Psychometric tests as a tool to improve screening and access to credit: Evidence from Peru[1]

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Abstract:

This paper studies the use of psychometric tests, designed by the Entrepreneurial Finance Lab (EFL), as a tool to screen out high credit risk and potentially increase access to credit for small business owners in Peru. We use administrative data covering the period from June 2011 to April 2014 to compare usage of debt and repayment behavior across entrepreneurs who were offered a loan based on the traditional credit scoring method vs. the EFL tool. We find that the psychometric test can lower the risk of the loan portfolio when used as a secondary screening mechanism for already banked entrepreneurs, i.e. those with a credit history. For unbanked entrepreneurs, i.e. those without a credit history, using the EFL tool can increase access to credit without increasing portfolio risk.

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1. Introduction

Given the important role played by small and medium enterprises (SMEs) in a healthy and dynamic economy, many studies have attempted to understand the factors that affect their creation and performance.[5] These studies show that SMEs face greater financial constraints than large companies and that these constraints could be one of the factors that limit their growth (Hall 1989, Beck et al. 2006, Beck and Demirgüç-Kunt 2006, Beck et al. 2008, Cavallo et al. 2010, Ibarraran et al. 2010, Canton et al. 2013, Mateev et al. 2013). SMEs face greater financial constraints 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, implying that financial institutions have difficulties assessing their risk (de la Torre et al. 2009).

This paper studies a novel intervention that aims to improve credit information on SMEs. A large literature has examined the role of information sharing and credit bureaus in reducing information asymmetries and increasing credit to SMEs (see for example Brown, Jappelli, and Pagano 2009, Love and Mylenko 2003, Martinez Peria and Singh 2014). However, credit bureaus do not always emerge due to coordination problems between lenders and where they exist the information provided by them may be limited for legal and institutional reasons. In addition, credit bureaus are often subject to a chicken-and-egg problem. Bureau information is most useful for making credit decisions for 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.

The Entrepreneurial Finance Lab (EFL) has thus 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 predict entrepreneurs' repayment behavior. We study the effectiveness of this tool in reducing credit risk for SME loans, as well as in expanding access to credit for small firms, in the context of a pilot exercise conducted in Peru. The implementing institution, the fifth largest commercial bank in Peru, piloted the EFL tool starting in March 2012, with the goal of expanding their lending to SMEs. Loan applicants were screened by the EFL tool and all applicants that achieved a score higher than a threshold set by the implementing institution were offered a loan.

Peru has several private credit bureaus that cover 100% of the adult population and thus all applicants also had a traditional credit score. However, for individuals who have not had a loan from a formal financial institution in the past, the credit score is primarily based on demographic

[5] Numerous studies have documented the important role played by SMEs in the process of industrialization and economic development (Liedholm 2002, Beck et al. 2005, Beck and Demirguc-Kunt 2006, Ayyagari et al. 2007, Nichter and Goldmark 2009, Liedholm and Mead 2013). These firms often employ most of the workforce (Ayyagari et al. 2007, Haltiwanger and Krizan 1999, Hijzen 2010, Ibsen and Westergaard-Nielsen 2011, Haltiwanger et al. 2013). In Latin America, Angel Pulido (2010), Lecuona Valenzuela (2009), Solimano et al. (2007) and Ferraro and Stumpo (2010) provide evidence on the role of SMEs in Colombia, Mexico, Chile, and Brazil, respectively.

information and not on their credit history. We call these individuals “unbanked”. Applicants who had a traditional credit score in an acceptable range (as defined by the implementing institution) were also offered a loan, even if their EFL score was below the threshold.

This set-up allows us to test two hypotheses related to different uses of the EFL tool (i) as a secondary screening mechanism for entrepreneurs accepted under the traditional credit scoring method, to lower the risk of the SME loan portfolio, and (ii) as a skimming mechanism for applicants rejected under the traditional credit scoring method, to offer more loans without increasing the risk of the portfolio. We also test whether the EFL tool can increase access to credit for the unbanked whose traditional credit score might be uninformative to banks.

