Does Formal Credit Lead to more Financial Inclusion or Distress? Results Using an Algorithm-based Loan among Underserved Clients in Paraguay*

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Through a regression discontinuity, we measure the impact of being offered a credit after a formal bank in Paraguay deployed a new credit product with an algorithm-based strict decision rule for clients who could not be evaluated with traditional methods. Using administrative data from the country's credit bureau, we find that applicants deemed loan-eligible saw a substantial and long-lasting increase in the number of information requests made to the bureau, particularly from formal sources (finance companies and cooperatives). We find limited evidence that these applicants saw an increase in the amount of debt declared as unpaid but did experience lower credit score. Self-reported outcomes for a subset of applicants suggest significant economic benefits for those who became loan-eligible, the main channel being lower credit costs. Heterogeneity analysis suggests that applicants who were previously unknown to the financial sector benefited more from being granted loan eligibility without falling into default, while those who had previously had more interactions with the credit market simply worsened their financial situation. This suggests that granting loans using new technologies to construct alternative screening mechanisms may be particularly beneficial when targeted to clients with limited credit market experience.

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1 Introduction

Access to finance from the formal credit sector is out of reach for millions of poor and informally employed people across the world, and remains a major barrier to economic development. Underlining its importance, financial inclusion is mentioned as a target in half of the UN's 17 Sustainable Development Goals (SDGs). Banks who wish to help new clients gain access to financial markets are, however, often faced with limited information about these individuals, leading them to seek alternative mechanisms to allocate credit. What is the consequences of offering typically excluded populations access to credit through an alternative selection mechanism? Would it help them integrate in the credit market or lead them to higher indebtedness? Would they be better or worse off?

While various studies have looked at how the entrance of new competitors in a market, particularly microfinance institutions, impact the welfare of potential recipients, few studies have focused on the impact of access to credit at the individual borrower level. In this paper, we take advantage of the fact that a formal bank in Paraguay developed a credit product targeting an underserved population and determined loan eligibility based on a strict assignment rule. This algorithm-based approach allowed us to measure the impact of obtaining a formal loan offer on credit outcomes by comparing individuals who just met the score threshold and were offered a loan, to those who were just below the threshold and were denied access. We use administrative data from Paraguay's credit bureau in our analysis of credit outcomes, in addition to survey data collected from a subset of applicants.

Traditionally, banks use applicants' credit history to assess credit risk and make loan decisions. When credit records are absent or limited, banks usually rely on collateral or other guarantees. However, this information is typically not available for clients at the base of the pyramid, many of whom have never had access to formal credit and lack documented credit records. Similarly, most workers at the base of the pyramid have few assets suitable for collateral, and without a formal job they cannot show a steady stream of income to support loan payments. Consequently, it is difficult for banks to assess their creditworthiness using traditional methods, further solidifying barriers for entering the formal financial market for this population. But the financial sector has found in new technologies a potential alternative that can be harnessed to determine credit worthiness for a population that is not well known by the market. What are the consequences of being selected using such an alternative mechanism?

To study the impact of offering a loan to individuals in this context, we collaborated with Banco Familiar, a formal financial institution in Paraguay that has experience working with traditionally underserved segments. Specifically, in 2012 the bank deployed a new lending product known as "Credicedula", with a scoring system specially designed for the unbanked, informal sector population. Risk profiles in this new system are constructed independently of credit history, giving greater weight to additional variables such as demographics and earnings estimates according to geographical location and economic activity. These variables are generally not included in a typical credit analysis. The information is coarse and categorical in a sense, but it aims to help reduce the risk associated with clients obtaining their first ever formal loan or first formal loan of a given size and maturity. However, this alternative credit scoring approach may not only open the door to credit for individuals without a credit history, but also to individuals who have been locked out of the market because of past negative credit behavior. Note that all applicants had a credit score in the credit bureau at the moment of application, but some had more or less exposure to the system before their application.

Credicedula also had the particularity of being a fast application and approval loan product. Loans were offered automatically to individuals whose predicted probability of default (as generated by Banco Familiar's scoring system) was equal or below 0.196, and the decision was made within minutes of the client's application. This rule was strictly followed, with the loan officer playing no role in lending decisions. In collaboration with Banco Familiar, we obtained information regarding the loan applications of people with scores within 0.004 of the cut-off, for a total of 1,060 individuals [1]. We use a regression discontinuity (RD) design and compare the situation of applicants who were just above the cut-off to those who were just below. We show that 70 percent of individuals who were deemed just eligible for a Credicedula loan accepted the offer, while nobody who was deemed ineligible was offered one. We thus have a strong "first stage".

Our main hypothesis is that being offered this loan can lead to more and better access to the financial system if it allows individuals to establish a credit history or if it increases the confidence of the individual's creditworthiness in the market (as suggested by Karlan and Zinman, 2010). To study this, we collected information about the credit behavior of these individuals from Inforconf (now purchased by Equifax), Paraguay's credit bureau, in March 2017, about two to three years after their application to Banco Familiar. [2] Through this database, we obtained information about each request made by a credit provider to the credit bureau to obtain information regarding a client, an activity that is usually associated with a credit request. [3] We also obtained each individual's credit score and information regarding whether they had any unpaid debt reported to the authorities. Using a regression discontinuity framework, we then measured the impact of being deemed just eligible for a loan, irrespective of whether the client accepted the offer or not,

[1]The range of the predicted probability of default was between 0.1 and 0.5. We are thus focusing on individuals very similar in terms of the bank's scoring system (within the 0.192-0.2 range; 0.004 above and below the 0.196 cut-off).

[2]The credit bureau in Paraguay has a large number of institutions reporting to it. This includes all formal banks, as well as cooperatives, finance companies, commercial credit providers, and moneylenders.

[3]Such requests may also be made by financial institutions looking to offer credit to or evaluate a current client who may be facing repayment difficulties.

on credit outcomes.

To validate our empirical strategy, we first find no evidence that individuals who were eligible for the loan differed in their access to credit or their formal credit score before their application to “Credicedula”. This suggests that our analysis is indeed capturing the impact of being offered a formal loan and not differences in applicants’ characteristics. We then find that applicants who scored just above the loan eligibility threshold had substantially more requests in their credit reports after they were offered the loan compared to applicants who just missed the cut-off. This increase in requests was mostly from two types of formal financial institutions that are very active in this market, namely finance companies and cooperatives, and not from moneylenders or creditors linked to commercial products. This suggests that this first loan offer from Banco Familiar may have opened the door to new credit opportunities from other financial institutions for these individuals, which could have improved their financial well-being.

We then evaluate if there is any difference between individuals who scored just above and below the loan eligibility threshold in terms of their subsequent debt levels. We find no evidence that individuals around the cut-off had more unpaid debt declared to Equifax in any of our measures (extensive margin, intensive margin, amounts, etc.). However, we acknowledge the noise around these types of measures since our estimates’ confidence intervals are relatively wide. We nevertheless find that individuals who received the loan offer had substantially lower credit scores as reported by the credit bureau two to three years later, and that more of them had a default reported. While part of this outcome may be mechanical, it may be linked to the fact that this population had a high probability of late payment and that this was penalized by the credit bureau, despite this loan debt no longer appearing as being unpaid by the time we consulted their file. This suggests that offering credit to this population may have increased their access to the financial system, but at the cost of leading some individuals to have worse credit records.

Finally, based on a small sample of the individuals (with a slightly larger window of scores) we interviewed to assess self-reported financial well-being, we confirm the conclusions obtained through administrative data. Individuals who were just loan-eligible reported paying less in credit costs, improving their capacity to face shocks, and evaluated their financial position more positively two to three years after the loan application. We think this is due to Credicedula offering lower interest rates than alternative options for applicants at the margin and that these applicants appear to have later obtained credit from other finance companies and credit cooperatives that charged lower rates than the informal moneylenders that they may have previously relied on.

Once we test for heterogeneity in the impact of loan eligibility on credit outcomes, we find that those who benefited the most in terms of increased access to the credit market were those with initially limited interactions with creditors, despite the fact that they took the loans in the same proportion as those with more credit experience. This is consistent with the hypothesis that the loan offer was particularly useful for applicants with weaker credit records that had been restricting their access to credit markets or that it helped clients who thought they had no creditworthiness update their beliefs positively. Similarly, we find that individuals who had more previous exposure to the credit system at the time of application ended up with higher default levels and worse credit scores two to three years later. On the other hand, eligible applicants with limited previous experience in the financial sector appear to have been spared the negative impact on their credit score. This suggests that offering credit to individuals who have had little or no access to credit previously may be more beneficial than offering credit to individuals facing difficulty accessing formal lending due to their bad credit track records. Therefore, the use of an alternative screening mechanism for credit such as Credicedula may be most impactful when targeted to individuals with less previous exposure to the credit market.

The rest of the paper is organized as follows. Section 2 briefly describes the most relevant related literature, Section 3 describes the loan product our partner bank employed and the credit market in Paraguay, Section 4 describes the data and empirical strategy, Section 5 presents our results, and Section 6 concludes.

2 Related Literature

Access to finance has been one of the most important policy and academic issues discussed among those focusing on understanding and reducing the large differences between developed and developing countries. Financial innovations such as microcredit were developed as potential solutions for the lack of credit access among the poor in low- and middle-income countries (Meager, 2019).

Our work relates to studies that have evaluated the impact of granting credit to individuals and firms. A number of studies have looked at the expansion of the financial sector in a given regional area. Studies that have looked at the impact of formal bank expansions through non-experimental methods (Agarwal et al., 2017; Bruhn and Love, 2014; Burgess and Pande, 2005; Burgess et al., 2005) have generally found that they have led to thicker financial markets and positive outcomes such as reduced poverty and increased labor incomes. Experimental evaluations of microcredit expansions have found more muted benefits. As summarized by Banerjee et al. (2015a), experimental studies in general have found limited demand for the new microcredit offerings and also limited impacts on consumption, income generation, etc. They also found no evidence of negative outcomes. For example, Banerjee et al. (2015b) find that slums in India that experienced benefits from increased access to microcredit for existing businesses through higher investments and profits, also saw a decrease in temptation goods consumption to the benefit of durables. While interesting, these studies do not allow for comparison between the impact at the individual-level of receiving a loan in a market with a fixed credit supply and the impact of having the entire market facing more credit availability. Our study focuses on the former.

A few studies have evaluated the impact of granting an individual loan. Karlan and Zinman (2010) measure, through a randomized control trial (RCT) with applicants who were marginally rejected for a loan, the impact of offering a microloan product in South Africa with an annual interest rate of 200 percent and a four-month maturity. Their results show the loan was used for repaying other loans and generated a clear increase in income, mostly because it seems to have helped loan recipients remain employed over the study period. The authors repeat this experiment through an RCT in the Philippines (Karlan and Zinman, 2011), focusing on loans with an interest rate of 60 percent, including fees, and a 13-week maturity with weekly payments. Similar to the South Africa case, access to credit increased, however the authors find no effect on consumption. They also find that microcredit did not lead entrepreneurs to grow their businesses, but did help them smooth economic shocks. In Pakistan, Gine and Mansuri (2014) randomized the amount of the loan through a lottery, but power issues prevent them from saying much about the impact of obtaining this additional amount of credit.

Overall, the mix of results from these RCTs suggest that while there is demand for more credit, even at high costs, it is unclear how greater access translates into better economic outcomes for credit recipients. In this paper, we try to understand why this may be the case, using administrative data to explore how gaining access to credit may have negative impacts on beneficiaries, something that these other studies were unable to look at in detail. We then complement this using survey data, which shows muted impact on overall economic welfare but positive impact on financial well-being, mostly because the subsequent loans obtained by these individuals appear to have had lower costs than existing alternatives.

Agarwal et al. (2018) look at the market level expansion of microcredit in Rwanda but focus, like us, on the credit outcomes at the individual level. They show that the expansion of a microcredit organization allowed the good quality unbanked individuals that it served to signal their creditworthiness to the rest of the financial sector. Our study is able to focus on the impact for individuals instead of markets through an RD in which the cut-off point is exogenous to the client scoring of banks. Like us, Agarwal et al. (2018) also use administrative data to measure credit market integration to solve some issues related to surveys (Johnson et al., 2006). We complement our administrative data with survey data to obtain a clearer picture of the impact of credit access.

