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Abstract

We collaborated with the Entrepreneurial Finance Lab (EFL) and a large bank in Peru to study the use of psychometrics for small and medium-sized enterprise (SME) lending. Applicants used a psychometric tool and those who achieved a score higher than a threshold were offered a loan. Using a regression discontinuity design and credit bureau data we find that the tool increased SME loan use 54 percentage points for applicants without a credit history, without leading to worse repayment behavior. This increase in borrowing resulted primarily from financial institutions other than our partner bank. For applicants with a credit history, the tool did not increase SME loan use.

JEL Classification: D82, G21, G32
Keywords: Asymmetric information, psychometrics, credit risk, access to credit

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1 Introduction

Small and medium-sized enterprises (SMEs) tend to face greater financial constraints than large firms, in part because they are subject to information asymmetries that are less salient for large firms. SMEs often lack audited financial statements and other information about their operations, and as a result, financial institutions have difficulties assessing the risk of lending to them (De la Torre et al., 2009).

Several studies have documented that information sharing, credit bureaus, and credit scoring can increase credit to SMEs (Berger et al., 2005; Brown et al., 2009; Love and Mylenko, 2003; Martinez Peria and Singh, 2014). However, not all countries have credit bureaus and where bureaus exist, the information they provide may be limited, for legal and institutional reasons. For example, the average credit bureau in Latin America and the Caribbean complies with only half of best practices and covers only 41.2% of the adult population (Doing Business Report 2017).

Thus, even though credit scoring can improve SMEs' access to credit, it may take years to pass legislation that will lead to improvements in the quality and depth of the information recorded by credit bureaus. Even after credit bureaus are set up and working well, building an accurate credit-scoring model often requires several years of credit history. Additionally, loan applicants are subject to a chicken-and-egg problem. Bureau information is most useful for making credit decisions regarding loan applicants with a detailed credit history, but applicants can only build that history by getting credit, for which they need a good credit history. Therefore, credit markets in many countries may have to rely on alternative lending technologies to screen potential clients.

One such alternative lending technology relies on psychometric testing to screen loan applicants. This paper studies the effectiveness of a psychometric tool for lending to SMEs in the context of a pilot exercise conducted by EFL, a fintech company founded in 2010, and a financial institution in Peru. EFL has developed an alternative credit information tool that can potentially be used by lenders to better screen loan applicants. This tool uses a psychometric application to assess the SME owner's creditworthiness. According to EFL's website, the tool has been used to screen close to 1 million loan applications in 15 countries across four continents as financial institutions are exploring how to incorporate the tool into their lending process.[1]

The pilot exercise in Peru was the first implementation of the EFL tool in Latin America and relied on the "Africa v2 psychometric credit score", which was based on information from 920 observations with loan repayment data, almost all of which were from Africa. The financial institution participating in the exercise, one of the five largest commercial banks in Peru (we refer to this bank as our "partner bank"), piloted the EFL tool starting in March 2012, with the goal of expanding its SME portfolio. At the time, our partner bank was not very active in the SME market. Its conventional screening method, which relied on a three-digit credit score from Equifax Peru and a site visit to the SME, was better suited for

[1] https://www.eflglobal.com/ accessed on March 27, 2017. In November 2017, EFL merged with Lenddo, which uses mobile and digital footprint data for credit scoring. For more information on LenddoEFL, see include1billion.com.

larger companies and resulted in a high rate of credit rejection in the SME segment.[2]

During the pilot exercise, SME loan applicants were screened by the EFL tool and received a three-digit psychometric credit score. All applicants who achieved a score higher than a threshold set by our partner bank were offered a loan, making it possible to use a regression discontinuity (RD) design to evaluate the effectiveness of the tool.[3] The cutoff was set arbitrarily by our partner bank, as the bank had no historical information with which to set it. Applicants with a score below the EFL threshold were also offered a loan if they were approved under the bank's conventional screening method. Only SMEs that were rejected under both screening methods were not offered a loan from our partner bank.

The way in which our partner bank applied the EFL tool differs from the way other financial institutions have used it. When credit bureau information exists, financial institutions typically use this information to approve prospective good credit clients and reject prospective bad credit clients. Some of these rejected applicants may however be profitable clients, particularly if they are rejected not because of bad credit bureau information but because of lack of information i.e. because they have thin credit bureau files. The EFL tool is often used to assess the creditworthiness of these thin file clients. Different from this typical use, our partner bank used the EFL tool to grant credit to all types of applicants including those with thin credit bureau files and those with bad credit bureau information.

A reason why our partner bank was willing to test the EFL using applicants with bad credit histories may be that in order to calibrate the model, they needed to observe a minimum number of defaults. Additionally, the pilot project included a Risk Sharing Guarantee Facility financed by the Inter-American Development Bank (IDB). This Risk Sharing Facility covered up to a maximum fraction of the credit exposure (principal and interest) for guaranteed loans after exhausting the first loss amount to be assumed by our partner bank. This guarantee may also have influenced the effort exerted by our partner bank when monitoring loans and collecting payment.

We study the effectiveness of the EFL tool in increasing access to credit for loan applicants and we also ask whether this increased access results in worse repayment behavior. That is, we first investigate whether being offered a loan by our partner bank based on their EFL score increased the overall use of SME credit in our sample. Clearly, SMEs with an EFL score above the threshold were more likely to obtain a loan from our partner bank than those with an EFL score below this threshold. However, SMEs with an EFL score below the threshold could potentially have gotten a loan from other financial institutions different from our partner bank, in which case loan use may not increase. Second, we ask whether SMEs that were offered a loan based on the EFL tool exhibit repayment behavior different from SMEs that were not offered a loan based on the EFL tool.

We estimate the causal impact of the EFL tool on SME loan use and repayment behavior using several regression discontinuity (RD) methods around the EFL score threshold. For this analysis, we obtained detailed data on formal credit usage and credit scores from Equifax Peru. We use the Equifax credit score four years after the loan application as a measure of

[2] Peru's credit bureaus cover 100% of the adult population, so that everybody has a credit score, but for individuals without a credit history this credit score is primarily based on demographic information.

[3] Figure A.1 in the appendix shows the distribution of EFL scores for all SME loan applicants in our sample, below and above the selected threshold.

repayment behavior. Since the EFL tool may be particularly relevant for loan applicants who do not have a credit history, we conduct our analysis in the full sample of applicants, as well as in two subsamples: (i) applicants with thin credit bureau files and (ii) applicants with thick credit bureau files. We define applicants with a "thick credit bureau file" as those applicants whose Equifax score was based on their credit history and applicants with a "thin credit bureau file" as those whose Equifax score was based on demographics and other sources, such as the tax authority.

Our results show that in the full sample of applicants, the EFL tool increased the probability of taking out a new SME loan from any financial institution during the six months following the pilot loan application by up to 19 percentage points (compared to about 59% just below the EFL score threshold). When analyzing the subsamples, we see that the effect of the EFL tool on taking out a new SME loan during the six months following the application is much larger for applicants with thin credit bureau files, with an increase of up to 59 percentage points (compared to about 10% just below the EFL score thresholds). For this subsample, the increase in borrowing resulted primarily from financial institutions other than our partner bank. This finding is consistent with staff from our partner bank stating that applicants used their loan approval letters to secure more advantageous loans from other institutions. For applicants with thick credit bureau files, we find no significant effect on overall short-run loan use. Instead, we find a significant increase in the probability of taking out a loan from our partner bank only. Thick file applicants were offered a loan from our partner bank based on the EFL tool even if they had low traditional credit scores, i.e. if they had bad credit information in their thick files. However, applicants with low credit scores are unlikely to have gotten loans from other institutions due to their bad credit history and thus loan approval letters from our partner bank would have been less useful for these applicants than for thin file applicants.

