45)			
Amount Requested (MXN)	19220	16104	15718	22063	0.542	0.000	0.000
	(17444)	(17363)	(16273)	(17512)			
Approved Amount (MXN)**	15502	16412	16321	14766	0.906	0.022	0.031
	(11760)	(11456)	(10216)	(12421)			
Interest Rate (%)	37.06	37.19	37.33	36.90	0.641	0.480	0.294
	(6.4)	(4.85)	(3.89)	(7.69)			
N	6186	1269	1580	3337			

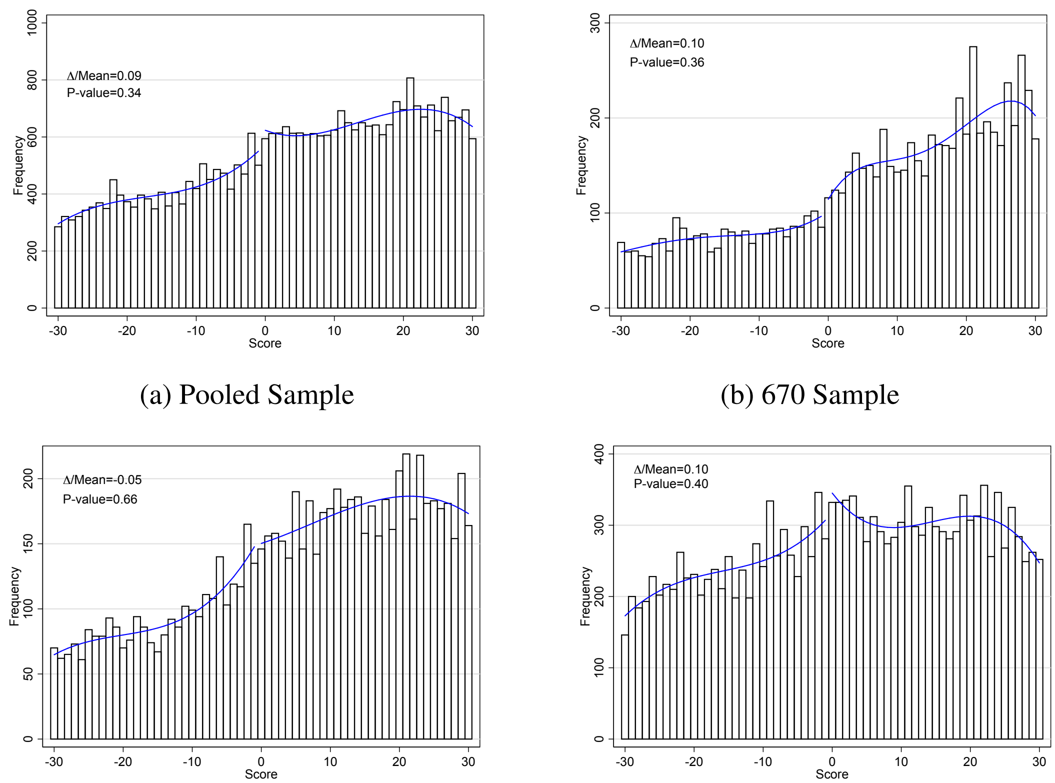
Notes: This table presents summary statistics of our sample of applicants that had a credit score within the $+/-$ 30 points range around the threshold at the moment of application (means and standard deviations). The first column reports summary statistics for the pooled sample. The last three columns report summary statistics for each of the three sub-samples. Observations with a cutoff of 700 points correspond to applications made in 2010, and between January and April of 2011, observations with a cuff of 670 correspond to applications made between June and November of 2011, and observations with a cutoff of 680 correspond to applications made between December 2011 and April 2012. † The variable was constructed using the information of all the credit cards that were open at some time during the year previous to the bank's decision. ‡ We only consider the credit cards that were in fact active at the moment of the decision. ** Conditional on approval.

Figure 1: Percentage of Approved Applications by Score and Cutoff



Notes: The figure presents the percentage of credit card applications that were approved by the bank for each pair of values of the credit score. It also presents a polynomial fit of degree three to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Figure 2: Distribution of Credit Score with a Polynomial Fit



(a) Pooled Sample

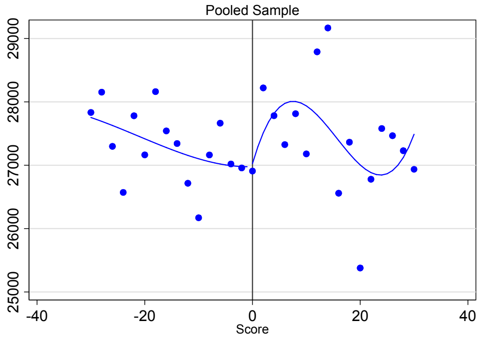
(b) 670 Sample

(c) 680 Sample

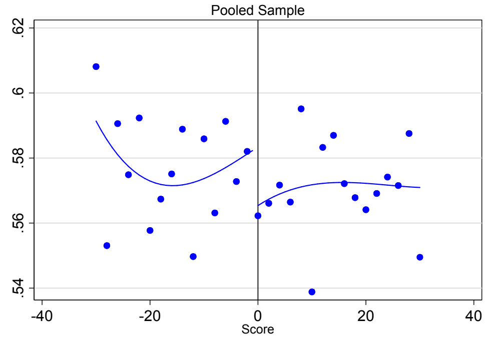
(d) 700 Sample

Notes: The figure presents the frequency distribution of credit scores in the population of applicants. The size of each bin corresponds to one point of the credit score. Panel (a) shows the histogram for the pooled sample with the score standardized so that 0 equals the threshold score for each subsample. Panels (b), (c) and (d) show the histogram of the raw score for each subsample separately. 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 discontinuity.

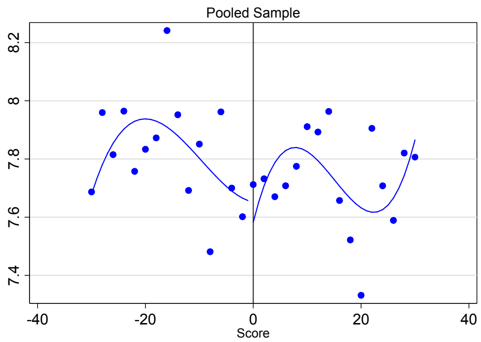
Figure 3: Pre-Treatment Characteristics



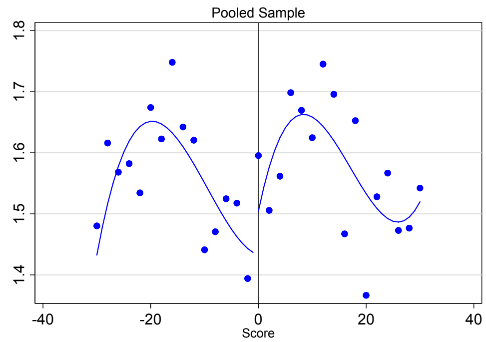
(a) Income (Log)



(b) % Male



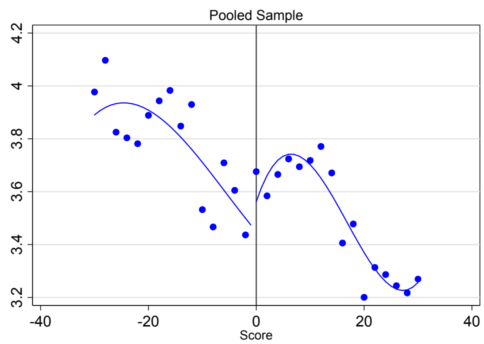
(c) Tenure in Bureau



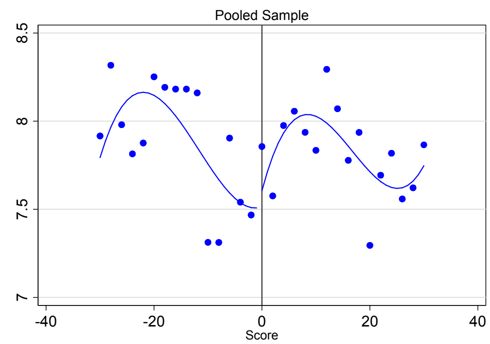
(d) # CC 30 days before

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30. Panel (a) presents the logarithm of each applicant's income, panel (b) refers to the percentage of males in each score, panel (c) to the years each person has been in the bureau and panel (d) to the number of active credit cards they had 30 days before. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

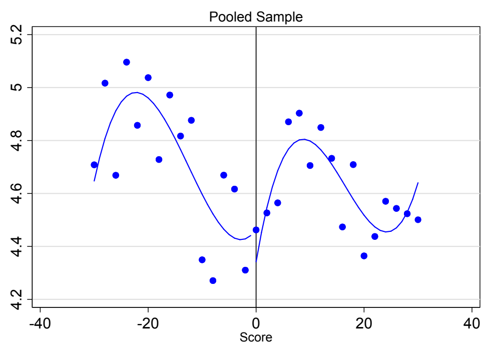
Figure 3: Pre-Treatment Characteristics



(e) Number of active credits 30 days before



(f) Sum of credit lines before (Log)



(g) CC Debt

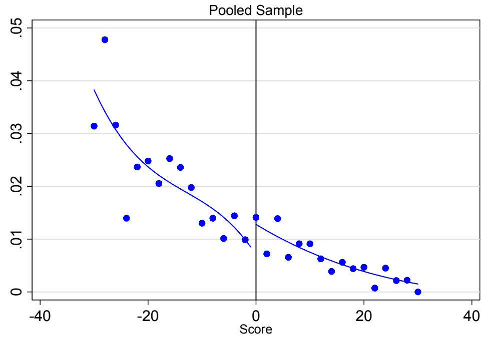
Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30. Panel (e) presents the number of active credits each applicant had 30 days before the application, panel (f) refers to the logarithm of the total lines they had before, panel (g) to the logarithm credit card debt held by each person. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Table 2: Tests of Quasi-Random Assignment of Pre-Determined Characteristics

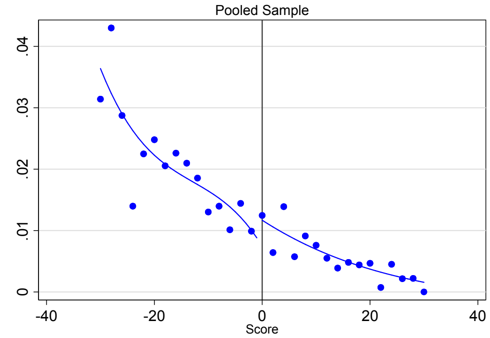
	Income (Log)	Male	Tenure (Years)	$\#CC$ 30 Days Before	# Credit Lines 30 Days Before	Sum of Credit Lines in Credit Bureau (Log)	CC Debt (Log)
Panel A: Pooled Sample							
Above Cutoff	-0.0210	-0.0192	-0.0697	0.0715	0.113	0.0776	-0.00705
	(0.0430)	(0.0123)	(0.260)	(0.183)	(0.309)	(0.437)	(0.244)
Mean Dep. Var.	9.97	0.58	7.71	1.49	3.59	7.60	3.86
N	32346	32346	32346	32346	32346	32346	32346
Panel B: By Cutoff							
Above Cutoff 670	0.00237	0.0103	-0.0958	0.168	0.166	-0.0987	-0.167
	(0.0733)	(0.0343)	(0.495)	(0.218)	(0.422)	(0.670)	(0.352)
Above Cutoff 680	0.0105	-0.0593*	0.672	0.173	0.312	0.464	0.336
	(0.0620)	(0.0343)	(0.448)	(0.206)	(0.429)	(0.506)	(0.270)
Above Cutoff 700	-0.0373	-0.00709	-0.422*	-0.00769	0.0148	0.00124	-0.147
	(0.0492)	(0.0187)	(0.240)	(0.206)	(0.328)	(0.497)	(0.353)
Panel C: Means[-5;-1] from threshold							
Pooled cutoffs	9.97	0.58	7.71	1.49	3.59	7.60	3.86
670	9.96	0.55	8.09	1.37	3.72	7.88	3.53
680	10.04	0.58	7.74	1.40	3.69	8.01	2.78
700	9.94	0.59	7.57	1.58	3.49	7.32	4.45
N	32346	32346	32346	32346	32346	32346	32346
Panel D: Joint Testing (p-values)							
670 = 680 = 700	0.671	0.408	0.030	0.552	0.672	0.519	0.491
670 = 680	0.931	0.223	0.153	0.976	0.562	0.288	0.298
680 = 700	0.435	0.214	0.008	0.321	0.441	0.425	0.261
670 = 700	0.609	0.667	0.497	0.342	0.718	0.870	0.957

Notes: This table presents the results of tests of quasi-random assignment of credit cards around the cutoff. The estimates were obtained by OLS regressions of the applicant's characteristic 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 reported in parenthesis. Income is self-reported income at moment of application. Male is a dummy variable for Male applicants. Tenure is the number of years of tenure in the Mexican Credit Bureau. Number of credit cards 30 days before are the number of active credit cards the applicant had 30 days before the application date. Number of Credits is the total number of other credits that the applicant had 30 days before the application date. Sum of lines in Credit Bureau is the logarithm of the total credit line the individual had before the application. The next variable is the logarithm of the total credit card debt. The last column is the logarithm of the requested line in the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

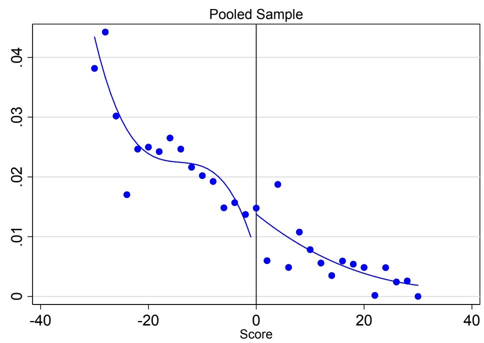
Figure 4: Pre-Approval Outcome Variables



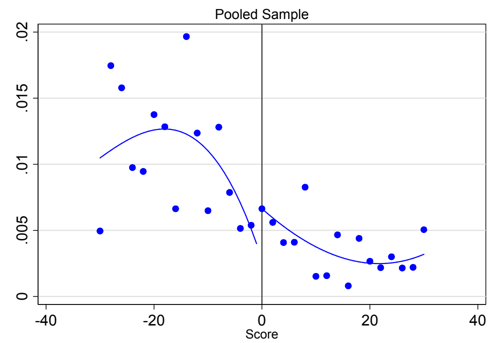
(a) Number of credit cards with 2 or less months delinquency in the last 6 months



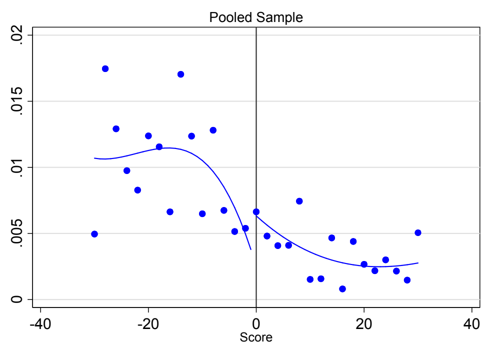
(b) Probability of credit card with 2 or less months delinquency in the last 6 months



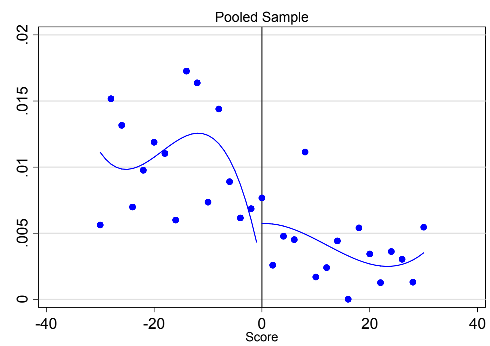
(c) Share of credit cards with 2 or less months delinquency in the last 6 months



(d) Number of credit cards ever in default in the last 6 months



(e) Probability of of credit card in default in the last 6 months



(f) Share of credit cards in default in the last 6 months

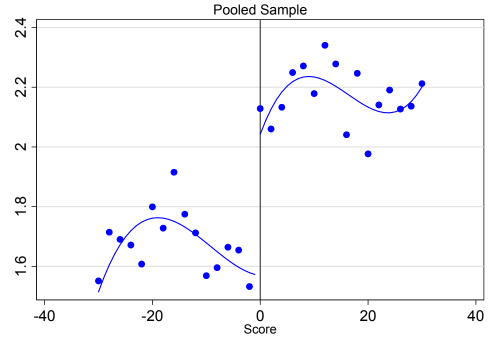
Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30. Panel (a) presents the number of credit cards with two months delinquency at the moment of application. Panel (b) is a indicator variable which is equal to one if the person had a card with 2 months delinquency. Panel (c) is the share of cards with two months delinquency. Panel (d) Is the number of cards ever in default before the application (up to 84 months before), where default is defined as late payment of 3 or more months. Panel (e) is a variable indicating wether the person ever had a credit card in default. Panel (f) is the share of credit cards that have ever been in default. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Table 3: Tests of Quasi-Random Assignment on Pre-Approval Outcome Variables

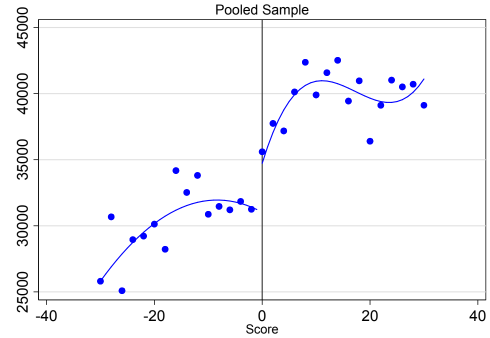
	$\#CC$ with 2 Month Delinq. in the last 6 months	Probability of CC ever with 2 Month delinq. in the last 6 months	Share of CC ever with 2 Month delinq. in the last 6 months	$\#CC$ Ever in Default in the last 6 months	Probability of CC in Default in the last 6 months	Share of CC in Default in the last 6 months
			Panel A: Pooled Sample			
Above Cutoff	0.00571*	0.00422	0.00427	0.00385	0.00384*	0.00213
	(0.00334)	(0.00324)	(0.00282)	(0.00233)	(0.00217)	(0.00195)
Mean Dep. Var.	0.01	0.01	0.01	0.01	0.00	0.00
N	32346	32346	32346	32346	32346	32346
			Panel B: By Cutoff			
Above Cutoff 670	0.00586	0.00437	0.00151	0.00809	0.00919	0.00488
	(0.0137)	(0.0123)	(0.00971)	(0.0117)	(0.0113)	(0.00768)
Above Cutoff 680	0.00821	0.00637	0.00977	0.00917	0.00755	0.00272
	(0.00864)	(0.00794)	(0.00613)	(0.0100)	(0.00931)	(0.00608)
Above Cutoff 700	0.00329	0.00197	0.00196	-0.000311	0.0000353	0.000638
	(0.00404)	(0.00352)	(0.00271)	(0.00297)	(0.00294)	(0.00243)
			Panel C: Means [-5;-1] from thresholds			
Pooled cutoffs	0.011	0.011	0.007	0.005	0.005	0.003
670	0.022	0.022	0.015	0.007	0.007	0.004
680	0.011	0.011	0.006	0.005	0.005	0.003
700	0.008	0.008	0.005	0.005	0.004	0.003
N	32346	32346	32346	32346	32346	32346
			Panel D: Joint Testing (p-values)			
$670 = 680 = 700$	0.894	0.885	0.483	0.323	0.275	0.773
$670 = 680$	0.889	0.894	0.403	0.956	0.931	0.851
$680 = 700$	0.645	0.630	0.289	0.438	0.514	0.787
$670 = 700$	0.863	0.858	0.966	0.430	0.368	0.554

Notes: This table presents the results of tests of quasi-random assignment of credit cards around the cutoff. The estimates were obtained by OLS regressions of the applicant's characteristic 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 reported in parenthesis. The variable in column 1 is the number of credit cards that had a late payment of two months at the moment of application. The second column reports the discontinuity on a dummy for the people with at least one card with such delay on payment. Next is the share of cards with that delay. Column 4 reports the discontinuity in the number of cards that were ever in default before the application (up to 84 months before), where default is defined as late payment of 3 or more months. The probability of default transforms the count of credit cards in default into a binary value equal to one if the applicant committed default. The share of credit cards in default is the number of credit cards in default divided by the total number of cards available at the moment of application. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

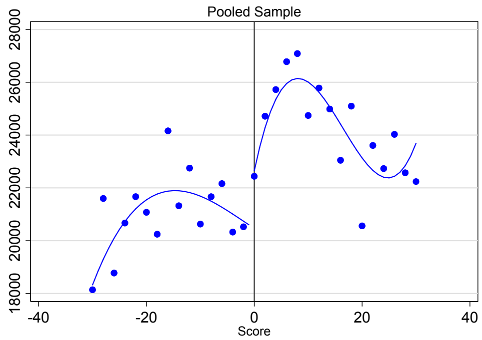
Figure 5: Effect on Credit Cards and Limit Availability