We use monthly data on formal credit usage and repayment behavior collected by the Superintendencia de Banca y Seguros (SBS) in Peru—from June 2011 to April 2014—as well as data collected by the implementing institution and EFL on the 1,993 potential clients that were part of the pilot exercise.

Our results show that the EFL tool can reduce the risk of the portfolio for banked entrepreneurs when it is used to complement the traditional credit scoring method. Banked entrepreneurs accepted under the traditional method but rejected based on their EFL score are 8.6 percentage points more likely to have been in arrears by more than 90 days during the 12 months after being screened by the EFL tool, compared to 14.5% of entrepreneurs accepted by both methods. We do not find evidence that the EFL tool can reduce the risk of the portfolio for unbanked entrepreneurs who have been approved through the traditional screening process.

We also find that the EFL tool can be used to extend credit to some unbanked entrepreneurs who were rejected under the traditional credit scoring method, without increasing the risk of the portfolio. However, for banked entrepreneurs, the EFL tool does not perform well as a skimming mechanism in the context examined in this paper.

To study the impact of the EFL tool on access to credit for unbanked entrepreneurs, we compare credit use of loan applicants with an EFL score just below and above the threshold set by the implementing institution. We find evidence that those above the threshold are more likely to become banked than those below the threshold (mostly through loans from the implementing institution).

Our paper contributes to the literature studying the relationship between individual characteristics (based on personality traits) and repayment behavior. Klinger, Khwaja, and del Carpio (2013), analyzed data from 1,580 small business owners with loans from banks and microfinance institutions in Peru, Kenya, Colombia, and South Africa and find that the entrepreneurs’ business profitability and their repayment behavior are strongly correlated with the entrepreneurs’ personality traits. Similarly, Klinger, Khwaja and LaMonte (2013) and Klinger, Castro, Szenkman, and Khwaja (2013) studied the repayment behavior of entrepreneurs in Peru and Argentina, respectively, and compared this behavior with other countries in which they applied the same psychometric tool. Their results show that despite the differences in the distribution of personality traits among countries, the dimensions that are related to business performance and credit risk are common across countries (Klinger, Castro, Szenkman, and Khwaja 2013).

In this paper, we go one step further and examine the potential of the psychometric credit application as a tool to manage portfolio risk and to increase access to credit compared to a traditional credit scoring method. Our paper is the first external study examining the predictive power of psychometric credit scoring, i.e. using independently collected data on repayment behavior and not co-authored by a person affiliated with EFL.

The rest of the paper is organized as follows. Section 2 discusses the EFL tool, the implementation of the tool by the institution, and the hypotheses to be tested. Section 3 describes the data and methodology. Section 4 presents the empirical results. Section 5 examines an extension of the results: the use of updated EFL scores generated using a new model. Finally, section 6 concludes.

2. Background and analytical framework

2.1 Innovative screening methods: The EFL tool

To solve the information asymmetries that banks face when screening SMEs—low quality, reduced information available to assess the growth potential and risk profile of SMEs; and the limited ability to gather that information at a low cost—banks in the U.S. have shifted their focus away from business operations and towards the business owner. In the mid-1990s, large U.S. banks started developing credit scoring models based on (i) data they had collected on SMEs or that was available via commercial credit bureaus and on (ii) SME owners' personal consumer data obtained from consumer credit bureaus (Berger and Frame 2006, Berger and Udell 2006).[6]

In the U.S., the wide adoption of credit scoring has led to an increase in the quantity of credit extended to SMEs; an increase in lending to relatively opaque, risky businesses; an increase in lending within low-income areas; an increase in lending in areas outside the banks' local markets; and an increase in loan maturities (Berger, Frame, and Miller 2005). But not all countries have well developed credit bureaus that include the rich information on SMEs and consumers needed to build a reliable credit scoring model. The average credit bureau in a Latin

[6] Mester (1997) states that standardized models developed commercially for lenders without enough loan volumes to build their own models "found that the most important indicators of small-business loan performance were characteristics of the business owner rather than the business itself. For example, the owner's credit history was more predictive that the net worth or profitability of the business." This result reflects the correlation between personal and business success and the commingling of the finances of the business and the owner (Berger, Frame, and Miller, 2005).