We also find that offering a loan to all applicants based on the EFL tool leads to worse repayment behavior vis-à-vis SMEs that were rejected by the EFL tool, in terms of applicants having lower Equifax credit scores three to four years after the loan application. This effect seems to be driven by applicants with thick credit bureau files, who took out a loan from our partner institution thanks to the EFL tool. Due to the specific setting of this pilot exercise, the negative effect on repayment behavior may thus stem from applicants with bad credit histories receiving loans and possibly from reduced monitoring and collection efforts due to the credit guarantee received by our partner bank. We do not find strong evidence of worse repayment behavior among applicants with thin credit bureau files. Finally, we study whether loan applicants receive additional loans in the medium-run (24 to 31 months after the pilot), but we do not find this to be the case in either the full sample or the subsamples.

Overall, our results suggest that psychometric credit scoring is a viable screening method for loan applicants who do not have a credit history. The way in which the EFL tool was used in the pilot exercise in Peru, i.e., by applying the psychometric tool to all clients irrespective of their credit history, also highlights the power of thick credit bureau information. That is, when bad credit information exists, it seems most beneficial for financial institutions to rely only on this information in their lending decisions. For loan applicants with thick credit bureau files there is another potential use of the EFL tool. Arráiz, Bruhn, and Stucchi (2017) find evidence that the EFL tool can lower the risk of the loan portfolio when used as a secondary screening mechanism for SMEs with a credit history. Similar to this paper, Arráiz et al. (2016) also conclude that the EFL tool can allow lenders to offer credit to SMEs that do not have a credit history and who were rejected based on their conventional credit scores, without leading to more default. One limitation of their result is that it is not necessarily based on causal evidence, since it compares all SMEs who got loans thanks to the conventional screening method vs those who got loans based exclusively on their EFL score, without relying on an identification strategy that zooms in on groups with comparable characteristics as is the case with the RD method used here.

The rest of the paper is organized as follows. Section 2 discusses the background and implementation of EFL's psychometric credit scoring tool. Section 3 describes the data and Section 4 presents the identification strategy. Section 5 presents the empirical results. Finally, Section 6 concludes.

2 Background and implementation of EFL's psychometric credit-scoring tool

Psychometrics is a branch of psychology that designs assessment tools to measure personality traits, skills, knowledge, abilities, and attitudes. One advantage of psychometric tools is that they make it possible to screen many people at a low cost. Employers have long used these tools to select personnel. Research has found that tests of general intelligence (general mental ability), integrity, and conscientiousness—along with work sample tests—are the selection methods best able to predict overall job performance (Schmidt and Hunter, 1998). These tests, in combination, predict overall job performance better than a review of the candidate's job experience, level of education, employment interview results, peer ratings, and reference checks (Schmidt and Hunter, 1998).

While the use of psychometrics in predicting job performance is common, there are other areas where these tools are starting to be applied to reduce screening costs. One example is in SME finance, where screening credit applicants is costly and time consuming and psychometric tools may offer a low-cost alternative. The use of psychometrics in screening credit applicants was first pioneered by the Entrepreneurial Finance Lab (EFL), which in 2006 started developing psychometric credit scores at Harvard University. Since then, EFL has expanded its business worldwide, collaborating with leading financial institutions, and winning global awards such as the African Business Award for Innovation and the G-20 SME Finance Challenge, which recognized EFL as one of the most innovative solutions to SME Finance in the world.

Relying on psychometric tools to screen SME loan applicants departs from the typical uses of such tools and thus required EFL to develop a psychometric credit-scoring tool from scratch. EFL researchers started by quantifying the characteristics of people who had defaulted on a past loan versus those who had not, and of people who owned small businesses with high versus low profits. The researchers grouped these characteristics into three categories: personality, intelligence, and integrity (Klinger et al., 2013b). They initially worked with a personality assessment based on the five-factor or "Big Five" model Costa and MacCrae (1992), an intelligence assessment based on digit span recall tests (a component of the

Wechsler Adult Intelligence Scale), the Raven's Progressive Matrices tests (Spearman, 1946), and an integrity assessment adapted from Bernardin and Cooke (1993).

The researchers' hypothesis was that these assessments would allow them to identify the two main determinants of an entrepreneur's intrinsic risk: the ability to repay a loan, and the willingness to do so.[4]

Entrepreneurial traits, measured via personality and intelligence tests, determine an entrepreneur's ability to generate cash flows in the future—cash flows that can, in turn, be used to repay any debt owed. Honesty and integrity traits, measured via the integrity test, determine the entrepreneur's willingness to pay, independent of the ability to do so.

After identifying questions that could potentially predict credit risk and trying out a first prototype of their tool, EFL developed a commercial application based on the responses to their tool and subsequent default behavior. The commercial application is based on the same quantitative methods used to generate conventional credit scores. It contains psychometric questions developed internally and licensed by third parties relating to individual attitudes, beliefs, integrity, and performance, as well as conventional questions and the collection of metadata (i.e., how the applicant interacted with the tool). The EFL tool has been constantly improving. The version that was used in the pilot we study was the "Africa v2 psychometric credit score", and was initially created based on 920 pilot tests in Africa. The most recent version of this tool currently relies on 386,244 tests with loan repayment data, including tests from Latin America, where further refinements have been made according to the local context.

The EFL tool is designed to be similar to the qualitative assessments that loan officers perform. In practice, the SME owner who is in charge of the business decisions takes the test on a tablet, smartphone or PC. The application does not require access to the internet and thus allows the lenders to administer the tool either at a branch or in the field. The application uses many common techniques to prevent fraud, such as designing questions with no obvious right or wrong answers, randomizing the content of the application and the order in which questions appear to make each application different, or analyzing whether answers display unusual and unlikely patterns, to detect if for example, loan officers are assisting applicants.[5]

The EFL application generates a 3-digit score that ranks the relative credit risk of the person who took the test. Lenders can use this score in different ways, such as setting cutoffs for approvals, or modifying the price, size, or other margins of a loan. Some examples of the types of questions that are asked in the EFL application are illustrated in appendix Table

[4] An extensive body of literature has documented links between personality or intelligence tests and entrepreneurship or business performance (Ciavarella et al., 2004; De Mel et al., 2008, 2010; Djankov et al., 2007; Zhao and Seibert, 2006). To date, the existing evidence on integrity and willingness to repay loans comes from EFL itself (Klinger et al., 2013b). A higher integrity score is related to a lower probability of default (honest entrepreneurs default less) and also to lower business profits (honest entrepreneurs are less profitable). Further evidence comes from a pilot of the EFL tool among Argentinean SMEs (Klinger et al., 2013a). The EFL tool was administered to a random sample of 255 SMEs borrowing from a public bank. For each SME, the EFL responses were then compared to its repayment history with the bank. SMEs that were rejected by the psychometric-based scorecard were up to four times more likely to have defaulted on their past loans than those accepted by the scorecard.

[5] Information from EFL website (https://www.eflglobal.com/).

A1.