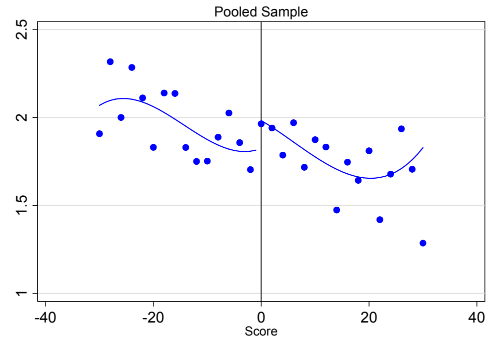
(a) Active CC one month after application



(b) Effect on credit limit (MXN)



(c) Effect on CC debt (MXN)



(d) Credit Bureau enquiries 6 months after

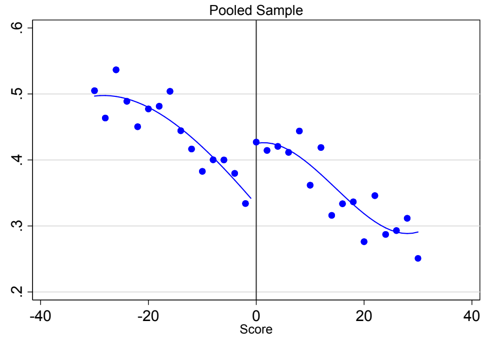
Notes: The figures presents the mean of number of credit cards one month after application, credit card limit and debt in 2012, and additional enquiries in the following six months. For each pair of values of the standardized credit score between standardized scores of -30 and 30 for the pooled sample of applicants. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Table 4: Regression Discontinuity Estimates of the Effect of Approval on Credit Availability and Debt

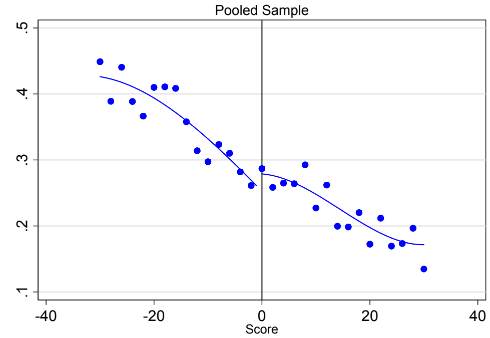
	Probability of Approval	$\#CC$ 30 Days After	Credit Limit in CC Dec 2012 (Log)	Debt in CC Dec 2012 (Log)	Total Debt (excluding CC) Dec 2012 (Log)	Total limit Over 50th percentile V^1	Total limit Over 50th percentile V^2	Probability of debt over 50th percentile V^1	Probability of debt over 50th percentile V^2
					Panel A: OLS				
Pooled cutoffs	0.439***	0.417***	0.0468	0.102***	0.0714	0.0668***	-0.0305***	0.0735***	-0.00783
	(0.0154)	(0.0275)	(0.0367)	(0.0347)	(0.0750)	(0.0138)	(0.00955)	(0.0141)	(0.0125)
Above cutoff 670	0.469***	0.454***	0.303***	0.172	0.211**	0.160***	-0.00106	-0.00140	-0.0807**
	(0.0577)	(0.0477)	(0.0928)	(0.109)	(0.105)	(0.0361)	(0.0350)	(0.0408)	(0.0310)
Above cutoff 680	0.391***	0.380***	0.0387	0.160**	0.127	0.0504*	-0.00121	0.0838***	0.0199
	(0.0417)	(0.0560)	(0.0492)	(0.0795)	(0.152)	(0.0264)	(0.0190)	(0.0274)	(0.0225)
Above cutoff 700	0.440***	0.408***	-0.0387	0.0436	0.000400	0.0386	-0.0565***	0.0871***	-0.00153
	(0.0140)	(0.0331)	(0.0671)	(0.0498)	(0.0871)	(0.0240)	(0.0163)	(0.0173)	(0.0149)
					Panel B: IV				
Pooled cutoffs		0.949***	0.110	0.238***	0.163	0.152***	-0.0695***	0.168***	-0.0178
		(0.0384)	(0.0865)	(0.0820)	(0.173)	(0.0294)	(0.0221)	(0.0350)	(0.0283)
Approved 670		0.969***	0.651***	0.370	0.446*	0.341***	-0.00276	-0.00204	-0.172***
		(0.0447)	(0.203)	(0.236)	(0.238)	(0.0894)	(0.0736)	(0.0857)	(0.0550)
Approved 680		0.973***	0.103	0.411**	0.325	0.129**	-0.00337	0.215***	0.0508
		(0.0555)	(0.127)	(0.191)	(0.390)	(0.0623)	(0.0479)	(0.0730)	(0.0576)
Approved 700		0.928***	-0.0785	0.107	0.00214	0.0876	-0.128***	0.198***	-0.00290
		(0.0686)	(0.153)	(0.112)	(0.197)	(0.0542)	(0.0395)	(0.0394)	(0.0337)
					Panel C: Means [-5;-1] from cutoff				
Pooled cutoffs	0.02	1.633	7.358	6.671	7.662	0.531	0.377	0.406	0.284
670	0.01	1.426	6.826	6.399	7.849	0.437	0.349	0.389	0.305
680	0.00	1.516	7.070	6.310	7.769	0.495	0.413	0.397	0.346
700	0.03	1.752	7.661	6.923	7.553	0.578	0.370	0.414	0.249
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
					Panel D: Joint Testing (p-values)				
$670 = 680 = 700$	0.485	0.507	0.0258	0.285	0.303	0.00961	0.125	0.140	0.0806
$670 = 680$	0.350	0.388	0.0116	0.939	0.679	0.00334	0.997	0.0512	0.0267
$680 = 700$	0.232	0.669	0.387	0.173	0.329	0.765	0.0489	0.921	0.331
$670 = 700$	0.630	0.249	0.0118	0.364	0.205	0.0147	0.211	0.0878	0.0377

Notes: This table reports the RD estimates of eligibility on credit availability and debt. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. In column (1) the dependent variable is a binary variable that indicates the approval of a credit card application. In columns (2) and (3) the dependent variable is the number of active credit cards one month after the application and the total credit limit (observed in December 2012) of those cards, respectively. In column (4) the dependent variable is the total credit limit in all active credit cards in December 2012. In columns (5) and (6) the dependent variables is the (log) debt in all active credit cards and all active loans not in default in December 2012, respectively, where default is measured as a delay of payment of at least 3 months. The dependent variable in column (7) is the total credit card debt in all active credit cards in December 2012, independently of the default status. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0. All regressions control for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

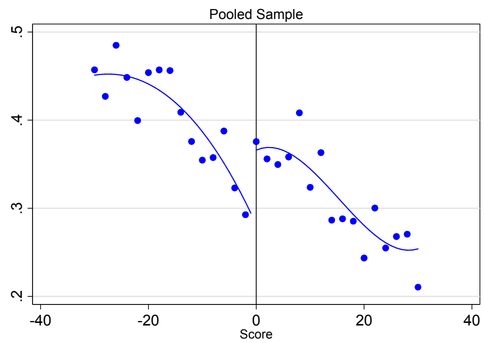
Figure 6: Effect on Different Measures of Delinquency



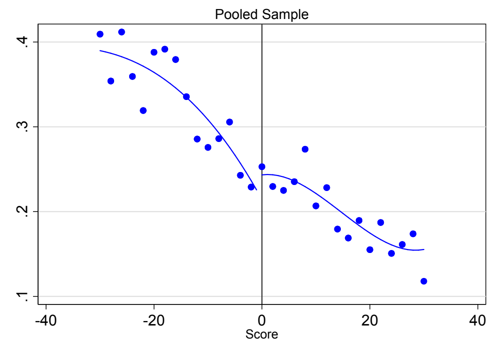
(a) # CC Ever with 2 Month Delinquency †



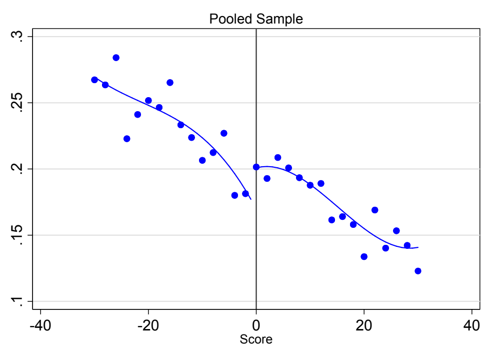
(b) # CC Ever with 2 Month Delinquency ‡



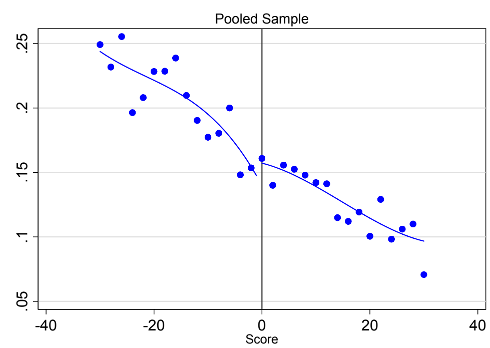
(c) # CC Ever in Default †



(d) # CC Ever in Default ‡



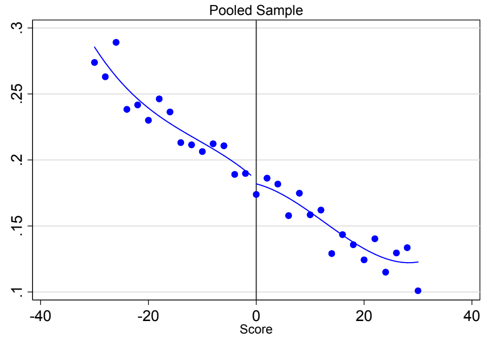
(e) Probability of CC Default †



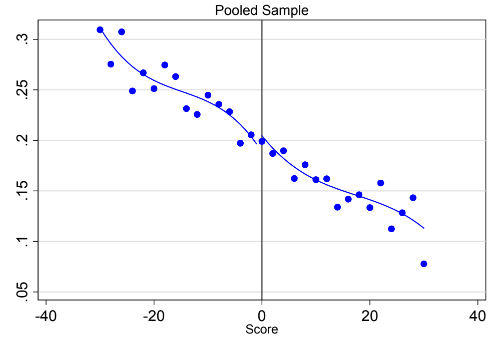
(f) Probability of CC Default ‡

Notes: The figures presents the mean of several measures of default for each pair of values of the standardized credit score between standardized scores of -30 and 30. Panels (a) and (b) show the average across applicants of the number of total credit cards that were 3 months delinquent at any point in time since the date of the application to December 2012, (a) includes all open CC whereas (b) is only for CC already open at the moment of application. Panels (c) and (d) show the average across applicants of the number of total credit card that were ever in default since the date of application, (c) includes all open CC whereas (d) is only for CC already open at the moment of application. Panels (e) and (f) show an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application, (e) includes all open CC whereas (f) is only for CC already open at the moment of application. All present a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

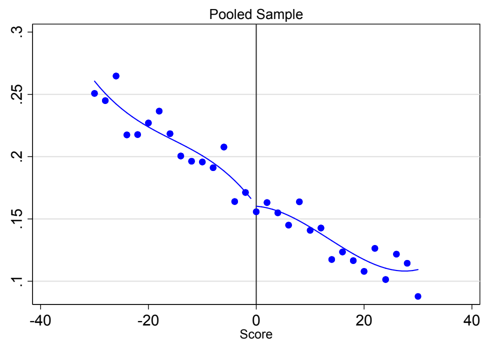
Figure 7: Effect on Different Measures of Delinquency



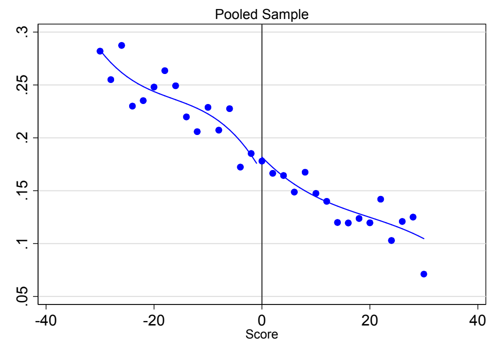
(a) Share of CC Ever with 2 Month Delinquency †



(b) Share of CC Ever with 2 Month Delinquency ‡



(c) Share of CC Ever in Default †



(d) Share of CC Ever in Default ‡

Notes: The figures presents the mean of several measures of default for each pair of values of the standardized credit score between standardized scores of -30 and 30. Panels (a) and (b) show the average across applicants of the number of total credit cards that were 3 months delinquent at any point in time since the date of the application to December 2012, (a) includes all open CC whereas (b) is only for CC already open at the moment of application. Panels (c) and (d) show the average across applicants of the number of total credit card that were ever in default since the date of application, (c) includes all open CC whereas (d) is only for CC already open at the moment of application. Panels (e) and (f) show an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application, (e) includes all open CC whereas (f) is only for CC already open at the moment of application. All present a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

Table 5: Regression Discontinuity Estimates of the Effect of Approval on Different Measures of Delinquency

	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
Panel A: OLS									
Pooled cutoffs	0.0838***	0.0421***	0.000898	0.0771***	0.0293***	0.00288	-0.0177	0.00614	-0.00922
	(0.0288)	(0.0104)	(0.0077)	(0.0265)	(0.0103)	(0.0076)	(0.0509)	(0.0142)	(0.0110)
Above cutoff 670	0.188**	0.107***	0.0717**	0.176***	0.0815***	0.0533**	0.122	0.0761**	0.0579*
	(0.0747)	(0.0333)	(0.0311)	(0.0460)	(0.0232)	(0.0234)	(0.1380)	(0.0358)	(0.0335)
Above cutoff 680	0.111***	0.0579***	0.00813	0.0909***	0.0507***	0.015	0.0282	0.0414**	0.00681
	(0.0299)	(0.0178)	(0.0132)	(0.0273)	(0.0181)	(0.0136)	(0.0659)	(0.0200)	(0.0128)
Above cutoff 700	0.0379	0.00999	-0.0285**	0.0378	-0.000472	-0.0224*	-0.0876	-0.0361	-0.0412**
	(0.0472)	(0.0171)	(0.0133)	(0.0492)	(0.0171)	(0.0123)	(0.0718)	(0.0221)	(0.0164)
Panel B: IV									
Pooled cutoffs	0.191***	0.0959***	0.00211	0.176***	0.0667***	0.00676	-0.0403	0.0140	-0.0210
	(0.0632)	(0.0236)	(0.0179)	(0.0576)	(0.0230)	(0.0176)	(0.115)	(0.0321)	(0.0249)
Approved 670	0.400**	0.229***	0.154**	0.375***	0.174***	0.115**	0.259	0.162**	0.123*
	(0.161)	(0.0730)	(0.0649)	(0.105)	(0.0532)	(0.0480)	(0.285)	(0.0735)	(0.0703)
Approved 680	0.283***	0.148***	0.0215	0.233***	0.130**	0.0390	0.0718	0.106*	0.0172
	(0.0993)	(0.0561)	(0.0349)	(0.0832)	(0.0538)	(0.0364)	(0.171)	(0.0564)	(0.0334)
Approved 700	0.0861	0.0226	-0.0639**	0.0859	-0.00121	-0.0501*	-0.200	-0.0825*	-0.0939**
	(0.107)	(0.0390)	(0.0300)	(0.112)	(0.0390)	(0.0279)	(0.163)	(0.0494)	(0.0367)
Panel C: Means [-5;0] from cutoff									
Pooled cutoffs	0.38	0.22	0.15	0.34	0.20	0.14	0.48	0.27	0.14
670	0.33	0.22	0.16	0.29	0.20	0.15	0.52	0.29	0.15
680	0.19	0.12	0.09	0.15	0.10	0.07	0.28	0.18	0.10
700	0.48	0.26	0.18	0.43	0.24	0.16	0.57	0.30	0.16
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
Panel D: Joint Testing (p-values)									
$670 = 680 = 700$	0.121	0.012	0.013	0.078	0.005	0.008	0.080	0.008	0.004
$670 = 680$	0.406	0.264	0.101	0.186	0.399	0.217	0.615	0.417	0.206
$680 = 700$	0.299	0.096	0.085	0.444	0.054	0.072	0.224	0.003	0.005
$670 = 700$	0.052	0.009	0.007	0.028	0.005	0.005	0.129	0.024	0.017

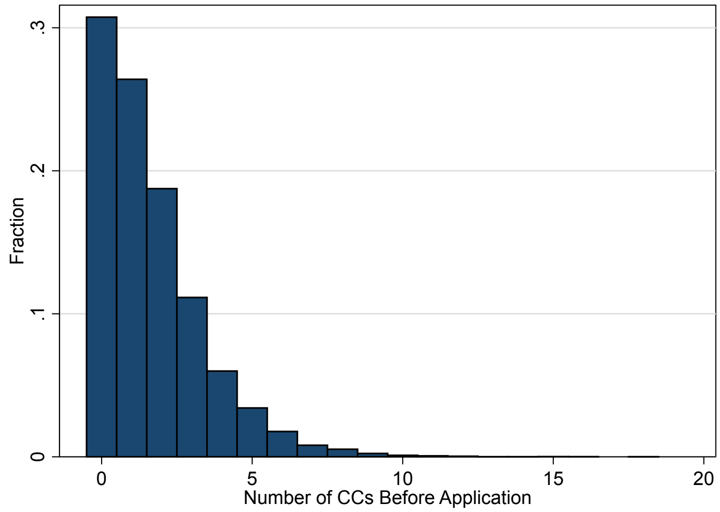
Notes: This table reports the RD on default on all cards open at some time between the application and Dec 2012. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In column (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating whether the applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from the applicant in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever in default since the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are just as (4) (6) and (7) but represent credit lines different than credit cards, rather than CC. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 6: Regression Discontinuity Estimates of the Effect of Approval on Different Measures of Delinquency on Credit Cards Active at the Moment of Application Only

	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
				Panel A: OLS					
Pooled cutoffs	0.0179	0.0217**	0.0134	0.0221	0.0149	0.0124	0.0394	0.0215*	0.0135
	(0.0247)	(0.0106)	(0.0081)	(0.0227)	(0.0099)	(0.0077)	(0.0326)	(0.0115)	(0.0115)
Above cutoff 670	0.0776	0.0473	0.0632**	0.0880**	0.0519**	0.0584***	0.127	0.0787**	0.0631**
	(0.0648)	(0.0315)	(0.0261)	(0.0405)	(0.0232)	(0.0192)	(0.0941)	(0.0324)	(0.0264)
Above cutoff 680	0.0636**	0.0392**	0.0131	0.0593**	0.0321*	0.0166	0.0491	0.0291	0.0193
	(0.0260)	(0.0179)	(0.0132)	(0.0257)	(0.0181)	(0.0138)	(0.0334)	(0.0202)	(0.0138)
Above cutoff 700	-0.0201	0.00531	-0.00402	-0.0156	-0.00571	-0.00626	0.0016	-0.00471	-0.00907
	(0.0427)	(0.0160)	(0.0128)	(0.0412)	(0.0147)	(0.0125)	(0.0476)	(0.0199)	(0.0165)
				Panel B: IV					
Pooled cutoffs	0.0408	0.0495**	0.0305	0.0503	0.0340	0.0284	0.0897	0.0490*	0.0308
	(0.0556)	(0.0242)	(0.0186)	(0.0509)	(0.0227)	(0.0178)	(0.0732)	(0.0258)	(0.0258)
Approved 670	0.165	0.101	0.134**	0.187*	0.110**	0.124***	0.271	0.167***	0.134**
	(0.143)	(0.0706)	(0.0584)	(0.0968)	(0.0555)	(0.0433)	(0.194)	(0.0639)	(0.0533)
Approved 680	0.163**	0.100*	0.0334	0.152**	0.0821*	0.0424	0.126	0.0743	0.0493
	(0.0795)	(0.0521)	(0.0358)	(0.0701)	(0.0490)	(0.0361)	(0.0909)	(0.0556)	(0.0368)
Approved 700	-0.0457	0.0121	-0.00917	-0.0354	-0.0129	-0.0142	0.00359	-0.0107	-0.0208
	(0.0964)	(0.0363)	(0.0289)	(0.0929)	(0.0332)	(0.0281)	(0.108)	(0.0450)	(0.0372)
				Panel C: Means [-5;0] from cutoff					
Pooled cutoffs	0.29	0.18	0.14	0.25	0.16	0.12	0.31	0.21	0.14
670	0.26	0.18	0.15	0.23	0.17	0.14	0.39	0.26	0.17
680	0.18	0.12	0.09	0.14	0.10	0.07	0.24	0.18	0.11
700	0.35	0.21	0.15	0.32	0.19	0.14	0.31	0.21	0.14
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
				Panel D: Joint Testing (p-values)					
$670 = 680 = 700$	0.272	0.210	0.096	0.237	0.065	0.045	0.340	0.153	0.078
$670 = 680$	0.858	0.848	0.126	0.556	0.557	0.109	0.490	0.214	0.132
$680 = 700$	0.161	0.137	0.372	0.180	0.089	0.212	0.315	0.264	0.146
$670 = 700$	0.208	0.273	0.034	0.097	0.058	0.014	0.244	0.056	0.028

Notes: This table reports the RD estimates on default on all cards opened before the application and still open after the bank's decision. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. We include all credit cards that were active at the moment of the application and those opened lated. In column (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating whether the applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from the applicant in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever in default since the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are similarly defined as (4) (6) and (7), but represent credit lines other than credit cards. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure 8: Histogram of Number of Credit Cards at the Moment of Application



Notes: This histogram represents the number of credit cards each applicant had active at the moment of application.