A contemporaneous study to ours is that of Burke et al. (2019), who studied the impacts of credit builder loans in the United States by partnering with a local credit union to randomly offer these loans to its members. They find similar heterogeneity in their results to what we found:

recipients who are new to the credit market benefit from the loans while those who are not, fare worse. The main difference is that we are focusing on a credit market that is less organized and sophisticated and that we look at a new mechanism for screening clients, not at a product whose characteristic should only be attractive to those without credit history. The similarity in results is interesting, despite the different characteristics of the product and market we each studied.

This paper, because of its design, also contributes to the literature on the role of credit officers in the loan process. Our partner bank completely eliminated the role of the loan officer by using only an algorithm to assess credit eligibility. Loan officers make decisions based on the information available to them and the incentives they face. Some studies have found that securitization significantly increases risk-taking by loan officers (Keys et al., 2010) while others have emphasized the role of contract incentives (Cole et al., 2015). Typically, loan officers have access to both "hard information", such as that collected by Banco Familiar's algorithm, and "soft information", as detailed by Liberti and Petersen (2018). Many studies have found that "soft information" is relatively crucial in decreasing risk-exposure (see for example Agarwal and Ben-David, 2018; Iyer et al., 2016; Lin et al., 2013), suggesting that the use of an algorithm on its own may lead to more risky loans being granted, which appears to be the case for some clients in our study.

Our study employs a similar strategy to one that has been used to assess the impact of granting credit to firms. Banerjee and Duflo (2014) have shown that targeting credit to firms may allow them to increase their sales and profits, indicating that firms are not just credit rationed, but also credit constrained. Fracassi et al. (2016) use a credit scoring method like ours to look at lending to small firms in the United States. Startups who marginally qualified to receive a loan were more likely to survive, enjoy higher revenues, and create more jobs than those who were marginally excluded. Similarly, Arráiz et al. (2018), studied the impact of psychometric tools as a credit screening mechanism for micro, small and medium-sized enterprise lending in Peru. While they focus on a completely different type of client and screening mechanism, our results are similar. They also find that becoming eligible for a loan led to more lending to firms with limited credit histories.

3 Credit Markets in Paraguay

3.1 Overview

Paraguay's financial system has remained stable over the last few decades. Formal financial institutions in the country can be classified into four different categories: banks, finance companies, cooperatives, and other types of institutions. Banks are supervised by the Central Bank, can offer deposits and credit services, and have a capital requirement of 10 billion Guaranis (Gs).[4] Finance companies are similar to banks in their rights and obligations, but only have a 5 billion Gs capital requirement. Cooperatives, on the other hand, are not supervised by the same authority and follow very different rules in terms of capitalization, interest rates, and other factors. Our database also includes other types of actors such as store-based credit, credit cards, and moneylenders.

The microfinance sector in particular has developed at a fast pace in recent years, mostly through the expansion of cooperatives. This has increased competition in this sub-market of the financial sector. It has also encouraged traditional banks to expand into less traditional markets and incentivized finance companies, already well-established in this segment, to become banks. Access to banking services has therefore improved in Paraguay, yet remains among the lowest in Latin America and the Caribbean.[5] Although microfinance has had, and continues to have, a positive impact on improving access to banking services and financial inclusion, the traditional institutions supplying these services have so far been unable to reach segments with higher levels of informality (i.e., populations with incomes of less than US$3/day and independent workers in the informal sector). According to World Bank data (Global Findex 2017), only 31 percent of Paraguayans have access to the formal financial sector, compared to a regional average of 54 percent. In addition, only 13 percent of Paraguayans report having obtained credit from a formal financial institution in the past year. These figures are worse for individuals with lower incomes and without credit histories.

In 2014, the World Bank published the results of a survey of financial institutions in Paraguay,[6] including the interest rates charged by different types of institutions. For example, the average interest rate for commercial bank loans was 19 percent, whereas finance companies charged 34 percent and cooperatives, 24 percent. These are average rates for the entire population; the rates obtained by the low-income individuals with limited credit histories included in our study may differ substantially from these averages. In a survey of our target population in Azevedo et al. (2019), we asked participants about their current credit interest rates by type of lending institution. We found that banks, moneylenders, and store credit all charged average interest rates of about 40 percent. Finance companies charged slightly less at 37 percent, and cooperatives were the cheapest source of credit at 29 percent. The interest rates paid by our respondents also varied greatly. This suggests that switching from current financing sources to cooperatives would allow the individuals in our population to lower their interest rates. We will come back to this idea when we explore our results in more detail in Section 5.

[4] At the time of the loan offer, the exchange rate was about 5,000 Gs per USD. For the survey period, it was closer to 5,500 Gs per USD

[5] See "Who Are the Unbanked? Uncovering the Financial Inclusion Gap," World Bank, 2011

[6] Available at http://www.incoop.gov.py/v2/?page_id=4948

3.2 Credicedula

This study was conducted in collaboration with Banco Familiar, a bank that was originally formed as a finance company in 1992 and became a bank in 2009. Since its creation, Banco Familiar has served a broader client base than traditional banks, developing new credit products tailored to the needs of low-income borrowers. The bank's client base has increased from 110,000 in 2009 to 600,000 in 2019, most of whom were formerly unbanked individuals.

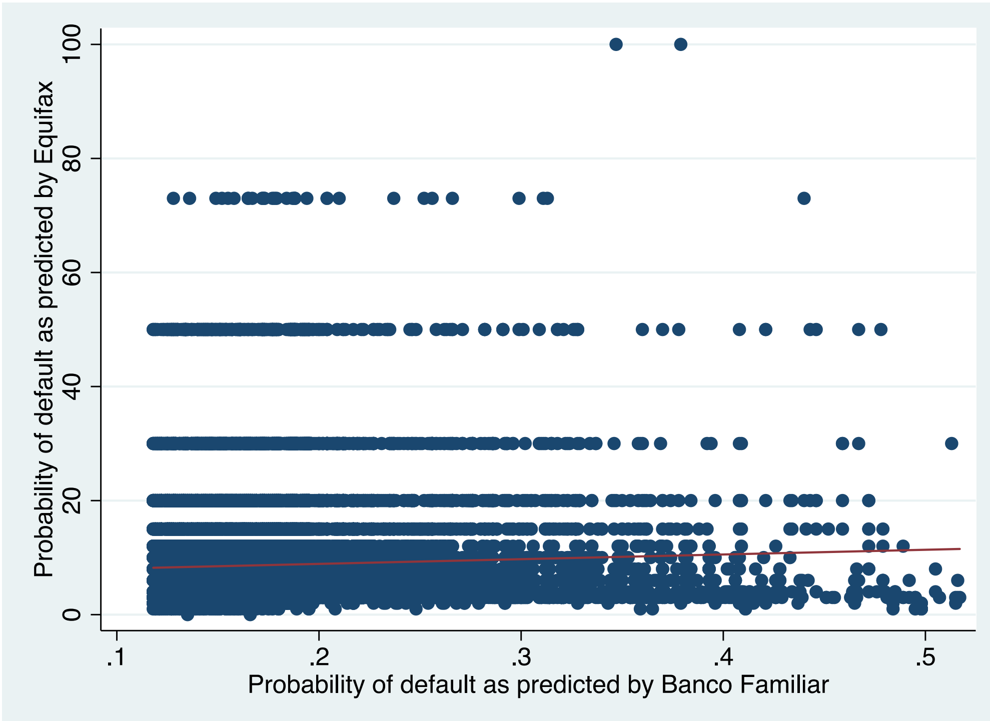
In 2012, Banco Familiar developed a credit product and scoring system known as "Credicedula", which mainly, but not exclusively, targeted the unbanked and informal sector population. The publicity for this product targeted people who were unable to demonstrate their income. The system calculated a score based on demographic information, such as age, gender, and address, as recorded by the person's national ID card ("cedula" in Spanish, thus explaining the name of the product), as well as applicants' answers to a series of short questions. Credit decisions were made by an algorithm and no leeway was given to the credit officer. Loans were approved in 20 minutes or less and were backed by debt insurance against events such as death, disability, and hospitalization. This allowed the bank to lower collection risk, and the client to maintain a good credit history in the face of difficult circumstances. Loans to beneficiaries were for up to US$450 with a one-year term at interest rates governed by the Central Bank (around 40 percent).

The bank's algorithm calculated a probability of late payment for each applicant, independent of credit history, giving greater weight to additional variables such as demographics, earnings estimates according to economic activity, and some additional elements that were not revealed to us by the bank. The probability of default estimated by the algorithm ranged from 0.1 to 0.5. The cut-off score of 0.196 was set as the maximum probability of late payment that would still guarantee profitability of the product: applicants with higher predicted probabilities were not offered a loan. Banco Familiar had previously developed other scoring analysis methodologies, but Credicedula was the first one designed specifically for analysis of independent workers with no credit history.

Figure 1 shows that while the credit score generated by the Credicedula algorithm is positively correlated with the score provided by Equifax, the relationship is relatively weak. This suggests that Credicedula was able to provide access to formal loans to individuals who may have been screened out through traditional methods.

The product was launched in March 2012. In December 2013, Banco Familiar expanded the reach of the product through a phone-based application process with the collaboration of the cell phone company, Tigo. The bank initially anticipated that over 80,000 informal workers at the base of the pyramid with stable incomes, but unable to prove it, would benefit from the product; however, further analysis of Banco Familiar's client base suggested more modest demand. Clients

Figure 1. Density of applications by score, full sample



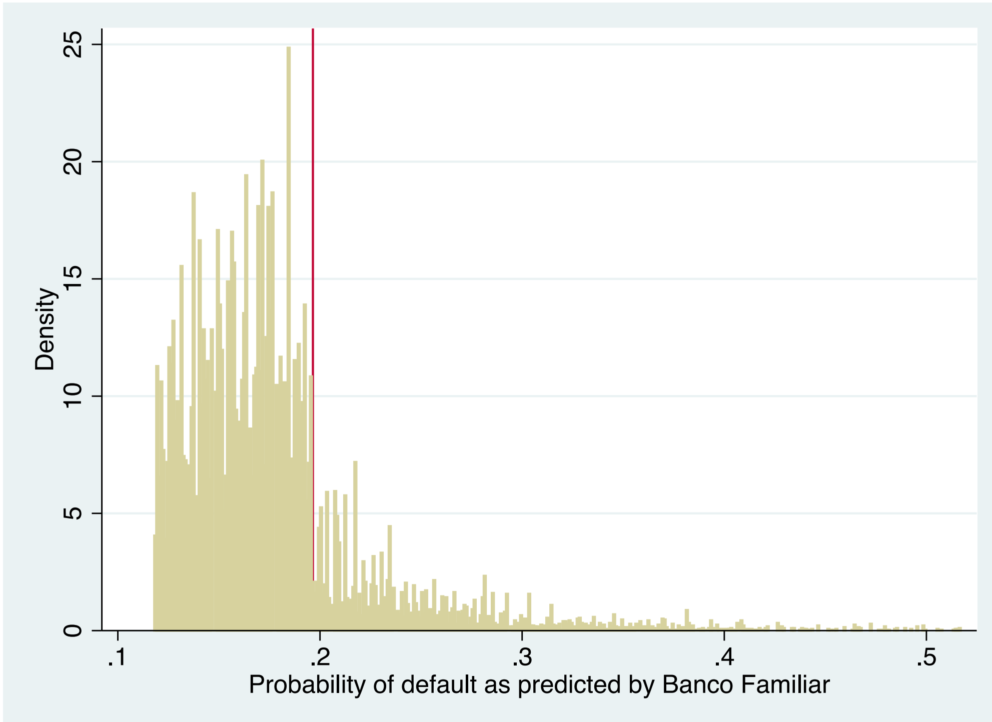
were also less "new" to the credit market than anticipated. Initial results from product lending showed that only 33 percent of clients had never obtained credit before (formal or informal), and 39 percent were accessing formal credit for the first time (previously using only informal lenders), implying that 28 percent had previously obtained formal loans.

When looking at the approximately 10,000 applicants between 2014 and 2015,[7] we observe that a large majority (82 percent) were approved for the loan, with a predicted probability of late payment at or below 0.196.