In March 2012, our partner bank started to pilot EFL's psychometric credit-scoring model in Peru, with the objective of expanding commercial lending to SMEs. At the time, our partner bank had only a small SME portfolio and they were interested in testing whether the EFL tool could help them enhance their credit approval process. SMEs who applied for a working capital loan (up to 18 months in duration with an average loan size of $3,855) were screened by the EFL tool as part of the application process. The EFL application took on average 45 minutes to complete (the current version takes 25 minutes). Applicants who achieved a score on the EFL application higher than a threshold defined by our partner bank were offered a loan, independently of whether or not they would have been offered a loan based on the conventional screening method used by the bank. Figure A.1 in the appendix shows the distribution of EFL scores, below and above the selected threshold, for the SME loan applicants in our sample.

Applicants with a score below the EFL threshold were also offered a loan if they were approved under the institution's conventional screening method. This conventional screening method relied on a credit score from Equifax Peru and a site visit to the SME. All applicants had an Equifax credit score, but for unbanked individuals, i.e. those who do not have a credit history, this credit score is primarily based on demographic information. Only SMEs that were rejected under both screening methods were not offered a loan from our partner bank during the pilot exercise. Appendix Table A2 shows the number of loan applicants classified by whether they were rejected or accepted based on each screening method.[6]

3 Data

We obtained data on 1,909 SMEs that applied for a working capital loan with our partner bank between March 2012 and August 2013, from two sources. The first source is an EFL questionnaire that the bank administered at the time of loan application. These data include the EFL score and the date when the entrepreneur was screened by the EFL tool, as well as background characteristics, such as the applicant's age, gender, and business sales. Our partner bank also shared with us the threshold EFL score it used to determine whether or not to offer a loan, and they indicated whether they would have offered the applicant a loan based on their conventional screening method.

In addition, for each loan applicant, the data includes the national ID number (DNI) and, if their business is registered under the business name instead of the individual's name, it also includes the business' tax payer number (RUC). Out of the 1,909 SMEs in the data, all provided their DNI and 1,327 also provided a RUC. However, for 20 SMEs, the DNIs and RUCs are inconsistent with each other, suggesting typos. We drop these observations from the sample to avoid using wrong information from our second data source. We also drop 6 observations where two DNIs reported the same RUC, that is, three SMEs where two co-owners seem to each have applied for a loan. In these cases, it is not possible to cleanly assign an EFL score to the SME as the unit of observation. Thus, we end up with a sample

[6] For unknown reasons, this variable is missing for 21 loan applicants in our sample.

of 1,883 SMEs.[7]

Our second data source corresponds to credit information owned by Equifax Peru, the largest credit bureau in the country. For the DNIs and RUCs in the EFL data, we purchased five years of monthly information on borrowing from Equifax, covering the time period from May 2011 to April 2016.[8]

One of Equifax's main sources of information is the Peruvian Bank Supervisor's (SBS) *Central de Riesgos*. SBS collects data directly from all regulated financial institutions on a monthly basis, covering the universe of commercial banks, as well as all regulated non-bank financial institutions, such as *Cajas Municipales*, *Cajas Rurales* and microfinance institutions.[9] For each ID number in any given month, we obtained the total amount borrowed from each SBS supervised financial institution in Peru. The total amount borrowed is disaggregated into eight different loan types: microloans, loans to small firms, loans to medium firms, loans to large firms, loans to corporations, non-revolving consumption loans, revolving consumption loans, and mortgages. If a borrower has more than one loan of the same type with the same intuition, Equifax reports only the sum of these loans, with no information on how many loans constitute this total amount. Given our sample of SME loan applicants, most loans correspond to consumption credit and SME loans (which include loans to micro, small and medium-sized firms), with 78% and 84% of the SMEs in our sample having these types of loans. We drop information on loans to large firms, corporations and mortgages. Less than 1% of the SMEs in our sample have loans to large firms or corporations, and about 8.5% have mortgages. We keep information on consumption loans to examine whether loan applicants substitute SME loans for consumption loans.

Equifax also calculates credit scores for consumer loans, microfinance loans, and business loans. Our partner bank used the microfinance loan score in their conventional screening method. Equifax staff also advised us that for SMEs, the microfinance loan score would be the most relevant one. We thus purchased the microfinance loan score for two points in time (i) the month when the SME applied for the loan with our partner bank, to be used as a background variable, and (ii) April 2016, to be used as an outcome variable. For the credit score in the month when the SME applied for the loan, Equifax included a dummy variable indicating whether this score was primarily based on their credit history, i.e. a "thick file", or on demographics and other sources, such as the Peruvian tax authority (SUNAT), i.e. a "thin file".

To measure loan use based on the Equifax data, we created a dummy equal to one if either the DNI or RUC associated with a loan applicant shows an increase in the amount outstanding from a given financial institution for a given loan type (where the increase could be either from an amount of 0 if the applicant did not already have this type of loan from this financial institution or otherwise an increase from a positive amount). We use four different dummy variables corresponding to the following loan types: (i) SME loan from any financial institution (including our partner bank), (ii) SME loan from our partner bank, (iii) SME loan from a financial institution different from our partner bank, and (iv) consumption

[7] The fraction of the sample dropped is not significantly different below and above the EFL threshold.

[8] By law, Equifax is not allowed to provide data that is older than five years.

[9] For any given month, these institutions report information on their loan portfolio on the 23rd of the following month, so that data is available with about a two month time lag.

loan from any financial institution. We define these four dummies for three different time periods: (i) the pre-application period, comprising 6 months before the loan application, (ii) the immediate post-application period, comprising 6 months after the loan application, and (iii) the medium run, comprising two years after the loan application, that is, loan outcomes 24 months to 31 months after the SME applied for a loan. The immediate post-application period allows 6 months for loans to be processed and disbursed and also provides some time for applicants to potentially shop around with other banks for other loan offers. Given that the maximum loan term reported by our partner bank was 18 months, we then define the medium run as starting at 24 months, i.e. 18 months after the initial 6 months, to arrive at a time when applicants may want to renew their loans. We chose the endpoint of 31 months since this is the last month for which we have data for the full sample.[10]

Table A3 in the appendix provides summary statistics for our background variables as well as pre-application loan use and credit scores. Column 1 in Table A3 panel A shows that the loan applicants in our sample were on average 39 years old and 50% of them were female. Average annual business revenues were about US$12,000. Close to 20% of applicants would not have received a loan offer from our partner bank based on the conventional screening method. At the time of the application, 22% of loan applicants did not have credit with a formal financial institution.

Column 1 in Table A3 panel B reports Equifax data for the pre-application period. About 52% took out a new SME loan from any financial institution during the 6 months preceding the loan application and about 43% took out a new consumption loan. Almost all new SME loans came from banks other than our partner institution, which reflects the fact that our partner institution was not very active in the SME segment before the EFL pilot.

4 Identification strategy

We estimate the effect of being offered a loan using the EFL tool on loan use and repayment behavior using a non-parametric regression discontinuity (RD) design. Let X_i be the psychometric score and $\overline{x}$ the threshold set by the bank. Without loss of generality, the threshold can be set to $\overline{x} = 0$. This psychometric score determines whether a SME i is offered a loan ($X_i \geq 0$) or not ($X_i < 0$). Let $Y_i(1)$ and $Y_i(0)$ be random variables denoting the potential outcomes with and without the loan offer, respectively. We cannot observe both potential outcomes at the same time; we observe only one depending the psychometric score. The observed random sample is $(Y_i, X_i)'$, $i = 1, 2, ..., n$, where $Y_i = Y_i(0)(1 - T_i) + Y_i(1)T_i$ with $T_i = \mathbf{1}[X_i = 0]$ and $\mathbf{1}[\cdot]$ is an indicator function. The parameter of interest is the average treatment effect at the threshold, i.e.,

$$\alpha = E[(Y_i(1) - Y_i(0) \mid X_i = \overline{x}] \tag{1}$$

[10] As a robustness check, we also used two alternative definitions of loan use: (i) a dummy equal to one if either the DNI or RUC associated with a loan applicant has any SME loan amount outstanding from a given financial institution and (ii) the total volume of SME loans from all financial institutions. Our main results with these alternative measures are reported in the appendix and are similar to the results using the loan increase dummy.