Table 7: Regression Discontinuity Estimates of the Effect of Additional Credit Limit on Different Measures of Delinquency on All Credit Cards

	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
Panel A: IV									
Approved Amount 670	0.0234**	0.0134***	0.00891**	0.0220***	0.0102***	0.00663**	0.0150	0.00942**	0.00712*
	(0.00937)	(0.00434)	(0.00384)	(0.00613)	(0.00328)	(0.00285)	(0.0164)	(0.00421)	(0.00399)
Approved Amount 680	0.0188***	0.00982***	0.00137	0.0155**	0.00858**	0.00253	0.00465	0.00693*	0.00110
	(0.00681)	(0.00379)	(0.00230)	(0.00606)	(0.00366)	(0.00242)	(0.0112)	(0.00369)	(0.00218)
Approved Amount 700	0.00585	0.00150	-0.00452**	0.00584	-0.000137	-0.00355*	-0.0139	-0.00576*	-0.00654***
	(0.00759)	(0.00275)	(0.00200)	(0.00787)	(0.00271)	(0.00187)	(0.0111)	(0.00336)	(0.00252)
Panel B: Means [-5;0] from cutoff									
670	0.33	0.22	0.16	0.29	0.20	0.15	0.52	0.29	0.15
680	0.19	0.12	0.09	0.15	0.10	0.07	0.28	0.18	0.10
700	0.48	0.26	0.18	0.43	0.24	0.16	0.57	0.30	0.16
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
Panel C: Joint Testing (p-values)									
$670 = 680 = 700$	0.220	0.030	0.004	0.253	0.028	0.003	0.060	0.001	0.001
$670 = 680$	0.741	0.608	0.143	0.514	0.792	0.351	0.674	0.693	0.257
$680 = 700$	0.318	0.122	0.086	0.445	0.080	0.080	0.224	0.002	0.003
$670 = 700$	0.095	0.020	0.002	0.105	0.020	0.001	0.080	0.011	0.006

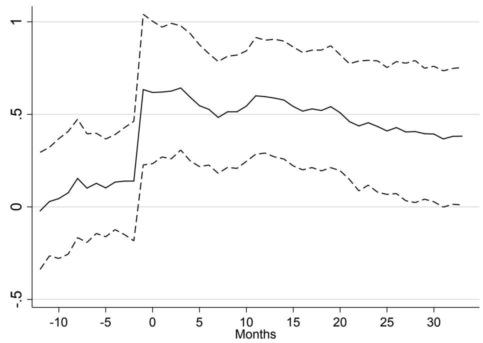
Notes: This table reports the RD estimates of eligibility on default. Panel A presents the IV results for each subsample. Credit limit refers to the additional credit limit granted by Bank A to approved applications (rejected applications were coded as zero additional credit limit) and was instrumented with the cutoff rule. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In columns (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In columns (2) the dependent variable is the number of total credit cards that were ever in default since the date of application. In columns (3) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (4) is the share of credit cards default since the date of application. In column (5) we use the total number of credit cards closed after the application. Column (6) is defined similarly than column (5), but excludes the new credit card for approved applicants. The dependent variable in column (7) focuses in the short term by looking at default in the first six months after the application. he last column presents the results for an index variable which consists of the average of the z-scores of the first variables. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table 8: Regression Discontinuity Estimates of the Effect of Additional Credit Limit on Different Measures of Delinquency on Credit Cards Active at the Moment of Application Only

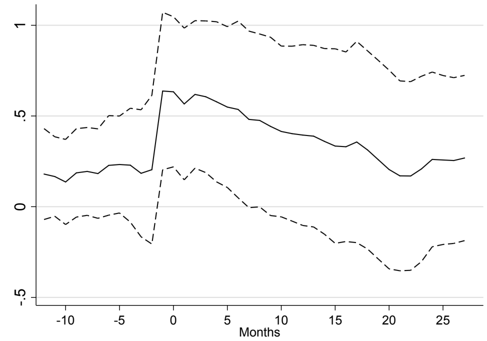
	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
Panel A: IV									
Approved Amount 670	0.00963	0.00591	0.00785**	0.0109*	0.00646*	0.00726***	0.0158	0.00978***	0.00784**
	(0.00833)	(0.00414)	(0.00349)	(0.00565)	(0.00336)	(0.00271)	(0.0111)	(0.00372)	(0.00309)
Approved Amount 680	0.0107**	0.00664*	0.00223	0.0100**	0.00543	0.00282	0.00835	0.00493	0.00327
	(0.00527)	(0.00350)	(0.00239)	(0.00501)	(0.00337)	(0.00247)	(0.00622)	(0.00361)	(0.00240)
Approved Amount 700	-0.00324	0.000799	-0.000674	-0.00253	-0.000942	-0.00103	0.000168	-0.000797	-0.00148
	(0.00668)	(0.00254)	(0.00200)	(0.00644)	(0.00229)	(0.00192)	(0.00741)	(0.00309)	(0.00254)
Panel B: Means [-5;0] from cutoff									
670	0.26	0.18	0.15	0.23	0.17	0.14	0.39	0.26	0.17
680	0.18	0.12	0.09	0.14	0.10	0.07	0.24	0.18	0.11
700	0.35	0.21	0.15	0.32	0.19	0.14	0.31	0.21	0.14
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
Panel C: Joint Testing (p-values)									
$670 = 680 = 700$	0.318	0.271	0.119	0.323	0.106	0.064	0.314	0.116	0.052
$670 = 680$	0.923	0.909	0.240	0.901	0.845	0.252	0.620	0.420	0.281
$680 = 700$	0.179	0.164	0.375	0.193	0.103	0.209	0.295	0.250	0.130
$670 = 700$	0.228	0.336	0.045	0.148	0.097	0.022	0.243	0.045	0.022

Notes: This table reports the RD estimates of eligibility on default. Panel A presents the IV results for each subsample. Credit limit refers to the additional credit limit granted by Bank A to approved applications (rejected applications were coded as zero additional credit limit) and was instrumented with the cutoff rule. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In columns (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In columns (2) the dependent variable is the number of total credit cards that were ever in default since the date of application. In columns (3) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (4) is the share of credit cards default since the date of application. In column (5) we use the total number of credit cards closed after the application. Column (6) is defined similarly than column (5), but excludes the new credit card for approved applicants. The dependent variable in column (7) focuses in the short term by looking at default in the first six months after the application. he last column presents the results for an index variable which consists of the average of the z-scores of the first variables. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

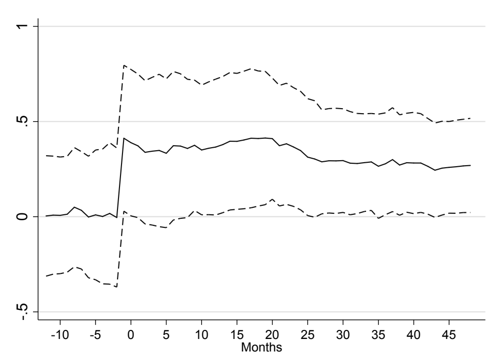
Figure 9: Effects of Credit Card Availability over Time



(a) 670 Cutoff



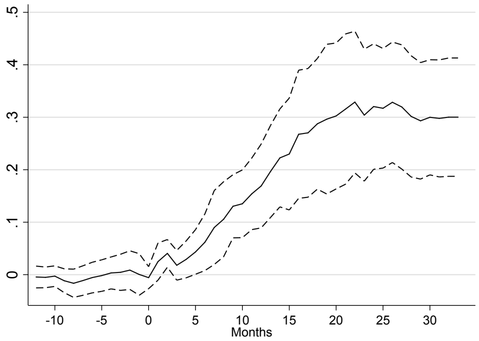
(b) 680 Cutoff



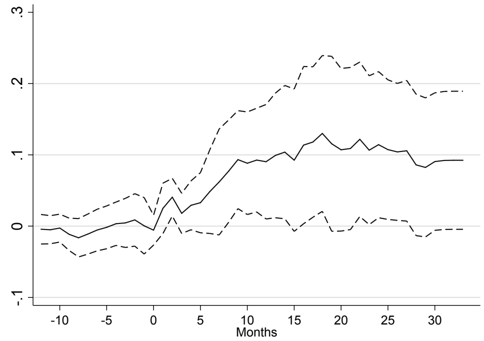
(c) 700 Cutoff

Notes: This graphs represents the effect of an applicant being above the cutoff on the number of credit cards for different months before and after the application. The effect is estimated by obtaining each variable through time and then making an OLS regression with being above or below the cutoff.

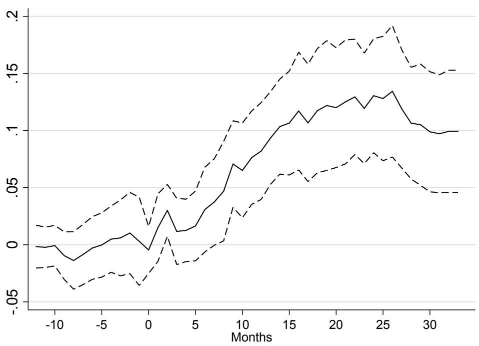
Figure 10: Effects of Credit Limit, Debt and Default over Time - 670 Cutoff



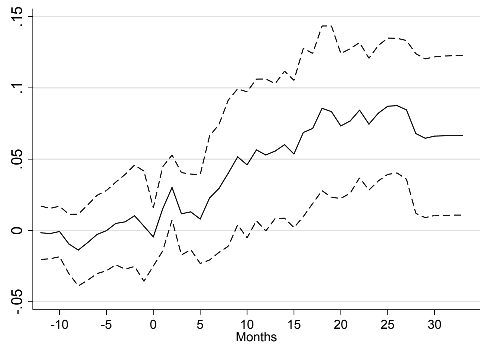
(a) Defaulted cards by month (Cumulative) †



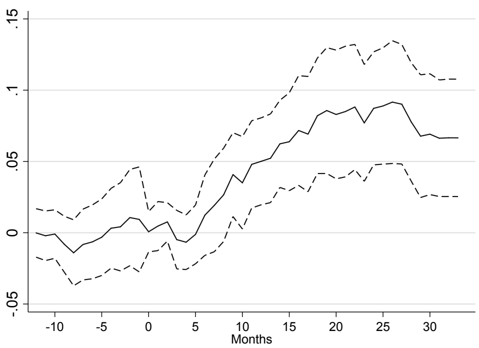
(b) Defaulted cards by month (Cumulative) ‡



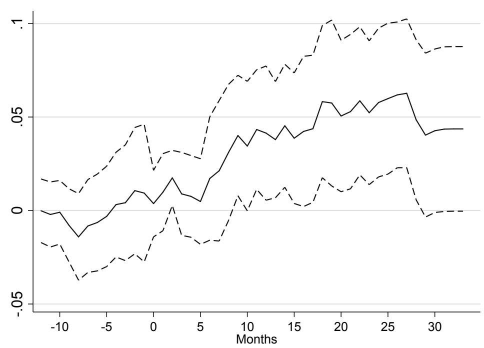
(c) Probability of default (Cumulative) †



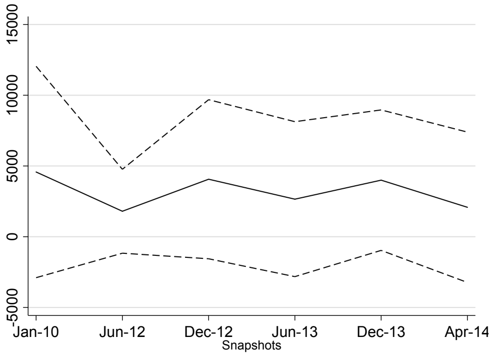
(d) Probability of default (Cumulative) ‡



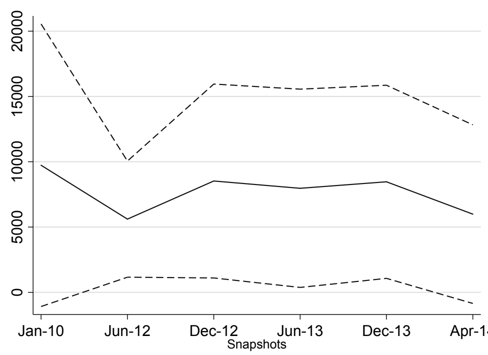
(e) Share of cards in default (Cumulative) †



(f) Share of cards in default (Cumulative) ‡



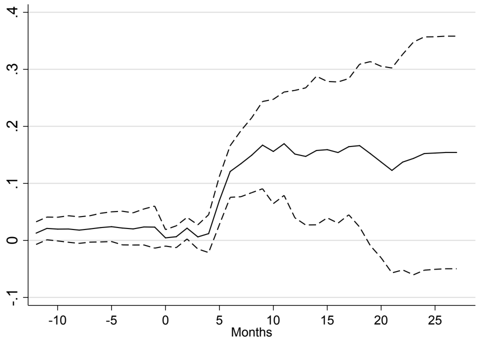
(g) Debt by snapshot



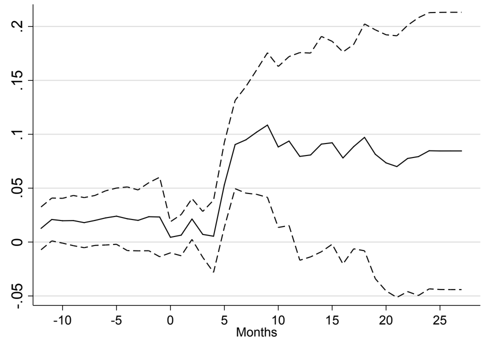
(h) Credit limit by snapshot

Notes: This figure represents the effect of an applicant being above the cutoff on the number of credit cards for different months before and after the application for the sample which had 670 points as their cutoff. Panels (a) and (b) are the effect on the number of cards in default on all the cards and on the cards already open at the moment of application respectively. Panels (c) and (d) are the effect on an indicator variable which represented if the person had a card in default on all the cards or on the cards already open

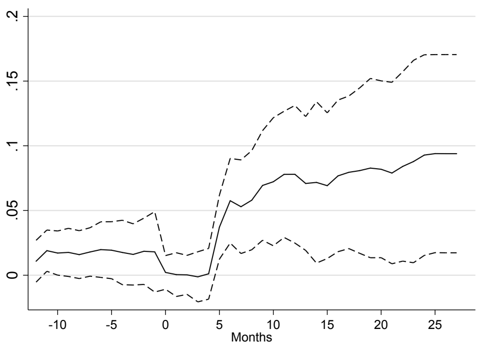
Figure 11: Effects of Credit Limit, Debt and Default over Time - 680 Cutoff



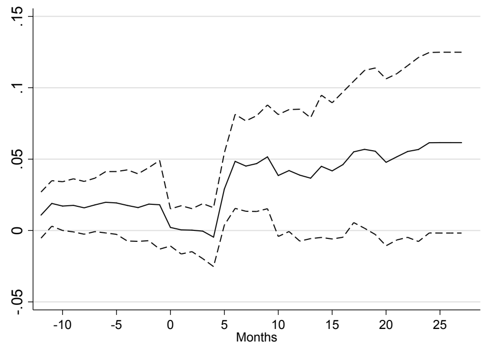
(a) Defaulted cards by month (Cumulative) †



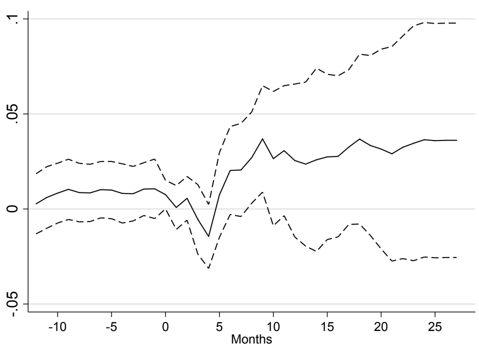
(b) Defaulted cards by month (Cumulative) ‡



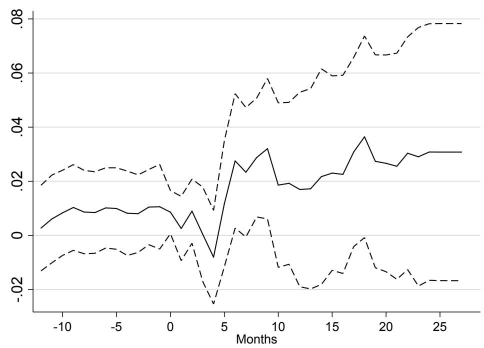
(c) Probability of default (Cumulative) †



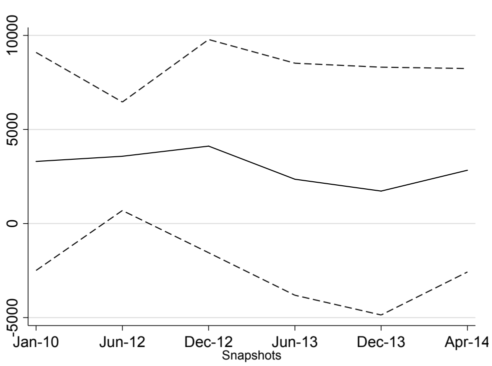
(d) Probability of default (Cumulative) ‡



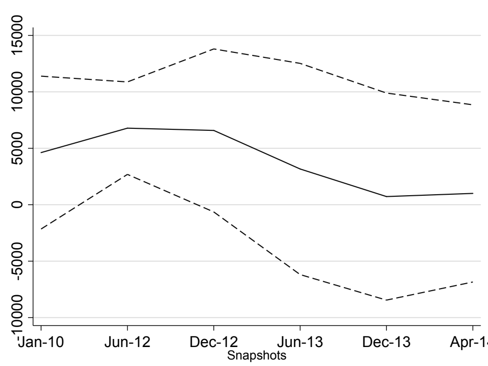
(e) Share of cards in default (Cumulative) †



(f) Share of cards in default (Cumulative) ‡



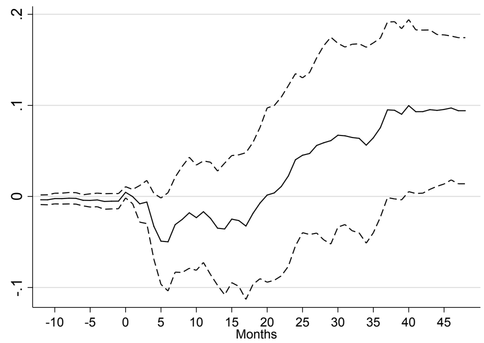
(g) Debt by snapshot



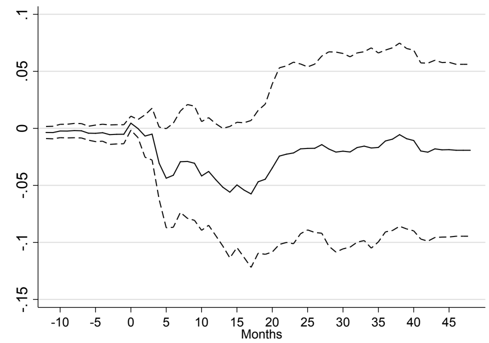
(h) Credit limit by snapshot

Notes: This figure represents the effect of an applicant being above the cutoff on the number of credit cards at the moment for different months before and after the application for the sample which had 680 points as their cutoff. Panels (a) and (b) are the effect on the number of cards in default on all the cards and on the cards already open at the moment of application respectively. Panels (c) and (d) are the effect on an indicator variable which represented if the person had a card in default on all the cards or on

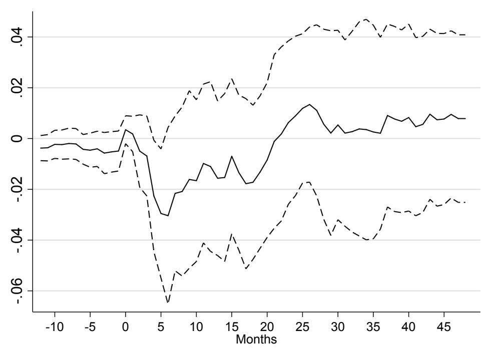
Figure 12: Effects of Credit Limit, Debt and Default over Time - 700 Cutoff



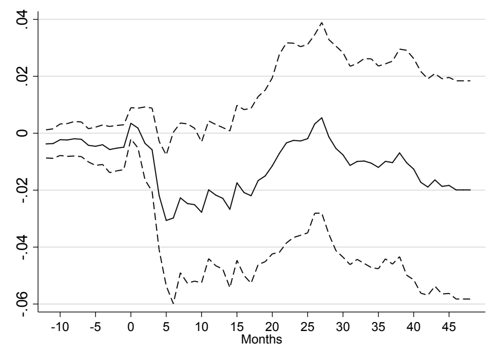
(a) Defaulted cards by month (Cumulative) †