America and Caribbean country complies with only half of best practices and covers 39.3% of the adult population (Doing Business Report 2014). Credit bureau coverage is even lower in other world regions, except for OECD high-income countries.

Thus, even though credit scoring represents a potential solution to improve access to credit for SMEs, it can take many years to pass legislation that will lead to improvements in the quality and depth of information recorded in credit bureaus as well as to increase the bureaus' coverage. In addition, banks may be reluctant to share proprietary information with other banks (Bruhn, Farazi and Kanz 2013), and even after credit bureaus are set up and are working well, building an accurate credit scoring model often requires many years of history. In the meantime, credit markets in developing countries may have to rely on alternative lending technologies to screen potential clients.

One such alternative is the use of psychometric tools. Psychometric tests make it possible to screen many people at a low cost. They have been extensively used in the selection of personnel and the results show that general intelligence tests (general mental ability), integrity tests, and conscientiousness tests are, along with work sample tests, the selection methods with the strongest ability to predict overall job performance (Schmidt and Hunter 1998)—especially when the applicant is matched with the competencies required to do the job. These tests, in combination, are superior to the candidate's job experience, level of education, employment interview results, peer ratings, and reference checks in their ability to predict overall job performance.

Using psychometric tests to screen out high credit risk SME owners, however, departs from the traditional use of the psychometric tools to predict overall job performance. Under the assumption that there is a trait or set of traits that characterize low vs. high credit risk entrepreneurs, the psychometrician's task is to identify that set of traits and construct a measure that has appropriate psychometric properties and predictive utility. The questions identified by the psychometrician have to be systematically tested on real-world credit applicants, and their predictive validity established by best practices of credit scoring.

EFL started to develop a psychometric credit scoring tool by quantifying individual characteristics related to defaulters versus non-defaulters and high-profit versus low-profit small business owners across three different areas: personality, intelligence, and integrity (Klinger et al. 2013). They originally worked with a personality assessment based on the five-factor or "Big Five" model (Costa and McCrae 1992), an intelligence assessment based on digit span recall (a component of the Wechsler Adult Intelligence Scale), Ravens Progressive Matrices tests (Spearman 1946), and an integrity assessment adapted from Bernardin and Cooke (1993).

EFL's hypothesis was that these assessments would allow them to identify the two main drivers of an entrepreneur's intrinsic risk: ability to pay and willingness to pay. The entrepreneurial traits—measured via personality and intelligence tests—determine the entrepreneur's ability to generate cash flows in the future so that his business can repay the loans; the honesty and integrity traits—measured via the integrity test—determine the entrepreneur's willingness to pay independently of his ability to pay.[7]

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 psychometric credit tool and subsequent default behavior. The commercial application is based on the same quantitative methods used to generate traditional credit scores. It contains psychometric questions developed internally and licensed by third parties relating to attitudes, beliefs, integrity, and performance, as well as traditional questions and the collection of metadata (i.e. how the applicant interacted with the tool).

2.2 The implementation of EFL tool

In March 2012, the implementing institution started to pilot EFL's psychometric credit scoring model, with the objective of expanding its commercial lending towards SMEs. Entrepreneurs who applied for a working capital loan (up to 18-month in duration with an average loan size of US$3,855) were screened by the EFL tool as part of the application process.[8] The EFL credit application used at this time took on average 45 minutes to complete (the current version takes 25 minutes). To be approved for a loan, the entrepreneur either had to get a score on the EFL credit application above a threshold defined by the institution or had to be approved under the traditional screening method used by the institution.[9] Only entrepreneurs who were rejected under both screening methods were not offered a loan (figure 1).

All applicants had a credit score from one of Peru's private credit bureaus, which the implementing institution uses in their traditional screening method. However, for "unbanked" individuals, i.e. those who have not had a loan from a formal financial institution in the past, this credit score is primarily based on demographic information.

