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

Appendix – For Online Publication

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Appendix A. Merging Procedure and Sample Selection

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

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

Appendix B. Variable Construction

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

Table B.1: List of Variables

Variable	Description	Source
Credit Score	Credit score computed by the Credit Bureau at the moment of application	Bank A
Income (MXN)	Monthly income	Social Security Admin.
Male	1 = Male; 0 = Female	Bank A
Tenure in Bureau (Years)	Number of years since entrance into Bureau's records	Credit Bureau
# of non-Bank A CC 30 days before	Number of non-bank A credit cards that are active 30 days before bank A made the approval decision	Credit Bureau
# of Active Credits 30 days before	Number of total credits and loans that are active 30 days before bank A made the approval decision	Credit Bureau

Variable	Description	Source
Total Debt (MXN)	Total outstanding debt in January 2010 in active credits that were not in default	Credit Bureau
Total Limit (MXN)	Total credit limit in January 2010 in active credits that were not in default	Credit Bureau
# CC in Default†	Number of credit cards in default before bank A's decision. Default is measured as a late payment beyond 90 days, partial or total debt not recovered, fraud committed by the client	Credit Bureau
Probability of CC in Default†	Indicator that the number of credit cards in default before bank A's decision is positive	Credit Bureau
Share of CC in Default†	Number of credit cards in default before bank A's decision as a fraction of number of credit cards that were active at some point before the decision	Credit Bureau
# CC in 2 Months Delinquency†	Number of credit cards with 2-months late payments before bank A's decision	Credit Bureau
Probability of CC in 2 Months Delinquency†	Indicator that the number of credit cards with 2-months late payments before bank A's decision is positive	Credit Bureau
Share of CC in 2 Months Delinquency†	Number of credit cards with 2-months late payments before bank A's decision as a fraction of number of credit cards that were active at some point before the decision	Credit Bureau
Approved	Indicator that bank A approved the application and granted a new credit card	Bank A
Amount Requested (MXN)	Amount requested by the applicant to be the credit limit of the potentially new credit card	Bank A
Approved Amount (MXN)**	Amount requested by the applicant to be the credit limit of the potentially new credit card, conditional on being approved	Bank A
$\#CC$ 1 Month After	# of Active credit cards 1 month after the application	Credit Bureau
$\#CC$ 6 Months After	# of Active credit cards 6 months after the application	Credit Bureau
$\#CC$ 12 Months After	# of Active credit cards 12 months after the application	Credit Bureau
$\#CC$ 18 Months After	# of Active credit cards 18 months after the application	Credit Bureau
# Credit Lines 6 Months After (Excl. CC)	# of Active credits (excluding credit cards) 6 months after the application	Credit Bureau
# Credit Lines 18 Months After (Excl. CC)	# of Active credits (excluding credit cards) 18 months after the application	Credit Bureau
Prob. of CC with 2M Delinq. (6 and 18 months)	Indicator that client had a 2-months late payment in any credit card within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Share of CC with 2M Delinq. (6 and 18 months)	Number of credit cards with 2-months late payment as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Prob. of CC in Default (6 and 18 months)	Indicator that client defaulted on any credit card within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Share of CC in Default (6 and 18 months)	Number of credit cards in default as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes credit cards active at application or opened later)	Credit Bureau
Prob. of CC with 2M Delinq. ‡ (18 months)	Indicator that client had a 2-months late payment in any credit card within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Share of CC with 2M Delinq. ‡ (18 months)	Number of credit cards with 2-months late payment as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Prob. of CC in Default ‡ (18 months)	Indicator that client defaulted on any credit card within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Share of CC in Default ‡ (18 months)	Number of credit cards in default as a fraction of the number of credit cards within the first 6 and 18 months after the application (it includes only credit cards active at application)	Credit Bureau
Prob. Of Credit Lines in Default Excl. CC † (18 months)	Indicator that client defaulted on any credit (excluding credit cards) within the first 18 months after the application (it includes credits active at application or opened later)	Credit Bureau
Share of Credit Lines in Default Excl. CC † (18 months)	Number of credits (excluding credit cards) in default as a fraction of the number of credits (excluding credit cards) within the first 18 months after the application (it includes credits active at application or opened later)	Credit Bureau
Prob. Of Credit Lines in Default Excl. CC ‡ (18 months)	Indicator that client defaulted on any credit (excluding credit cards) within the first 18 months after the application (it includes only credits active at application)	Credit Bureau

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

Appendix C. Context and Summary Statistics

C.1 The Mexican Credit Card Market

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

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

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

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

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

After a default episode, Bank A and most banks in Mexico do not go after debts smaller than 60,000-100,000 MXN, as collection costs are high and courts slow and ineffective. When faced with credit card default, banks in Mexico sell the defaulted debt to collection agencies at about 90% discount. Thus, defaults are highly costly for banks. On the other hand, the main cost of default a borrower faces is a negative credit history at the Credit Bureau. Castellanos et al. (2018) have found that a loan default in Mexico subtracts close to 100 points from credit scores and makes it much harder to get loans in the future.

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

C.3 Descriptive Statistics

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

We want to highlight a subset of statistics, starting with monthly income as reported to the Social Security administration. Income varies with the score: It is 11,055 MXN (about

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

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

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

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

660 USD) for the 670 applicants and 14,199 MXN for the 700 applicants. This means that when we talk about going after extra-marginal borrowers by offering loans to lower credit score applicants, it also means giving loans to lower income applicants.[27] This level of income would place our applicants' sample in the third quarter of the household income distribution in Mexico (INEGI (2012)). However, given the large variation in income, applicants kept in our estimation sample span a large portion of the Mexican income distribution, with most of the observations concentrated between the 5th to 8th higher deciles. From the CB data, we see that the population in the study has on average been in the Credit Bureau records for almost 8 years and has an average of 3.7 loans – these include personal loans, car loans, mortgages, credit cards, etc. Applicants in the 700 group have 39,021 MXN pesos in total outstanding debt, while those in the 670 set have 31,310 MXN. This means that our applicants use loans other than cards since the average credit card debt is 8,439 MXN (about 505 USD, not reported), about a quarter of total debt.