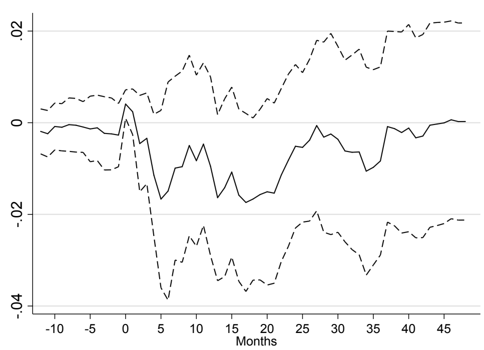
(b) Defaulted cards by month (Cumulative) ‡



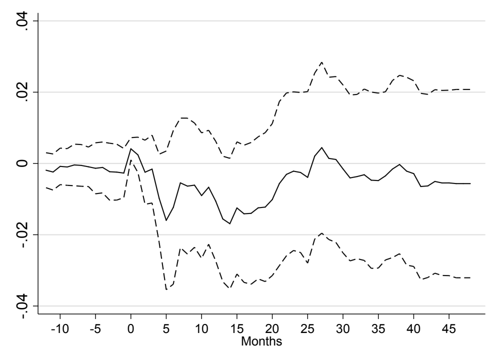
(c) Probability of default (Cumulative) †



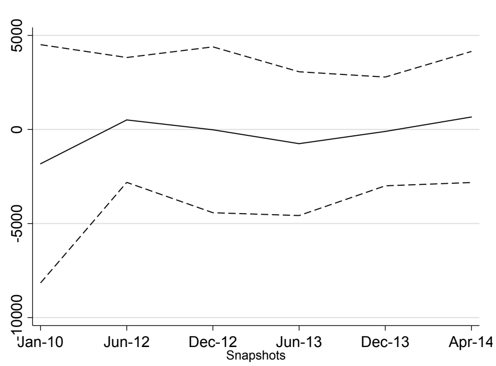
(d) Probability of default (Cumulative) ‡



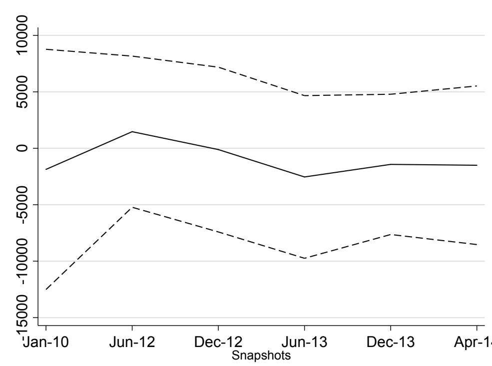
(e) Share of cards in default (Cumulative) †



(f) Share of cards in default (Cumulative) ‡



(g) Debt by snapshot



(h) Credit limit by snapshot

Notes: This figure represents the effect of an applicant being above the cutoff on the number of credit cards at the moment for different months before and after the application for the sample which had 700 points as their cutoff. Panels (a) and (b) are the effect on the number of cards in default on all the cards and on the cards already open at the moment of application respectively. Panels (c) and (d) are the effect on an indicator variable which represented if the person had a card in default on all the cards or on

APPENDIX

A Description of Merging Procedure and Sample Selection

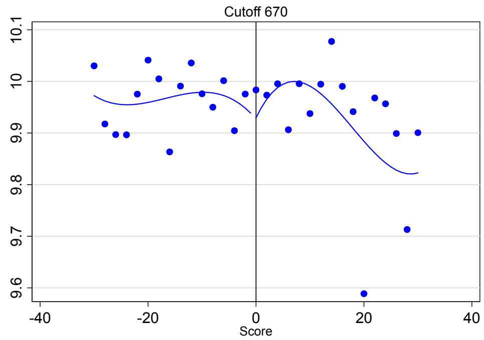
Our merging procedure starts with data from the entire sample of applications for a Bank A credit card made between January 2010 and September 2012. Out of 604,509 original observations we keep observations from applicants for which the first 10 digits of the Mexican government Tax ID and the first and last name uniquely identifies an application. We also keep the last application made by each individual only (in case the same individual applied multiple times). After this procedure, 484,835 individuals/applications remain in the sample. The financial information provided by the CNBV corresponds to 457,918 applicants, which implies a 94,4% matching rate.

Given our matched sample of 457,918 applications, we proceed to select our final sample. There are three criteria that determine which applications remain in the sample. First, since Bank A has a much more lax approval policy with their existing clients (those who have a bank account at the moment of application), no discontinuity in the probability of approval can be exploited. We keep only applications from individuals that didn't have a bank account in Bank A at the moment of application. Second, during certain months within the sample period Bank A run 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. Third, we found that some other Mexican banks had a similar approval policy for credit card applications, which generated discontinuities in the number of active credit cards at the moment of the application in Bank A. Therefore, we excluded all applicants that had credit cards from any of those banks at the moment of application. After this selection process, 106,444 applications are left with credit scores between 400 and 800. Finally, given the local nature of the RD design, we narrow 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.

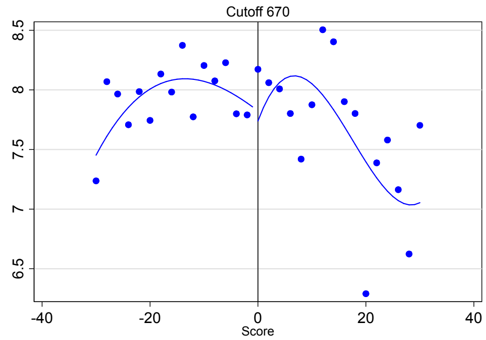
B Graphical Results by Cutoff Value

B.1 Pre-Treatment Characteristics

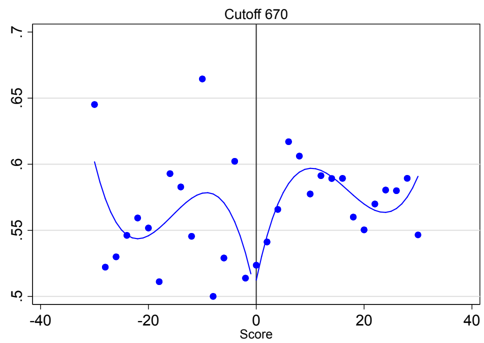
Figure B1.1: Pre-Treatment Characteristics for Sample with a Threshold of 670



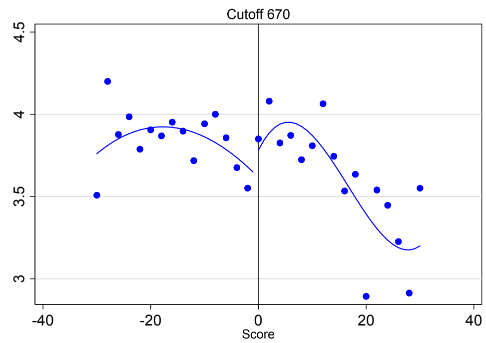
(a) Income (Log)



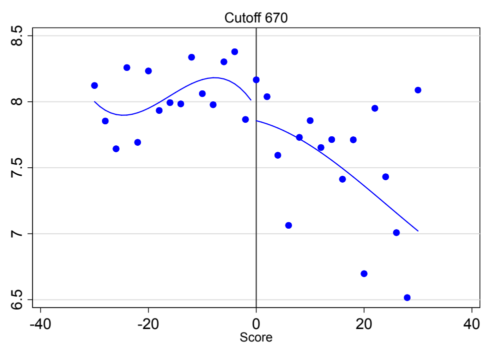
(b) Sum of credit lines before (Log)



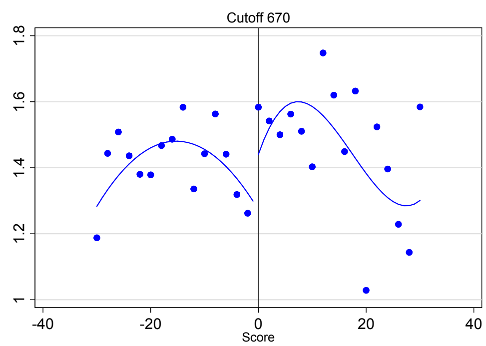
(c) % Male



(d) Number of active credits 30 days before



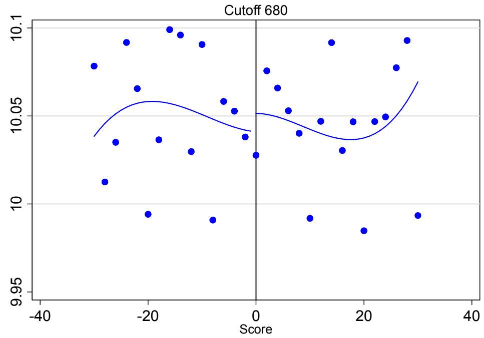
(e) Tenure in Bureau



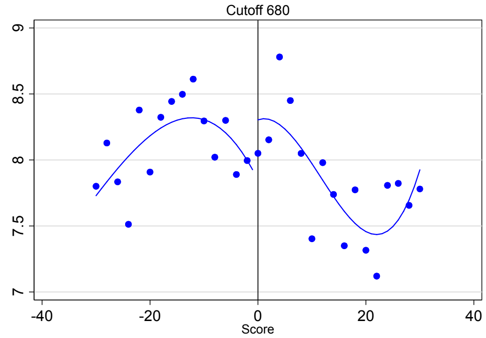
(f) # CC 30 days before

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the 670 cutoff. (a) Presents the logarithm of each applicant income. (b) refest to the sum of credit lines the applicant had before the application. (c) refers to the percentage of males in each score. (d) to the number of credits each had 30 days before. (e) To the years each person had been in the bureau and (f) to the number of credit cards each had 30 days before. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process

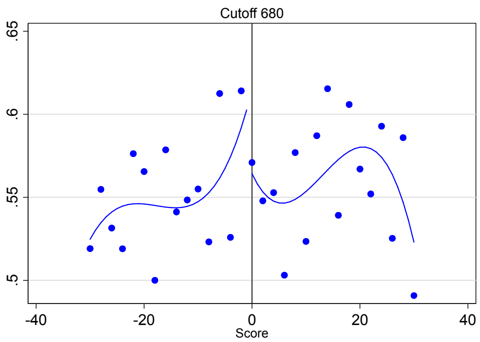
Figure B1.2: Pre-Treatment Characteristics for Sample with a Threshold of 680



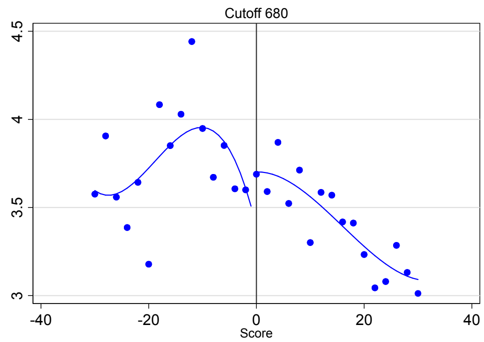
(a) Income (Log)



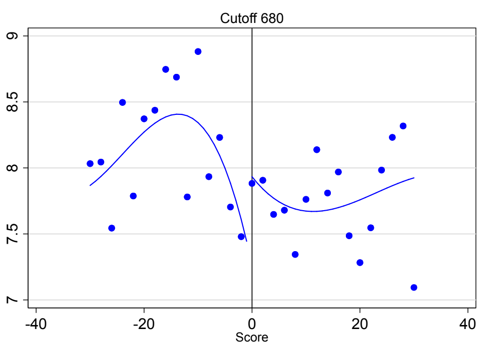
(b) Sum of credit lines before (Log)



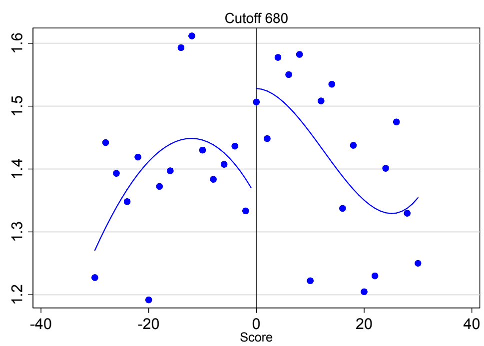
(c) % Male



(d) Number of active credits 30 days before



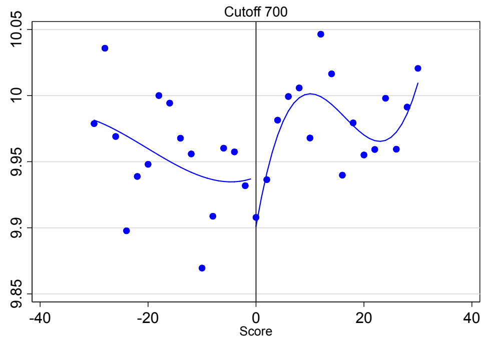
(e) Tenure in Bureau



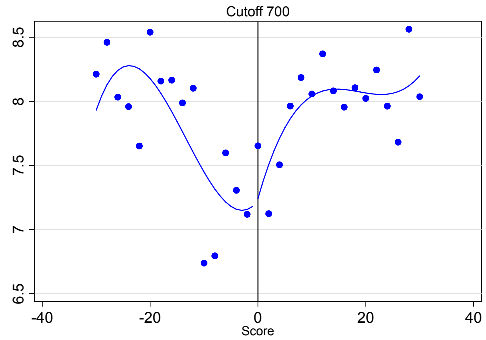
(f) # CC 30 days before

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the 680 cutoff. (a) Presents the logarithm of each applicant income. (b) refest to the sum of credit lines the applicant had before the application. (c) refers to the percentage of males in each score. (d) to the number of credits each had 30 days before. (e) To the years each person had been in the bureau and (f) to the number of credit cards each had 30 days before. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

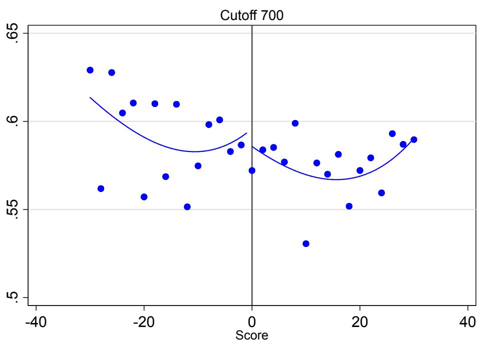
Figure B1.3: Pre-Treatment Characteristics for Sample with a Threshold of 700



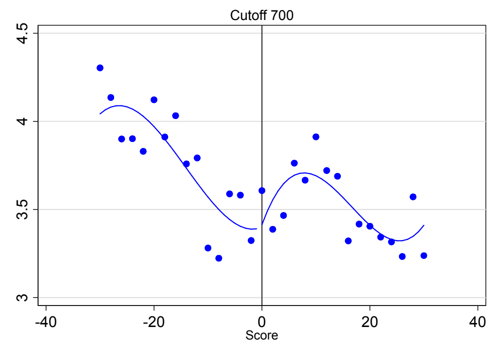
(a) Income (Log)



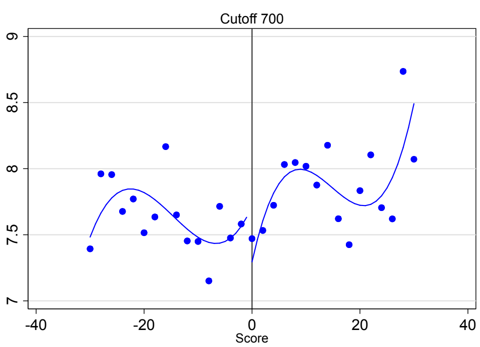
(b) Sum of credit lines before (Log)



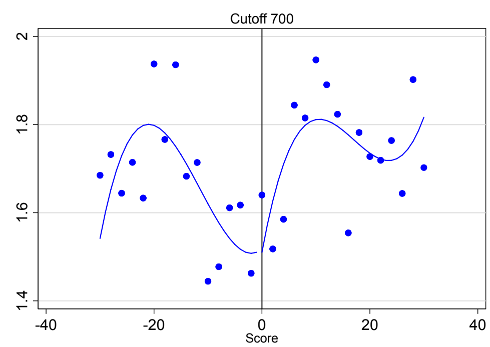
(c) % Male



(d) Number of active credits 30 days before



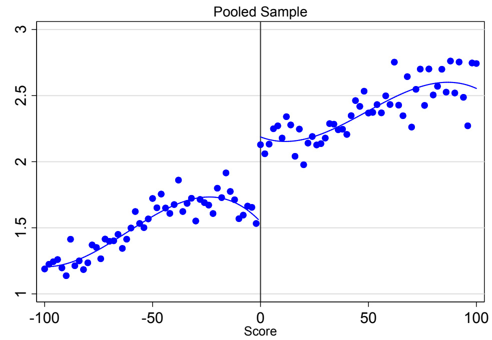
(e) Tenure in Bureau



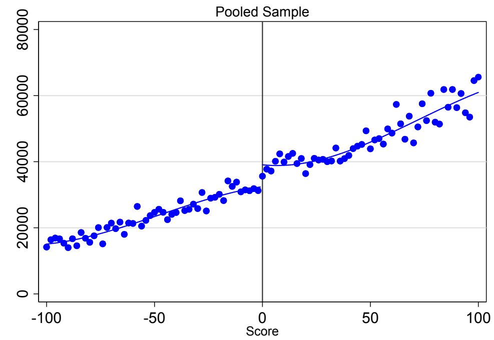
(f) # CC 30 days before

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the 700 cutoff. (a) Presents the logarithm of each applicant income. (b) refest to the sum of credit lines the applicant had before the application. (c) refers to the percentage of males in each score. (d) to the number of credits each had 30 days before. (e) To the years each person had been in the bureau and (f) to the number of credit cards each had 30 days before. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

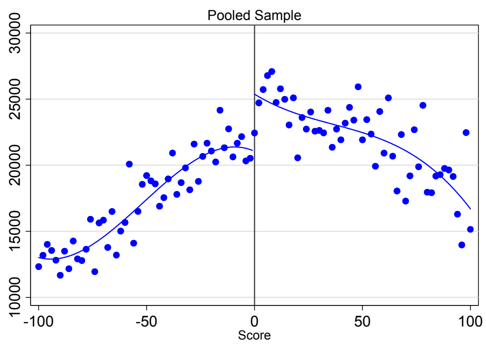
Figure B1.4: Effect on Credit Cards and Limit Availability



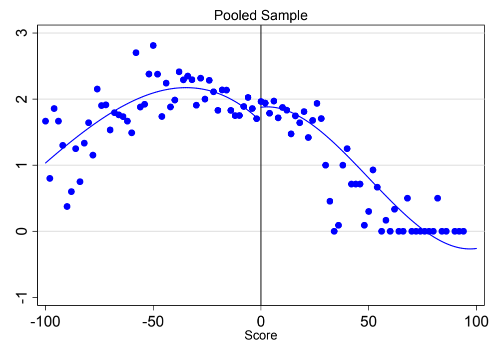
(a) Active CC one month after application



(b) Effect on credit limit (MXN)



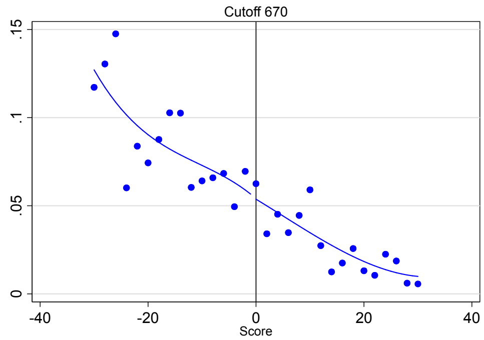
(c) Effect on CC debt (MXN)



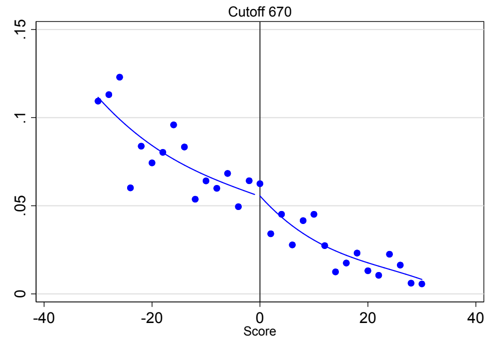
(d) Credit Bureau enquiries 6 months after

Notes: The figures presents the mean of number of credit cards one month after application, credit card limit and debt in 2012, and additional enquiries in the following six months. For each pair of values of the standardized credit score between standardized scores of -100 and 100 for the pooled sample of applicants. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

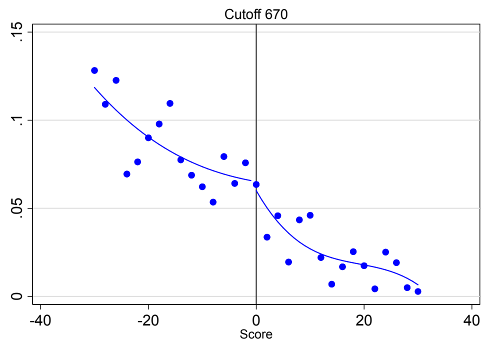
Figure B1.5: Pre-Approval Outcome Variables for Sample with a Threshold of 670