Figure 2 shows the distribution of applicants according to their score. We see a clear pattern that individuals who were going to be deemed eligible were more likely to officially apply for it. The average loan size requested was about 700,000 Gs (about US$140 at that time), while the average size of approved loans was almost one million Gs (about US$200), suggesting that applicants requesting the smallest amounts were rejected. Average self-reported monthly income at the moment of application was 1.35 million Gs (about US$270). Half of the applicants were self-employed while another 20 percent were employed at firms that were not complying with their legal contributions for workers, making it difficult for the individual to demonstrate their income. The remaining 30 percent worked in the formal sector and around 55 percent were

[7]We focused our analysis on more recent clients, anticipating that it would be easier to collect survey data from them, as well as to avoid possible information deletions from the credit bureau for older clients.

Figure 2. Density of applications by predicted probability of default, full sample



women.

4 Data and Empirical Strategy

Having described the credit product and the algorithm-based scoring system, we will now explain how we measured its impact on applicants' credit outcomes.

4.1 Data

Our main analysis uses administrative data combining the information we received from Banco Familiar with data obtained from Paraguay's credit bureau (Equifax). This approach has the advantage of not being subject to self-reporting and not suffering from attrition. The information we obtained from Banco Familiar about each individual included: (1) date of application to Credicedula (within the two-year window between 2014-2015); (2) whether or not the loan was approved; (3) the predicted probability of default computed by the algorithm; (4) some of the information (income and occupation) used to calculate the predicted probability of default; and (5) the credit score provided by the credit bureau at the moment of application (even though this information was not used in the calculation, it was requested by the bank). It is important to note that while the credit product was supposedly targeting people without credit histories, Banco Familiar obtained a credit score for each individual in the list of applicants, suggesting that the credit bureau was at least able to provide a creditworthiness qualification for each of them.

We merged this information with a March 2017 credit report provided by the credit bureau for each applicant (for a report example, see the Appendix, A.1 and A.2. Since our focus was on applicants who were as close as possible to the eligibility cut-off, we picked the smallest window around the cut-off where we would have at least 1,000 applicants in our sample, also taking into consideration the cost incurred by Banco Familiar to provide us with the information on each applicant and by the research team which had to digitize the information received from PDF format. This translated into looking at the 1,060 applicants whose probability of default was estimated by the algorithm to be within 0.004 of the cut-off of 0.196 (that is, between 0.192 and 0.200). The credit reports include all credit check requests made by financial institutions in Paraguay reported to the credit bureau in the three years prior to the date of our request, that is between March 2014 and March 2017. This includes all banks, finance companies, cooperatives, commercial entities that offer consumer credit, credit cards, car dealers, etc. We have the date each request was made and the requesting entity. We eliminated requests that were made three days before and three days after the application to Credicedula because we felt that these were likely to reflect some "shopping around" behavior by the applicant. Nevertheless, results do not change significantly when using the full set of requests. The information provided by the credit bureau does not include the actual loans taken out by each individual.

The credit report does, however, include a list of all debt that lenders had reported as overdue as of March 2017, the date it was reported, and the amount pending repayment. A financial institution is able to report unpaid debt once the payment is more than 90 days overdue. By law, the credit bureau cannot inform us about debt that was defaulted on more than three years prior to our request (before March 2014). We also re-center this information with respect to the date of application to Credicedula, although, given the short-term memory of the credit bureau system, almost no applicant has an unpaid debt registered before their application to Credicedula. Finally, for each individual, the credit report also includes a credit score in the form of a letter (A to N and then X). A is considered the best possible credit score and X is the worst, reserved for individuals who defaulted on their debt. We transform the alphabet credit score into a predicted probability of default based on a table provided by the credit bureau.[8]

We first re-center the information regarding the credit report requests compared to the date of the application to Credicedula. This allows us to verify that applicants above and below

[8]We use the midpoint of the range of probability of default as shown in https://www.prestamena.com/blog/75/las-fajas-en-informconf-y-lo-que-representan.html.

the threshold had similar behavior in the credit market before their application to Credicedula. Since the application date for some individuals is earlier than others, we normalize the number of requests by 100 days. For example, imagine that two applicants in our sample have 10 requests each after their application to Credicedula, but one person applied in March 2015 while the other applied in September 2014. We calculate that the first individual will have 1.37 requests per 100 days (10/(3*365)) but the second will have 1.10 requests per 100 days since he or she had six more months to obtain requests until March 2017. The average person in our sample received 0.9 requests per 100 days before their application to Credicedula and 1.16 requests per 100 days after.

We complement this administrative data with survey data that we were able to obtain for a subset of the total population of applicants. We conducted two different surveys, one in the second semester of 2016 and one in the second semester of 2017. Our survey thus provides us with complementary information from the same time period as the administrative data. Through these surveys, we measured income, expenditures, savings, financial difficulties, and self-reported financial well-being, as well as an index of well-being measured by four questions regarding stress and happiness. We were only able to find 512 individuals out of the approximately 10,000 who had applied to Credicedula in the Gran AsunciÃşn region during our period of interest from 2014 to 2015. Of these, only 16 were within our 0.004 window around the cut-off. However, 82 individuals fall within a slightly larger window (0.012), and this is the sample we employ in our complementary analysis.

We argue that the number of credit check requests an individual receives is a good proxy for her inclusion within the credit market, based on a combination of the information collected from our 16 survey participants and the data we retrieved from Equifax for each of them. Using these individuals, we constructed a panel of observations for the period before their application to Banco Familiar, between their application to Banco Familiar and the first survey, and finally between the first and second survey. We collect information in the survey regarding whether they requested credit during each of these periods and whether they received a loan. We regress this against the number of requests in the Equifax record per 100 days, the variable which we will use as our main outcome, including person and time fixed effects. We cluster standard errors at the person-level. Table 1 shows that the probability of requesting credit and also that of receiving a loan is positively and significatively correlated with the number of credit requests received by Equifax for each individual. Given the small number of observations, we verify that our results are robust to the use of bootstrapped standard errors instead of asymptotic ones. While we acknowledge that this is a small sample of observations, this table seems to support our use of requests to Equifax as a valid measure of integration within the credit market.

Table 1. Correlation between financial inclusion and requests to Equifax

	Requested credit		Awarded loan	
# requests to Equifax per 100 days	0.125	0.223	0.168	0.249
cluster s.e.	(0.061)*	(0.091)*	(0.054)***	(0.085)**
Cluster Bootstrap s.e.	(0.063)**	(0.105)**	(0.054)***	(0.098)**
time-period fixed effects	Yes	Yes	Yes	Yes
person fixed effects	No	Yes	No	Yes
Observations	38	38	38	38

Potential sample size is 48 since there are 16 individuals and 3 time periods for each. There are 10 missing values. 6 are missing because these individuals were not interviewed in the 3rd period. For these individuals, we have only 2 observations. 2 are missing because their Credicedula request preceded March 30, 2014, implying that we have no data for the first period in that case. 2 are missing because the interview we conducted did not include a credit question for periods preceding the Credicedula request. Bootstrapping is preformed on Stata with seed 22 and 10.000 reps.

4.2 Empirical strategy

We have chosen to use a regression discontinuity design (RD) to estimate the impact of Credicedula for two main reasons. First, we have the predicted probability of default estimated by Banco Familiar's algorithm for each applicant. Second, the credit eligibility decision was made entirely based on that score and on no other source of information. Applicants who had an estimated probability of default below or equal to 0.196 were offered the loan, while those above that threshold were denied. However, this approach is not without challenges. The predicted probability of default, while probably continuous in its construction, was given to us as a discrete variable, rounded up to the third decimal. This means that we do not have a continuous variable, as is ideally the case in RD analysis. In particular, for most of our analysis, we have information on individuals who are within 0.004 of the cut-off score, implying that we basically have eight bins over which we can conduct our analysis. We thus use the discrete RD approximation with a polynomial estimation on each side of the discontinuity, as suggested by Card and Shore-Sheppard (2004), Kane (2003) and DiNardo and Lee (2004).

We estimate the following equation where the outcome of a person i, Y_{ip} who had predicted probability of default p is regressed on our running variable $X = p - 0.196$

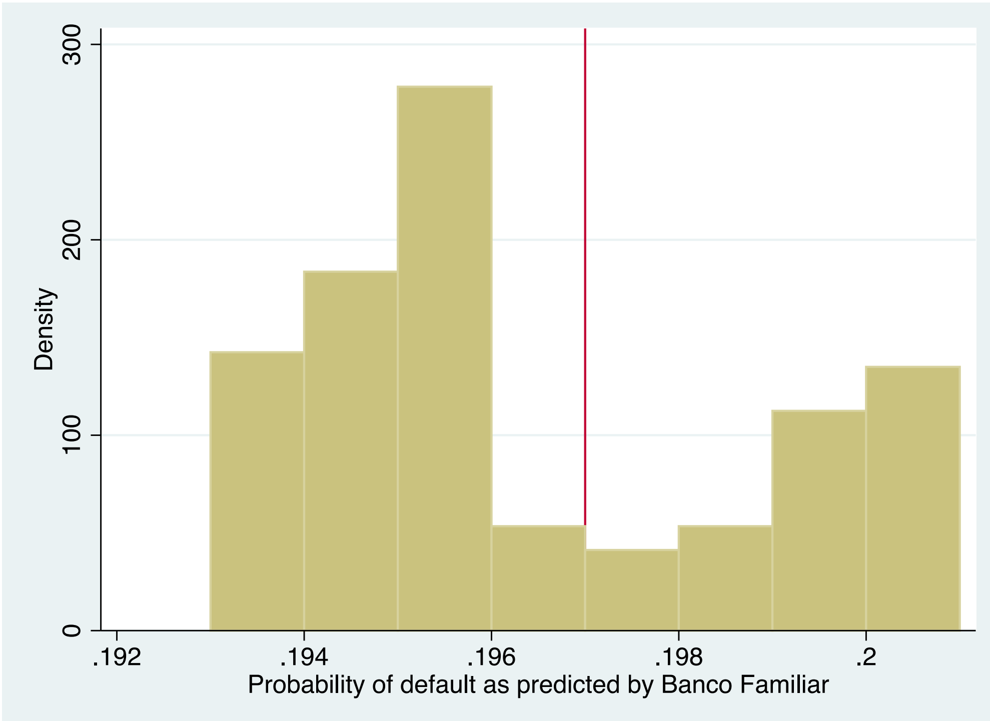
$$\bar{Y}_{ip} = \alpha + \beta \cdot \mathbb{1}\{X \leq 0\} + \gamma_1 \cdot X \cdot \mathbb{1}\{X \leq 0\} + \gamma_2 \cdot X \cdot \mathbb{1}\{X > 0\} + \varepsilon_{ip} \tag{1}$$

We do not find the bandwidth using methods suggested by Calonico et al. (2019) because our small number of data points prevents the proposed method from converging in many cases. Furthermore, we already selected our bandwidth implicitly by only collecting administrative data on applicants that were within 0.004 points of the cut-off. Nevertheless, we have verified the robustness of our results to smaller windows (we cannot test larger windows since we do not have the data to do so). We estimate a linear polynomial on each side of the discontinuity. In order to emphasize the discontinuity, we use triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease linearly with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). We also check the robustness of the results to the use of local linear regressions as suggested by Calonico et al. (2019) and performed by the rdrobust command in Stata, also using triangular kernel weights. The only difference between the main polynomial specification and the non-parametric one is thus how the function is estimated on each side of the discontinuity, one being linear while the other uses a local linear regression.

For this strategy to be valid, we need assurance that the score was not manipulated either by applicants or by loan officers. Figure 2 suggests that individuals who were likely to be approved for a loan were more likely to be applying for Credicedula, shedding doubt on our empirical strategy. Banco Familiar suggested that this could be due to the high popularity of the product during its initial roll-out, causing overwhelmed credit officers to simply not enter the data into the system when an applicant was deemed ineligible for credit. In Appendix Figure A.3, we repeat the same histogram but divide the data between applications presented in 2014 and 2015. We observe that the bunching above the cut-off decreases over time, granting some credibility to their explanation. Furthermore, this explanation would imply that despite this potential bunching, our results would still remain unbiased because the bunching would not be correlated with characteristics of the applicants but instead with how busy the credit officer was at the moment of the application (assuming that those applicants who were entered in the system were a representative sample of all those who were not entered).