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

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

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

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

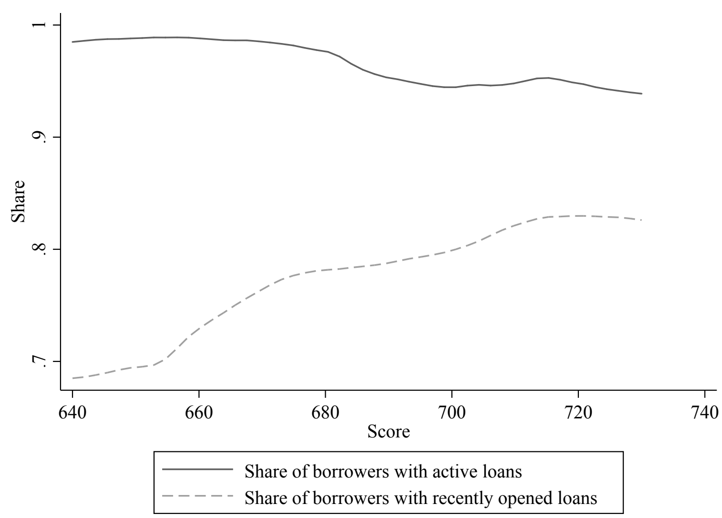
[29]A separate issue is that the CB by law has to delete defaulted loans from their dataset after some years as a function of default severity. If the defaulted debt is less than 113 MXN the bad credit history is deleted within a year, if it is between 113 and 2,260 MXN it is deleted after 2 years, those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

applicants requested 20,599 MXN, approved applications received on average a credit limit of 15,667 MXN (940 USD). The fact that people are applying, that they get 25% lower limits than requested, and that they accept interest rates of 37% per year (this number does not include fees, APRs are higher, not in table) may suggest that they are liquidity constrained. Note also that given that total debt is 36,579 (and the limit of credit lines is 47,977 MXN), card approval represents a substantial increase in borrowing opportunities.

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

C.4 Loans are frequently awarded below 670

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

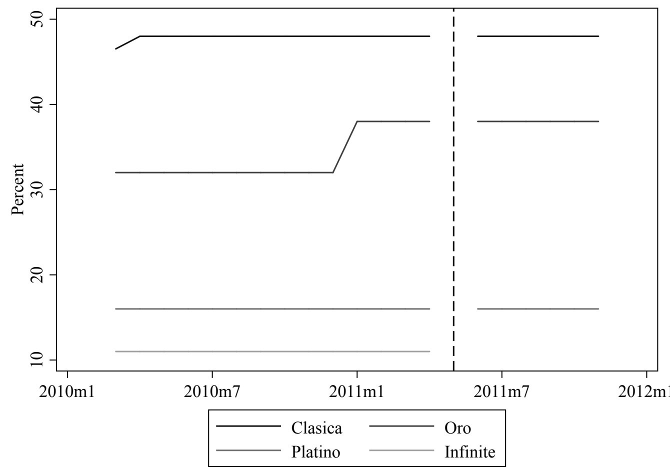


Notes: This figure plots the fraction of borrowers who have at least one active loan at the time of application (solid line)—i.e. a loan that is reported as open by the lender—and the fraction of borrowers with loans that were originated within 6 months of the application date (dashed line), as a function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

Appendix D. Additional Tables and Figures

D.1 Characteristics of Bank A's Credit Card

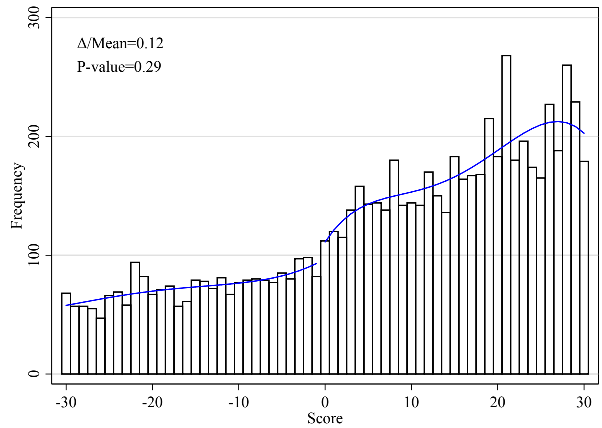
Figure D.1: Average Interest Rate over Time



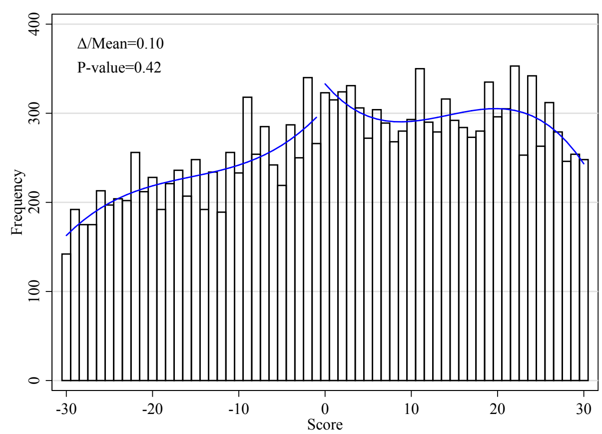
Notes: This figure shows the average interest rate charged by each type of credit card that Bank A offered to approved applicants. The sample consists of all applicants with standardized credit scores at most 30 points above or 30 points below their respective cutoff value. The vertical line denotes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

D.2 Smoothness tests

Figure D.2: The Distribution of Credit Scores



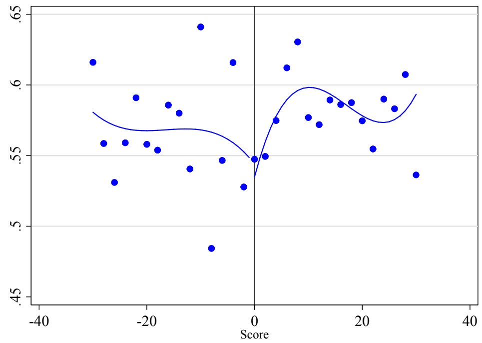
(a) 670 Sample



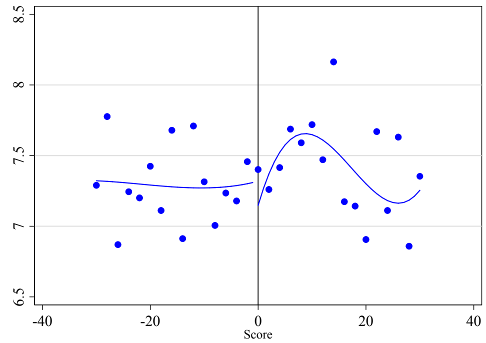
(b) 700 Sample

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

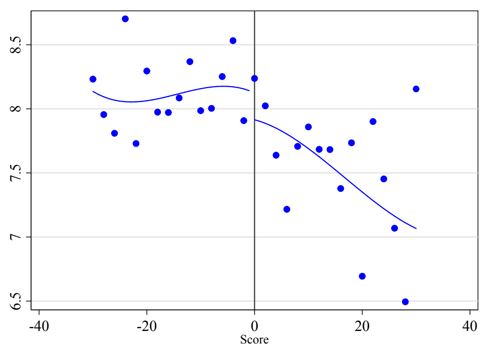
Figure D.3: Pre-Treatment Characteristics – 670 Sample