As shown in figure 1, not all entrepreneurs who were offered a loan ended up getting a loan from the implementing institution. Some applicants secured loans with other financial institutions. For example, our data suggests that about 51.6% of unbanked entrepreneurs who were approved got a loan from a formal institution (including the implementing institution), but only 23.6% got a loan from the implementing institution. According to the implementing institution personnel,

[7] An extensive literature has documented links between personality or intelligence tests and entrepreneurship or business performance (Ciavarella et al. 2004, De Mel et al. 2007, de Mel et al. 2010, Djankov et al. 2007, Zhao and Seibert 2006). To date, the only evidence on integrity and willingness to repay loans comes from EFL itself (Klinger et al. 2013). A higher score on integrity is related to a lower probability of default—honest entrepreneurs default less—but is also related to lower business profits—honest entrepreneurs are less profitable.

[8] The implementing institution is the fifth largest commercial bank in Peru in terms of assets, balance of its loan portfolio, and deposit taking (Superintendencia de Banca, Seguros y AFP, Balance Sheets at December 2014). In 2013, IFC acquired 12.67% of the institution's shares.

[9] Banks set the EFL credit application score approval/denial threshold according to their risk appetite.

some unbanked entrepreneurs used approval letters provided by the institution to secure other loans that were disbursed faster or had different conditions.

Figure 1. Credit decisions based on EFL score and traditional method

		Traditional method decision (TM)	
		Accept	Reject
EFL decision	Accept	(1) Accepted 659 entrepreneurs (20.6% unbanked) (23.5% got loan from the implementing institution)	(2) Accepted 158 entrepreneurs (10.1% unbanked) (24.7% got loan from the implementing institution)
	Reject	(3) Accepted 860 entrepreneurs (25.1% unbanked) (29.3% got loan from the implementing institution)	(4) Rejected 209 entrepreneurs (7.2% unbanked) (0% got loan from the implementing institution)

Source: Authors' own calculation

2.3 Hypotheses

We specify two hypotheses that correspond to different ways in which banks can apply the EFL tool in their credit risk management and lending decisions. We test these hypotheses by comparing the repayment behavior of different groups in figure 1, separately for banked and unbanked entrepreneurs.

Hypothesis 1: Risk reduction. Entrepreneurs who were accepted under the traditional method but rejected based on their EFL score display worse loan repayment behavior than entrepreneurs who were accepted under both methods.[10] In terms of figure 1, this hypothesis implies that entrepreneurs in (3) have worse repayment behavior than entrepreneurs in (1). If this hypothesis is true, the EFL credit application can be used as a secondary screening mechanism to lower the risk of the SME loan portfolio.

Hypothesis 2: Credit to new borrowers. Entrepreneurs who were rejected under the traditional method but accepted based on their EFL score do not display worse loan repayment behavior than entrepreneurs who were accepted under the traditional model.[11] In terms of figure 1, this hypothesis implies that entrepreneurs in (2) have no worse repayment behavior than entrepreneurs in (1) + (3). If this hypothesis is true, banks can use the EFL tool to give credit to borrowers they would otherwise have rejected without increasing the risk of their SME portfolio.

[10] To test this hypothesis for banked entrepreneurs we can use 1167 observations, which allow us to detect a difference of 5.3 percentage points between groups; for unbanked entrepreneurs we can only use 352 observations, which allows us to detect a difference of 13.7 percentage points between groups. In both cases the calculations were done for an 80% power and a 95% confidence level for the binary indicators with the lowest incidence.

[11] To test this hypothesis for banked entrepreneurs we can use 1309 observations, which allow us to detect a difference of 8.8 percentage points between groups; for unbanked entrepreneurs we can only use 368 observations, which allow us to detect a difference of 29.5 percentage points between groups. In both cases the calculations were done for 80% power and 95% confidence level for the binary indicator with the lowest incidence.

Since not all applicants who were offered a loan accepted the loan and some obtained loans from other banks, we also examine the fraction of clients obtaining loans as an additional outcome of interest for each hypothesis. Comparing loan take-up in different groups provides information about how the size of the portfolio might change with different screening techniques.