Under a mild continuity condition, Hahn et al. (2001) show that this parameter is non-parametrically identifiable as the difference of two conditional expectations evaluated at the (induced) boundary point $\overline{x} = 0$,

$$\alpha = \lim_{x \to 0^+} E[Y_i \mid X_i = x] - \lim_{x \to 0^-} E[Y_i \mid X_i = x] \tag{2}$$

The estimation of α focuses on flexible approximation, near the cutoff $\overline{x} = 0$ of the regression functions $\lim_{x \to 0^-} E[Y_i \mid X_i = x] = E[Y_i(0) \mid X_i]$ (from the left) and $\lim_{x \to 0^+} E[Y_i \mid X_i = x] = E[Y_i(1) \mid X_i]$ (from the right). Following Calonico et al. (2014a) we use local polynomial regression estimators of various orders to approximate these unknown regression functions.

We implement the estimation with the Stata `rdrobust` command described in Calonico et al. (2014a). This command estimates the RD treatment effect by using kernel-based local polynomials within a bandwidth (h) on either side of the EFL score threshold. The choice of bandwidth for the RD estimation is an important task in carrying out estimation in practice, since empirical results can be sensitive to which observations are used in the analysis (Cattaneo and Vazquez-Bare, 2016). To examine robustness of our results we consider three different polynomial orders, 0, 1, and 2, of the local polynomial used to construct the point estimator and, for a given polynomial order, we select the mean-squared error optimal bandwidth using Calonico et al. (2014a,b). This optimal bandwidth varies for each outcome variable and increases with the specified polynomial order. For example, for our immediate post-application period loan use dummy variables, it ranges from 9 to 16 points for polynomial order zero, from 17 to 24 points for polynomial order 1, and from 27 to 35 points for polynomial order 2. Our `rdrobust` regressions keep the default kernel (triangular) and they control for the time (month and year) when the SME applied for a loan. We report robust bias-corrected p-values which account for the bias involved in estimating the optimal bandwidth.

As an additional robustness check, we also implement a randomization inference method following Cattaneo et al. (2015) and Cattaneo et al. (2017), with the Stata rdrandinf command described in Cattaneo et al. (2016). We select the window for the local randomization with the `rdwinselect` command using our four background variables listed in Table A3 panel A (age, gender, sales, and whether the application would have been approved under the conventional screening method). We start with a 2 point window around the EFL score threshold. The command then selects the largest window in which these covariates are balanced according to p-values calculated with randomization inference methods. The selected window size is 4 points around the threshold. Our results from the randomization inference method thus represent the effects of the EFL tool on loan use and repayment behavior in a very small bandwidth around the EFL score threshold. Column 2 in A3 panels A and B shows summary statistics for our background and pre-application loan use variables for applicants who scored within 4 points below the threshold. Overall, the characteristics of this small sample are quite similar to those of the full sample (column 1 in Table A3 panels A and B).

As a visual check of our results, we also show regression discontinuity plots using the `rdplot` Stata command developed by Calonico et al. (2014b). We plot the data for a bandwidth of 20 around the EFL score threshold with a global polynomial of order one and 95% confidence intervals for each bin (we let the command select the number of bins using its data-driven procedure with the default setting).

The RD estimation relies on the assumption that our outcomes of interest would be continuous at the EFL score threshold if our partner bank had not offered them a loan based on scoring above this threshold. While we cannot test this assumption directly, we can examine whether applicants' background characteristics and pre-application loan use are continuous at the EFL score threshold. The main idea behind this test is that if those characteristics are not continuous it would be difficult to claim continuity in the outcome variables in the absence of the treatment. Columns 3 through 10 in Table A3 report the estimated discontinuities at the threshold and corresponding p-values from the four different RD methods described above (local polynomial regression with optimal bandwidth for polynomial order 0, 1, 2, and randomization inference). We do not find a statistically significant discontinuity in the variables in Table A3 for any of the methods. This finding is also consistent with the fact that the threshold was selected by the bank and not announced to borrowers and therefore borrowers were not able to behave strategically.

5 Results

Table 1 displays the RD impact estimates for the effect of the EFL tool on loan use in the immediate post-application period. The structure of this table is the same as for Table A3, showing the averages of the outcome variables for the whole sample and just below the EFL score threshold in columns 1 and 2, respectively. Columns 3 through 10 display the impact estimates from four different RD methods, with the corresponding bandwidths and number of observations. All methods show a statistically significant increase in the probability of taking out a new SME loan from any financial institution during the six months following the loan application. The magnitude of this effect ranges from a 14.9 to a 19.1 percentage point increase, relative to an average probability of 58.6% just below the EFL score threshold.

Figure 1 plots the RD graph for short-run loan use. Figure 1a illustrates the finding from Table A3 panel B that the probability of taking out a new SME loan from any financial institution did not display a discontinuity at the EFL score threshold during the six months *before* the loan application. In contrast, figure 1b shows a clear upward jump in the probability of taking out a new SME loan from any financial institution at the threshold during the six months *after* the loan application. Consistent with the results in Table 1, visual inspection of the data thus also suggests that the EFL tool increased loan use for applicants above the threshold.

Figure 1b and the numbers in Table 1 show that a maximum of about 78% of SMEs above the EFL threshold ended up taking out a new SME loan. Although all of them had applied for a loan and were offered a loan, some applicants may have decided against taking out the loan due to changes in circumstances or the conditions they were offered. In conversations with staff from our partner bank, they stated that some applicants used their loan approval letters to secure more advantageous loans from other institutions. To test this hypothesis, Table 1 examines the impact of the EFL tool on obtaining a new loan from our partner bank and from other financial institutions separately. The effect on loan use appears to be driven entirely by new loans from our partner bank, where the EFL tool almost doubles the probability of obtaining a new loan (by up to 32 percentage points from about 17% below the EFL score threshold). The effect of the EFL tool on loans from other financial institutions is positive, but it is not statistically significant.