More comforting is that the pattern visible in the overall data disappears once we focus on our tight window around the discontinuity. Figure 3 shows the histogram of the applicants depending on their predicted probability of default as calculated by Banco Familiar. This figure shows that there is no evidence of a strong discontinuity right at 0.l96, although we have more applicants who are eligible than non-eligible. This suggests that there was no clear pattern exactly at the cut-off that may bias our results. Formally, a McCrary-like test using Equation (1) where the outcome is the log number of observations reports a coefficient of 0.69 with a standard error of 0.73, suggesting that we cannot reject that the distribution of the observations around the cut-off is smooth. Since the number of observations in our survey within 0.004 points of the cut-off is very small (16 people), we expand it to a broader range of individuals within 0.008 and 0.012 points (51 and 82 observations, respectively). It is comforting to know that the McCrary

Figure 3. Density of applicants around the cut-off



continues to indicate no significant change in density at the exact point of the cut-off.[9]

We can further verify the validity of our identifying assumption by estimating whether there was any discontinuity in outcomes that were measured before Credicedula was offered to selected applicants. If our RD strategy is valid, we should find that before individuals were offered this loan, those deemed just ineligible and just eligible should be identical. Table 2 shows exactly this. The first column regresses the number of requests per 100 days from all creditors before the application to Credicedula. We observe that individuals who were just eligible for the loan were no more likely to have received more requests before their application to Banco Familiar than those who were not eligible. Similar results were obtained when using local linear regressions, as shown in column (2). In column (3), we regress only requests from Banco Familiar to check whether applicants just above or below the cut-off differed in their credit interaction with Banco Familiar before the application. We find no evidence that requests from Banco Familiar were different between loan eligible and ineligible applicants before the application, suggesting that the pattern behind the algorithm had not been exploited at the same threshold previously by Banco Familiar. Finally, in column (4), we show that there was no difference between those deemed just ineligible and just eligible in the credit score provided by Equifax. This suggests

[9] When looking at the range of 0.189 to 0.204, we find a coefficient of 0.42 with a standard error of 0.54 and when looking at the range of 0.185 to 0.209, we find a coefficient of 0.69 with a standard error of 0.45.

that the information contained in the algorithm constructed by Banco Familiar was sufficiently orthogonal to that from the Credit Bureau such that other institutions would not have made a difference between these individuals before their application to Credicedula.

Table 2. Discontinuity in pre-Credicedula characteristics

	Requests per 100 days before loan application			Equifax's prob. of default at application
	All creditors	All creditors	Banco Familiar	
	(1)	(2)	(3)	(4)
Loan eligible	0.09	0.01	0.13	2.14
	(0.19)	(0.32)	(0.08)	(1.58)
Dep. var. mean amongst ineligible	0.60	0.60	0.09	8.43
Method	LP	NP	LP	LP

N=1,060 for all regressions. Method: NP stands for non-parametric. In the NP setting, we use local linear regression with triangular kernel weights. LP stands for linear polynomial. In the LP setting, triangular kernel weights are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

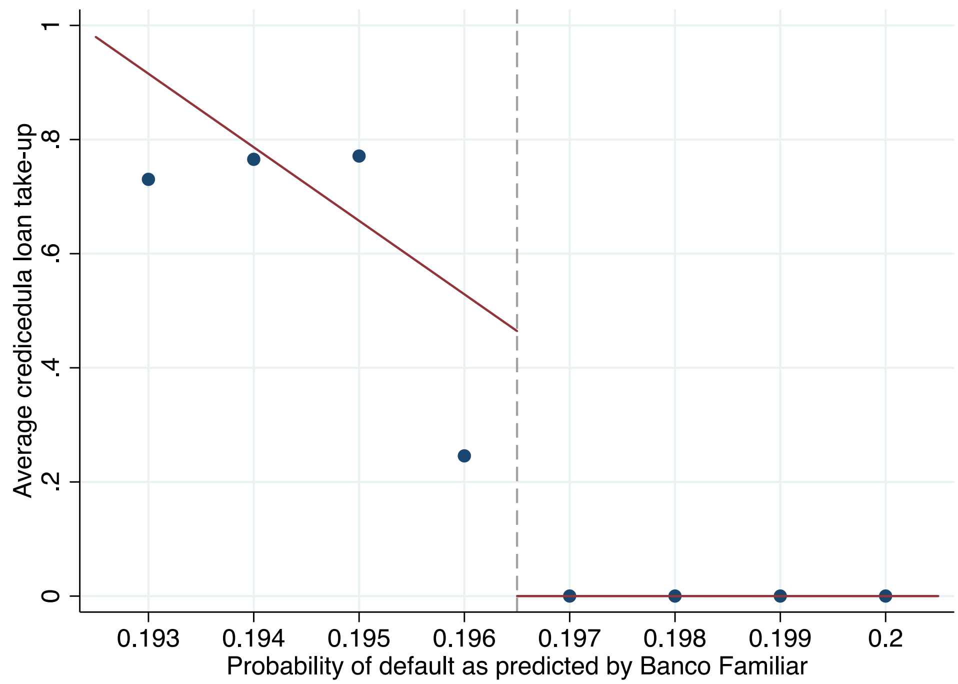
5 Results

Having described our empirical strategy and data, we now turn to measuring the impact of being offered a loan. We begin by showing that individuals who were deemed just eligible for a loan were more likely to accept the loan offer from Banco Familiar. That is, we have a valid first stage. We show, in Figure 4, that nobody who was non-eligible received a loan from Banco Familiar. The portion of eligible applicants who took the loan is close to 70 percent. Formally, we find an effect of being just eligible for a loan of 46 percent on the probability of taking out a loan with Banco Familiar when estimating it with Equation (1).

This loan product was relatively popular, unlike the one evaluated by Arráiz et al. (2019) in that different types of clients seem to have taken the loan at similar rates. Thus, the introduction of this new screening tool did not, in this context, lead to adverse selection like in theirs. Formally, Appendix Table A.1 shows the rate of loan acceptance by applicants' characteristics. The first panel separates individuals by the credit score reported by Equifax at the moment of their application to Credicedula. We denote "better" credit scores with the letters A through F and "worse" scores as the letters G to N. Applicants in the first group had a predicted probability of default of less than 8 percent, as measured by Equifax. Applicants in the second group exposed lenders to higher risks as calculated by Equifax. The next panel separates applicants depending on the number of requests per 100 days reported to Equifax before their application for the Credicedula loan. About a third of our applicants had no requests in the credit bureau between March 2014 and their application to Banco Familiar. About a third of our applicants had some requests, but fewer than one request per 100 days, before their application. Finally, another third of the applicants had more than one request per 100 days before their application. The next panel divides our sample into "formal" workers (those employed by the public sector or a private firm that complied with requirements in terms of worker contributions) and "informal" workers (homemakers, independent workers, and workers in firms that did not comply with contribution obligations). Finally, the last panel evaluates benefits by income-level. We divide our sample at 1.5 million Gs (about US$300), almost at the median, based on the income individuals reported at the moment of the loan application. The table shows extremely similar rates of loan take-up across individuals with better or worse credit scores, those with more or less experience and those with more or less income. Only in the case of formality do we see a larger acceptance rate among those who were particularly targeted for the product, namely informal workers.

Despite this first stage, we continue presenting reduced form analysis because it is unclear to us if an applicant to Credicedula could simply leverage the fact of being approved for a loan, even without taking it out, to improve their creditworthiness with other financial providers. For that reason, we will present only discontinuities in outcomes as follows and not the instrumental variable results which would require that the full impact of being granted a loan occur through its actual receipt.

Figure 4. Effect of loan eligibility on loan take-up

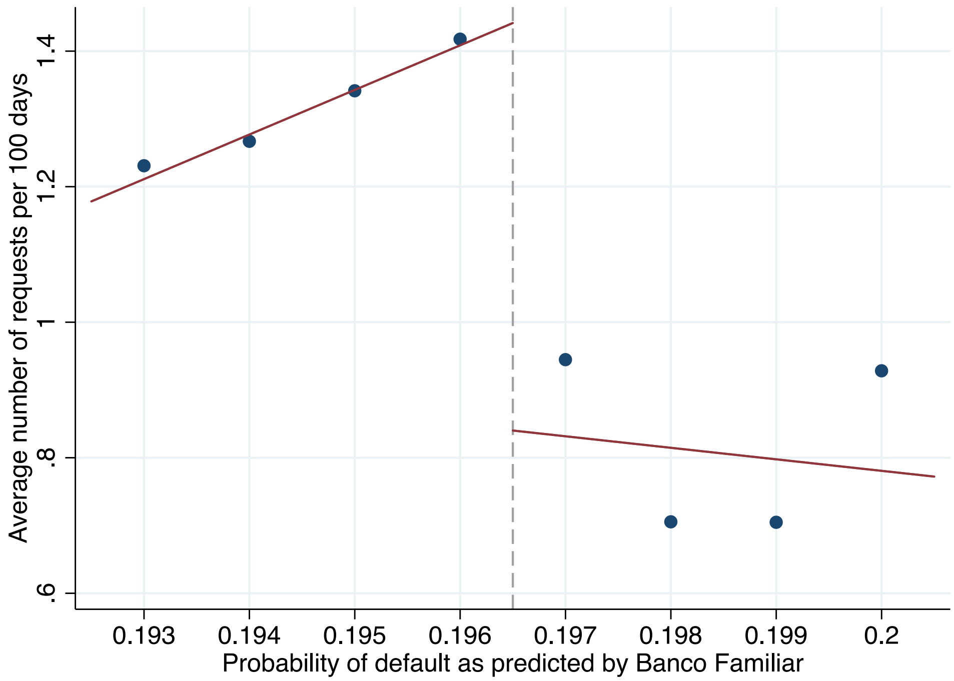


5.1 Credit Bureau Requests

We start by evaluating how being loan eligible influenced requests received by the credit bureau for each individual. We first pool all requests by type of institution, including Banco Familiar. Figure 5 shows a clear pattern that, after the application to Credicedula, individuals who were just eligible saw many more requests to the credit bureau than those who were just ineligible.

We next quantify the impact of loan eligibility on requests to the credit bureau by estimating Equation (1) formally, reporting the results in Table 3. The first column reports the impact of being loan-eligible on the number of requests per 100 days after the individual's application to Banco Familiar. We find a strong, statistically significant effect of being loan eligible on post-Credicedula requests to the credit bureau. The magnitude is similar to the one shown in the previous figure. We explore how sensitive this result is to the use of a local linear polynomial on each side of the discontinuity and find, in Column (2) that results remain fairly similar when using non-parametric methods. However, one could be concerned that the moment in which a customer applied for Credicedula could influence their relationship with the credit market. For example, maybe the most financially integrated applicants arrived to Credicedula before those who were less financially savvy. To check for this concern, we repeat the analysis but this time

Figure 5. Average number of requests per 100 days after Credicedula, by predicted probability of default



using quarter-individual outcomes and adding fixed effects for quarter-year and also for how far this quarter-year is from the moment of application (1 quarter after, 2 quarters after, etc.). We find that introducing these controls barely changes the significance nor the magnitude of the coefficient. Since a quarter has around 90 days and thus, having 0.47 more requests per quarter translates into 0.52 more requests per 100 days, the coefficient in Column (3) is almost the same size as that presented in Column (1). Finally, Column (4) suggests that the probability of having any request in a quarter also increased by about 15 percent, suggesting that the added number of requests comes both from the extensive and intensive margin.

Having shown that this effect seems to be relatively robust, we now turn to exploring heterogeneity in the type of requests made. The top panel of Table 4 shows that the overall increase of 0.5 requests per 100 days is stronger within the first year but is still significant and similar in magnitude even when looking at least one year after the initial loan application. This suggests that being approved for a formal loan through Credicedula appears to have opened long-term opportunities for these individuals in the credit market. In Appendix Table A.2, we show that these results are fairly robust to the definition of the bandwidth. In Appendix Table A.3, we show that very similar results are obtained when using non-parametric estimation methods.