An additional question of interest is to which extent using the EFL tool can provide access to loans for unbanked entrepreneurs who may have difficulties obtaining a loan since they do not have a credit history. We thus also test the following third hypothesis.

Hypothesis 3: Banking the unbanked. Unbanked entrepreneurs who were accepted based on their EFL score have a greater probability of getting a loan than unbanked entrepreneurs who were rejected based on their EFL score. In terms of figure 1, this hypothesis implies that unbanked clients in (1) + (2) are more likely to have a loan after being screened by the EFL tool than unbanked clients in (3) + (4). Since clients in these two groups are likely to have very different characteristics, we also restrict the sample here to the unbanked around the EFL threshold defined by the implementing institution to compare only clients with similar characteristics.

3. Data, Descriptive Statistics, and Methodology

3.1 Data sources

We obtained data from EFL collected through the questionnaire that the implementing institution personnel administered during the loan application process for 1,993 entrepreneurs screened by the EFL tool between March 2012 and August 2013. These data include the EFL score and the date when the entrepreneur was screened by the EFL tool, as well as their age, gender, marital status, business sales, and sector of activity.[12]

The EFL scores used for the pilot were initially generated by a model built with data pooled across multiple African countries where EFL had tested its credit scoring model (EFL Africa model v2).[13] After some time passed, and enough observations were generated by the

[12] The questionnaire administered by EFL also includes the entrepreneur's years of education, number of dependents, entrepreneurship family history, psychological profile; as well as their business age, number of businesses started, business assets, etc. Because this information is used to calculate the score, EFL restricted access to it.

[13] Using pooled data has the advantage of improving predictive power due to larger samples, but it has the disadvantage of combining data across different cultures and across financial institutions serving different market segments via different products. Klinger et al. (2013d) find that traits explaining default and business size are not consistently homogeneous across countries or market segments. However, using data exclusively obtained from the implementing bank is costly and time consuming and may not generate large enough samples to overcome low statistical power and over-fitting issues. EFL therefore uses an adaptive model—a Bayesian hierarchical logit model—which assumes that the behavior of covariates vary by country, market segment, and financial institution. The parameters estimated by the model are a weighted combination that uses the pooled data across countries and

implementing institution, EFL adapted the model giving more weight to the implementing institution's data. EFL recalculated the scores for our sample using the new model (EFL Global model v1—the first to incorporate non-African data). We use these new scores in section 5 as an extension of our results.

Table 1. Descriptive statistics

	Accepted by Both Models		Rejected by Trad. Model and Accepted by EFL		Accepted by Trad. Model and Rejected by EFL		Rejected by Both Models	
	Banked	Unbanked	Banked	Unbanked	Banked	Unbanked	Banked	Unbanked
EFL Score (Old Model)	423.61	421.57	421.54	415.44	347.67	344.01	345.06	342.40
EFL Score (New Model)	444.89	446.06	439.09	435.63	432.60	430.38	428.76	421.36
Age	43.820	44.338	40.465	40.000	37.338	34.190	35.485	33.200
Female	0.489	0.471	0.514	0.375	0.501	0.486	0.526	0.600
log_sales	10.187	10.028	10.517	10.392	9.920	9.574	9.754	9.365
Debt to sales ratio	1.724	0.101	1.495	0.065	1.507	0.029	1.499	0.000
Marital Status								
Divorced	0.033	0.022	0.035	0.000	0.020	0.023	0.026	0.000
Living with partner	0.023	0.044	0.035	0.063	0.076	0.074	0.057	0.000
Married	0.361	0.375	0.289	0.375	0.217	0.162	0.175	0.133
Separated	0.013	0.022	0.014	0.000	0.009	0.005	0.026	0.067
Single	0.558	0.507	0.627	0.563	0.674	0.731	0.706	0.800
Widowed	0.011	0.029	0.000	0.000	0.003	0.005	0.010	0.000
Business sector								
Agriculture	0.006	0.000	0.000	0.000	0.009	0.005	0.005	0.000
Commerce	0.753	0.838	0.718	0.938	0.716	0.750	0.737	0.733
Other Services	0.124	0.103	0.176	0.000	0.157	0.130	0.149	0.133
Manufacturing	0.117	0.059	0.106	0.063	0.118	0.116	0.108	0.133
Classified as "Normal" at the SBS	0.939	N.A.	0.718	N.A.	0.964	N.A.	0.737	N.A.
Number of Observations	523	136	142	16	644	216	194	15

Source: Authors' own calculation
Note: The table displays averages of the variables in each group.