The last question we examine in Table 1 is whether the increase in SME loan use was accompanied by a decrease in the other frequently used credit product in our sample, i.e. consumptions loans. The hypothesis here is that applicants may use consumption loans as a source of finance if they are not able to obtain SME loans. However, we do not find any evidence that the probability of taking out a consumption loan changes due to the EFL tool for the whole sample. Since the information added by the EFL tool may be particularly useful for clients that have no credit history, i.e. those with "thin files" in the credit bureau, the impact on access may be greater for this group. To test this hypothesis, we replicate the analysis from Table 1 after splitting the sample into those with thin and tick credit bureau files (as defined in Section 3). Table 2 shows the RD impact estimates on short-run loan use for applicants with thin credit bureau files. The estimates for taking out an SME loan from any financial institution are two to three times as big as in the full sample, ranging from 34.2 to 53.5 percentage points. The table also shows that this effect is driven by financial institutions other than our partner bank. That is, obtaining a loan offer from our partner bank appears to have helped applicants with thin credit bureau files to obtain loans from other institutions. Table 3 shows the short-run loan use results for applicants with thick credit bureau files. Here, we see no significant effect on SME loan use from other financial institutions, but we find an increase in the probability of having a loan from our partner bank. These findings are likely due to the fact that applicants with an EFL score above the threshold were offered a loan from our partner bank even if they had low traditional credit scores, i.e. if they had bad credit information in their thick files. However, these applicants with low credit scores are unlikely to have gotten loans from other institutions due to their bad credit history and thus loan approval letters from our partner bank would have been less useful for these applicants than for thin file applicants. The result in Tables 2 and 3 thus confirm the hypothesis that the EFL tool was particularly useful for increasing access to credit for applicants with thin credit bureau files.

Tables A4 through A6 in the appendix examine the effects of the EFL tool on short-run loan use for our alternative measures of loan use: a dummy for having an SME loan and the total SME loan volume. Table A4 includes all applicants, while Table A5 includes applicants with thin credit bureau files and Table A6 applicants with thick credit bureau files only. The results mirror those in Tables 1 through 3. The EFL tool increases the probability of having a loan and the loan volume from any financial institution for applicants with thin credit bureau files and these increases seems to be primarily driven by institutions other than our partner bank. For applicants with thick credit bureau files, the EFL tool increases the probability of having a loan and loan volume from our partner bank only.

Table 4 examines the effect of the EFL tool on repayment behavior as measured by the Equifax credit score in April 2016 (about four years after the loan application).[11] We find

[11] As noted previously, the Equifax score is available for all SME loan applicants in our sample.

that offering a loan based on the EFL tool leads to a statistically significant decrease in applicants' April 2016 credit score, ranging from 113 to 241 points, relative to 537 points below the EFL score threshold. There was no statistical difference around the threshold in Equifax credit scores at the time of application (Table A3, panel B). And even though the credit score may decrease as loan use increases since current debt amounts are one factor that goes into calculating the credit score, by April 2016 the applicants in our sample should have repaid the loans they obtained as part of the pilot exercise (we do not find an effect on medium-run loan use, as discussed below).

Figure 2 illustrates the effect of the EFL tool on the Equifax credit score visually. At the time of the loan application, there was no discontinuity in the credit score of SMEs in our sample at the EFL score threshold (figure 2a). In April 2016, however, the credit score showed a downward jump at the threshold (figure 2b).

Table 4 also shows that the effect of the EFL tool on the Equifax credit score is only statistically significant for applicants with thick credit bureau files and the coefficients are larger for these applicants than for those with thin credit bureau files. This reduction in the Equifax credit score among thick file applicants, which is potentially due to worse repayment behavior, could be caused by two factors (i) our partner bank offered loans to applicants with bad credit histories if their EFL score was above the threshold and (ii) the portfolio of loans from our partner bank that were part of the pilot exercise had a credit guarantee which may have lowered monitoring and collection incentives, even though the guarantee would be triggered after exhausting the first loss amount to be assumed by our partner bank. As shown in Table 3, loan use for thick file applicants increased only through our partner bank (unlike loan use for thin file applicants which increased through other financial institutions), which makes the two factors above particularly relevant for thick file clients.

Given the positive effect on short-term loan use and the negative effect on the Equifax credit score in the case of thick file applicants, we now ask how the EFL tool affected medium-run loan use. Table 5 shows that the RD analysis finds no effect of the EFL tool on loan use 24 to 31 months after the initial loan application. Some of the estimated coefficients are positive, while others are negative, but for the most part, they are all close to zero and none of them are statistically significant. Table A7 in the appendix shows the corresponding results for our two other measures of loan use. We obtained similar results for the subsamples of thin and thick file applicants (results are not shown).

6 Conclusions

We study the use of a psychometric credit application to better assess credit risk and extend credit to SMEs. The psychometric credit application was developed by EFL with the goal of identifying traits that characterize the credit risk posed by loan recipients, traits that make it possible to select loan applicants who can generate enough cash flow to service their debt and who are willing to repay their debt. In the context of a pilot exercise conducted by one of the five largest banks in Peru, we find that the EFL tool can increase SME loan use in the short-run. The increase in SME loan use is particularly large for applicants with thin credit bureau files, usually shunned by the formal financial sector. For this group, we find that the increase in access is not accompanied by a statistically significant reduction in the Equifax credit score (our measure of repayment behavior) suggesting the EFL tool is a viable screening method for this group. For applicants with thick credit bureau files, the EFL tool does not lead to increased access other than from our partner bank and it does lead to a statistically significant reduction in the Equifax credit score, which may in part be due to worse repayment behavior. Potential reasons for this negative effect are that (i) the EFL tool was applied to all applicants regardless of their credit history and applicants with bad credit histories were offered a loan if their EFL score was above the threshold and (ii) our partner bank may have exerted less effort when monitoring loans and collecting payments during the pilot project due to the credit guarantee that covered the pool of eligible loans?after exhausting the first loss amount to be assumed by our partner bank. Our findings here highlight the importance of credit history information for assessing credit risk and serving the SME market.

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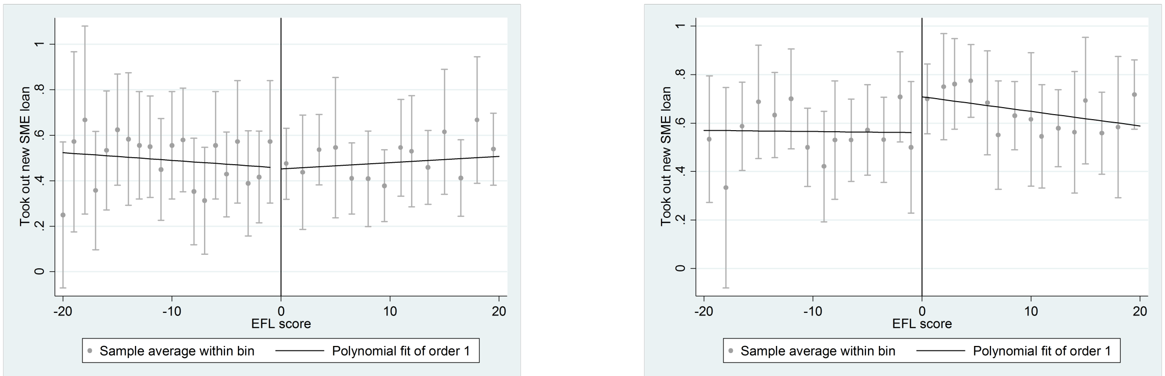
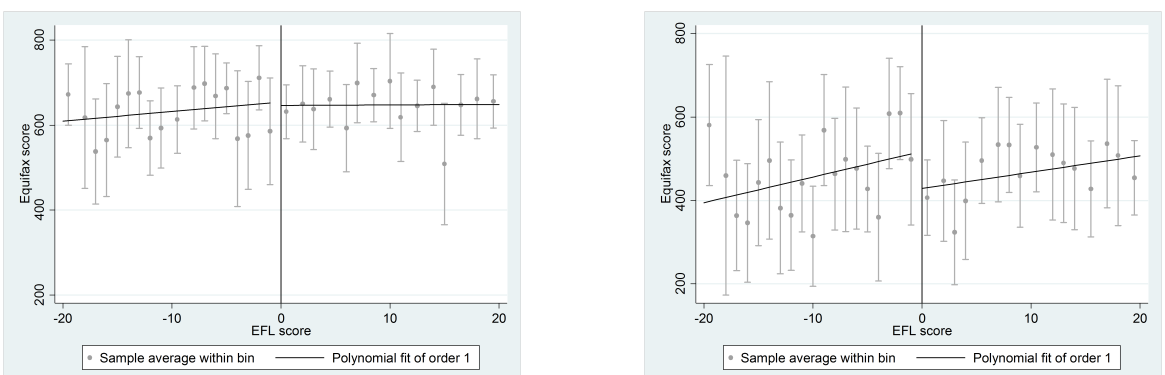