A key question is regarding the quality of the financial institutions that these individuals are

Table 3. Impact of loan-eligibility on requests to Credit Bureau after Credicedula

	Requests per 100 days		Requests per quarter	
			Number	dummy
	(1)	(2)	(3)	(4)
Loan eligible	0.60***	0.58***	0.48***	0.15***
	(0.15)	(0.16)	(0.11)	(0.04)
Mean of dep. var. amongst ineligible	0.82	0.82	0.63	0.37
Method	LP	NP	DM	DM
Obs.	1,060	1,060	13,520	13,520

Method: NP stands for non-parametric. In the NP setting, we use local linear regression RD with triangular kernel weights. LP stands for linear polynomial. In the LP setting, triangular kernel weights are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). DM stands for dynamic model. Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

now interacting with. For example, we could observe a higher number of requests because the individual is now desperate to refinance their credit at any terms (probably worse) in order to pay the existing credit. In the bottom panel of Table 4, , we separate institutions into Banco Familiar, other banks, finance companies, cooperatives, store-based credit, and formal moneylenders based on their names as specified in the credit report. We observe that while there is an increase in the number of requests from Banco Familiar (which granted the loan), this is relatively small in magnitude and concentrated between 100 and 365 days after the loan was granted. Since the Credicedula loan term was for one year, this is unlikely to be a renewal and could even be refinancing. We see no change in the number of requests from other banks suggesting that, unfortunately, this loan from Banco Familiar did not help these individuals increase their access to the most valued institutions in the credit market. However, we do see a strong impact on requests from finance companies and cooperatives. This suggests that Credicedula led individuals to gain access to other formal loans that are similar or better in terms of interest rates, as discussed earlier. The effect does not dissipate in the longer-run for finance companies and cooperatives. We find no aggregate impact on information requests from retail-linked institutions, but do see a small impact in the short-run. Individuals may have used their Credicedula loan to purchase durable goods which they also partially financed with store credit. The fact that this appears to dissipate quickly suggests that individuals did not resort to that type of expensive credit in the longer-term, something that appears to be positive for the applicants. Finally, we see small but positive impacts of becoming loan eligible on requests coming from moneylenders, which offer loans at the highest rates.

Table 4. Impact of eligibility on number of requests for information

Characteristic	Mean of dep. var. amongst ineligible	Requests per 100 days made during... Whole period	Within 100 days	Between 100 and 365 days	After 365 days
Total	0.82	0.60***	0.80***	0.78***	0.47***
		(0.15)	(0.28)	(0.20)	(0.16)
		By type of institution			
Banco Familiar	0.10	0.11***	0.02	0.22***	0.06
		(0.03)	(0.05)	(0.06)	(0.04)
Other banks	0.09	0.03	0.01	0.06	0.02
		(0.03)	(0.06)	(0.04)	(0.03)
Finance Company	0.10	0.19***	0.20**	0.23***	0.15***
		(0.05)	(0.10)	(0.07)	(0.05)
Cooperative	0.05	0.08***	0.12**	0.08**	0.08***
		(0.03)	(0.05)	(0.03)	(0.03)
Store credit	0.38	0.10	0.37**	0.15*	0.03
		(0.06)	(0.16)	(0.08)	(0.07)
Moneylenders	0.04	0.03	0.07*	-0.01	0.05*
		(0.02)	(0.04)	(0.03)	(0.03)

N=1060 for all regressions. All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

In summary, our results seem to suggest that being deemed just eligible for a formal loan increased the interaction of individuals with the credit market, that these effects were relatively long-lasting, that they were concentrated among finance companies and cooperatives.

5.2 Unpaid debt

We now turn to exploring whether the unpaid debt levels reported to the credit bureau changed for individuals after they were deemed creditworthy by Credicedula. Using the same estimating equation, we now focus on the following outcome variables: the number and amount of unpaid loans reported as of March 2017 and the probability of having any unpaid debt at that same point in time. We can then use the date that the debt was reported to be overdue to look at short- versus long-term outcomes, though this is conditional on the debt still being in the person's record in March 2017.

We find that on aggregate, being deemed just loan eligible had no impact on unpaid debt, as shown in the first column of Table 5. The magnitude of the coefficients, however, are relatively large and positive. Once we divide it by relative time period compared to the loan application, we observe small, negative but rarely significant coefficients for the first 100 days. Since by law Banco Familiar would not have been able to report default for Credicedula until 90 days after the payments were stopped, this pattern may be due to the fact that some clients used Credicedula to repay debts from other lenders that were going to incur default, while those who did not receive the Credicedula loan were unable to do so. We also find evidence of an increase in the number and probability of having unpaid credit between 100 and 365 days after the loan application. This appears to completely disappear in a longer time horizon. This suggests that individuals who were just loan eligible may have faced increased financial stress in the short-term due to this greater access to formal credit which may have led some to default on their loans. Data on the amount of debt is just too noisy to derive any conclusions. Estimates with different bandwidths continue to provide a similar conclusion overall, as shown in Appendix Table A.4. Panel B also shows that similar, although even weaker impacts on unpaid debt are found when using non-parametric estimation.

We find limited evidence that impact differed by financial institution. We see no impact for unpaid debt from Banco Familiar suggesting that the small short-run increase in defaults was for loans obtained from other lenders.[10]

[10] Results are available upon request

Table 5. Impact of eligibility on unpaid debt

Measures of unpaid debt	Mean of dep. var. amongst ineligible	Debt defaulted on during... Whole period	Within 100 days	Between 100 and 365 days	After 365 days
		Panel A: Linear polynomial			
Number of loans in default	0.81	0.39	-0.06*	0.27**	0.18
		(0.26)	(0.04)	(0.13)	(0.22)
Prob. of having unpaid debt	0.40	0.11	-0.03	0.13**	0.09
		(0.07)	(0.02)	(0.06)	(0.07)
Total unpaid debt (000s Gs)	1,403	552	-120	331	340
		(690)	(93)	(261)	(608)
		Panel B: Non-parametric estimation			
Number of loans in default	0.81	0.34	-0.07	0.23*	0.18
		(0.27)	(0.06)	(0.12)	(0.23)
Prob. of having unpaid debt	0.40	0.09	-0.03	0.11	0.09
		(0.09)	(0.03)	(0.07)	(0.09)
Total unpaid debt (000s Gs)	1,403	515	-131	302	344
		(716)	(165)	(208)	(656)

N=1,060 for all regressions. All regressions have triangular kernel weights. For the linear polynomial, these are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

5.3 Credit Score

Finally, we also measure the impact of being just above the loan eligibility cut-off threshold on the applicant's credit score as reported by the credit bureau in March 2017 when we obtained the credit reports. Equifax did not provide us with information about how credit scores are constructed in Paraguay. However, we think that the credit score is not generated like it is in the United States where applying for credit immediately lowers one's credit score. In particular, most reporters to Equifax in Paraguay, including Banco Familiar, are "negative" reporters. That is, they only report to Equifax when a client is late with payments, not when they take out a new loan or when they pay their debt on time. This prevents the automatic relationship between credit scores and obtaining credit that we may expect in other settings. However, since other financial institutions in Paraguay are "positive" reporters, we cannot exclude that part of the effect we are measuring could be mechanical.

In Table 6 we show that being just eligible for a loan significantly worsened applicants' credit scores in the credit bureau two to three years later. Given that the credit score is a letter category, we first employ the same linearization as explained earlier, transforming each letter into a probability of default. We find that individuals who were deemed just loan eligible had a credit score (at Equifax) that implied they were 15 percent more likely to default than those who were denied that same loan. This is a substantial downgrade in credit quality, versus the score estimated for the same applicants by the Credicedula algorithm. We next dig deeper into the source of that effect. We observe that there is a lower probability of applicants being in the first two groups of letters and a very strong increase in the ex-post probability of having the letter X, implying a past default. Comparing an individual's credit score in March 2017 to their score at the moment of application, we observe that applicants deemed loan eligible were 11 percent more likely to have worse credit scores in 2017 versus applicants who were deemed too risky to be given the loan. This finding highlights the potential downside of increasing financial market access for very marginal individuals. Results are fairly similar across bandwidths as shown in Appendix Table A.5 but are somewhat weaker using a non-parametric approach, as shown in Appendix Table A.6.

Table 6. Impact of eligibility on credit score

	Mean amongst ineligible	Effect of eligibility
Ex-post pred. prob. of default	36.59	15.87***
		(5.96)
Prob. of Score ABCDEF	0.21	-0.11*
		(0.06)
Prob. of Score GHIJ	0.34	-0.10
		(0.07)
Prob. of Score KLMN	0.23	0.11*
		(0.06)
Prob. of Score X (Default)	0.26	0.15**
		(0.07)
Improved score	0.16	-0.10*
		(0.06)
Kept score	0.07	-0.01
		(0.04)
Worsened score	0.76	0.10
		(0.06)

N=1,060 for all regressions. The probability of default is calculated by Equifax and then published as a letter-score where each letter corresponds to an interval. For reference, A=0, B=1, C=2, D=3, E=4, F=6, G=8, H=10, I=12, J=15, K=20, L=30, M=50, N=73, X=100. All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

5.4 Self-reported Outcomes

Having shown that access to an initial loan appears to have generated more future interactions with the credit market with limited negative consequences in terms of indebtedness, we now turn to evaluate whether this translated into a broader impact on the welfare of beneficiaries. For that purpose, we use the survey data we collected from a subset of applicants. Because we have too few individuals within 0.004 of our cut-off (only 16 people), we expand our window to report results for bandwidths that are from 0.008 to 0.012 from the cut-off (82 people). As the bandwidth expands, we gain precision through a larger number of data points, but we also potentially face more problems linked to endogenous location on one side of the discontinuity. We must present two caveats to this analysis. First, the 512 individuals we were able to locate to participate in the survey had slightly worse Equifax credit scores than those who we could not locate. The difference is small, about a two percentage point higher probability of default and only significant in the largest two bandwidths, but it implies that our results are representative of individuals with a worse previous credit record than the ones for the full sample. Secondly, we have differential "attrition" around the cut-off. Being eligible increased the probability of being found by our surveyors by about two percentage points, again only significantly so in the two largest bandwidths. As in surveys there is typically a higher chance of finding the "best" individuals overall (i.e., those with the better observables), the differential attrition may result in our eligible group including individuals with worse observables than the non-eligible group since more individuals were surveyed in the former group. [11] This should lead us to downward biases in our estimations.

Results for these outcomes are reported in Table 7, using two time periods. Our first survey was conducted in the second semester of 2016, corresponding to one to two years after the application to Banco Familiar. We present these results in the first three columns. Our second survey was conducted in the second semester of 2017, corresponding to two to three years after the application to Credicedula. We present these results in the last three columns. Each column represents a different bandwidth.

We first present results for 2016. We find strong evidence that those who were deemed just eligible to obtain credit faced lower credit costs one to two years later. This suggests that access to Credicedula or other sources of credit did allow recipients to pay less in interest costs every month. It also suggests that the benefit of gaining access to a formal loan through Credicedula (versus the alternative credit sources available to these populations) outweighs the negative impact of the lower credit scores they subsequently received, as shown in the previous sub-section. While not reported here, we found no evidence that getting the Credicedula loan improved re-

[11] Results available upon request.

cipients' budget balance, suggesting that they may have simply redirected these resources to other spending categories. We also find that they were less likely to have sought credit in the last six months maybe because they had obtained the credit they needed, although this is only significant in one of the bandwidth specifications. We find that no other outcome appears to be statistically significantly different between applicants who were deemed just loan eligible and those who were just rejected in 2016.

When we look at a longer horizon with the second survey conducted in 2017 (two to three years after the application), we observe even more interesting evidence that the loan may have had positive benefits for those who became eligible. We find evidence that individuals who just qualified for the loan continued to experience lower credit costs. They reported facing fewer difficulties with paying bills every month, suggesting that they could better smooth financial shocks. We find no evidence that this led them to seek more credit or save more. However, participants who were just eligible for the loan reported significantly better financial well-being. Given that the scale was from one to 10, an increase of four to seven is a very large impact for that variable. We find no evidence of an impact based on an index of four questions regarding emotional well-being. Results are fairly similar when using non-parametric estimates, although the low number of observations complicated the computation. We show these results in Appendix Table A.7. The main difference is that we do find a significant and negative impact on emotional well-being in that case.

Overall, these results suggest that not only did being offered a formal loan open the doors of the credit market for these applicants, it also appears to have had some longer-lasting positive impacts on other economic outcomes, despite the lower credit scores that seem to have followed the loan offer one to three years later.