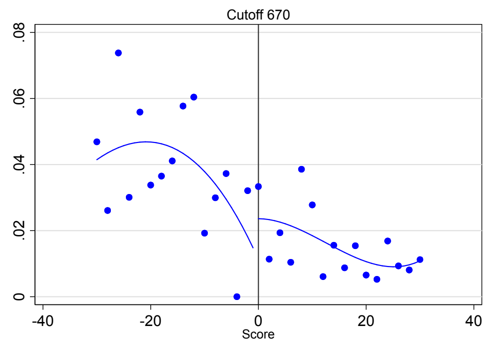
(a) Number of credit cards with 2 or less Months Delinquency



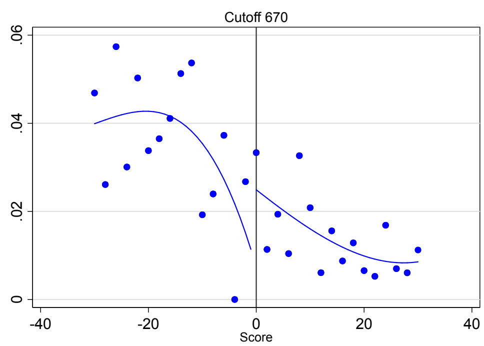
(b) Probability of credit card with 2 or less Months Delinquency



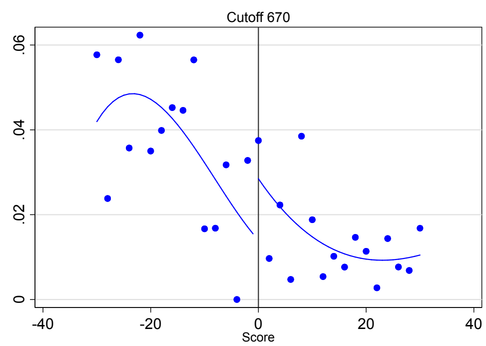
(c) Share of credit cards with 2 or less Months Delinquency



(d) Number of credit cards ever in Default



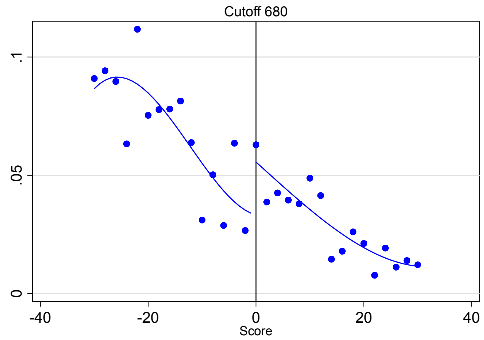
(e) Probability of of credit card in Default



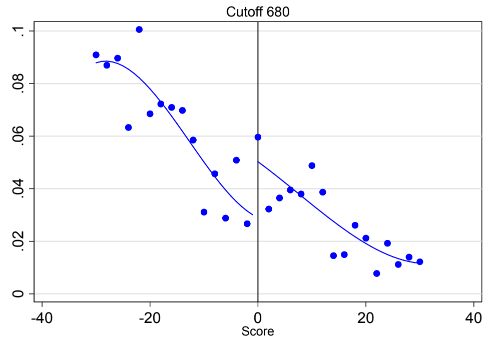
(f) Share of credit cards in Default

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 which had 670 as their cutoff value. (a) represents the number of credit cards with 2 month delinquency each person had had. Pabel (b) is a indicator variable which is one if the person has a card with 2 months delinquency. Panel (c) is the share of cards in 2 month delinquency. Panel (d) Is the number of cards ever in default the person has. Panel (e) is a variable indicating wether the person ever had a credit card in default. Panel (f) is the share of credit cards the person has which have ever been in default. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

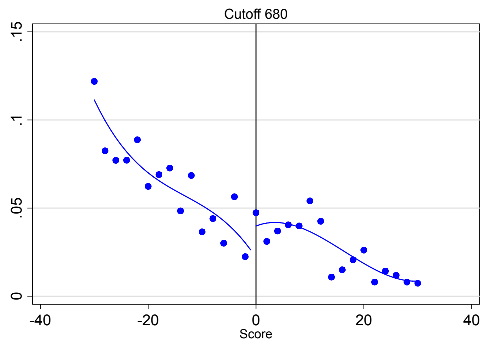
Figure B1.6: Pre-Approval Outcome Variables for Sample with a Threshold of 680



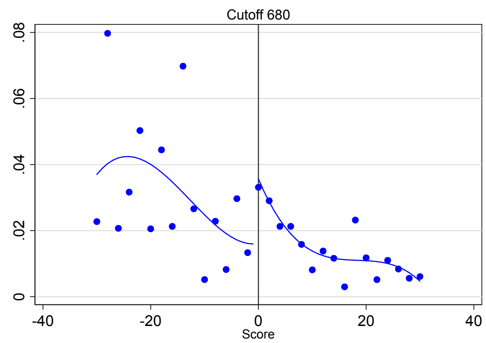
(a) Number of credit cards with 2 or less Months Delinquency



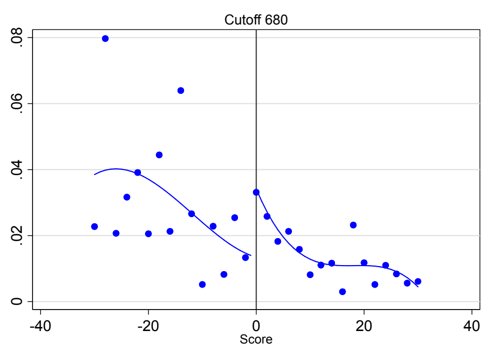
(b) Probability of credit card with 2 or less Months Delinquency



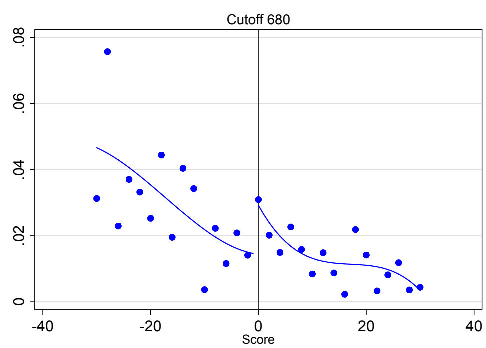
(c) Share of credit cards with 2 or less Months Delinquency



(d) Number of credit cards ever in Default



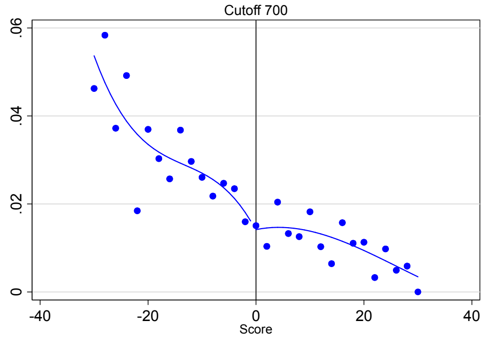
(e) Probability of of credit card in Default



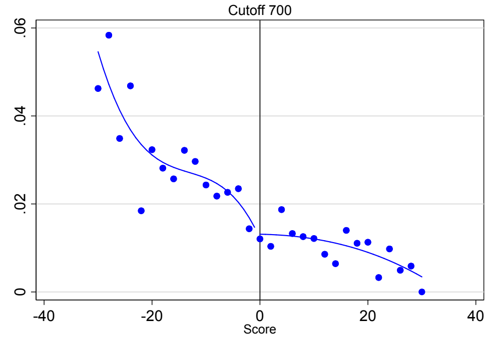
(f) Share of credit cards in Default

Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 which had 680 as their cutoff value. (a) represents the number of credit cards with 2 month delinquency each person had had. Pabel (b) is a indicator variable which is one if the person has a card with 2 months delinquency. Panel (c) is the share of cards in 2 month delinquency. Panel (d) Is the number of cards ever in default the person has. Panel (e) is a variable indicating wether the person ever had a credit card in default. Panel (f) is the share of credit cards the person has which have ever been in default. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

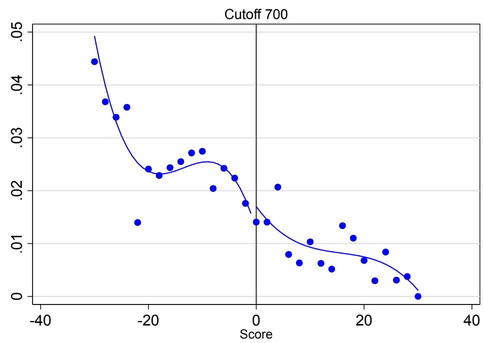
Figure B1.7: Pre-Approval Outcome Variables for Sample with a Threshold of 700



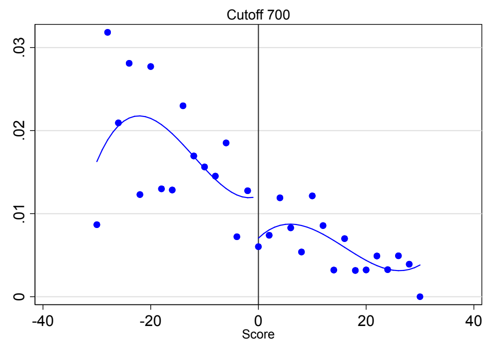
(a) Number of credit cards with 2 or less Months Delinquency



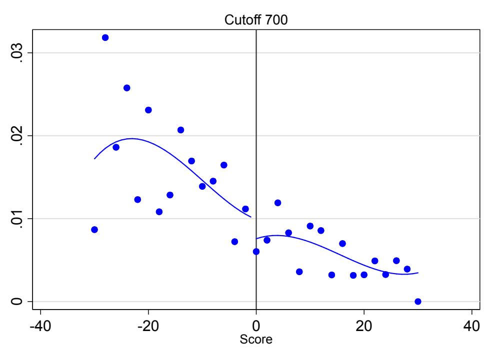
(b) Probability of credit card with 2 or less Months Delinquency



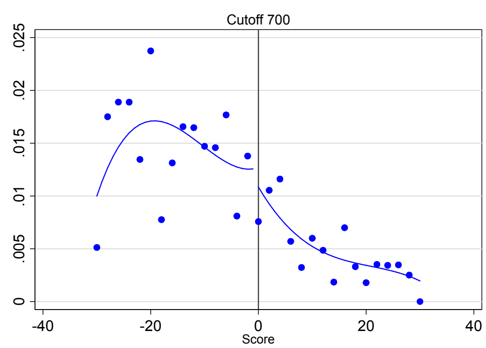
(c) Share of credit cards with 2 or less Months Delinquency



(d) Number of credit cards ever in Default



(e) Probability of of credit card in Default

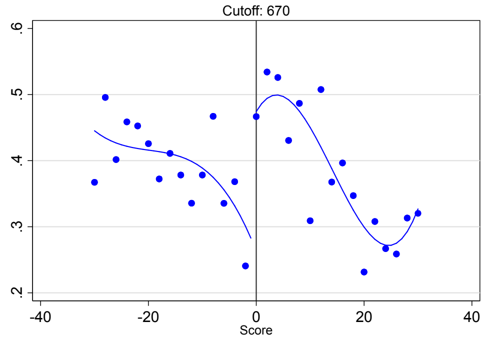


(f) Share of credit cards in Default

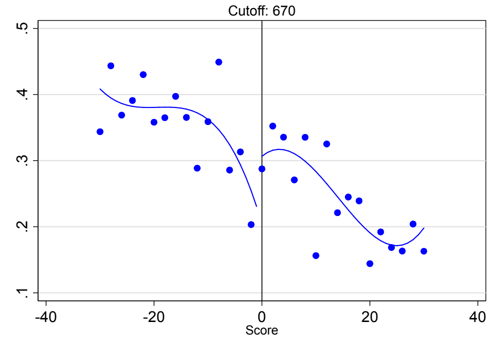
Notes: These figures present the mean of predetermined characteristics for each pair of values of the standardized credit score between standardized scores of -30 and 30 which had 680 as their cutoff value. (a) represents the number of credit cards with 2 month delinquency each person had had. Pabel (b) is a indicator variable which is one if the person has a card with 2 months delinquency. Panel (c) is the share of cards in 2 month delinquency. Panel (d) Is the number of cards ever in default the person has. Panel (e) is a variable indicating wether the person ever had a credit card in default. Panel (f) is the share of credit cards the person has which have ever been in default. It also presents a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ in both sides of the threshold. The vertical line located at 0 represents the cutoff value used by the bank in its assignment process.

B.2 Effect on Default Rates

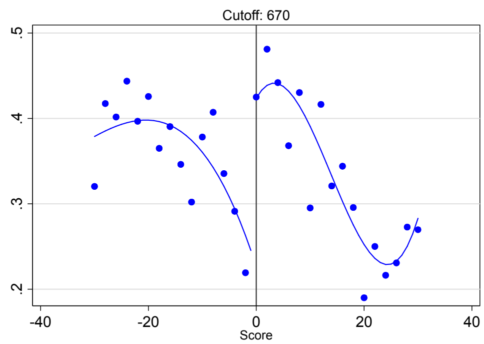
Figure B3.1: Effect on Different Measures of Delinquency for Sample with a Threshold of 670



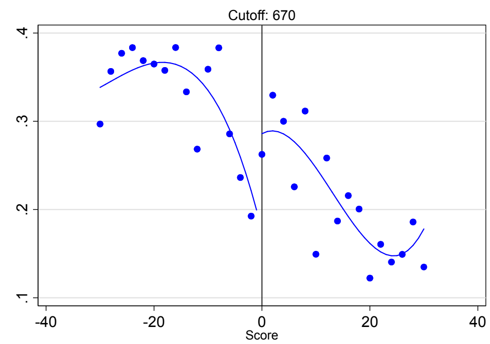
(a) #CC Ever with 2 Month Delinquency †



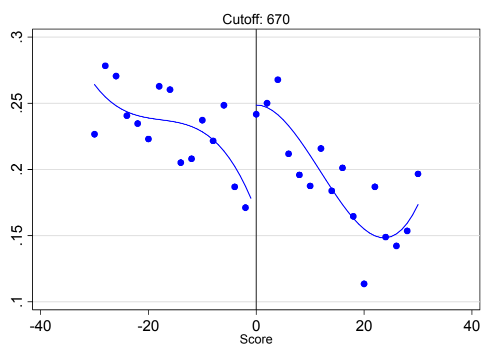
(b) #CC Ever with 2 Month Delinquency ‡



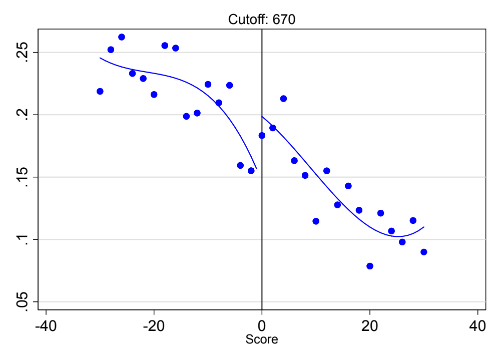
(c) #CC Ever in Default †



(d) #CC Ever in Default ‡



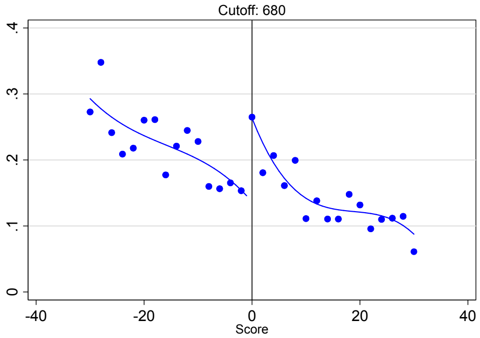
(e) Probability of CC Default †



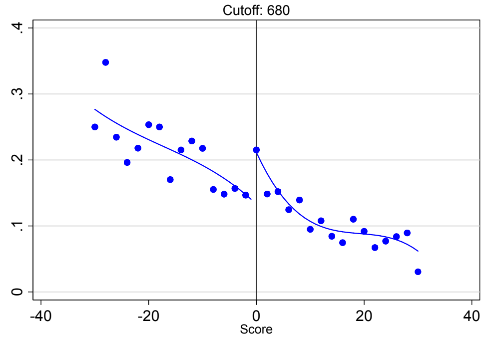
(f) Probability of CC Default ‡

Notes: The figures presents the mean of several measures of default for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the sample of applicants with a threshold of 670 in their credit score. Panels (a) and (b) show the average across applicants of the number of total credit cards that were 2 months delinquent at any point in time since the date of the application to December 2012. Panels (c) and (d) show the average across applicants of the number of total credit card that were ever in default since the date of application to December 2012. The probability of default, Panels (e) and (f), is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application.The figures in the left include all credit cards active at or opened after the application, including the credit card received by approved applications. The figures in the right include only credit cards active at the moment of application.

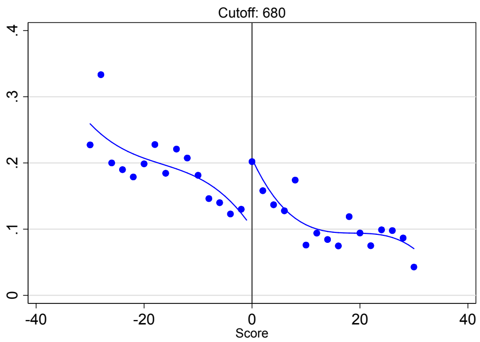
Figure B3.2: Effect on Different Measures of Delinquency for Sample with a Threshold of 680



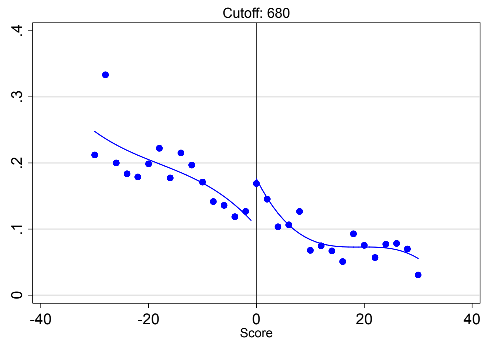
(a) #CC Ever with 2 Month Delinquency †



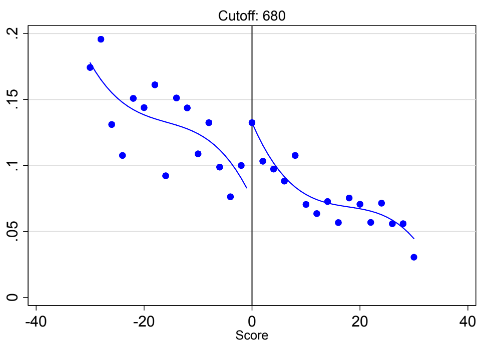
(b) #CC Ever with 2 Month Delinquency ‡



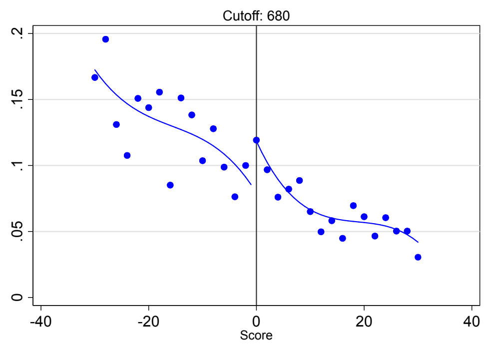
(c) #CC Ever in Default †



(d) #CC Ever in Default ‡



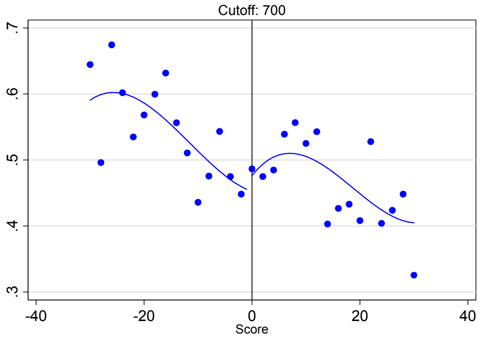
(e) Probability of CC Default †



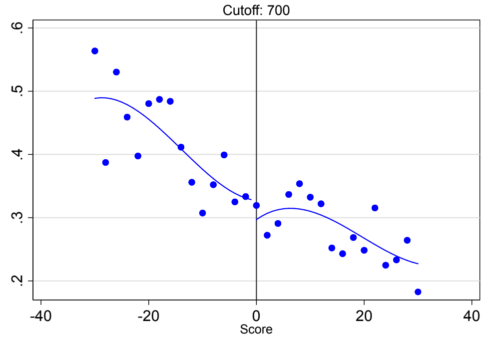
(f) Probability of CC Default ‡

Notes: The figures presents the mean of several measures of default for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the sample of applicants with a threshold of 680 in their credit score. Panels (a) and (b) show the average across applicants of the number of total credit cards that were 2 months delinquent at any point in time since the date of the application to December 2012. Panels (c) and (d) show the average across applicants of the number of total credit card that were ever in default since the date of application to December 2012. The probability of default, Panels (e) and (f), is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application.The figures in the left include all credit cards active at or opened after the application, including the credit card received by approved applications. The figures in the right include only credit cards active at the moment of application.