(a) 6 months before the application **(b)** 6 months after the application

Figure 1: Regression Discontinuity Plots for Short-Run Loan Use

Notes: This plot was generated using the `rdplot` Stata command developed by Calonico et al. (2014b) for a bandwidth of 20 around the EFL score threshold with a global polynomial of order one and 95% confidence intervals for each bin. The dependent variable is a dummy variable =1 if the applicant took out a new SME loan from any financial intuition within the time frame specified in the title.



(a) at the time of loan application **(b)** in April 2016

Figure 2: Regression Discontinuity Plot for Equifax Credit Score

Notes: This plot was generated using the `rdplot` Stata command developed by Calonico et al. (2014b) for a bandwidth of 20 around the EFL score threshold with a global polynomial of order one and 95% confidence intervals for each bin. The dependent variable is the Equifax credit score.

Table 1: Short-Run Loan Outcomes: First Six Months after Loan Application

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1883	N=70	p-value	N	p-value	N	p-value	N	p-value	N
Obtained new SME loan	0.655	0.586	0.149	10.4	0.189	19.7	0.191	30.6	0.157	4
	(0.476)	(0.496)	0.021	392	0.032	676	0.056	933	0.036	167
Obtained new SME loan from partner bank	0.291	0.171	0.240	9.2	0.289	18.9	0.317	26.7	0.251	4
	(0.454)	(0.380)	0.000	361	0.000	648	0.001	848	0.002	167
Obtained new SME loan from any other financial institution	0.557	0.500	0.087	15.4	0.100	23.5	0.095	35.1	0.088	4
	(0.497)	(0.504)	0.140	567	0.279	783	0.360	1038	0.276	167
Obtained new consumption loan	0.453	0.486	-0.058	15.8	0.020	16.7	0.019	31.3	0.030	4
	(0.498)	(0.503)	0.345	567	0.615	598	0.692	962	0.784	167

Notes: All outcome variables are dummy variables and refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table 2: Short-Run Loan Outcomes: First Six Months after Loan Application
Sample of clients that at the time of credit application had *thin* credit bureau files

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=366	N=11	p-value	N	p-value	N	p-value	N	p-value	N
Obtained new SME loan	0.317	0.181	0.342	10.8	0.494	16.5	0.535	24.8	0.390	4
	(0.466)	(0.405)	0.008	72	0.009	111	0.018	153	0.089	25
Obtained new SME loan from partner bank	0.156	0.091	0.108	14.2	0.133	23.6	0.152	29.4	0.052	4
	(0.363)	(0.302)	0.204	104	0.253	151	0.224	168	1	25
Obtained new SME loan from any other financial institution	0.216	0.091	0.245	10.9	0.332	17.0	0.357	25.0	0.338	4
	(0.412)	(0.302)	0.035	72	0.073	119	0.127	157	0.087	25
Obtained new consumption loan	0.104	0.182	-0.136	15.9	-0.195	26.3	-0.212	33.1	-0.039	4
	(0.305)	(0.405)	0.109	107	0.254	162	0.394	187	1	25

Notes: All outcome variables are dummy variables and refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table 3: Short-Run Loan Outcomes: First Six Months after Loan Application
Sample of clients that at the time of credit application had *thick* credit bureau files

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1517	N=59	p-value	N	p-value	N	p-value	N	p-value	N
Obtained new SME loan	0.736	0.661	0.107	1 3.7	0.113	26.9	0.130	37.1	0.110	4
	(0.441)	(0.477)	0.095	411	0.174	686	0.180	863	0.172	142
Obtained new SME loan from	0.324	0.186	0.296	7.8	0.340	17.4	0.373	25.4	0.283	4
partner bank	(0.468)	(0.393)	0.000	235	0.000	511	0.000	672	0.001	142
Obtained new SME loan from	0.639	0.576	0.057	17.9	0.054	25.2	0.039	29.7	0.038	4
any other financial institution	(0.481)	(0.498)	0.344	511	0.682	672	0.723	715	0.718	142
Obtained new	0.537	0.542	-0.043	16.0	0.025	19.5	0.040	34.4	0.036	4
consumption loan	(0.499)	(0.502)	0.629	487	0.630	543	0.567	823	0.721	142

Notes: All outcome variables are dummy variables and refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table 4: Credit Performance: Equifax Credit Score in April 2016

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N	N	p-value	N	p-value	N	p-value	N	p-value	N
All applicants	583.3	695.9	-4.1	19.2	-101.5	19.4	-165.4	25.7	-121.0	4
	(303.4)	(298.4)	0.002	318	0.000	538	0.000	726	0.000	167
	1883	70								
Applicants with thin credit	0.324	0.186	0.296	7.8	0.340	17.4	0.373	25.4	0.283	4
bureau files at the time of the	(267.3)	(256.2)	0.722	133	0.236	133	0.151	157	0.250	25
credit application	366	11								
Applicants with thick credit	434.3	507.7	-106.2	8.8	-177.3	17.5	-234.3	22.2	-144.5	4
bureau files at the time of the	(304.5)	(298.3)	0.004	265	0 .001	511	0.001	606	0.005	142
credit application	366	11								

Notes: Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table 5: Medium-Run Loan Outcomes: 24 to 31 Months after Loan Application

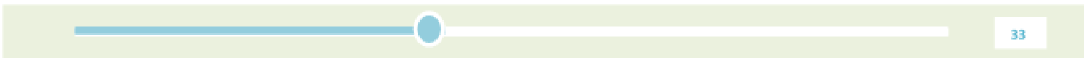
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1883	N=70	p-value	N	p-value	N	p-value	N	p-value	N
Obtained new SME loan	583.3	695.9	-4.1	19.2	-101.5	19.4	-165.4	25.7	-121.0	4
	(303.4)	(298.4)	0.002	318	0.000	538	0.000	726	0.000	167
	1883	70								
Applicants with thin credit	0.324	0.186	0.296	7.8	0.340	17.4	0.373	25.4	0.283	4
bureau files at the time of the	(267.3)	(256.2)	0.722	133	0.236	133	0.151	157	0.250	25
credit application	366	11								
Applicants with thick credit	434.3	507.7	-106.2	8.8	-177.3	17.5	-234.3	22.2	-144.5	4
bureau files at the time of the	(304.5)	(298.3)	0.004	265	0 .001	511	0.001	606	0.005	142
credit application	366	11								

Notes: Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

A Appendix

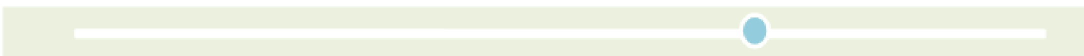
Table A1: Examples of Questions Asked in the EFL Application

Example 1. How many hours in a typical week do you work?