The implementing institution shared with us the threshold in the EFL score they used to determine whether or not to make a loan offer. For each loan applicant, the institution also let us know which decision they would have taken based on the score provided by the private credit bureau. Due to confidentiality reasons, the institution could not share the credit bureau score itself with us. Through EFL, we later obtained access to this score for 57% of the entrepreneurs in our sample.

the data available for a particular country and segment (tailored model); the more data is available for a particular country and segment, the larger the weight placed on the tailored model. Additionally, the more homogeneous the behavior of a covariate across countries, the larger the weight put on the global model for that particular variable.

We also have credit history data from the public credit registry managed by the SBS. All financial institutions subject to credit risk—including credit unions not authorized to receive deposits—have to provide monthly data to this public credit registry. Each month the SBS reports maximum number of days in arrears (across all financial institutions), total debt, and a classification of debtors into one of five status categories: normal, with potential payment problems, poor payment, doubtful payment, and loss.[14] Only "banked" entrepreneurs, i.e. those who have had a loan within the formal financial system in the past, appear in the public credit registry data. About 76% of the entrepreneurs in our sample were banked at the time they were screened by the EFL tool.

Table 1 shows descriptive statistics for the four possible scenarios described in figure 1, for banked and unbanked entrepreneurs separately.

3.2 Repayment behavior and access to credit indicators

To assess loan repayment behavior, we use the status of the entrepreneur, at different points in time after being screened by the EFL tool, in the public credit registry managed by the SBS.[15]

We defined several variables to assess the entrepreneurs' repayment behavior: a binary variable equal to one if their classification, 12 months after being screened by the EFL tool, was worse than "normal" and zero if their classification was "normal"; a binary variable equal to one if the maximum number of days was 90 days or more 12 months after being screened by the EFL tool, and 0 if it was less than 90 days; a binary variable equal to one if the maximum number of days in arrears was 90 days or more at any time during the 12 months after being screened by the EFL tool, and 0 if it was less than 90 days during the same period. We also use the total number of days in arrears 6 and 12 months after being screened by the EFL tool.

We examine use of credit as well. The SBS data does not specify from which financial institution entrepreneurs have a loan—it only reports total amount of debt each month. We thus coded binary variables equal to one if any increase in the total amount of debt was detected one and six months after being screened by the EFL tool (compared to one month before being screened by the EFL tool) and zero otherwise. We also use a binary variable equal to one if the person has

[14] Entrepreneurs are identified in the SBS database based on their national ID number or on their business tax ID number. An entrepreneur with consumer credit or microcredit is classified as normal if he is up to 8 days in arrears, as showing potential payment problem if he is between 9 and up to 30 days in arrears, as substandard if he is between 31 and up to 60 days in arrears, as doubtful if he is between 61 and up to 120 days in arrears, and as a loss if he is more than 120 days in arrears.

[15] The public credit bureau managed by the SBS receives the classification given to the entrepreneur by the different financial institutions with which he maintains credit. The classification we are using for this analysis corresponds to the highest risk classification provided by any institution; the classification given by the implementing institution based on the entrepreneurs' days in arrears may differ from the classification based on days in arrears with other financial institutions.

any classification in the SBS's credit bureau 12 months after being screened by the EFL tool, and 0 if the person does not have any classification (does not have credit from a formal financial institutions subject to credit risk).

Table A1 in the Appendix shows the correlations between our repayment behavior and access to credit indicators with the EFL and credit bureau scores, in the sample of entrepreneurs for which we have both scores. For both scores, a higher value is associated with better repayment behavior. Entrepreneurs with a higher EFL score also have a lower probability of using credit.