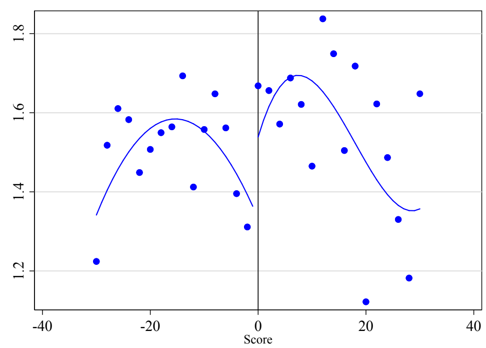
(a) % Male



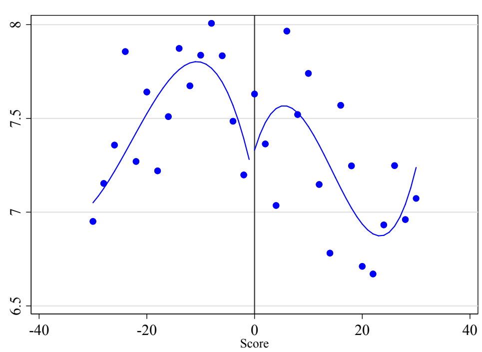
(b) Amount requested (Log)



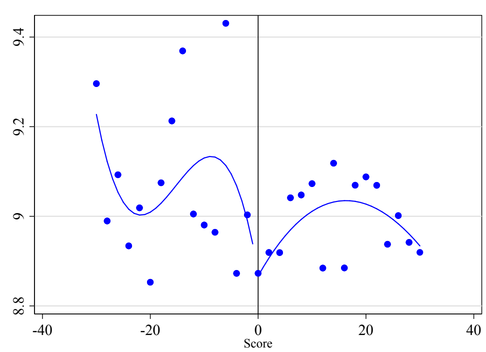
(c) Tenure in Bureau



(d) # CC 30 days before



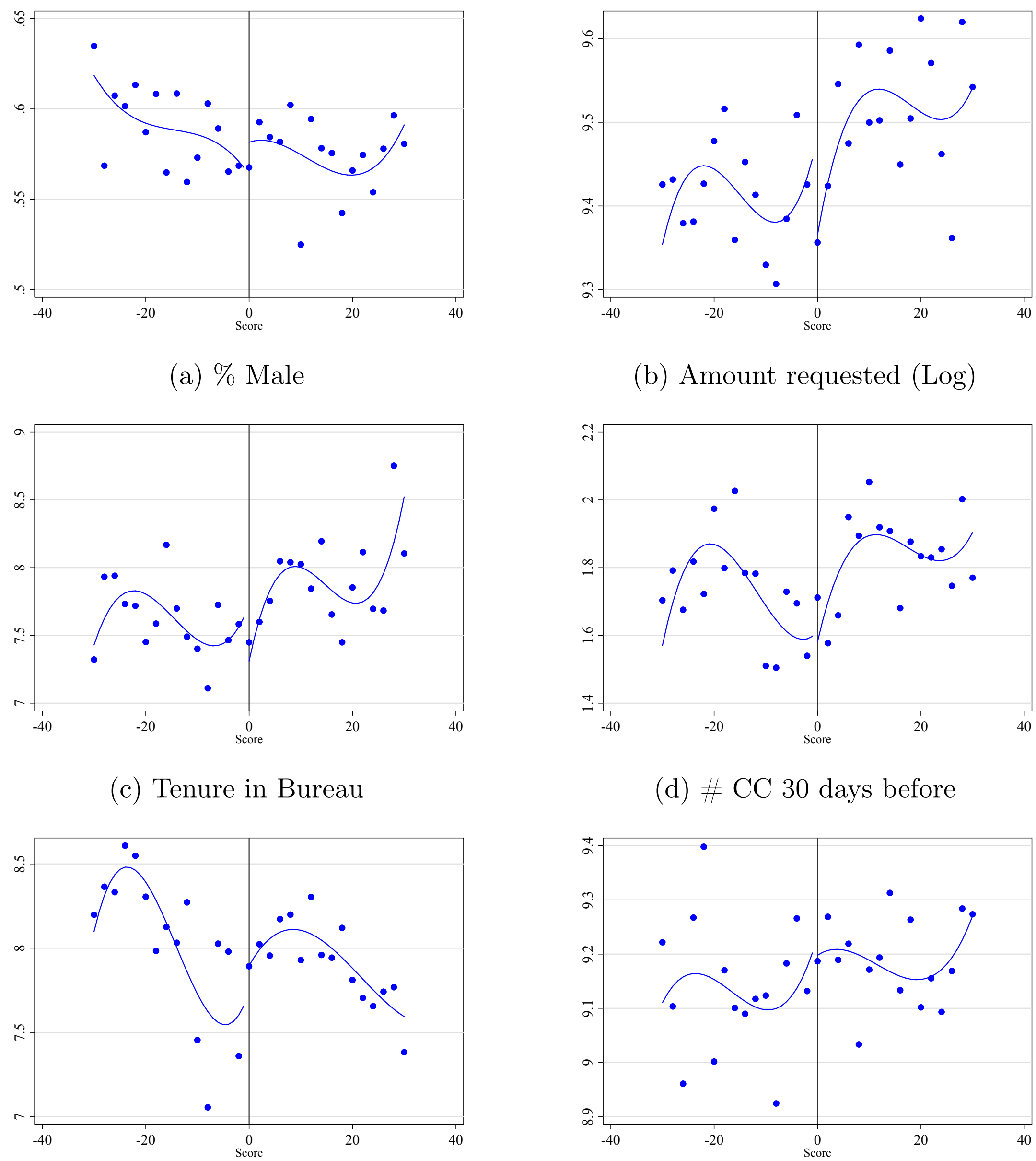
(e) Total debt (Log)



(f) Income (Log)

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

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



(a) % Male

(b) Amount requested (Log)