Table 7. Impact of loan eligibility on self-reported outcomes

	Short-term impacts (2016)			Long-term impacts (2017)		
RD window	[.185, .208]	[.187, .206]	[.189, .204]	[.185, .208]	[.187, .206]	[.189, .204]
Expenses on credit (log)	-9.91**	-10.55**	-10.48*	-13.46***	-12.64**	-11.38*
	(4.17)	(5.09)	(6.14)	(4.61)	(5.49)	(6.59)
Trouble paying bills (dummy)	-0.34	-0.18	-0.15	-0.49	-0.81*	-1.02*
	(0.32)	(0.39)	(0.46)	(0.39)	(0.46)	(0.56)
Number of months (trouble)	0.02	0.00	-0.70	-3.45**	-4.14**	-4.45**
	(2.42)	(2.88)	(3.41)	(1.62)	(1.86)	(2.15)
Sought credit	-0.73**	-0.68	-0.68	-0.47	-0.44	-0.40
	(0.35)	(0.43)	(0.51)	(0.39)	(0.46)	(0.53)
Saved last month (dummy)	0.04	0.24	0.23	0.49	0.74	0.83
	(0.29)	(0.34)	(0.39)	(0.37)	(0.45)	(0.55)
Self-reported financial well-being	-1.24	-0.78	-1.31	2.18	3.92*	6.55**
	(1.90)	(2.35)	(2.80)	(1.90)	(2.22)	(2.46)
Index of emotional well-being	-0.30	-0.28	0.29	-1.08	-1.01	-0.62
	(0.67)	(0.81)	(0.95)	(0.65)	(0.77)	(0.91)
Observations	82	64	51	52	43	34

There are 30 fewer observations in 2017 because of attrition. All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2).* p<0.1, ** p<0.05, *** p<0.01.

5.5 Heterogeneity analysis

Having shown that the average applicant benefited from becoming loan eligible, we now turn to explore whether some applicants benefited more than others.

If loan eligibility allowed the credit market to learn more about the applicant, we would expect that the impact of loan eligibility would depend on the information the credit market had about the applicant at the moment eligibility was granted. Table 8 shows the impact of being loan eligible on the number of requests per 100 days, separating the sample by applicant characteristics, using the same categories as in Appendix Table A.1. The first panel separates individuals by the credit score reported by Equifax at the moment of their application to Credicedula. Only people with worse initial credit reports benefited from being deemed loan eligible in the long-run. This could be because the market was able to learn about their good behavior or that their self-confidence increase through the loan offer. In the immediate short-run, applicants with a better credit score also increased their interaction with the credit market but this did not last past the first 100 days.

The next panel separates applicants depending on the number of requests per 100 days re-

Table 8. Impact of eligibility on number of requests for information, by clients' characteristics

Characteristic	Mean of dep. var. amongst ineligible	Requests per 100 days made during... Whole period	Within 100 days	Between 100 and 365 days	After 365 days
		By ex-ante credit score			
Better credit scores	0.69	0.24	0.78***	0.38	0.06
(N= 505)		(0.16)	(0.25)	(0.24)	(0.20)
Worse credit scores	1.07	0.80***	0.57	0.99***	0.79***
(N= 555)		(0.23)	(0.47)	(0.31)	(0.26)
		By number of requests per 100 days before Credicedula			
None	0.60	0.53**	1.15***	1.15***	0.03
(N= 362)		(0.24)	(0.32)	(0.39)	(0.25)
At or below 1	0.83	0.64***	0.54	0.45*	0.88***
(N= 361)		(0.19)	(0.34)	(0.23)	(0.24)
Above 1	1.34	0.32	0.23	0.52	0.18
(N= 337)		(0.33)	(0.73)	(0.41)	(0.37)
		By employment formality			
Formal sector	1.08	1.04***	1.25**	1.19***	0.89**
(N= 305)		(0.34)	(0.61)	(0.44)	(0.36)
Informal sector	0.71	0.43***	0.58*	0.70***	0.24
(N= 691)		(0.16)	(0.33)	(0.23)	(0.19)
		By monthly income			
Below 1.5M Gs.	0.71	0.38**	0.37	0.49**	0.38*
(N= 461)		(0.17)	(0.30)	(0.21)	(0.23)
At or above 1.5M Gs.	0.93	0.64***	1.00**	0.81**	0.46*
(N= 599)		(0.23)	(0.45)	(0.32)	(0.24)

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

ported to Equifax before their application for the Credicedula loan. In agreement with our hypothesis, we find that those who had less exposure to the financial sector before becoming loan eligible are the ones who benefited the most from being offered the loan. Those who had no previous requests appear to have experienced a significant increase in the number of requests made to Equifax per 100 days in the year after the loan was offered but nothing long-lasting. This may be because they were unable to fulfill their loan obligation. For eligible applicants who were a bit better known by the financial sector, we see large increases in requests, statistically different from 0, in the mid- to long-term. Those who had experienced a large number of requests before their application to Credicedula were not observed to increase their number of requests at any point in time after becoming eligible. This would fit our hypothesis that the credit market did not learn anything new about these individuals through the loan eligibility or that they did not update their self-confidence since they were already very comfortable approaching lenders.

We next explore the impact by employment formality, as recorded at the moment of application. This loan product was designed for people with difficulty demonstrating their source of income, suggesting that informal workers could particularly benefit from accessing it. Nevertheless, we find that both formal and informal sector applicants who were deemed just eligible for the loan experienced increased requests for information to the credit bureau following the loan offer. The effect was even more durable for those who were in the formal sector, suggesting that this product may have solved other types of barriers related to accessing the financial market beyond informality. This is particularly surprising given that these formal workers were less likely to take up the loan than informal ones.

Finally, the last panel evaluates benefits by income-level. It may be that our results in the top two panels are actually driven by a correlation between credit history and income. The fact that individuals who were less well-known and rated by the credit market benefited more, may just be hiding the fact that these individuals were poorer. We find, maybe surprisingly, that loan eligibility particularly benefited the individuals with the highest incomes. The difference is particularly marked in the short-run. This supports our hypothesis that the impact of loan eligibility is more likely to be due to improved information available on these individuals provided to the credit market than through other channels. Appendix Table A.8 shows that we reach the same conclusion when using a non-parametric specification.

In Table 9, we present the results for the impact of loan eligibility on the probability of having unpaid debt according to client characteristics. The results shown here are similar to those derived from other measures. The first panel divides individuals by their ex-ante credit score, as we did in Table 8. While Table 8 shows that applicants with worse credit scores experienced more of an increase in requests, we do not observe an increase in defaults for this group. The point estimates are very small and sometimes negative. For applicants with the best credit scores, we observe a larger positive effect that is not often significant. It also appears to be fairly short-lived. The next panel divides individuals by the number of requests per 100 days they had in their credit report before their application to Credicedula. Interestingly, applicants who had less interaction with the formal financial sector before Credicedula show no evidence of increased default. Most of the coefficients are negative, although not significantly different from 0. However, for those individuals who had already interacted substantially with the credit market, just obtaining a loan significantly increased their probability of having unpaid debt at the moment of our analysis. This appears to be particularly strong in the mid- to long-term. This suggests that applicants who needed to rely on Credicedula despite their previous access to the credit market may have been clients with "bad" credit behavior or past negative shocks and this continued when they obtained Credicedula.

As far as differences among applicants in terms of employment, we find no evidence that the effect of loan eligibility on the probability of having unpaid debt differs by job formality. The last panel looks at heterogeneity by income. Surprisingly, we find that less poor individuals show a greater increase in unpaid debt, particularly in the long-run. Robustness of these results to the use of non-parametric estimation is demonstrated in Appendix Table A.9.

We next explore whether there is heterogeneity in the credit score results. We focus on our linearized credit score measure, in terms of the predicted probability of default associated with each letter. The first panel in Table 10 shows that only for those with the best initial credit report did the credit score significantly differ between those just eligible and those not eligible. However, the magnitudes for the two groups are similar. This may thus be more a reflection that those with higher credit scores were able to fall more dramatically, thus increasing the precision of the estimate.

The next panel separates individuals by previous exposure to the credit market. We find that applicants who had more exposure prior to applying for Credicedula ended up with lower credit scores after becoming loan eligible. This suggests that the negative effect of the loan on credit scores may be concentrated among people who had previously had more interactions with the credit market. Granting a loan to these individuals simply increases their probability of default. But for those who were previously unknown to creditors, the loan does not appear to have had a negative impact on credit scores.

We next separate individuals by employment and find that both formal and informal workers suffered a decrease in their credit scores, with those in the formal sector faring worse. This relates again to the explanation above. Those in the formal sector who were deemed just eligible for the loan probably had a history of poor repayment and therefore giving new credit to these individuals did not improve their financial welfare. A similar story can be told for the division by income.

Table 9. Impact of eligibility on probability of having unpaid debt, by applicants' characteristics

Characteristic	Mean of dep. var. amongst ineligible	Defaults during... Whole period	Within 100 days	Between 100 and 365 days	After 365 days
		By ex-ante credit score			
Better credit score	0.31	0.14	0.00	0.15	0.02
(N= 505)		(0.10)	(0.02)	(0.07)	(0.09)
Worse credit score	0.57	0.02	-0.07	0.08	0.12
(N= 555)		(0.10)	(0.04)	(0.09)	(0.10)
		By requests per 100 days before Credicedula			
None	0.36	-0.05	0.00	0.12	-0.14
(N= 342)		(0.13)	(0.02)	(0.09)	(0.13)
At or below 1	0.38	-0.03	-0.05*	-0.06	0.09
(N= 361)		(0.12)	(0.03)	(0.10)	(0.10)
Above 1	0.51	0.40***	-0.05	0.37***	0.30**
(N= 357)		(0.13)	(0.07)	(0.12)	(0.13)
		By employment formality			
Formal sector	0.42	0.14	0.05	0.13	0.13
(N= 305)		(0.14)	(0.04)	(0.11)	(0.13)
Informal sector	0.40	0.12	-0.04	0.11	0.09
(N= 691)		(0.09)	(0.03)	(0.07)	(0.09)
		By monthly income			
Below 1.5M Gs.	0.40	0.00	0.02	0.09	-0.02
(N= 461)		(0.11)	(0.04)	(0.09)	(0.10)
At or above 1.5M Gs.	0.40	0.17*	-0.08**	0.15*	0.17*
(N= 599)		(0.10)	(0.03)	(0.08)	(0.10)

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

Results are similar in terms of magnitude but noisier when using a non-parametric approach, as shown in Appendix Table A.10.

Overall, our results suggest that the average positive impact of becoming loan eligible we documented above is particularly strong for individuals who had limited interactions with the credit market before their application to Credicedula. Those individuals were more integrated to the credit market, had no more unpaid debt and did not see a statistically significant impact on their credit score after being deemed loan eligible. For individuals who were already interacting

Table 10. Impact of eligibility on credit score (predicted probability of default), by applicant characteristics

Characteristic	Mean amongst ineligible	Impact on Equifax credit score	Obs.
		By ex-ante credit score	
Best credit scores	29.62	16.17**	505
		(8.17)	
Worse credit scores	50.07	13.86	555
		(8.75)	
		By number of requests per 100 days before Credicedula	
None	31.48	11.10	362
		(10.47)	
At or below 1	33.45	13.07	361
		(9.47)	
Above 1	56.32	20.74*	337
		(11.97)	
		By employment formality	
Formal sector	40.27	27.78**	305
		(11.55)	
Informal sector	35.58	15.34**	691
		(7.44)	
		By monthly income	
Below 1.5M Gs	37.07	6.23	461
		(9.15)	
At or above 1.5M Gs.	36.11	22.80***	599
		(8.32)	

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

substantially with the credit market, there were less benefits in terms of market integration and more costs in terms of increased indebtedness and worse credit scores.

6 Conclusions

This paper has explored the causal effect of being offered a loan on financial outcomes at the individual-level using a regression discontinuity design generated by a new algorithm-based mechanism to screen applicants who could not be evaluated with traditional methods. We find strong evidence that being deemed just eligible for a loan increases one's interaction with the formal financial market, did not influence their level of indebtedness, worsen their credit score but had positive self-reported consequences. This may be because the loan increased the applicants' credibility in the eyes of the credit market or because of applicants became more confident in their interactions with creditors. We find that these results are particularly positive for applicants who were previously unknown by financial entities, where obtaining access to formal credit for the first-time opened doors to new opportunities in the financial market without negative impacts on credit scores or increasing defaults.