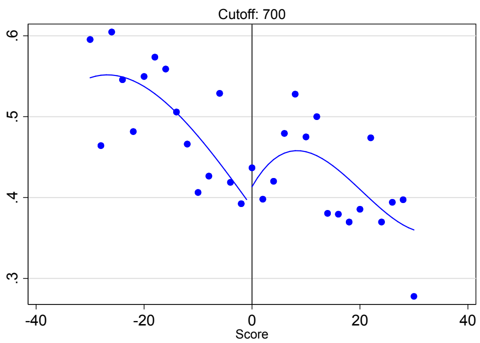
Figure B3.3: Effect on Different Measures of Delinquency for Sample with a Threshold of 700



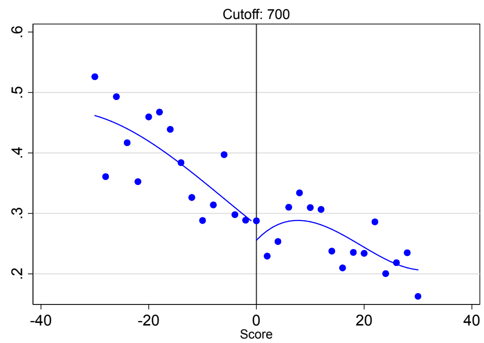
(a) #CC Ever with 2 Month Delinquency †



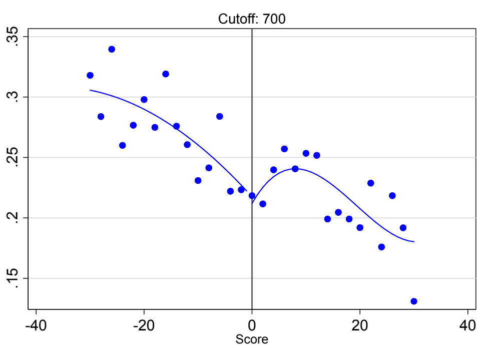
(b) #CC Ever with 2 Month Delinquency ‡



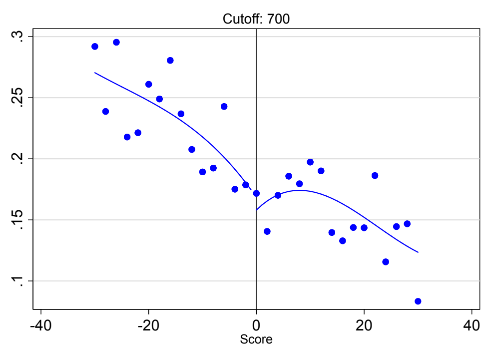
(c) #CC Ever in Default †



(d) #CC Ever in Default ‡



(e) Probability of CC Default †



(f) Probability of CC Default ‡

Notes: The figures presents the mean of several measures of default for each pair of values of the standardized credit score between standardized scores of -30 and 30 for the sample of applicants with a threshold of 700 in their credit score. Panels (a) and (b) show the average across applicants of the number of total credit cards that were 2 months delinquent at any point in time since the date of the application to December 2012. Panels (c) and (d) show the average across applicants of the number of total credit card that were ever in default since the date of application to December 2012. The probability of default, Panels (e) and (f), is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application.The figures in the left include all credit cards active at or opened after the application, including the credit card received by approved applications. The figures in the right include only credit cards active at the moment of application.

C Applicants' Characteristics by Number of CC

Table C.1: Summary Statistics

	Number of CC					
	0	1	2	3	4	5 or more
Panel A: Baseline Characteristics						
Income (MXN)	23170	24608	29428	30476	33712	41346
	(19078)	(18815)	(24803)	(23751)	(29378)	(34396)
Male	0.58	0.55	0.59	0.57	0.57	0.60
	(0.49)	(0.5)	(0.49)	(0.5)	(0.5)	(0.49)
Panel B: Pre-treatment Credit Characteristics						
Credit Score	690	688	688	689	691	691
	(13)	(13)	(13)	(13)	(12)	(12)
Tenure in Buro (Years)	6.28	7.50	8.29	8.95	8.63	10.88
	(4.46)	(4.57)	(4.75)	(4.82)	(4.34)	(4.48)
Sum of Active Lines before (MXN)	4061	15967	29181	39754	46610	73870
	(12251)	(21168)	(30333)	(34662)	(37684)	(40861)
# of non-Bank A CC 30 days before	0.00	0.95	1.88	2.84	3.80	5.99
	(0.06)	(0.31)	(0.46)	(0.55)	(0.59)	(1.85)
# of Active Credits 30 days before	1.76	2.90	4.06	5.23	6.30	9.14
	(1.6)	(1.75)	(1.99)	(2.21)	(2.2)	(3.03)
Average Utilization*	0.61	0.56	0.53	0.54	0.52	0.52
	(0.42)	(0.37)	(0.33)	(0.31)	(0.3)	(0.26)
CC Debt (MXN)	1000	5084	9219	13000	15639	26889
	(5255)	(9999)	(14388)	(16989)	(18317)	(21906)
Total Debt (MXN)	18165	25849	37036	47160	53248	87608
	(42888)	(47125)	(58137)	(66509)	(70221)	(84501)
Total CC Limit	35	13466	31147	46941	59211	96117
	(700)	(19536)	(34710)	(42127)	(46152)	(47133)
# CC ever in Default†	0.06	0.08	0.07	0.08	0.03	0.03
	(0.27)	(0.33)	(0.36)	(0.34)	(0.18)	(0.18)
Probability of CC Default†	0.05	0.07	0.05	0.06	0.03	0.03
	(0.22)	(0.25)	(0.23)	(0.24)	(0.18)	(0.18)
Share of CC in Default†	0.43	0.04	0.02	0.02	0.01	0.01
	(0.48)	(0.18)	(0.11)	(0.09)	(0.04)	(0.04)
# CC ever in 2 months delinquency†	0.07	0.12	0.11	0.10	0.08	0.07
	(0.29)	(0.39)	(0.4)	(0.41)	(0.3)	(0.27)
Probability of CC 2 months delinquency†	0.06	0.10	0.09	0.07	0.07	0.07
	(0.23)	(0.3)	(0.28)	(0.26)	(0.26)	(0.25)
Share of CC in 2 months delinquency†	0.48	0.07	0.04	0.03	0.02	0.01
	(0.49)	(0.23)	(0.14)	(0.11)	(0.07)	(0.05)
Panel C: Outcomes						
Approved	0.16	0.27	0.34	0.40	0.41	0.44
	(0.36)	(0.45)	(0.47)	(0.49)	(0.49)	(0.5)
Amount Requested (MXN)	15458	17034	20615	22640	26735	29865
	(14097)	(15054)	(18321)	(18912)	(21304)	(23248)
Approved Amount (MXN)**	9463	12722	16122	17728	17827	25854
	(7137)	(8251)	(11426)	(11904)	(13179)	(15412)
Interest Rate (%)	40.03	37.55	36.84	35.77	36.10	34.02
	(6.2)	(5.14)	(6.08)	(6.04)	(7.42)	(7.48)
N	1986	1619	1121	678	350	425

	Number of CC					
	0	1	2	3	4	5 or more
Panel D: Active Credit Cards at the moment of Application						
# CC ever in Default‡	-	0.02	0.02	0.03	0.02	0.01
	-	(0.16)	(0.14)	(0.22)	(0.13)	(0.11)
Probability of CC Default‡	-	0.02	0.02	0.03	0.02	0.01
	-	(0.16)	(0.13)	(0.16)	(0.13)	(0.11)
Share of CC in Default‡	-	0.03	0.01	0.01	0.00	0.00
	-	(0.16)	(0.08)	(0.07)	(0.03)	(0.03)
# CC ever in 2 months delinquency‡	-	0.05	0.05	0.05	0.03	0.04
	-	(0.22)	(0.23)	(0.27)	(0.18)	(0.2)
Probability of CC 2 months delinquency‡	-	0.05	0.04	0.03	0.02	0.04
	-	(0.22)	(0.2)	(0.18)	(0.15)	(0.2)
Share of CC in 2 months delinquency‡	-	0.05	0.03	0.02	0.01	0.01
	-	(0.22)	(0.12)	(0.1)	(0.05)	(0.05)
N	1986	1619	1121	678	350	425

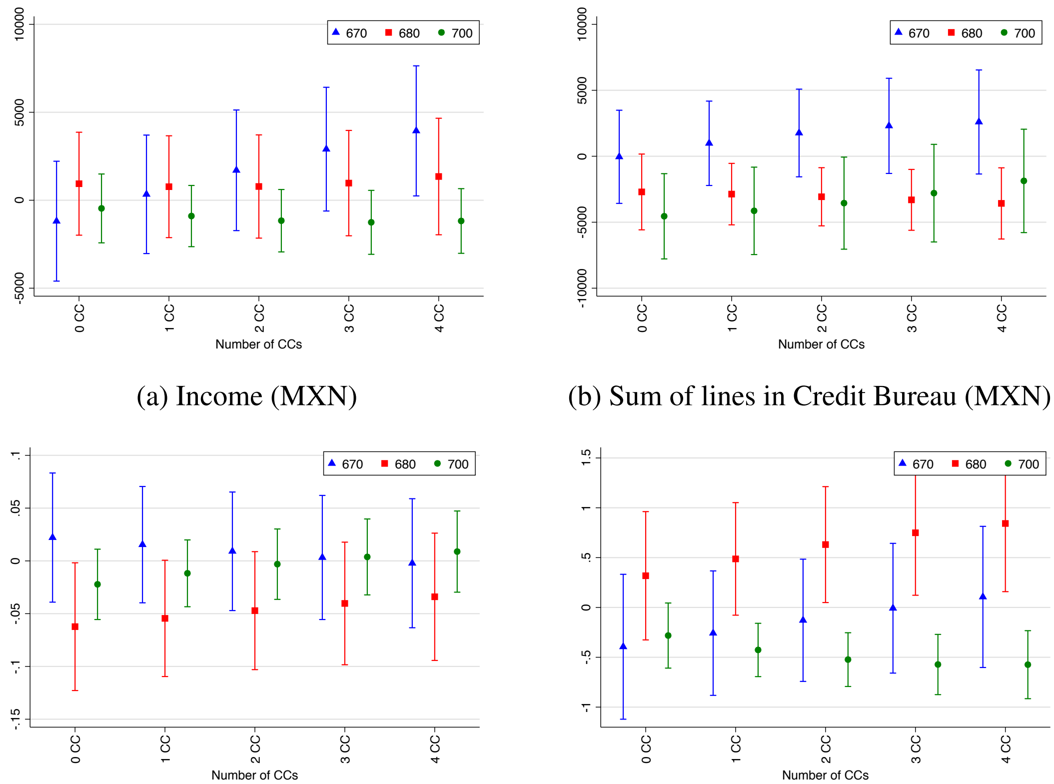
Notes: This table presents summary statistics of our sample of applicants (means and standard deviations) by number of credit cards at the moment of application. * Average utilization is the ratio of debt on credit limit, both measured in 2010. † The variable was constructed using the information of all the credit cards that were open at some time during the year previous to the bank's decision. ‡ We only consider the cards that were in fact active at the moment of the decision. ** Conditional on approval.

Table C.2: Tests of Quasi-Random Assignment of Pre-Determined Characteristics by Number of CC

	Income (Log)	Male	Tenure (Years)	$\#CC$ 30 Days Before	# Credit Lines 30 Days Before	Sum of Credit Lines in Credit Bureau (Log)	CC Debt (Log)	Amount Requested (Log)
				Panel A: 670				
Above Cutoff	-0.113	0.0160	-0.388	0.0204	-0.0561	-0.458	-0.319	-0.186
	(0.0831)	(0.0375)	(0.441)	(0.0350)	(0.238)	(0.315)	(0.308)	(0.280)
Above Cutoff×($\#CC$ before)	0.102**	-0.00439	0.140	-0.0162	0.128*	0.334***	0.0117	0.109
	(0.0403)	(0.0162)	(0.177)	(0.0275)	(0.0648)	(0.0948)	(0.141)	(0.156)
Above Cutoff×($\#CC$ before)^2	-0.00843*	0.000250	-0.00378	0.000834	-0.0360***	-0.0329***	-0.00494	-0.00923
	(0.00488)	(0.00258)	(0.0220)	(0.00605)	(0.00940)	(0.0101)	(0.0229)	(0.0249)
Mean Dep. Var.	9.98	0.53	8.06	1.42	3.74	7.85	3.52	7.29
Mean Indep. Var.	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47
				Panel B: 680				
Above Cutoff	-0.0119	-0.0720*	0.323	0.0321	0.186	-0.298	-0.0454	-0.597
	(0.0557)	(0.0386)	(0.393)	(0.0275)	(0.245)	(0.275)	(0.342)	(0.538)
Above Cutoff×($\#CC$ before)	0.00382	0.00807	0.181	-0.0506	-0.105	0.385***	0.115	-0.0592
	(0.0181)	(0.0163)	(0.187)	(0.0321)	(0.0792)	(0.111)	(0.134)	(0.153)
Above Cutoff×($\#CC$ before)^2	0.000867	-0.000223	-0.0128	0.00919	0.0181	-0.0442***	-0.00815	0.0255
	(0.00363)	(0.00252)	(0.0310)	(0.00700)	(0.0151)	(0.0138)	(0.0284)	(0.0233)
Mean Dep. Var.	10.04	0.58	7.79	1.45	3.71	8.00	2.78	7.14
Mean Indep. Var.	1.52	1.52	1.52	1.52	1.52	1.52	1.52	1.52
				Panel C: 700				
Above Cutoff	-0.0257	-0.0198	-0.278	0.0996**	0.234	0.0265	-0.0434	-0.0315
	(0.0418)	(0.0199)	(0.199)	(0.0375)	(0.142)	(0.258)	(0.226)	(0.116)
Above Cutoff×($\#CC$ before)	-0.00197	0.0119	-0.167*	-0.119***	-0.230***	0.0153	-0.0800	-0.0717**
	(0.0238)	(0.00882)	(0.0977)	(0.0273)	(0.0557)	(0.0688)	(0.0523)	(0.0292)
Above Cutoff×($\#CC$ before)^2	-0.000612	-0.000962	0.0236**	0.0212***	0.0332***	0.000790	0.0141***	0.00547
	(0.00385)	(0.00112)	(0.0113)	(0.00492)	(0.00880)	(0.00566)	(0.00529)	(0.00352)
Mean Dep. Var.	9.94	0.59	7.58	1.63	3.58	7.39	4.44	9.44
Mean Indep. Var.	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71
N	32346	32346	32346	32346	32346	32346	32346	32346
				Panel D: Joint Testing (p-values)				
$670 = 680 = 700$	0.108	0.554	0.020	0.174	0.000	0.028	0.613	0.257
$670 = 680$	0.123	0.358	0.496	0.783	0.026	0.515	0.606	0.620
$680 = 700$	0.654	0.613	0.005	0.219	0.545	0.026	0.447	0.117
$670 = 700$	0.021	0.627	0.465	0.050	0.000	0.064	0.795	0.473

Notes: This table presents the results of tests of quasi-random assignment of credit cards around the cutoff. The estimates were obtained by OLS regressions of the applicant's characteristic on a third order polynomial, allowing the intercept and the coefficients of the polynomial to differ at both sides of the cutoff. We also included a quadratic control of the number of credit cards active at the moment of application, with the interaction between the quadratic control and the variable of interest ("Above Cutoff"). Clustered standard errors at the credit score level reported in parenthesis. Income is self-reported income at moment of application. Male is a dummy variable for Male applicants. Tenure is the number of years of tenure in the Mexican Credit Bureau. Amount requested is the credit limit requested for the CC. The Gold CC Application is a dummy which indicates if the applicant applied for a gold credit card. Number of credit cards 30 days before are the number of active credit cards the applicant had 30 days before the application date. Number of Credits is the total number of other credits that the applicant had 30 days before the application date. Sum of lines in Credit Bureau is the logarithm of the total credit line the individual had before the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Figure C.1: Tests of Quasi-Random Assignment of Pre-Determined Characteristics by Number of CC



(a) Income (MXN)

(b) Sum of lines in Credit Bureau (MXN)

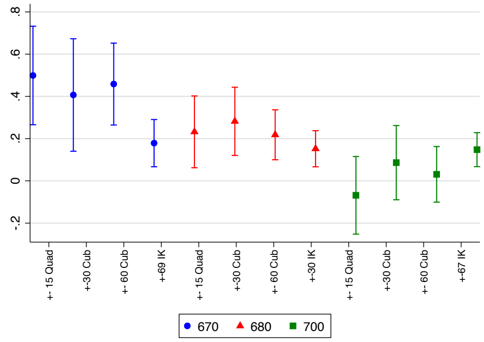
(c) Male

(d) Tenure years (LOG)

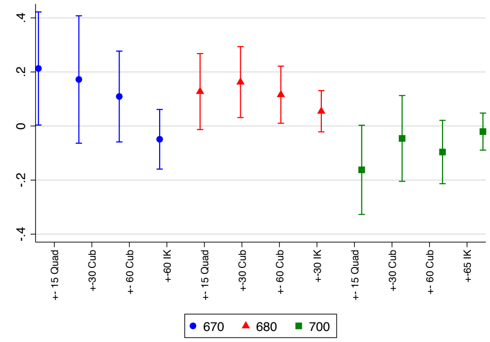
Notes: This graphs present the test of balance for being above the cutoff for the applicants on pre-application characteristics by number of credit cards at the moment of application. Each color represents a different cutoff. Panel (a) represents the effect on self-reportes Income. Panel (b) is the effect on the sum of credit lines.Panel (c) is the effect on a dummy variable indicating whether the applicant is a male. Panel (d) is the effect on the years the applicant had been in the credit bureau and panel (e) is the effect on the number of credit cards 30 days before the application.

D Robustness results with respect to bandwidth, polynomial degree and estimation methods

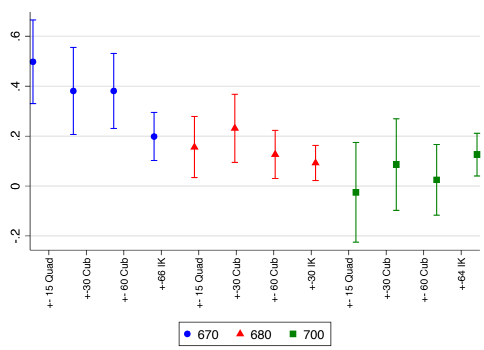
Figure D.1: Robustness of Baseline Results on Different Measures of Delinquency



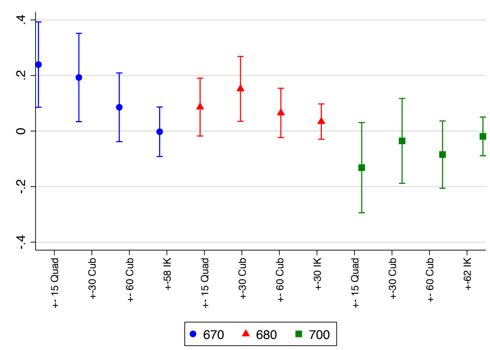
(a) #CC Ever with 2 Month Delinquency †



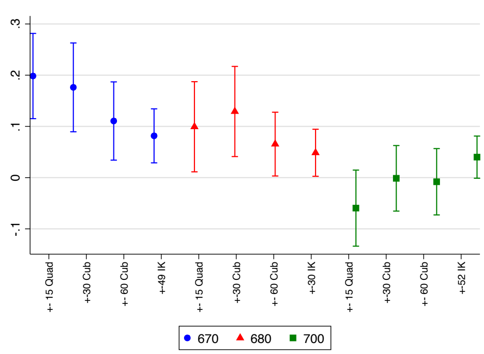
(b) #CC Ever with 2 Month Delinquency ‡



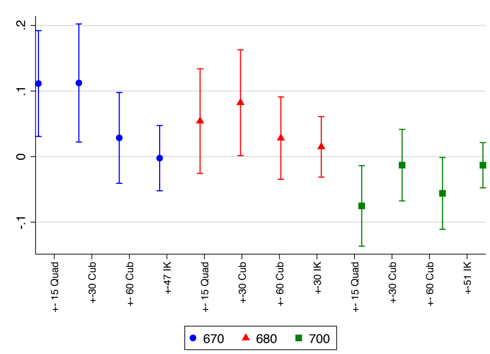
(c) #CC Ever in Default †



(d) #CC Ever in Default ‡



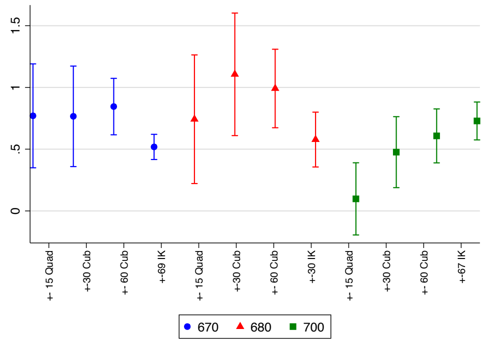
(e) Probability of CC Default †



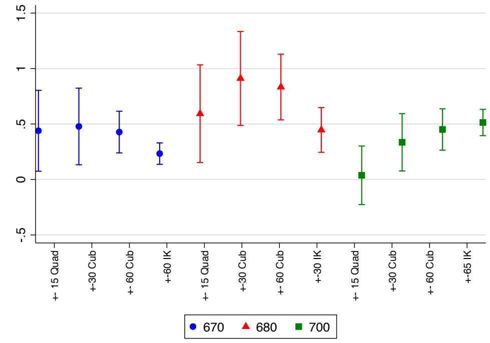
(f) Probability of CC Default ‡

Notes: The figures presents the effect of Approval on different measures of delinquency and default, using different polynomials (quadratic and cubic), different ranges above the cutoff (15, 30, 60) and those obtained from a local linear regression with optimal bandwidths provided by **?**. Each color represents a different cutoff. Panels (a) and (b) represent the effect on the number of credit cards ever in 2 month delinquency for all cards and cards only open at the moment of application respectively. Panels (c) and (d) represent the effect on the number of cards in default for all cards and cards only open at the moment of application respectively.Panels (e) and (f) represent the effect on a dummy variable indicating whether the applicant incurred in default for all cards and cards only open at the moment of application respectively.