(c) Tenure in Bureau

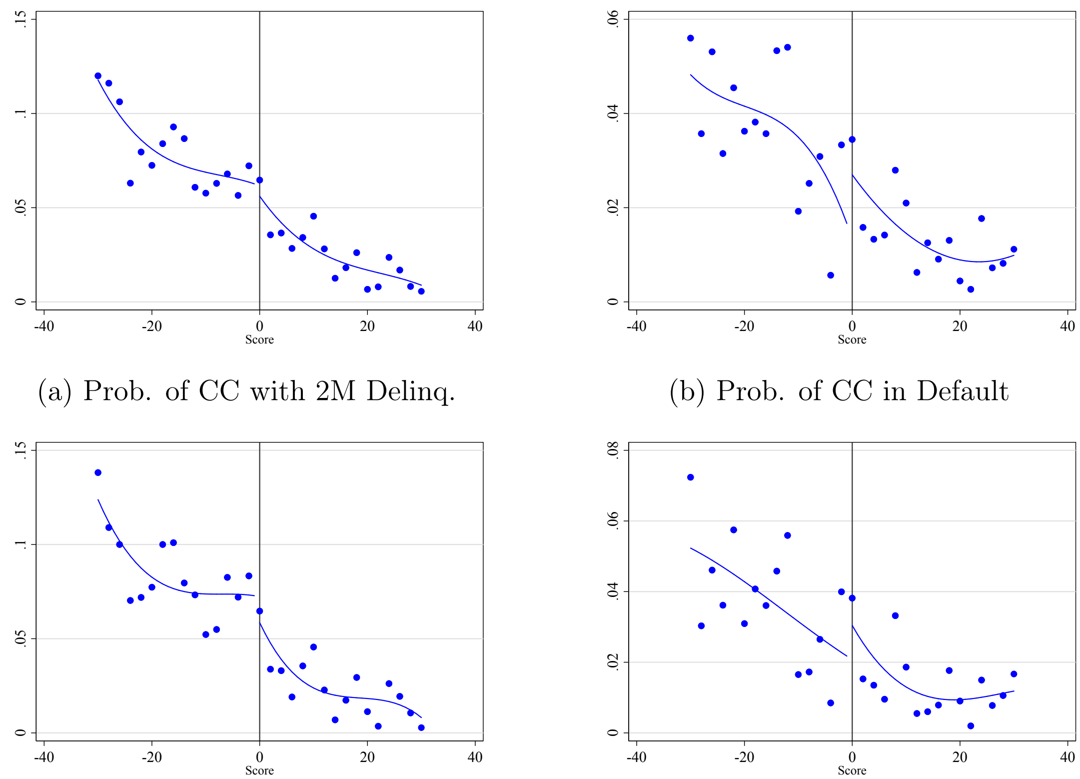
(d) # CC 30 days before

(e) Total debt (Log)

(f) Income (Log)

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

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

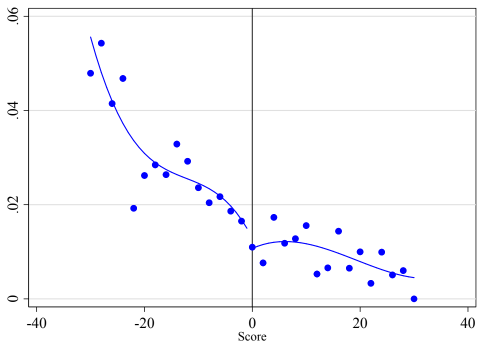


(a) Prob. of CC with 2M Delinq. (b) Prob. of CC in Default

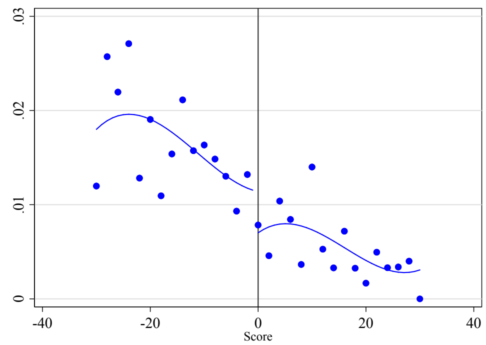
(c) Share of CC with 2M Delinq. (d) Share of CC in Default

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

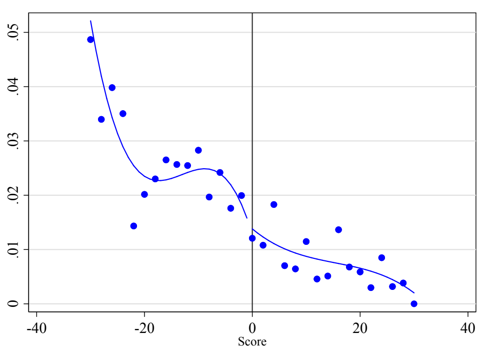
Figure D.6: Pre-Approval Outcome Variables – 700 Sample



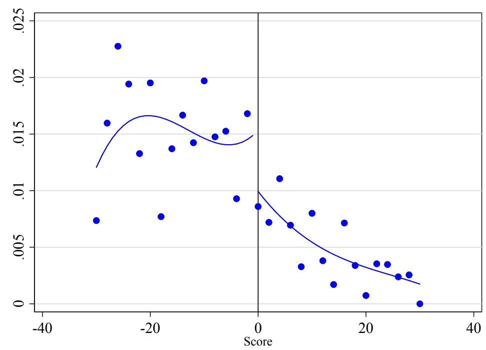
(a) Prob. of CC with 2M Delinq.



(b) Prob. of CC in Default



(c) Share of CC with 2M Delinq.

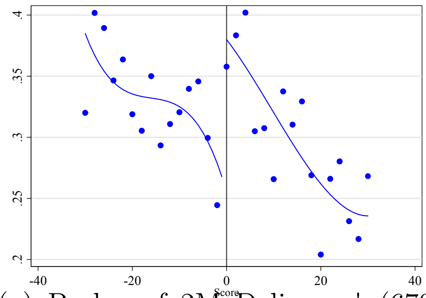


(d) Share of CC in Default

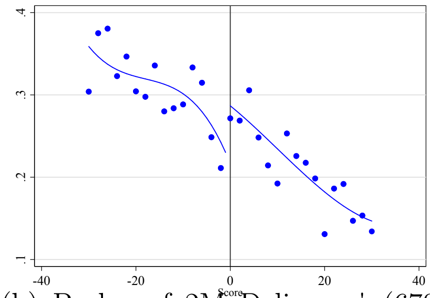
Notes: Each figure shows the mean of predetermined characteristics for each pair of values of the standardized credit score between -30 and 30. It also displays a polynomial fit of degree 3 to the raw data, allowing the intercept and the coefficients of the polynomial to differ on both sides of the threshold.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