These findings are relevant for public policy because they suggest that using alternative credit screening mechanisms may lead some marginal individuals to benefit from formal financial market access. This suggests that despite the fact that credit seems to be available to this population, access to a better type of loan (formal) can improve their financial situation two to three years down the road. The Credicedula loan product was privately profitable, suggesting that there is room for the private market to increase services for more marginal clients.

However, our results also suggest that on its own, this screening approach may also give eligibility to individuals who are locked out of the credit market based on past bad credit behavior. Thus, this alternative screening mechanism may be most useful when combined with a measure of how much interaction applicants have had with the credit market. Overall, this is an interesting conclusion because it suggests that policies to enhance access to finance should consider different approaches based on the depth of individuals' credit histories to better meet their needs. The role of an active credit bureau, which collects positive and negative information about financial institutions' clients, is thus essential for that task.

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A Additional Tables and Figures

Figure A.1. Example of credit report from Equifax, first page

Fecha: 30/03/2017 11:41:23 | **Informconf** una empresa Equifax | Pág:1/2

Informes Confidenciales
Primera Agencia Paraguaya de Informes Comerciales y Confidenciales

BANCO FAMILIAR S.A.E.C.A.
CHILE 1080 E/JEJUI EDIF.GRUPO GRAL.BºLA ENCAR ASUNCION (1 - 1 - 8 14)

Documento: [redacted] **Tipo Documento:** CEDULA DE IDENTIDAD
Nombre:
Apellido:
Sexo: **Fec.Nacimiento:** [redacted]
Estado Civil: **Nacionalidad:** PARAGUAYA

Informconf Credit Scoring M0200INF
Faja: X
El score que antecede es producto del cálculo estadístico de datos muestrales del comportamiento de los paraguayos, y se obtiene comparando los datos de este informe, con el comportamiento de grupos
Bajo ningún punto de vista, puede ser tomado como Juicio de Valor, de la intención de pago de la persona.

Histórico de Direcciones
Calle: [redacted] **Barrio:**
Ciudad: **Tel.:** **Prim. y Ult. Ref:** 18/04/2011 18/04/2011

Solicitudes de Informes (Últimos 3 años)

Afiliado	Fecha	Tipo Operación
CREDI AGIL(Tel: 2471000)	15/12/2014	Solo Consulta
INVERFIN S.A.E.C.A.(Tel: 2883300 / 282442)	30/12/2014	Solo Consulta
VISION BANCO S.A.E.C.A.(Tel: 4143000)	02/01/2015	Solo Consulta
BANCO FAMILIAR S.A.E.C.A. (S.O)(Tel: 4142000)	03/01/2015	Solo Consulta
SOLAR SA DE AHORRO Y PTMO. PARA LA VIVIENDA(Tel: 452100)	05/01/2015	Solo Consulta
FINANCIERA EL COMERCIO S.A.E.C.A.(Tel: 6188000)	05/01/2015	Solo Consulta
CREDITOTAL(Tel: 4184000)	07/01/2015	Solo Consulta
CHE DUO PRESTAMOS PERSONALES(Tel: 2388800)	16/01/2015	Solo Consulta
TELEFONICA CELULAR DEL PARAGUAY S.A.(Tel: 6189000 / 6189332)	19/01/2015	Solo Consulta
AMX PARAGUAY S.A.(Tel: 4178000 / 2499722)	21/01/2015	Solo Consulta
CREDI CLARA S.A.(Tel: 440502 / 443070)	22/01/2015	Solo Consulta
INVERFIN S.A.E.C.A.(Tel: 2883300 / 282442)	03/02/2015	Solo Consulta
AMX PARAGUAY S.A.(Tel: 4178000 / 2499722)	30/03/2015	Solo Consulta
CREDI AGIL(Tel: 2471000)	24/04/2015	Solo Consulta
SOLAR AHORRO Y FINANZAS S.A.E.C.A.(Tel: 452100)	25/06/2015	Solo Consulta
TELEFONICA CELULAR DEL PARAGUAY S.A.(Tel: 6189000 / 6189332)	26/06/2015	Solo Consulta
CREDITOTAL(Tel: 4184000)	20/07/2015	Solo Consulta
COOP.DE GRADUADOS EN CIENCIAS ECONOMICAS(Tel: 497195 / 446220)	11/08/2015	Solo Consulta
AMX PARAGUAY S.A.(Tel: 4178000 / 2499722)	31/08/2015	Solo Consulta
TECNO PARAGUAY S.A(Tel: 444901/3)	01/09/2015	Solo Consulta
VISION BANCO S.A.E.C.A.(Tel: 4143000)	22/09/2015	Solo Consulta
SOLAR AHORRO Y FINANZAS S.A.E.C.A.(Tel: 452100)	22/09/2015	Solo Consulta
JET TRADE ELECTRODOMESTICOS S.A.(Tel: 480879 / 424245)	15/12/2015	Solicitud de Crédito
CREDITOTAL(Tel: 4184000)	16/12/2015	Solo Consulta
ALEX S.A.(Tel: 645900)	21/01/2016	Solo Consulta
NUCLEO S.A.(Tel: 2199000)	28/01/2016	Solo Consulta
SOLAR AHORRO Y FINANZAS S.A.E.C.A.(Tel: 452100)	17/03/2016	Solo Consulta
SOLAR AHORRO Y FINANZAS S.A.E.C.A.(Tel: 452100)	05/05/2016	Solo Consulta
CREDITOTAL(Tel: 4184000)	24/06/2016	Solo Consulta
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Agente: [redacted]

Figure A.2. Example of credit report from Equifax, second page

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una empresa Equifax

Pág:2/2

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Solicitudes de Informes (Últimos 3 años)

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BANCO FAMILIAR S.A.E.C.A.(Tel: 4142000)	30/03/2017	Solo Consulta

Solicitudes de Informes (Resumen últimos 30 días)

Días	Hoy	1 a 5	6 a 10	11 a 15	16 a 20	21 a 25	26 a 30
Cantidad Período	1	0	0	0	0	0	0
Cantidad Acumulada	1	1	1	1	1	1	1

Obs: Se refiere a la cantidad de pedidos de información, por rango de días, que los Afiliados han realizado de esta persona en los últimos 30 días.

Solicitudes de Informes (Resumen últimos 3 años)

2014-04	2014-05	2014-06	2014-07	2014-08	2014-09	2014-10	2014-11	2014-12	2015-01	2015-02	2015-03
0	0	0	0	0	0	0	0	2	9	1	1
2015-04	**2015-05**	**2015-06**	**2015-07**	**2015-08**	**2015-09**	**2015-10**	**2015-11**	**2015-12**	**2016-01**	**2016-02**	**2016-03**
1	0	2	1	2	3	0	0	2	2	0	1
2016-04	**2016-05**	**2016-06**	**2016-07**	**2016-08**	**2016-09**	**2016-10**	**2016-11**	**2016-12**	**2017-01**	**2017-02**	**2017-03**
0	1	1	0	0	0	1	0	1	0	0	1

Obs: Se refiere a la cantidad de pedidos de información, por mes, que los Afiliados han realizado de esta persona en los últimos 36 meses.

Operaciones Morosas

Afiliado	Fecha Op.	Monto Operación	Mon.	Plazo	F.Inscrip.	F.Ultimo Pago	F.Vto. Pendiente	Saldo
CREDITOTAL	13/01/2016	6.055.192,00	Gs.	18M	15/12/2016	29/09/2016	15/09/2016	3.081.545,00
	Tipo Op.:	Deuda Deudor						
AMX PARAGUAY S.A.		559.511,00	Gs.	0M	09/01/2017		30/09/2016	559.511,00
	Tipo Op.:	Servicio Deudor						
NEXO S.A.E.C.A	27/06/2016	3.160.000,00	Gs.	10M	30/01/2017		27/07/2016	3.160.000,00
	Tipo Op.:	Deuda Deudor						

NO REGISTRAMOS EN NUESTRA BASE DE DATOS: L.Trabajo - Doc.Extraviados - Referencias - Demandas - Convocatorias - Quiebras - Remates - Inhabilitación de Cuentas - //[redacted]

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Operador: [redacted]
Agente: [redacted]

Figure A.3. Density of applications by Banco Familiar score and year of application

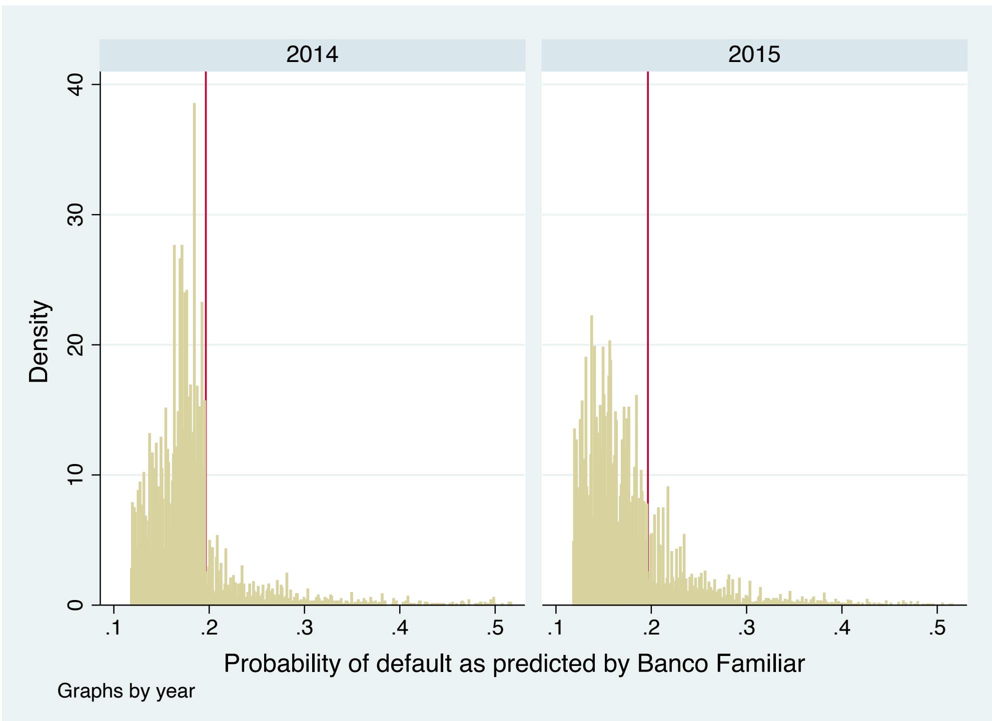

Table A.1. Impact of eligibility on loan take-up by individual characteristics

	Took loan
	By ex-ante credit score
Better credit scores	0.48***
(N= 505)	(0.07)
Worse credit score	0.44***
(N= 555)	(0.08)
	By Previous number of requests
None	0.41***
(N= 362)	(0.09)
At or below 1	0.49***
(N= 361)	(0.09)
Above 1	0.47***
(N= 337)	(0.12)
	By Employment formality
Formal sector	0.35***
(N= 305)	(0.12)
Informal sector	0.53***
(N= 691)	(0.06)
	By monthly income
Below 1.5M Gs.	0.47***
(N= 461)	(0.07)
At or above 1.5M Gs.	0.45***
(N= 599)	(0.08)

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.2. Robustness of RD impact of eligibility on number of requests for information to Equifax by bandwidth

Bandwidths	Whole period	Within 100 days	Between 100 and 365 days	After 365 days	Obs.
$.193 \leq$ pm $\leq .2$	0.60***	0.80***	0.78***	0.47***	1,060
	(0.15)	(0.28)	(0.20)	(0.16)	
$.194 \leq$ pm $\leq .199$	0.48***	0.50	0.61**	0.43**	766
	(0.18)	(0.34)	(0.25)	(0.21)	
$.195 \leq$ pm $\leq .198$	0.39	0.26	0.37	0.38	452
	(0.26)	(0.46)	(0.35)	(0.30)	
$.196 \leq$ pm $\leq .197$	0.47**	0.45	0.54**	0.42*	101
	(0.20)	(0.31)	(0.26)	(0.24)	

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

Table A.3. Impact of eligibility on number of requests for information, using non-parametric estimation