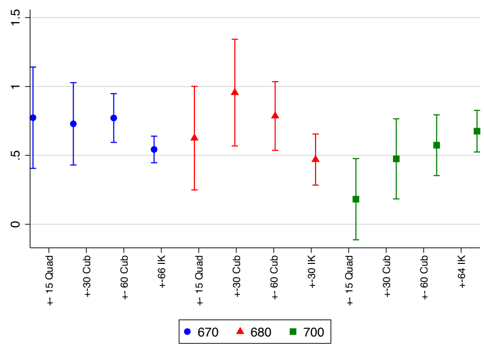
Figure D.2: Robustness of Interacted Results on Different Measures of Delinquency



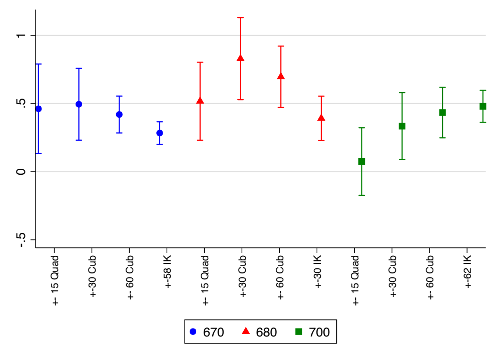
(a) #CC Ever with 2 Month Delinquency †



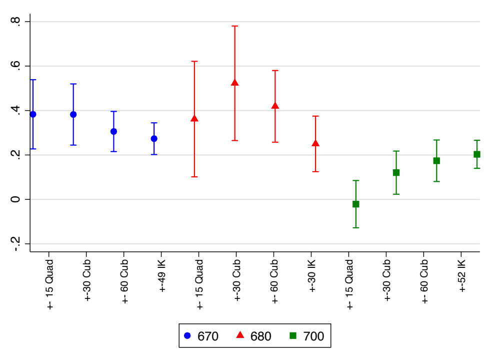
(b) #CC Ever with 2 Month Delinquency ‡



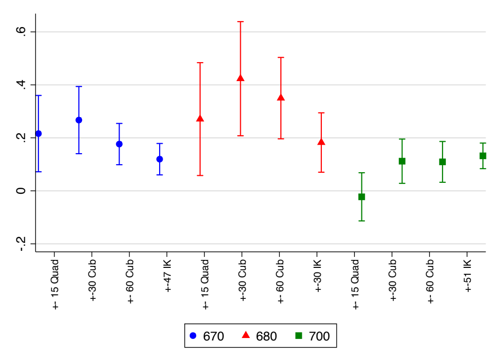
(c) #CC Ever in Default †



(d) #CC Ever in Default ‡



(e) Probability of CC Default †



(f) Probability of CC Default ‡

Notes: The figures presents the effect of Approval on different measures of delinquency and default, using different polynomials (quadratic and cubic), different ranges above the cutoff (15, 30, 60) and those obtained from a local linear regression with optimal bandwidths provided by **?**. Each color represents a different cutoff. Panels (a) and (b) represent the effect on the number of credit cards ever in 2 month delinquency for all cards and cards only open at the moment of application respectively. Panels (c) and (d) represent the effect on the number of cards in default for all cards and cards only open at the moment of application respectively.Panels (e) and (f) represent the effect on a dummy variable indicating whether the applicant incurred in default for all cards and cards only open at the moment of application respectively.

E Distributional Effects

Table E.1: Distributional Effects on Total Credit Card Debt

	Probability of debt over 25th percentile V^1	Probability of debt over 25th percentile V^2	Probability of debt over 50th percentile V^1	Probability of debt over 50th percentile V^2	Probability of debt over 75th percentile V^1	Probability of debt over 75th percentile V^2	Probability of debt over 90th percentile V^1	Probability of debt over 90th percentile V^2
Panel A: OLS								
Pooled cutoffs	0.0635***	-0.00735	0.0735***	-0.00783	0.0206	-0.0222**	0.00705	-0.0189
	(0.0135)	(0.0128)	(0.0141)	(0.0125)	(0.0167)	(0.0111)	(0.0138)	(0.0115)
Above cutoff 670	0.00555	-0.0813*	-0.00140	-0.0807**	0.0284	-0.0414	0.0158	-0.0194
	(0.0367)	(0.0424)	(0.0408)	(0.0310)	(0.0253)	(0.0262)	(0.0278)	(0.0228)
Above cutoff 680	0.0574***	0.0154	0.0838***	0.0199	-0.0276	-0.0828***	-0.00228	-0.0173
	(0.0172)	(0.0136)	(0.0274)	(0.0225)	(0.0198)	(0.0267)	(0.0138)	(0.0116)
Above cutoff 700	0.0804***	0.00495	0.0871***	-0.00153	0.0333	0.00795	0.00407	-0.0223
	(0.0265)	(0.0134)	(0.0173)	(0.0149)	(0.0261)	(0.0203)	(0.0239)	(0.0165)
Panel B: IV								
Pooled cutoffs	0.145***	-0.0168	0.168***	-0.0178	0.0469	-0.0505**	0.0161	-0.0431*
	(0.0322)	(0.0285)	(0.0350)	(0.0283)	(0.0386)	(0.0245)	(0.0313)	(0.0253)
Approved 670	0.0131	-0.173**	-0.00204	-0.172***	0.0606	-0.0880*	0.0335	-0.0414
	(0.0776)	(0.0796)	(0.0857)	(0.0550)	(0.0568)	(0.0514)	(0.0604)	(0.0456)
Approved 680	0.147***	0.0392	0.215***	0.0508	-0.0703	-0.212***	-0.00578	-0.0443
	(0.0444)	(0.0351)	(0.0730)	(0.0576)	(0.0524)	(0.0786)	(0.0350)	(0.0281)
Approved 700	0.183***	0.0116	0.198***	-0.00290	0.0764	0.0190	0.0101	-0.0500
	(0.0597)	(0.0301)	(0.0394)	(0.0337)	(0.0587)	(0.0459)	(0.0542)	(0.0378)
Panel C: Means [-5;-1] from cutoff								
Pooled	0.526	0.382	0.406	0.284	0.243	0.161	0.104	0.0703
670	0.505	0.400	0.389	0.305	0.207	0.160	0.0923	0.0725
680	0.534	0.479	0.397	0.346	0.238	0.191	0.0814	0.0704
700	0.529	0.333	0.414	0.249	0.257	0.148	0.119	0.0696
N	32291	32291	32291	32291	32291	32291	32291	32291
Panel D: Joint Testing (p-values)								
670 = 680 = 700	0.277	0.0808	0.140	0.0806	0.0728	0.0314	0.779	0.962
670 = 680	0.130	0.0271	0.0512	0.0267	0.0908	0.395	0.589	0.942
680 = 700	0.537	0.593	0.921	0.331	0.0587	0.0191	0.776	0.782
670 = 700	0.154	0.0615	0.0878	0.0377	0.904	0.151	0.795	0.921

Notes: This table reports the RD estimates on defaulted debt on all cards opened before the application and still open after the bank's decision. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In columns (1) the dependent variable is the logarithm of the total defaulted debt in all active CC in December 2012. In columns (2) and (3) the dependent variables are the share of CC with a defaulted debt larger than 2000 MXN (column (2) includes all active CC in December 2012 and column (3) keeps only those which were open before the application). In columns (4) and (5) the dependent variables are the share of CC with a defaulted debt larger than 6000 MXN (column (4) includes all active CC in December 2012 and column (5) keeps only those which were open before the application). All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis.

Table E.2: Distributional Effects on Total Credit Card Limit

	Total limit Over 25th percentile V^1	Total limit Over 25th percentile V^2	Total limit Over 50th percentile V^1	Total limit Over 50th percentile V^2	Total limit Over 75th percentile V^1	Total limit Over 75th percentile V^2	Total limit Over 90th percentile V^1	Total limit Over 90th percentile V^2
				Panel A: OLS				
Pooled cutoffs	0.0601***	-0.0273***	0.0668***	-0.0305***	0.0508***	-0.0110	0.0152*	-0.0224***
	(0.0106)	(0.00986)	(0.0138)	(0.00955)	(0.0106)	(0.00906)	(0.00878)	(0.00628)
Above cutoff 670	0.0985***	-0.0327	0.160***	-0.00106	0.0813**	-0.00999	0.0266	-0.0166
	(0.0322)	(0.0327)	(0.0361)	(0.0350)	(0.0342)	(0.0411)	(0.0211)	(0.0248)
Above cutoff 680	0.0437	-0.00448	0.0504*	-0.00121	0.0466***	-0.0155	-0.00206	-0.0246*
	(0.0311)	(0.0208)	(0.0264)	(0.0190)	(0.0169)	(0.0189)	(0.0144)	(0.0123)
Above cutoff 700	0.0502*	-0.0351**	0.0386	-0.0565***	0.0349*	-0.0149	0.0137	-0.0246**
	(0.0271)	(0.0143)	(0.0240)	(0.0163)	(0.0206)	(0.0173)	(0.0191)	(0.0115)
				Panel B: IV				
Pooled cutoffs	0.137***	-0.0622***	0.152***	-0.0695***	0.116***	-0.0251	0.0346*	-0.0511***
	(0.0240)	(0.0232)	(0.0294)	(0.0221)	(0.0234)	(0.0203)	(0.0199)	(0.0143)
Approved 670	0.211***	-0.0699	0.341***	-0.00276	0.173**	-0.0214	0.0566	-0.0355
	(0.0740)	(0.0679)	(0.0894)	(0.0736)	(0.0819)	(0.0855)	(0.0446)	(0.0527)
Approved 680	0.112	-0.0116	0.129**	-0.00337	0.119**	-0.0397	-0.00518	-0.0631**
	(0.0787)	(0.0530)	(0.0623)	(0.0479)	(0.0469)	(0.0492)	(0.0365)	(0.0320)
Approved 700	0.114*	-0.0797**	0.0876	-0.128***	0.0801*	-0.0330	0.0323	-0.0551**
	(0.0620)	(0.0332)	(0.0542)	(0.0395)	(0.0454)	(0.0395)	(0.0433)	(0.0265)
				Panel C: Means [-5;-1] from cutoff				
Pooled	0.671	0.514	0.531	0.377	0.310	0.197	0.161	0.0987
670	0.620	0.508	0.437	0.349	0.235	0.178	0.121	0.0879
680	0.645	0.588	0.495	0.413	0.255	0.200	0.119	0.0923
700	0.699	0.482	0.578	0.370	0.360	0.201	0.192	0.105
N	32291	32291	32291	32291	32291	32291	32291	32291
				Panel D: Joint Testing (p-values)				
670 = 680 = 700	0.352	0.527	0.00961	0.125	0.628	0.995	0.470	0.961
670 = 680	0.241	0.424	0.00334	0.997	0.394	0.920	0.260	0.779
680 = 700	0.906	0.313	0.765	0.0489	0.667	0.979	0.560	0.999
670 = 700	0.267	0.951	0.0147	0.211	0.340	0.924	0.715	0.804

Notes: This table reports the RD estimates on defaulted debt on all cards opened before the application and still open after the bank's decision. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In columns (1) the dependent variable is the logarithm of the total defaulted debt in all active CC in December 2012. In columns (2) and (3) the dependent variables are the share of CC with a defaulted debt larger than 2000 MXN (column (2) includes all active CC in December 2012 and column (3) keeps only those which were open before the application). In columns (4) and (5) the dependent variables are the share of CC with a defaulted debt larger than 6000 MXN (column (4) includes all active CC in December 2012 and column (5) keeps only those which were open before the application). All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis.

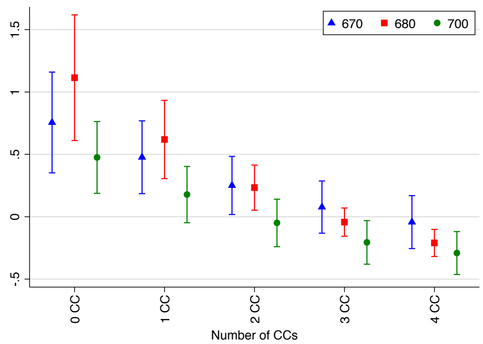
F Regression Discontinuity Estimates of the Effect of Approval on Different Measures of Delinquency by Number of Active Credit Cards at Application – IV Results

Table F.1: Regression Discontinuity Estimates of the Effect of Approval on Different Measures of Delinquency by Number of Active Credit Cards at Application – IV Results

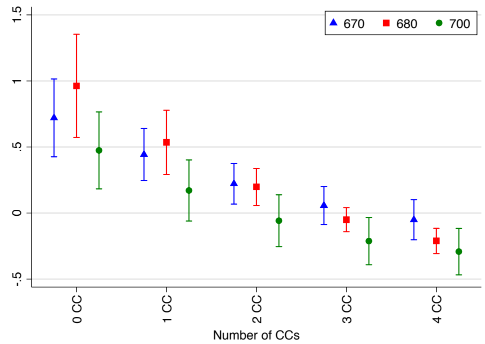
	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
				Panel A: Pooled					
	0.648***	0.301***	0.106***	0.628***	0.246***	0.110***	-0.119	-0.00722	-0.0660
	(0.124)	(0.0427)	(0.0333)	(0.120)	(0.0427)	(0.0342)	(0.181)	(0.0534)	(0.0404)
$\times(\#CC$ before)	-0.367***	-0.153***	-0.0812***	-0.368***	-0.140***	-0.0813***	0.0607	0.0126	0.0318**
	(0.0534)	(0.0176)	(0.0136)	(0.0510)	(0.0166)	(0.0132)	(0.0509)	(0.0165)	(0.0125)
$\times(\#CC$ before$)^2$	0.0375***	0.0138***	0.00848***	0.0383***	0.0137***	0.00853***	-0.00578	-0.000594	-0.00257**
	(0.00674)	(0.00204)	(0.00156)	(0.00640)	(0.00187)	(0.00154)	(0.00446)	(0.00148)	(0.00107)
. Var.	0.38	0.22	0.15	0.34	0.20	0.14	0.48	0.27	0.14
p. Var.	1.62	1.62	1.62	1.62	1.62	1.62	1.62	1.62	1.62
				Panel A: 670					
	0.756***	0.470***	0.332***	0.720***	0.378***	0.272***	0.321	0.188*	0.138
	(0.246)	(0.113)	(0.106)	(0.179)	(0.0832)	(0.0882)	(0.423)	(0.114)	(0.104)
$\times(\#CC$ before)	-0.305***	-0.227***	-0.168***	-0.306***	-0.199***	-0.152***	-0.0807	-0.0314	-0.0179
	(0.105)	(0.0370)	(0.0352)	(0.0954)	(0.0321)	(0.0320)	(0.133)	(0.0408)	(0.0336)
$\times(\#CC$ before$)^2$	0.0264	0.0234***	0.0187***	0.0282*	0.0215***	0.0174***	0.0122	0.00445	0.00248
	(0.0165)	(0.00471)	(0.00407)	(0.0154)	(0.00433)	(0.00380)	(0.0146)	(0.00470)	(0.00357)
. Var.	0.33	0.22	0.16	0.29	0.20	0.15	0.52	0.29	0.15
p. Var.	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47
				Panel B: 680					
	1.115***	0.598***	0.217**	0.962***	0.525***	0.236**	0.0753	0.183	-0.0163
	(0.306)	(0.171)	(0.0983)	(0.238)	(0.158)	(0.100)	(0.409)	(0.146)	(0.0832)
$\times(\#CC$ before)	-0.550***	-0.305***	-0.138***	-0.471***	-0.264***	-0.136***	0.00280	-0.0525	0.0205
	(0.137)	(0.0745)	(0.0439)	(0.107)	(0.0673)	(0.0430)	(0.164)	(0.0637)	(0.0369)
$\times(\#CC$ before$)^2$	0.0547***	0.0318***	0.0158***	0.0444***	0.0266***	0.0152***	-0.00130	0.00544	-0.00170
	(0.0160)	(0.00850)	(0.00491)	(0.0122)	(0.00762)	(0.00469)	(0.0168)	(0.00682)	(0.00391)
. Var.	0.19	0.12	0.09	0.15	0.10	0.07	0.28	0.18	0.10
p. Var.	1.52	1.52	1.52	1.52	1.52	1.52	1.52	1.52	1.52
				Panel C: 700					
	0.475***	0.166***	-0.00106	0.474***	0.121**	0.0158	-0.371	-0.135*	-0.163***
	(0.175)	(0.0612)	(0.0459)	(0.177)	(0.0590)	(0.0419)	(0.239)	(0.0755)	(0.0551)
$\times(\#CC$ before)	-0.333***	-0.108***	-0.0513***	-0.341***	-0.101***	-0.0540***	0.129**	0.0342*	0.0485***
	(0.0659)	(0.0204)	(0.0147)	(0.0631)	(0.0191)	(0.0134)	(0.0607)	(0.0197)	(0.0145)
$\times(\#CC$ before$)^2$	0.0354***	0.00963***	0.00564***	0.0373***	0.0103***	0.00591***	-0.0114**	-0.00224	-0.00378***
	(0.00814)	(0.00197)	(0.00146)	(0.00760)	(0.00181)	(0.00139)	(0.00506)	(0.00162)	(0.00121)
. Var.	0.48	0.26	0.18	0.43	0.24	0.16	0.57	0.30	0.16
p. Var.	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71	1.71
	32258	32258	32258	32258	32258	32258	32258	32258	32258
				Panel D: Joint Testing (p-values)					
$80 = 700$	0.220	0.009	0.013	0.215	0.004	0.011	0.280	0.046	0.038
80	0.179	0.418	0.852	0.176	0.423	0.972	0.631	0.578	0.559
00	0.471	0.098	0.181	0.424	0.127	0.184	0.675	0.033	0.041
00	0.177	0.039	0.015	0.157	0.033	0.016	0.319	0.057	0.070

s table reports the RD estimates on default on all cards which were open at the moment of application or at some other time after the application. It consists in an IV instrumenting approval as above the cutoff and also interacting it with the number of cards. The regression is splitter for different cutoffs. The sample consists of all with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. In column (1) the dependent variable is the number of total credit vere 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating e applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from nt in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever ince the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are similarly defined as (4) (6) t represent credit lines other than credit cards. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and nber of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis.

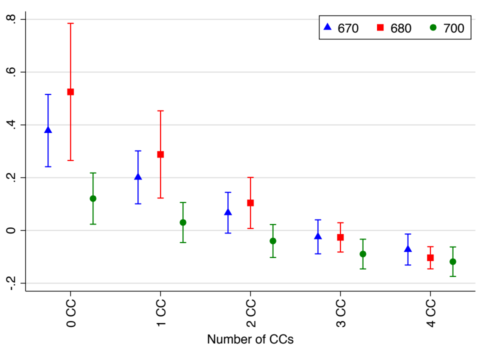
Figure F.1: Regression Discontinuity Estimates of the Effect of Approval on Different Measures of
Delinquency by Number of Active Credit Cards at Application – IV Results



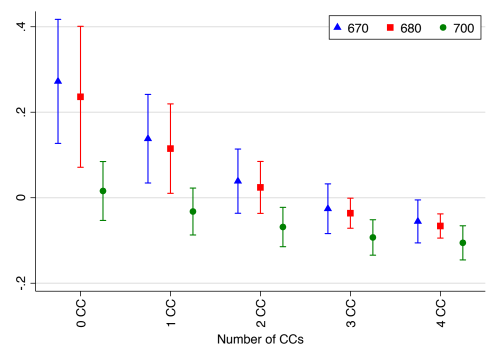
(a) $\#CC$ Ever with 2 Month Delinquency



(b) $\#CC$ Ever in Default



(c) Probability of CC Default



(d) Share of CC in Default

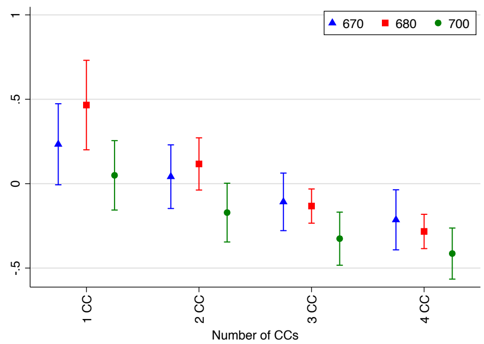
Notes: This panel shows the regression discontinuity estimates of the effect of approval on different measures of delinquency by number of active credit cards at application. Each color represents the estimation for a different cutoff. Panel (a) represents the number of cards ever in 2 months delinquency. Panel (b) represents the number of cards ever in default. Panel (c) represents an indicator variable of wether the person ever had a card in default. Panel (d) represents the share of cards in default.