D.3 Outcome variables

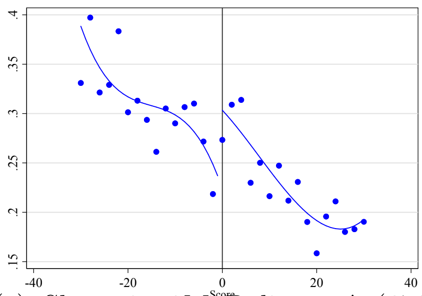
Figure D.7: The Effect on Long-Run Credit Card Delinquency



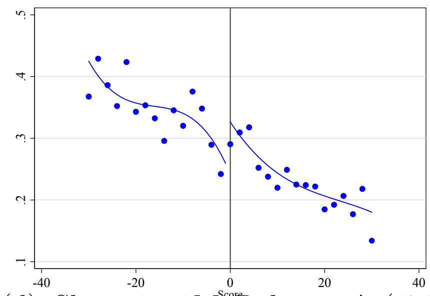
(a) Prob. of 2M Delinq. † (670 Sample)



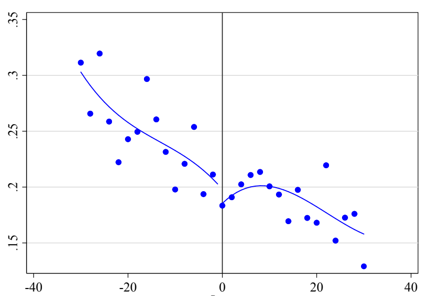
(b) Prob. of 2M Delinq. ‡ (670 Sample)



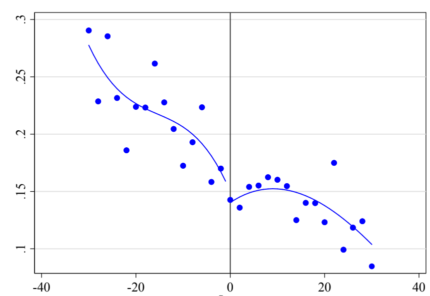
(c) Share in 2M Delinq. † (670 Sample)



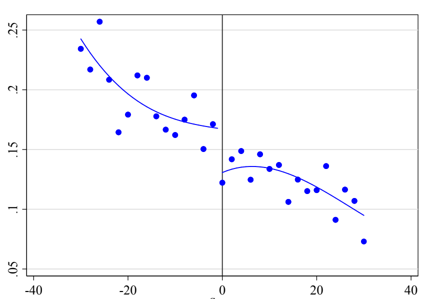
(d) Share in 2M Delinq. ‡ (670 Sample)



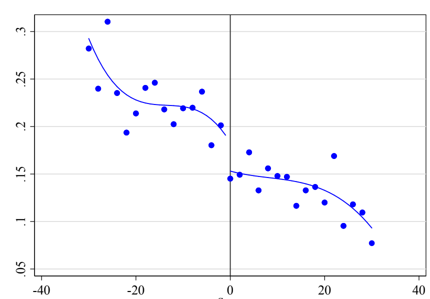
(e) Prob. of 2M Delinq. † (700 Sample)



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



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



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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

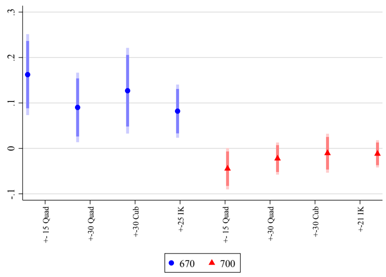
Table D.8: The Allocation of Long-run Default

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

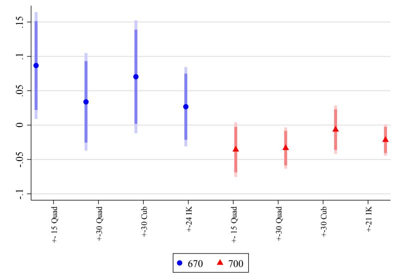
Notes: This table reports the RD estimates on default during the 18 months after the application. Panel A presents the OLS results for each sample, while Panel B presents the IV results for each sample. Panel C displays the mean of the dependent variable for applicants with standardized credit scores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

D.3.1 Robustness

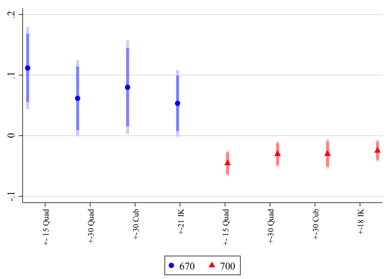
Figure D.8: Robustness of ITT Long-run Results



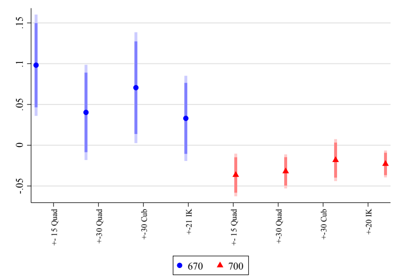
(a) Prob. of CC with 2M Delinq. †



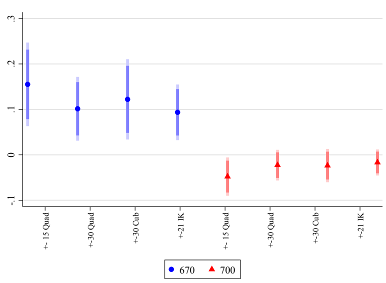
(b) Prob. of CC with 2M Delinq. ‡



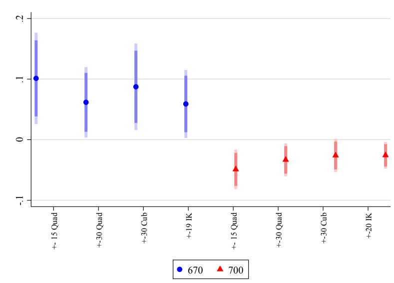
(c) Share of CC with 2M Delinq. †



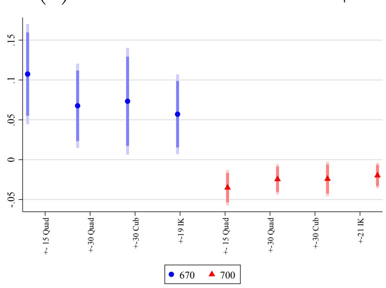
(d) Share of CC with 2M Delinq. ‡



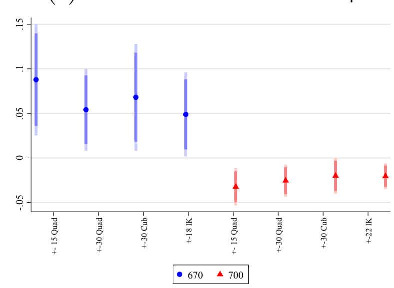
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