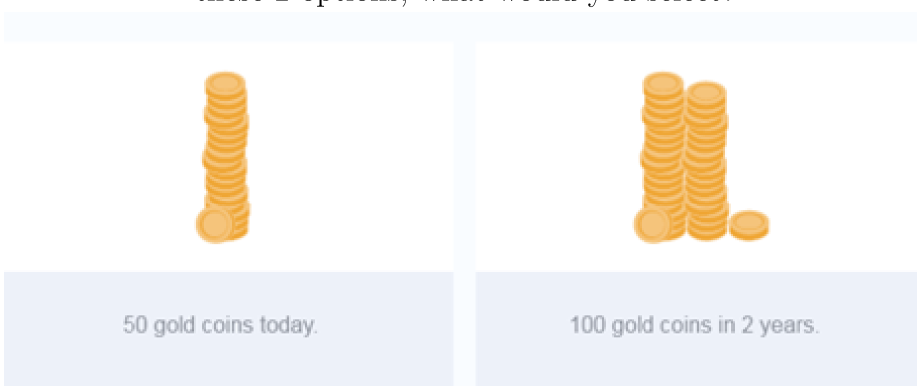
0 20 40 60 80+

Example 2. Move the slider to which statement best represent you

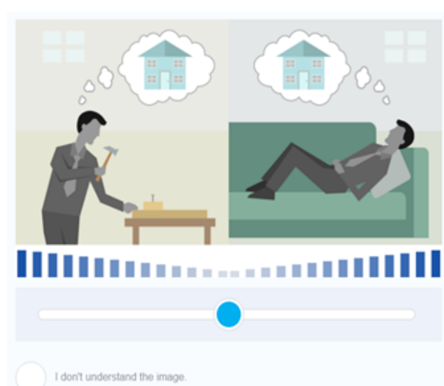


Problems tell me that I need to set new goals	I'm in the middle	Problems never make me question my goals

Example 3. If a family member offered you the choice between these 2 options, what would you select?



Example 4. Which image best represents how people in your community behave?



Notes: Questions come from the demonstration of the EFL application available on EFL's website (https://www.eflglobal.com/).

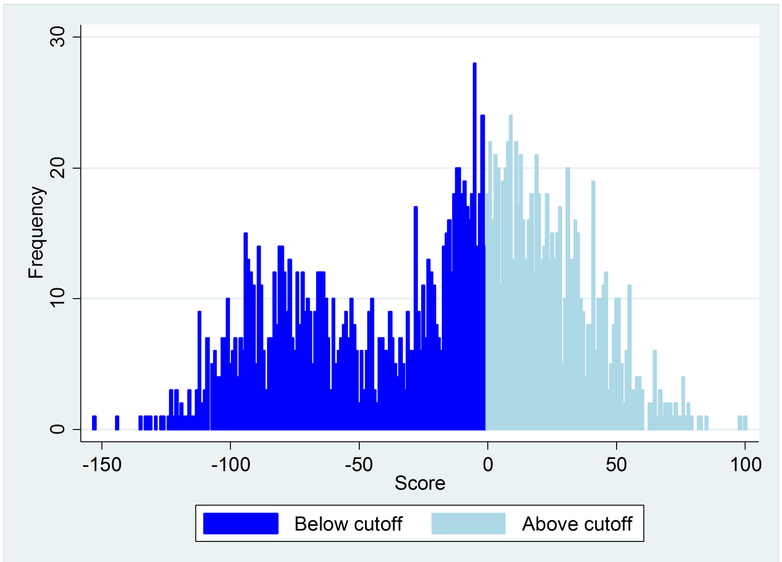


Figure A.1: Regression Discontinuity Plot for Equifax Credit Score

Notes: This figure shows the histogram of the EFL scores for the 1883 SMEs in our sample. We normalized the EFL scores to zero at the threshold set by our partner institution. All applicants with EFL scores above zero were offered a loan.

Table A2: Number of SME Loan Applicants by Outcome of Screening Method

	EFL screening	
Conventional screening:	Fail	Pass
Fail	206	154
Pass	851	651
Missing information	13	8

Notes: The total number of SME loan applicants in our sample is 1883. Applicants were offered a loan if they passed any of the two screening methods. The cell in grey shows that 154 loan applicants who would have not been offered a loan based on conventional screening, obtained a loan offer due to the EFL screening. For unknown reasons, the outcome of the conventional screening is missing for 21 loan applicants in our sample.

Table A3

Panel A: Background Characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N	N	p-value	N	p-value	N	p-value	N	p-value	N
Loan applicant's age	39	35	1.023	6.1	0.541	20.6	-0.620	40.1	1.546	4
	(11)	(8)	0.953	243	0.880	702	0.621	1110	0.224	167
	1883	70								
Applicant is female	0.499	0.529	0.040	14.7	0.078	31.0	0.084	41.9	0.049	4
	(0.500)	(0.503)	0.281	538	0.231	933	0.379	1136	0.644	167
	1883	70								
Log (business revenues)	9.983	9.618	0.210	7.4	0.150	19.5	0.098	33.7	0.184	4
	(1.100)	(0.891)	0.411	279	0.387	676	0.528	996	0.245	167
	1883	70								
EFX reject	0.193	0.265	-0.019	15.7	-0.015	22.8	0.000	26.9	-0.054	4
	(0.395)	(0.444)	0.574	559	0.913	743	0.934	839	0.467	163
	1862	68								
No credit at time of test	0.223	0.186	-0.006	16.8	0.006	20.0	0.011	30.0	0.000	4
	(0.416)	(0.392)	0.820	598	0.960	702	0.940	933	1.000	167
	1883	70								

Notes: Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Panel B: Pre-Application Loan Use and Credit Score

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N	N	p-value	N	p-value	N	p-value	N	p-value	N
Obtained new SME loan	0.518	0.471	-0.005	16.9	0.033	19.1	0.034	32.5	0.023	4.0
6 months before test	(0.500)	(0.503)	0.779	598	0.590	676	0.619	978	0.864	167
	1883	70								
Obtained new SME loan from	0.020	0.014	-0.009	9.0	-0.014	17.6	-0.020	32.3	-0.014	4.0
partner bank 6 months before test	(0.139)	(0.120)	0.240	318	0.199	630	0.188	978	0.384	167
	1883	70								
Obtained new SME loan from	0.513	0.457	-0.001	17.2	0.048	18.6	0.054	31.6	0.038	4.0
other FIs 6 months before test	(0.500)	(0.502)	0.849	630	0.469	648	0.480	962	0.630	167
	1883	70								
Obtained new consumption loan	0.431	0.471	-0.034	12.3	- 0.059	21.6	-0.045	28.0	-0.028	4.0
6 months before test	(0.495)	(0.503)	0.356	471	0.571	726	0.685	872	0.750	167
	1883	70								
Equifax score by time of test	636.802	622.471	4.074	16.2	-16.992	25.9	-15.254	30.5	11.106	4.0
	(216.553)	(251.394)	0.748	598	0.526	829	0.829	933	0.763	167
	1883	70								

Notes: Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table A4: Alternative Measures – Short-Run Loan Outcomes: First Six Months after Loan Application