Table F.2: Effect of Approval on Different Measures of Delinquency
on Credit Cards Active at the Moment of Application Only by Number of Active Credit Cards at Application – IV Results

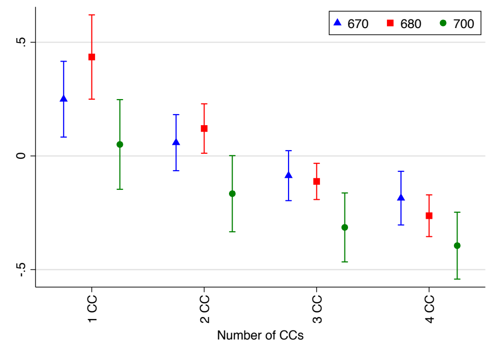
	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
Panel A: Pooled									
Approved	0.469***	0.232***	0.144***	0.471***	0.202***	0.136***	0.101	0.0528	0.0106
	(0.113)	(0.0432)	(0.0333)	(0.106)	(0.0399)	(0.0314)	(0.114)	(0.0423)	(0.0407)
Approved×($\#CC$ before)	-0.341***	-0.140***	-0.0913***	-0.338***	-0.133***	-0.0872***	-0.00545	-0.00267	0.0146
	(0.0468)	(0.0172)	(0.0135)	(0.0434)	(0.0160)	(0.0128)	(0.0328)	(0.0140)	(0.0122)
Approved×($\#CC$ before)^2	0.0343***	0.0132***	0.00936***	0.0345***	0.0133***	0.00903***	0.0000767	0.000221	-0.00123
	(0.00593)	(0.00195)	(0.00161)	(0.00548)	(0.00177)	(0.00153)	(0.00313)	(0.00139)	(0.00108)
Mean Dep. Var.	0.29	0.18	0.14	0.25	0.16	0.12	0.31	0.21	0.14
Mean Indep. Var.	1.62	1.62	1.62	1.62	1.62	1.62	1.62	1.62	1.62
Panel A: 670									
Approved	0.468**	0.261***	0.267***	0.487***	0.265***	0.253***	0.330	0.187*	0.142*
	(0.209)	(0.0982)	(0.0828)	(0.159)	(0.0774)	(0.0661)	(0.296)	(0.0969)	(0.0801)
Approved×($\#CC$ before)	-0.256***	-0.153***	-0.132***	-0.260***	-0.151***	-0.131***	-0.0666	-0.0197	-0.00667
	(0.0974)	(0.0345)	(0.0281)	(0.0889)	(0.0315)	(0.0248)	(0.100)	(0.0353)	(0.0305)
Approved×($\#CC$ before)^2	0.0214	0.0162***	0.0150***	0.0231	0.0166***	0.0151***	0.00874	0.00219	0.000659
	(0.0157)	(0.00453)	(0.00346)	(0.0147)	(0.00427)	(0.00313)	(0.0112)	(0.00420)	(0.00342)
Mean Dep. Var.	0.26	0.18	0.15	0.23	0.17	0.14	0.39	0.26	0.17
Mean Indep. Var.	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47	1.47
Panel B: 680									
Approved	0.914***	0.504***	0.245**	0.832***	0.424***	0.243***	0.206	0.118	0.0506
	(0.258)	(0.157)	(0.0992)	(0.182)	(0.131)	(0.0896)	(0.228)	(0.145)	(0.0925)
Approved×($\#CC$ before)	-0.498***	-0.276***	-0.151***	-0.437***	-0.229***	-0.141***	-0.0509	-0.0302	-0.00388
	(0.116)	(0.0677)	(0.0429)	(0.0845)	(0.0564)	(0.0382)	(0.0972)	(0.0632)	(0.0401)
Approved×($\#CC$ before)^2	0.0496***	0.0292***	0.0172***	0.0409***	0.0233***	0.0156***	0.00456	0.00320	0.00100
	(0.0137)	(0.00772)	(0.00486)	(0.00983)	(0.00645)	(0.00425)	(0.0101)	(0.00676)	(0.00420)
Mean Dep. Var.	0.18	0.12	0.09	0.14	0.10	0.07	0.24	0.18	0.11
Mean Indep. Var.	1.52	1.52	1.52	1.52	1.52	1.52	1.52	1.52	1.52
Panel C: 700									
Approved	0.336**	0.153***	0.0718	0.335**	0.112**	0.0583	-0.0401	-0.0209	-0.0556
	(0.157)	(0.0567)	(0.0441)	(0.149)	(0.0509)	(0.0429)	(0.151)	(0.0672)	(0.0540)
Approved×($\#CC$ before)	-0.320***	-0.109***	-0.0671***	-0.319***	-0.105***	-0.0617***	0.0357	0.00749	0.0251*
	(0.0567)	(0.0186)	(0.0133)	(0.0521)	(0.0171)	(0.0129)	(0.0383)	(0.0188)	(0.0141)
Approved×($\#CC$ before)^2	0.0331***	0.0101***	0.00684***	0.0341***	0.0108***	0.00651***	-0.00356	-0.000640	-0.00206*
	(0.00725)	(0.00185)	(0.00145)	(0.00656)	(0.00170)	(0.00134)	(0.00357)	(0.00171)	(0.00120)
Mean Dep. Var.	0.3	0.2	0.2	0.3	0.2	0.1	0.3	0.2	0.1
Mean Indep. Var.	1.7	1.7	1.7	1.7	1.7	1.7	1.7	1.7	1.7
N	32258	32258	32258	32258	32258	32258	32258	32258	32258
Panel D: Joint Testing (p-values)									
$670 = 680 = 700$	0.449	0.142	0.112	0.294	0.085	0.107	0.636	0.314	0.218
$670 = 680$	0.323	0.206	0.391	0.296	0.214	0.546	0.725	0.399	0.297
$680 = 700$	0.380	0.112	0.253	0.223	0.134	0.190	0.746	0.660	0.516
$670 = 700$	0.381	0.694	0.141	0.217	0.404	0.064	0.588	0.081	0.069

Notes: This table reports the RD estimates on default on all cards which were active at the moment of the application. It consists in an IV regression instrumenting approval as above the cutoff and also interacting it with the number of cards. The regression is splitter for different cutoffs. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. In column (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating whether the applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from the applicant in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever in default since the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are similarly defined as (4) (6) and (7), but represent credit lines other than credit cards. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis.

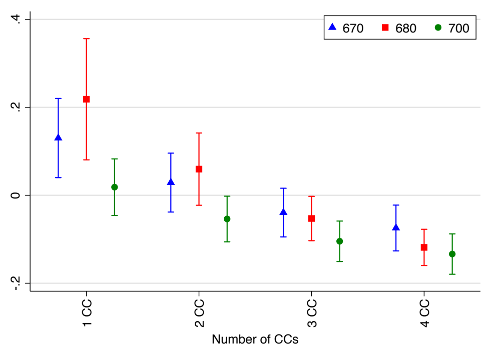
Figure F.2: Effect of Approval on Different Measures of Delinquency on Credit Cards Active at the
Moment of Application Only by Number of Active Credit Cards at Application – IV Results



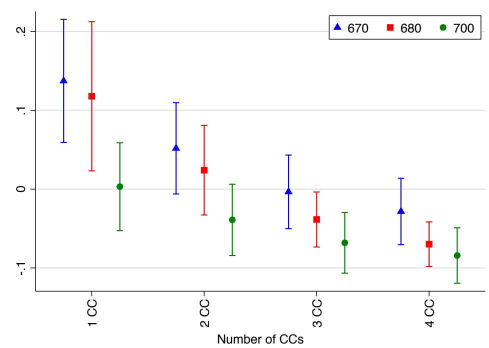
(a) $\#CC$ Ever with 2 Month Delinquency



(b) $\#CC$ Ever in Default



(c) Probability of CC Default



(d) Share of CC in Default

Notes: This panel shows the regression discontinuity estimates of the effect of approval on different measures of delinquency on the cards which were already active at the moment of application by number of active credit cards at application. Each color represents the estimation for a different cutoff. Panel (a) represents the number of cards ever in 2 months delinquency which were active at the moment of application. Panel (b) represents the number of cards ever in default which were active at the moment of application. Panel (c) represents an indicator variable of wether the person ever had a card in default from the cards which were active at the moment of application. Panel (d) represents the share of cards in default from the cards which were active at the moment of application.

G Year and month dummies effects

Table G.1: Effect of year and month dummies on basic results

	Probability of Approval	$\#CC$ 30 Days After	Credit Limit in CC Dec 2012 (Log)	Debt in CC Dec 2012 (Log)	Total Debt (excluding CC) Dec 2012 (Log)	Total limit Over 50th percentile V^1	Total limit Over 50th percentile V^2	Probability of debt over 50th percentile V^1	Probability of debt over 50th percentile V^2
Panel A: OLS									
Pooled cutoffs	0.431***	0.410***	0.0473	0.0988***	0.0712	0.0675***	-0.0354***	0.0665***	-0.0122
	(0.0161)	(0.0278)	(0.0365)	(0.0342)	(0.0749)	(0.0141)	(0.0108)	(0.0141)	(0.0101)
Above cutoff 670	0.460***	0.446***	0.301***	0.170	0.211*	0.163***	-0.0466	0.0233	-0.0823**
	(0.0608)	(0.0511)	(0.0931)	(0.110)	(0.106)	(0.0361)	(0.0303)	(0.0387)	(0.0344)
Above cutoff 680	0.393***	0.383***	0.0361	0.158*	0.125	0.0502*	-0.0160	0.0579***	0.0143
	(0.0412)	(0.0561)	(0.0494)	(0.0790)	(0.151)	(0.0279)	(0.0189)	(0.0205)	(0.0128)
Above cutoff 700	0.434***	0.403***	-0.0389	0.0402	0.00206	0.0391	-0.0411**	0.0790***	-0.00338
	(0.0146)	(0.0332)	(0.0673)	(0.0495)	(0.0882)	(0.0240)	(0.0176)	(0.0255)	(0.0128)
Panel B: IV									
Pooled cutoffs		0.950***	0.113	0.234***	0.165	0.156***	-0.0822***	0.154***	-0.0284
		(0.0385)	(0.0873)	(0.0819)	(0.176)	(0.0307)	(0.0255)	(0.0354)	(0.0227)
Approved 670		0.970***	0.655***	0.370	0.454*	0.352***	-0.101*	0.0524	-0.177***
		(0.0451)	(0.203)	(0.239)	(0.244)	(0.0909)	(0.0613)	(0.0860)	(0.0638)
Approved 680		0.975***	0.0965	0.403**	0.317	0.128**	-0.0409	0.147***	0.0357
		(0.0560)	(0.126)	(0.188)	(0.384)	(0.0652)	(0.0485)	(0.0524)	(0.0320)
Approved 700		0.928***	-0.0790	0.101	0.00732	0.0903*	-0.0944**	0.181***	-0.00780
		(0.0691)	(0.155)	(0.112)	(0.201)	(0.0547)	(0.0406)	(0.0579)	(0.0291)
Panel C: Means [-5;-1] from cutoff									
Pooled cutoffs	0.02	1.63	7.36	6.67	7.66	0.53	0.53	0.58	0.45
670	0.01	1.43	6.83	6.40	7.85	0.44	0.52	0.57	0.48
680	0.00	1.52	7.07	6.31	7.77	0.49	0.60	0.59	0.55
700	0.03	1.75	7.66	6.92	7.55	0.57	0.50	0.58	0.40
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
Panel D: Joint Testing (p-values)									
$670 = 680 = 700$	0.586	0.608	0.0255	0.287	0.329	0.00595	0.420	0.568	0.0342
$670 = 680$	0.425	0.469	0.0112	0.941	0.670	0.00184	0.266	0.357	0.0108
$680 = 700$	0.308	0.768	0.409	0.170	0.347	0.783	0.426	0.579	0.379
$670 = 700$	0.684	0.322	0.0124	0.364	0.215	0.0144	0.890	0.306	0.0464

Notes: This table reports the RD on default on all cards open at some time between the application and Dec 2012 when including month and year dummies. Each dummy represents a particular month and year when the application was made. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. Here we include all credit cards that were active at the moment of the application and those opened lated. In column (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating whether the applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from the applicant in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever in default since the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are just as (4) (6) and (7) but represent credit lines different than credit cards, rather than CC. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table G.2: Effect of year and month dummies on basic results for credit lines open before and after the bank's decision

	$\#CC$ Ever with 2 Month Delinquency	Probability of CC ever with 2 Month Delinquency	Share of CC everwith 2 Month Delinquency	$\#CC$ Ever in Default	Probability of CC Default	Share of CC in Default	# Credit Lines Ever in Default - Excl. CC	Probability of credit lines Default - Excl. CC	Share of credit lines in Default - Excl. CC
Panel A: OLS									
Pooled cutoffs	0.0833***	0.0412***	0.000376	0.0761***	0.0282***	0.00222	-0.0192	0.00600	-0.00942
	(0.0289)	(0.0104)	(0.00747)	(0.0272)	(0.0106)	(0.00792)	(0.0521)	(0.0145)	(0.0113)
Above cutoff 670	0.189**	0.109***	0.0736**	0.175***	0.0817***	0.0541**	0.128	0.0810**	0.0606*
	(0.0758)	(0.0339)	(0.0316)	(0.0467)	(0.0232)	(0.0237)	(0.140)	(0.0363)	(0.0338)
Above cutoff 680	0.111***	0.0577***	0.00865	0.0925***	0.0513***	0.0161	0.0310	0.0437**	0.00830
	(0.0290)	(0.0177)	(0.0130)	(0.0266)	(0.0180)	(0.0136)	(0.0663)	(0.0201)	(0.0127)
Above cutoff 700	0.0397	0.0109	-0.0282**	0.0387	0.000192	-0.0223*	-0.0867	-0.0354	-0.0410**
	(0.0473)	(0.0171)	(0.0132)	(0.0495)	(0.0173)	(0.0123)	(0.0721)	(0.0222)	(0.0165)
Panel B: IV									
Pooled cutoffs	0.193***	0.0955***	0.000897	0.177***	0.0655***	0.00530	-0.0446	0.0139	-0.0219
	(0.0642)	(0.0238)	(0.0177)	(0.0597)	(0.0239)	(0.0187)	(0.120)	(0.0334)	(0.0262)
Approved 670	0.410**	0.236***	0.160**	0.379***	0.177***	0.118**	0.276	0.175**	0.131*
	(0.165)	(0.0750)	(0.0666)	(0.108)	(0.0543)	(0.0494)	(0.293)	(0.0754)	(0.0718)
Approved 680	0.283***	0.147***	0.0228	0.235***	0.130**	0.0415	0.0784	0.111**	0.0210
	(0.0953)	(0.0548)	(0.0340)	(0.0798)	(0.0527)	(0.0361)	(0.170)	(0.0562)	(0.0331)
Approved 700	0.0920	0.0256	-0.0634**	0.0896	0.000861	-0.0501*	-0.199	-0.0812	-0.0940**
	(0.109)	(0.0394)	(0.0301)	(0.114)	(0.0398)	(0.0281)	(0.166)	(0.0500)	(0.0373)
Panel C: Means [-5;-1] from cutoff									
Pooled cutoffs	0.37	0.21	0.15	0.32	0.19	0.14	0.50	0.27	0.15
670	0.30	0.20	0.15	0.26	0.19	0.14	0.52	0.29	0.16
680	0.17	0.11	0.09	0.14	0.09	0.07	0.28	0.18	0.10
700	0.48	0.26	0.19	0.43	0.24	0.17	0.59	0.30	0.17
N	32291	32291	32291	32291	32291	32291	32291	32291	32291
Panel D: Joint Testing (p-values)									
$670 = 680 = 700$	0.124	0.0114	0.0115	0.0861	0.00506	0.00672	0.0745	0.00750	0.00390
$670 = 680$	0.405	0.254	0.0964	0.200	0.406	0.220	0.606	0.386	0.195
$680 = 700$	0.303	0.102	0.0817	0.436	0.0546	0.0646	0.218	0.00279	0.00381
$670 = 700$	0.0544	0.00876	0.00657	0.0305	0.00468	0.00455	0.125	0.0211	0.0158

Notes: This table reports the RD estimates on default on all cards opened before the application and still open after the bank's decision when including month and year dummies. Each dummy represents a particular month and year when the application was made.. Panel A presents the OLS results for each subsample, while Panel B presents the IV results for each subsample. The sample consists of all applicants with standardized credit score at most 30 points above or 30 points below of their respective cutoff value. We include all credit cards that were active at the moment of the application and those opened lated. In column (1) the dependent variable is the number of total credit cards that were 2 month delinquent at any point in time since the date of the application to December 2012. In column (2) the dependent variables is an indicator variable indicating whether the applicant incurred in a 2 month delinquency in any of his/her credit cards since the date of application. In column (3) the dependent variables is the share of cards from the applicant in which he/she incurred in a 2 month delinquency since the date of application. In column (4) the dependent variable is the number of total credit cards that were ever in default since the date of application. In column (5) the dependent variables is an indicator variable indicating whether the applicant defaulted in any of his/her credit cards since the date of application. The dependent variable in column (6) is the share of credit cards default since the date of application. Columns (7) (8) and (9) are similarly defined as (4) (6) and (7), but represent credit lines other than credit cards. All columns control for a third order polynomial, allowing for a discontinuity of the standardized score at the value of 0 and for the number of credit cards available at the moment of the application. Clustered standard errors at the credit score level reported in parenthesis. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Table H.1: Percentage of credit lines defaulted when default occurs

Number of credits during application	Defaulted credits after 3 months	Defaulted credits after 6 months	Defaulted credits after 12 months	N
1	100%	100%	100%	25
2	58%	60%	63%	149
3	48%	50%	52%	294
4	38%	42%	45%	369
5	33%	37%	40%	364
6	28%	33%	36%	388
7	30%	35%	39%	326
8	27%	31%	33%	220
9	25%	29%	34%	176
10	25%	29%	34%	140
11	27%	31%	34%	97
12	23%	26%	29%	70

Notes: This table focuses on those applicants that (a) got their application accepted, and (b) defaulted on some credit after being approved at some time up until Dec 2012 (i.e. post treatment). The table has one ro per group of people divided based on how many credits did they have during application. On the next columns we have the average percentage of credit lines each person defaulted on 3, 6, and 12 months after the first default.

H Default allocation

Table H.2: Default allocation

	Default 3 Months		Default 6 months		Default 12 months		Mean
Top credit	-0.0102		-0.00220		-0.000581		0.145
	(0.0100)		(0.0101)		(0.0101)		
Oldest line	0.0598***		0.0476***		0.0421***		0.0946
	(0.0122)		(0.0122)		(0.0123)		
5 most important banks	0.0571**	0.0527	0.0322	0.0431	0.0409	0.0503	0.0226
	(0.0252)	(0.0327)	(0.0253)	(0.0329)	(0.0254)	(0.0329)	
Secured loans	-0.0436**	-0.0259	-0.0409**	-0.0306	-0.0583***	-0.0554*	0.0513
	(0.0171)	(0.0302)	(0.0172)	(0.0304)	(0.0173)	(0.0304)	
Log credit limit		-0.0138***		-0.0124***		-0.0133***	8.322
		(0.00172)		(0.00173)		(0.00173)	
Log months old		0.00742***		0.00204		-0.00241	2.294
		(0.00287)		(0.00288)		(0.00289)	
Constant	0.293***	0.412***	0.337***	0.458***	0.371***	0.509***	
	(0.00387)	(0.0172)	(0.00389)	(0.0173)	(0.00390)	(0.0173)	
N	17575	11556	17575	11556	17575	11556	
Dependent mean	0.297	0.315	0.340	0.359	0.373	0.393	
R squared	0.231	0.325	0.278	0.361	0.302	0.381	

Notes: This table focuses on those applicants that (a) got their application accepted, and (b) defaulted on some credit after being approved at some time up until Dec 2012 (i.e. post treatment). The table contains regressions at a credit level where we try to find in which credits do applicants decide to default on. Columns 2, 4, and 6 have as independent variables 5 dummies: the maximal credit the person has, the oldest line, if the loan was provided by one of the 5 most important banks in the country and if the loan was a secured loan. The other columns replace the first two dummies with the log of the credit limit and the log of months that have passed since the credit was opened. The first two columns have, as dependent variables, which credits were defaulted on the first 3 months since the first default. The next 2 refer to the next 6 months since, and the last 2 columns account for all defaults on the first 12 months since the first default.