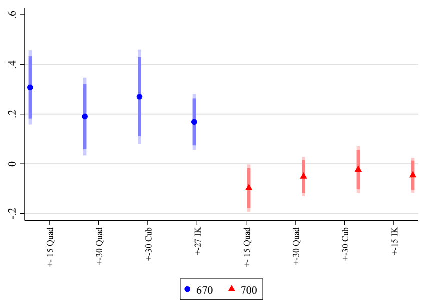
(g) Share of CC in Default †



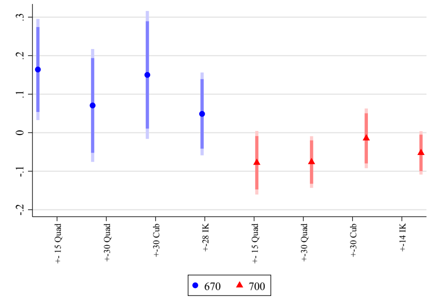
(h) Share of CC in Default ‡

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

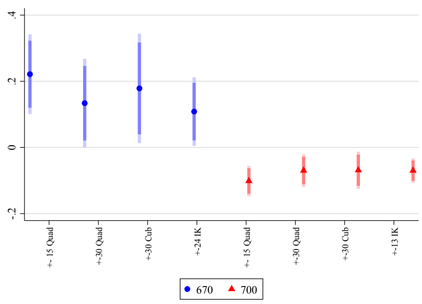
Figure D.9: Robustness of LATE Long-run Results



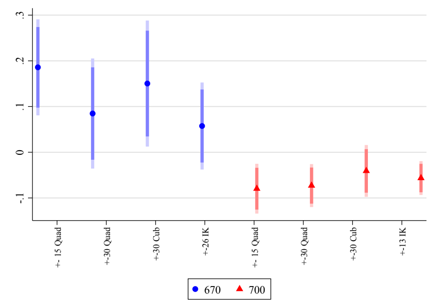
(a) Prob. of CC with 2M Delinq. †



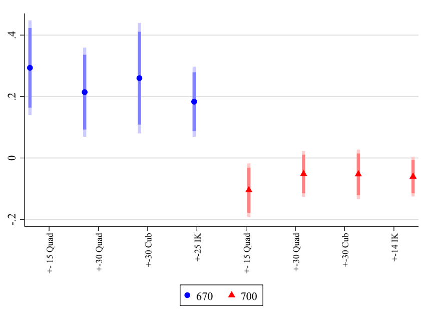
(b) Prob. of CC with 2M Delinq. ‡



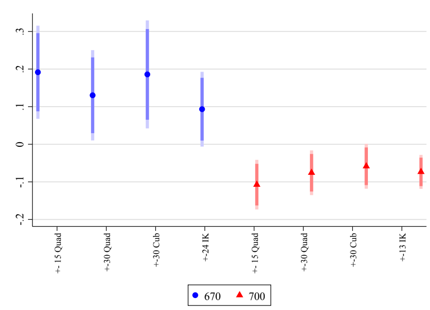
(c) Share of CC with 2M Delinq. †



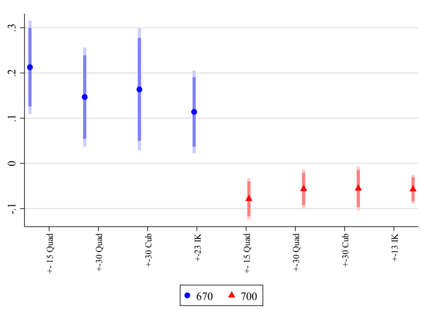
(d) Share of CC with 2M Delinq. ‡



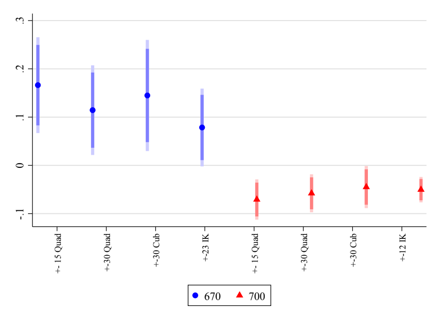
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



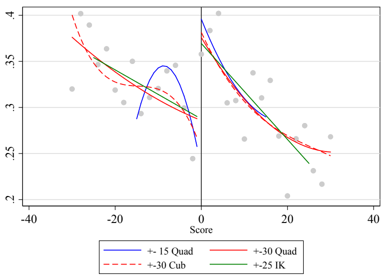
(g) Share of CC in Default †



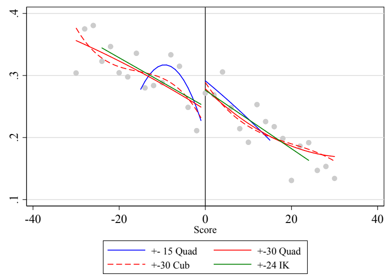
(h) Share of CC in Default ‡

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

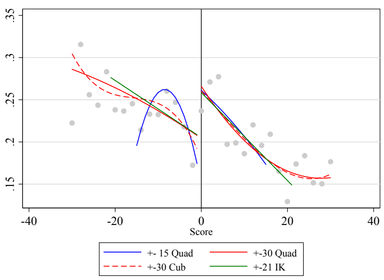
Figure D.10: Robustness of ITT Long-run Results