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1883	N=70	p-value	N	p-value	N	p-value	N	p-value	N
Has SME loan	0.750	0.729	0.063	17.6	0.101	19.8	0.104	27.5	0.086	4
	(0.433)	(0.448)	0 .220	630	0.206	676	0.244	872	0.264	167
Has SME loan from	0.295	0.171	0.242	8.9	0.292	18.8	0.321	26.5	0.251	4
partner bank	(0.456)	(0.380)	0.000	318	0.000	648	0.001	848	0.002	167
Has SME loan from	0.688	0.671	0.033	19.6	0.037	21.8	0.028	29.1	0.050	4
any other financial institution	(0.464)	(0.473)	0.524	676	0.696	726	0.733	917	0.493	167
Volume SME loan	7.531	7.153	0.642	17.7	0.740	19.4	0.582	30.0	0.628	4
	(4.592)	(4.556)	0.311	630	0.377	676	0.474	917	0.356	167
Volume SME loan from	2.623	1.420	2.084	8.4	2.503	18.4	2.736	26.1	2.118	4
partner bank	(4.109)	(3.179)	0.000	318	0.000	648	0.001	848	0.002	167
Volume SME loan from	6.897	6.653	0.342	14.2	0.079	20.8	-0.175	31.2	0.152	4
any other financial institution	(4.878)	(4.812)	0.853	538	0.988	702	0.935	962	0.826	167

Notes: The first three outcomes are dummy variables indicating whether applicant has an SME loan. The last three outcomes refer to the volume of the SME loan in logs (which is set to zero if the applicant does not have an SME loan). All outcome variables refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table A5: Alternative Measures Short-Run Loan Outcomes: First Six Months after Loan Application
Sample of clients that at the time of credit application had *thin* credit bureau files

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=366	N=11	p-value	N	p-value	N	p-value	N	p-value	N
Has SME loan	0.333	0.182	0.273	11.8	0.428	17.0	0.469	25.4	0.390	4
	(0.472)	(0.405)	0.035	87	0.026	111	0.043	157	0.089	25
Has SME loan from	0.156	0.091	0.108	14.2	0.133	23.6	0.152	29.4	0.052	4
partner bank	(0.363)	(0.302)	0.204	104	0.253	151	0.224	172	1.000	25
Has SME loan from	0.232	0.091	0.188	12.0	0.274	17.4	0.294	25.6	0.338	4
any other financial institution	(0.423)	(0.302)	0.104	87	0.144	119	0.222	157	0.087	25
Volume SME loan	2.988	1.551	2.299	11.6	3.533	16.7	3.662	26.4	3.053	4
	(4.373)	(3.452)	0.034	87	0.030	111	0.067	162	0.076	25
Volume SME loan from	1.274	0.776	0.800	16.0	1.083	23.1	1.184	27.3	0.289	4
partner bank	(3.024)	(2.575)	0.213	107	0.211	151	0.242	164	1.000	25
Volume SME loan from	2.133	0.775	1.539	12.5	2.302	16.8	2.366	26.3	2.764	4
any other financial institution	(4.028)	(2.571)	0.119	92	0.150	111	0.260	162	0.106	25

Notes: The first three outcomes are dummy variables indicating whether applicant has an SME loan. The last three outcomes refer to the volume of the SME loan in logs (which is set to zero if the applicant does not have an SME loan). All outcome variables refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table A6: Alternative Measures – Short-Run Loan Outcomes: First Six Months after Loan Application
Sample of clients that at the time of credit application had *thick* credit bureau files

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1517	N=59	p-value	N	p-value	N	p-value	N	p-value	N
Has SME loan	0.851	0.831	0.037	19.3	0.019	25.6	0.017	45.6	0.025	4
	(0.356)	(0.378)	0.531	543	0.901	672	0.848	962	0.805	142
Has SME loan from	0.329	0.186	0.299	7.6	0.342	17.4	0.374	25.4	0.283	4
partner bank	(0.470)	(0.393)	0.000	235	0.000	511	0.000	672	0.001	142
Has SME loan from	0.798	0.780	0.016	15.7	-0.013	28.6	-0.036	35.3	-0.009	4
any other financial institution	(0.402)	(0.418)	0.955	460	0.675	737	0.640	838	1.000	142
Volume SME loan	8.627	8.198	0.482	15.8	0.101	23.0	-0.063	35.7	0.119	4
	(3.923)	(3.947)	0.553	460	0.976	606	0.931	838	0.844	142
Volume SME loan from	2.948	1.541	2.523	7.7	2.920	17.3	3.181	25.1	2.415	4
partner bank	(4.267)	(3.285)	0.000	235	0.000	511	0.000	672	0.001	142
Volume SME loan from	8.047	7.749	-0.008	11.6	-0.501	25.0	-0.721	33.2	-0.393	4
any other financial institution	(4.340)	(4.317)	0.630	347	0.361	672	0.447	809	0.602	142

Notes: The first three outcomes are dummy variables indicating whether applicant has an SME loan. The last three outcomes refer to the volume of the SME loan in logs (which is set to zero if the applicant does not have an SME loan). All outcome variables refer to the first 6 months after the loan application. Columns 1 and 2 show the mean, standard deviation and number of observations of each variable. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).

Table A7: Alternative Measures – Medium-Run Loan Outcomes: 24 to 31 Months after Loan Application

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All sample	Below cutoff								
	Mean	Mean	Local pol. 0		Local pol. 1		Local pol. 2		Rand. inf.	
	(SE)	(SE)	RD coef.	BW	RD coef.	BW	RD coef.	BW	RD coef.	BW
	N=1883	N=70	p-value	N	p-value	N	p-value	N	p-value	N
Has SME loan	0.444	0.400	0.021	12.0	-0.006	20.8	-0.034	33.9	0.023	4
	(0.497)	(0.493)	0.987	434	0.742	702	0.622	996	0.891	167
Has SME loan from	0.055	0.043	0.041	13.0	0.042	21.3	0.030	27.9	0.019	4
partner bank	(0.228)	(0.204)	0.069	471	0.386	726	0.601	872	0.715	167
Has SME loan from	0.433	0.386	0.012	12.4	-0.024	20.9	-0.052	33.3	0.016	4
any other financial institution	(0.496)	(0.490)	0.854	471	0.600	702	0.518	996	0.875	167
Volume SME loan	4.584	3.986	0.054	10.7	-0.203	20.3	-0.470	33.6	0.121	4
	(5.281)	(5.001)	0.752	392	0.628	702	0.552	996	0.880	167
Volume SME loan from	0.504	0.377	0.360	12.5	0.393	20.0	0.274	28.1	0.163	4
partner bank	(2.126)	(1.805)	0.072	471	0.391	676	0.575	906	0.608	167
Volume SME loan from	4.476	3.819	-0.017	10.7	-0.311	20.4	-0.582	32.2	0.114	4
any other financial institution	(5.267)	(4.949)	0.642	392	0.547	702	0.523	978	0.887	167

Notes: The first three outcomes are dummy variables indicating whether applicant has an SME loan. The last three outcomes refer to the volume of the SME loan in logs (which is set to zero if the applicant does not have an SME loan). All outcome variables refer to the period of 24 to 31 months after the loan application. The sample in Column 2 (below cutoff) is within a bandwidth of 4. Columns 3 through 8 use the Stata `rdrobust` command for three different polynomial orders (0, 1, and 2). For a given polynomial order, we let the command select the mean-squared error optimal bandwidth. We report robust bias-corrected p-values. Columns 9 and 10 show the results from a randomization inference method using the Stata `rdrandinf`, where we selected the window size 4 for the local randomization with the `rdwinselect` command using four background variables (age, gender, sales, and whether the application would have been approved under the conventional screening method).