Characteristic	Whole period	Within 100 days	Between 100 and 365 days	After 365 days
Total	0.58***	0.73***	0.74***	0.46**
	(0.16)	(0.28)	(0.21)	(0.20)
		By type of institution		
Banco Familiar	0.11***	0.03	0.21***	0.05
	(0.03)	(0.07)	(0.05)	(0.05)
Other banks	0.03	0.01	0.06	0.02
	(0.04)	(0.08)	(0.05)	(0.04)
Finance Company	0.19***	0.17*	0.24***	0.15**
	(0.05)	(0.10)	(0.07)	(0.06)
Cooperative	0.09***	0.12**	0.08**	0.08***
	(0.03)	(0.05)	(0.04)	(0.03)
Store credit	0.08	0.34**	0.11	0.01
	(0.08)	(0.15)	(0.09)	(0.10)
Moneylenders	0.03	0.06	-0.01	0.04*
	(0.02)	(0.06)	(0.04)	(0.02)

N=1060 for all regressions. All regressions use STATA comand rdrobust and triangular weights. Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

Table A.4. Robustness of default results on bandwidth choices

Bandwidths	Whole period	Within 100 days	Between 100 and 365 days	After 365 days	Obs.
		Panel A: Number of loans in default			
$.193 \leq \text{pm} \leq .2$	0.39	-0.06*	0.27**	0.18	1,060
	(0.26)	(0.04)	(0.13)	(0.22)	
$.194 \leq \text{pm} \leq .199$	0.16	-0.10**	0.09	0.16	766
	(0.31)	(0.04)	(0.15)	(0.26)	
$.195 \leq \text{pm} \leq .198$	-0.35	-0.13**	0.04	-0.27	452
	(0.43)	(0.06)	(0.20)	(0.37)	
$.196 \leq \text{pm} \leq .197$	0.06	-0.09	0.12	0.03	101
	(0.29)	(0.06)	(0.13)	(0.25)	
		Panel B: Probability of defaulting			
$.193 \leq \text{pm} \leq .2$	0.11	-0.03	0.13**	0.09	1,060
	(0.07)	(0.02)	(0.06)	(0.07)	
$.194 \leq \text{pm} \leq .199$	0.05	-0.04	0.05	0.07	766
	(0.09)	(0.03)	(0.07)	(0.09)	
$.195 \leq \text{pm} \leq .198$	-0.13	-0.07	0.00	-0.09	452
	(0.12)	(0.04)	(0.10)	(0.12)	
$.196 \leq \text{pm} \leq .197$	-0.01	-0.05	0.04	0.02	101
	(0.10)	(0.03)	(0.07)	(0.09)	
		Panel C: Amount defaulted on (000s)			
$.193 \leq \text{pm} \leq .2$	552	-120	331	340	1,060
	(690)	(93)	(261)	(608)	
$.194 \leq \text{pm} \leq .199$	386	-167	204	349	766
	(811)	(120)	(300)	(710)	
$.195 \leq \text{pm} \leq .198$	-895	-348*	62	-609	452
	(1,130)	(183)	(386)	(1,005)	
$.196 \leq \text{pm} \leq .197$	14.68	-215	180	49	101
	(758)	(150)	(216)	(707)	

All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). * p<0.1, ** p<0.05, *** p<0.01.

Table A.5. Robustness of credit score results on bandwidth selection

RD window	Effect of eligibility [.193, .2]	Effect of eligibility [.194, .199]	Effect of eligibility [.194, .199]	Effect of eligibility [.196, .197]
Ex-post probability of default	15.87***	14.32**	5.54	10.72
	(5.96)	(7.27)	(10.15)	(8.55)
Prob. of Score ABCDEF	-0.11*	-0.13*	-0.05	-0.06
	(0.06)	(0.07)	(0.10)	(0.09)
Prob. of Score GHIJ	-0.10	-0.03	0.03	-0.03
	(0.07)	(0.08)	(0.11)	(0.09)
Prob. of Score KLMN	0.11*	0.12	0.15	0.10
	(0.06)	(0.08)	(0.11)	(0.09)
Prob. of Score X (Default)	0.15**	0.09	-0.02	0.07
	(0.07)	(0.09)	(0.12)	(0.10)
Improved score	-0.10*	-0.16**	-0.22**	-0.12
	(0.06)	(0.07)	(0.10)	(0.08)
Kept score	-0.01	-0.01	0.06	0.02
	(0.04)	(0.05)	(0.07)	(0.05)
Worsened score	0.10	0.17**	0.16	0.10
	(0.06)	(0.08)	(0.11)	(0.09)
Observations	1,060	766	452	101

The probability of default is calculated by Equifax and then published as a letter-score where each letter corresponds to an interval. For reference, A=0, B=1, C=2, D=3, E=4, F=6, G=8, H=10, I=12, J=15, K=20, L=30, M=50, N=73, X=100. All regressions have triangular kernel weights. These are equal to 4 for observations closest to discontinuity (score=.196 and score=.197) and decrease lineally with distance, equaling 1 for observations furthest away from discontinuity (score=.193 and score=.2). * p<0.1, ** p<0.05, *** p<0.01.

Table A.6. Impact of eligibility on credit score, non-parametric estimation

	Effect of eligibility
Ex-post probability of default	15.63**
	(7.20)
Prob. of Score ABCDEF	-0.11
	(0.08)
Prob. of Score GHIJ	-0.09
	(0.08)
Prob. of Score KLMN	0.11
	(0.08)
Prob. of Score X (Default)	0.14
	(0.09)
Improved score	-0.11
	(0.08)
Kept score	-0.01
	(0.05)
Worsened score	0.12
	(0.09)

N=1060 for all regressions. The probability of default is calculated by Equifax and then published as a letter-score where each letter corresponds to an interval. For reference, A=0, B=1, C=2, D=3, E=4, F=6, G=8, H=10, I=12, J=15, K=20, L=30, M=50, N=73, X=100. All regressions estimates are calculated using the rdrobust STATA command and use triangular kernel weights. * p<0.1, ** p<0.05, *** p<0.01.

Table A.7. Impact of loan eligibility on self-reported outcomes, non-parametric estimates

	Short-term impacts (2016)			Long-term impacts (2017)		
RD window	[.185, .208]	[.187, .206]	[.189, .204]	[.185, .208]	[.187, .206]	[.189, .204]
Expenses on credit (log)	-10.17***	-10.40**	-11.01**	-13.49***	-12.08***	
	(3.94)	(4.12)	(4.96)	(2.48)	(2.56)	
Trouble paying bills (dummy)	-0.29**	-0.18	-0.13	-0.54	-0.85	
	(0.13)	(0.12)	(0.13)	(0.55)	(0.67)	
Number of months (trouble)	0.07	-0.06	-1.46	-3.58*	-4.19**	
	(2.68)	(3.33)	(4.14)	(1.92)	(1.84)	
Sought credit	-0.74**	-0.67*	-0.71	-0.47	-0.39	
	(0.32)	(0.36)	(0.44)	(0.34)	(0.39)	
Saved last month (dummy)	0.08	0.25	0.26	0.52	0.78*	
	(0.30)	(0.33)	(0.41)	(0.35)	(0.42)	
Self-reported financial well-being	-1.23	-0.81	-1.03	2.46	4.42	
	(1.66)	(1.90)	(2.11)	(4.48)	(5.89)	
Index of emotional well-being	-0.28	-0.20	0.27	-1.06**	-0.95**	
	(0.58)	(0.62)	(0.81)	(0.46)	(0.47)	
Observations	82	64	51	52	43	

There are 30 fewer observations in 2017 because of attrition. The long-term impacts could not be computed for the smaller bandwidth because of the small number of observations. All regressions estimates are calculated using the rdrobust STATA command and use triangular kernel weights. * p<0.1, ** p<0.05, *** p<0.01.

Table A.8. Impact of eligibility on number of requests per 100 days for information, non-parametric specification

Chracteristic	Whole period	Within 100 days	Between 100 and 365 days	After 365 days
		By ex-ante credit score		
Better credit scores	0.22	0.75***	0.33	0.05
(N= 505)	(0.18)	(0.26)	(0.22)	(0.26)
Worse credit scores	0.81***	0.56	1.00***	0.80***
(N= 555)	(0.25)	(0.47)	(0.33)	(0.29)
		By requests per 100 days before Credicedula		
None	0.46*	1.14***	1.07***	-0.05
(N= 362)	(0.25)	(0.36)	(0.37)	(0.32)
At or below 1	0.68***	0.52	0.47	0.94***
(N= 361)	(0.24)	(0.45)	(0.31)	(0.31)
Above 1	0.34	0.22	0.55	0.20
(N= 337)	(0.37)	(0.65)	(0.47)	(0.44)
		By Employment formality		
Formal sector	1.06***	1.21*	1.20**	0.93*
(N= 305)	(0.40)	(0.64)	(0.53)	(0.48)
Informal sector	0.39**	0.48	0.64***	0.22
(N= 691)	(0.17)	(0.32)	(0.21)	(0.21)
		By monthly income		
Below 1.5M Gs.	0.34*	0.33	0.41*	0.36
(N= 461)	(0.18)	(0.38)	(0.22)	(0.22)
At or above 1.5M Gs.	0.63**	0.91**	0.80**	0.46
(N= 599)	(0.26)	(0.41)	(0.33)	(0.33)

All regressions use STATA command rdrobust and triangular kernel weights. Requests for information to Equifax within 3 days of the Banco Familiar application were eliminated. * p<0.1, ** p<0.05, *** p<0.01.

Table A.9. Impact of eligibility on probability of having unpaid debt, by applicants' characteristics, non-parametric estimation

Characteristic	Whole period	Within 100 days	Between 100 and 365 days	After 365 days
		By ex-ante credit score		
Best credit scores	0.13	-0.00	0.14	0.02
(N= 505)	(0.12)	(0.02)	(0.08)	(0.11)
Worse credit scores	0.02	-0.07	0.06	0.12
(N= 555)	(0.13)	(0.07)	(0.11)	(0.13)
		By number of requests per 100 days before Credicedula		
None	-0.06	0.00	0.12	-0.14
(N= 342)	(0.17)	(0.01)	(0.11)	(0.17)
At or below 1	-0.04	-0.04	-0.09	0.09
(N= 361)	(0.15)	(0.02)	(0.12)	(0.12)
Above 1	0.39**	-0.07	0.36***	0.29*
(N= 357)	(0.17)	(0.11)	(0.09)	(0.17)
		By employment formality		
Formal sector	0.16	0.05**	0.12	0.16
(N= 305)	(0.18)	(0.02)	(0.14)	(0.17)
Informal sector	0.10	-0.04	0.09	0.08
(N= 691)	(0.11)	(0.04)	(0.08)	(0.11)
		By monthly income		
Below 1.5M Gs.	-0.02	0.02	0.06	-0.03
(N= 461)	(0.14)	(0.02)	(0.10)	(0.13)
At or above 1.5M Gs.	0.16	-0.08	0.14	0.17
(N= 599)	(0.13)	(0.06)	(0.10)	(0.12)

All regressions use STATA command rdrobust and triangular kernel weights. * $p<0.1$, ** $p<0.05$, *** $p<0.01$.

Table A.10. Impact of eligibility on credit score (predicted probability of default), by applicant characteristics, non-parametric estimation

Characteristic	Effect of eligibility	Obs.
	By ex-ante credit score	
Best scores	13.79	505
	(10.09)	
Worse scores	13.60	555
	(11.17)	
	By number of requests per 100 days before Credicedula	
None	11.09	362
	(12.67)	
At or below 1	12.10	361
	(12.03)	
Above 1	16.91	337
	(15.85)	
	By employment formality	
Formal sector	23.03	305
	(15.36)	
Informal sector	15.27*	691
	(9.26)	
	By monthly income	
Below 1.5M Gs.	5.17	461
	(11.26)	
At or above 1.5M Gs.	22.15**	599
	(10.74)	

The probability of default is calculated by Equifax and then published as a letter-score where each letter corresponds to an interval. For reference, A=0, B=1, C=2, D=3, E=4, F=6, G=8, H=10, I=12, J=15, K=20, L=30, M=50, N=73, X=100. All regressions estimates are calculated using the rdrobust STATA command and use triangular kernel weights. * p<0.1, ** p<0.05, *** p<0.01.