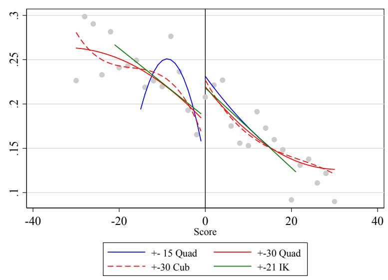
(a) Prob. of CC with 2M Delinq. †



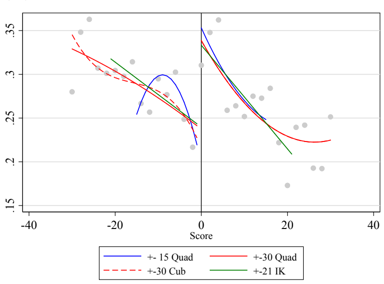
(b) Prob. of CC with 2M Delinq. ‡



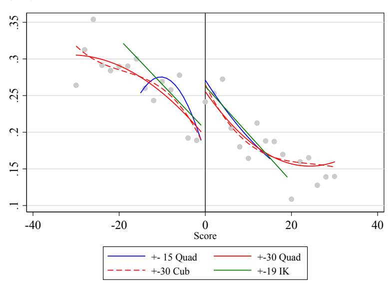
(c) Share of CC with 2M Delinq. †



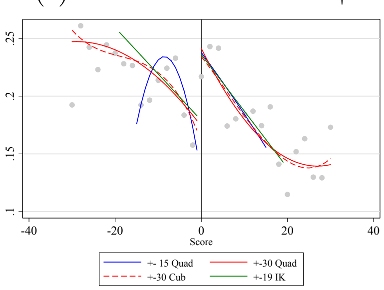
(d) Share of CC with 2M Delinq. ‡



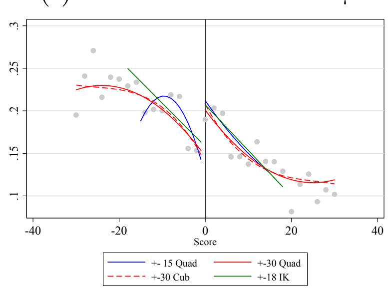
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



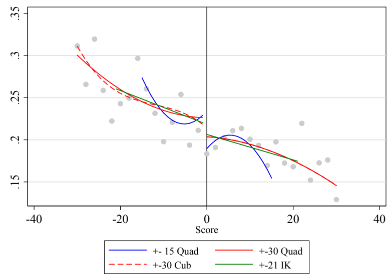
(g) Share of CC in Default †



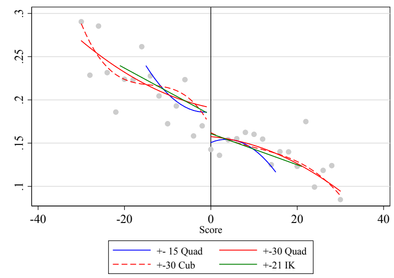
(h) Share of CC in Default ‡

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

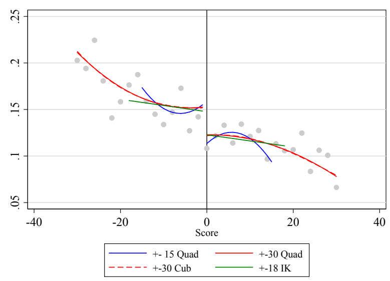
Figure D.11: Robustness of ITT Long-run Results



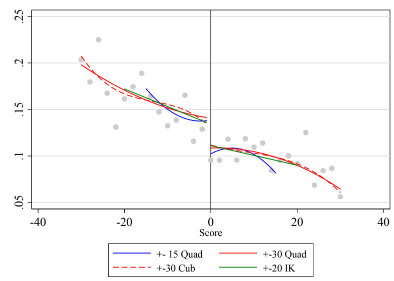
(a) Prob. of CC with 2M Delinq. †



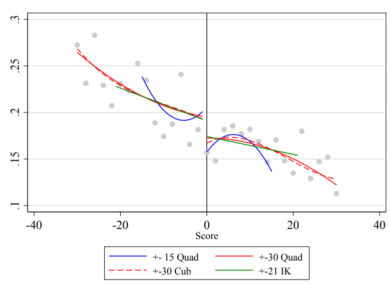
(b) Prob. of CC with 2M Delinq. ‡



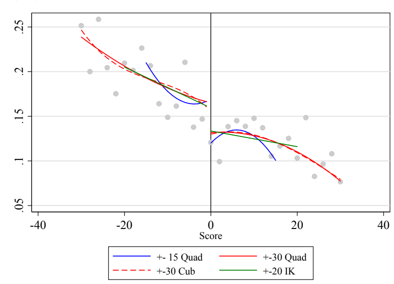
(c) Share of CC with 2M Delinq. †



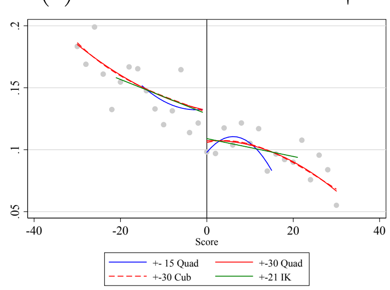
(d) Share of CC with 2M Delinq. ‡



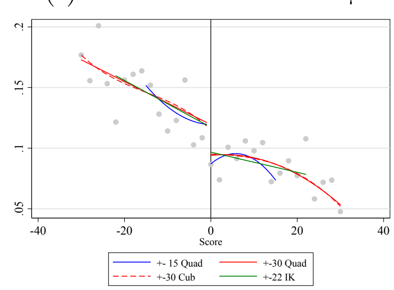
(e) Prob. of CC in Default †



(f) Prob. of CC in Default ‡



(g) Share of CC in Default †



(h) Share of CC in Default ‡

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

D.4 Comparing across thresholds

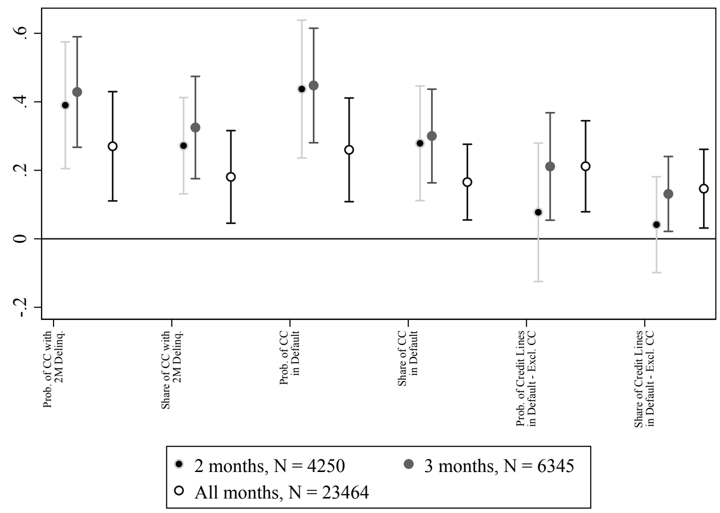
As a first test, Figures D.12 and D.13 in the Appendix plot estimates obtained using a 3-month (or 2-month) sample of contiguous months containing data on applications made in February, March, and April 2011 (or March and April 2011, respectively) for the estimates at the 700 threshold, and from June,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

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

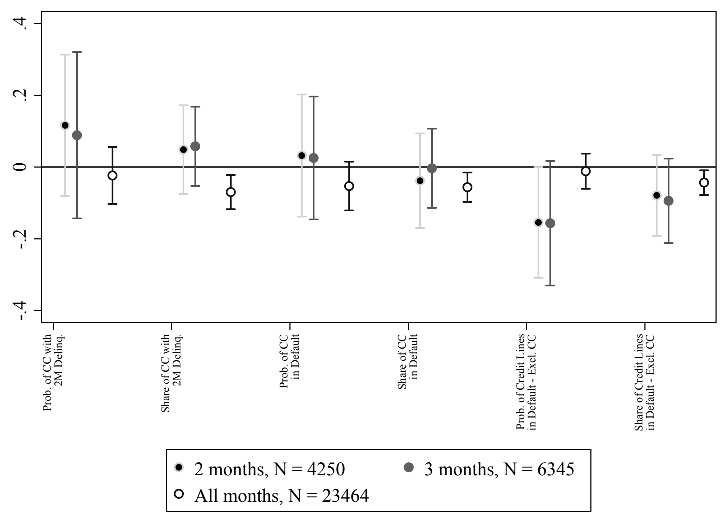
Figure D.15 in the Appendix presents a third check. It compares default rates for applicants who are "always-controls" regardless of the threshold regime—i.e., those with a score in the [640,660] range. We do this in order to not confound a differential treatment effect with a differential time trend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

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

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



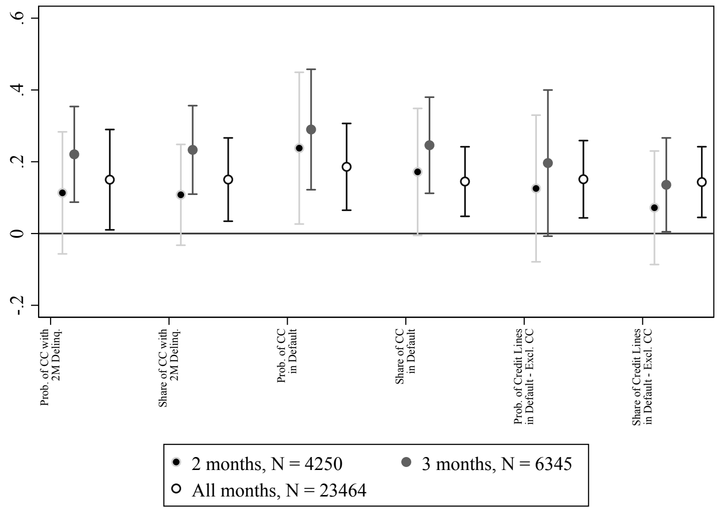
(a) 670 Cutoff



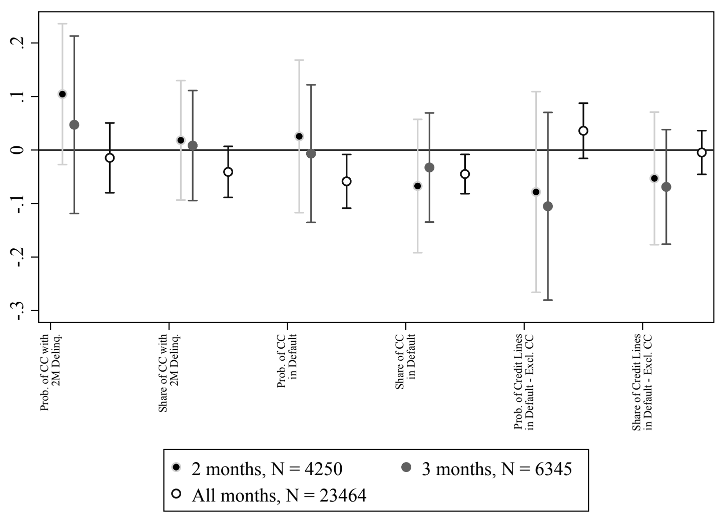
(b) 700 Cutoff

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

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



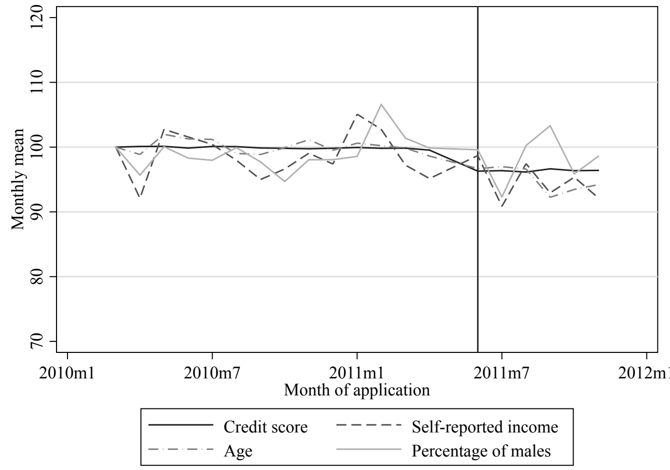
(a) 670 Cutoff



(b) 700 Cutoff

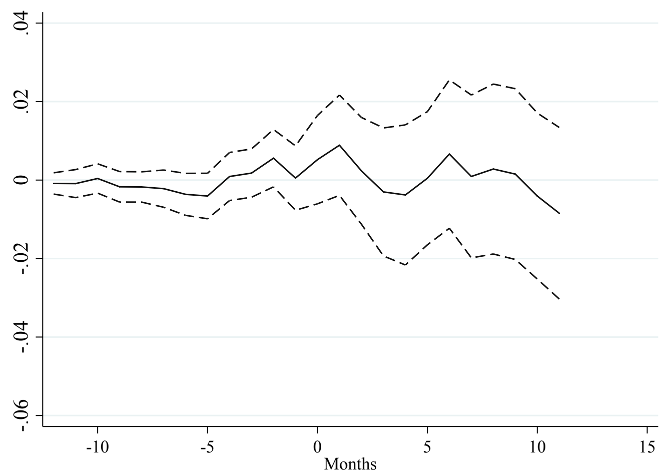
Notes: These figures present the estimated LATE effects for different populations of the 670 and 700 samples. The dependent variables were constructed including only credit cards that were active at application. Panel (a) presents the effects for the 670 sample, while Panel (b) presents them for the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

Figure D.14: Evolution of Average Applicants' Characteristics



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

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



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

Appendix E. Back of the Envelope Calculation

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

(4)

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

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

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

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

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