3. 3 ***Methodology***

We estimate linear regression models of the following form:

$$y_i = \alpha + \beta x_i + \varepsilon_i, \qquad i \in S.$$

Where y_i is either a continuous variable—for example total days in arrears for entrepreneur *i*—or a binary variable—for example, an indicator equal to one if the entrepreneur *i* has a classification worse than "normal" in the public credit registry and zero otherwise. In the binary case, our model is a linear probability model. x_i is an indicator defined differently depending on the hypothesis we are testing. For example, for hypothesis 1, the indicator is equal to one if the entrepreneur was rejected based on their EFL score and accepted under the traditional screening method and equal to zero if the entrepreneur was accepted based on their EFL score and under the traditional screening method. ε_i is the regression error term. S is the sample of interest; it varies according the hypothesis we are testing.

The estimates reported in tables 2-6 correspond to α and β for the specification above. Table A2 in the Appendix reports alternative specifications which control for characteristics of the entrepreneurs, such as age, gender, and marital status; business sales, and sector of activity. Table A2 also shows results using Probit instead of linear probability models, along with Horrace and Oaxaca (2006) tests. The results are robust to using these alternative specifications.

4. Empirical results

4.1 Testing hypothesis 1: Risk reduction

Table 2 reports our results for testing hypothesis 1: Entrepreneurs who were accepted under the traditional method but rejected based on their EFL score display worse loan repayment behavior than entrepreneurs who were accepted under both methods. The sample in table 2 includes only entrepreneurs who were accepted under the traditional method. Each couple of columns presents regressions of our outcome variables on a dummy variable equal to one if the entrepreneur was rejected based on their EFL score and accepted under the traditional model and equal to zero if the entrepreneur was accepted under both methods. The first column presents the constant coefficient—the average for entrepreneurs accepted under both methods—while the second column presents the dummy variable coefficient—the difference between entrepreneurs rejected and accepted based on their EFL score.

Table 2. Testing hypothesis 1: Risk reduction

	Banked + Unbanked		Banked		Unbanked	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.275***	0.035	0.273***	0.037	0.294***	0.016
	(0.019)	(0.025)	(0.020)	(0.027)	(0.064)	(0.078)
More than 90 days in arrears at SBS (12 months after app.)	0.125***	0.036*	0.122***	0.046**	0.152***	-0.032
	(0.015)	(0.020)	(0.015)	(0.022)	(0.053)	(0.063)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.151***	0.075***	0.145***	0.086***	0.207***	-0.007
	(0.015)	(0.021)	(0.015)	(0.023)	(0.053)	(0.065)
Number of days in arrears (6 months after app.)	13.326***	5.868***	12.029***	8.101***	24.691***	-10.847
	(1.403)	(2.086)	(1.381)	(2.215)	(6.240)	(6.952)
Number of days in arrears (12 months after app.)	26.799***	8.961**	27.120***	10.074**	23.925***	4.048
	(2.507)	(3.736)	(2.689)	(4.094)	(6.580)	(8.912)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.466***	0.062**	0.505***	0.071**	0.316***	0.068
	(0.019)	(0.026)	(0.022)	(0.029)	(0.040)	(0.052)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.528***	0.089***	0.568***	0.095***	0.375***	0.106**
	(0.019)	(0.026)	(0.022)	(0.029)	(0.042)	(0.054)
Classification at SBS (12 months after app.)	0.882***	0.006	1.000***	-0.002	0.426***	0.129**
	(0.013)	(0.017)	(0.000)	(0.002)	(0.043)	(0.054)
Loan from implementing institution	0.235***	0.058**	0.245***	0.064**	0.199***	0.047
	(0.017)	(0.023)	(0.019)	(0.026)	(0.034)	(0.045)
Number of observations	1519		1167		352	

Source: Authors' own calculations

Note: The sample includes all entrepreneurs accepted under the traditional method. § Difference between entrepreneurs rejected and accepted based on their EFL score. Ordinary least squares estimates. Outcome variables are for loans from all formal financial institutions, i.e. not limited to the implementing institution unless stated otherwise. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

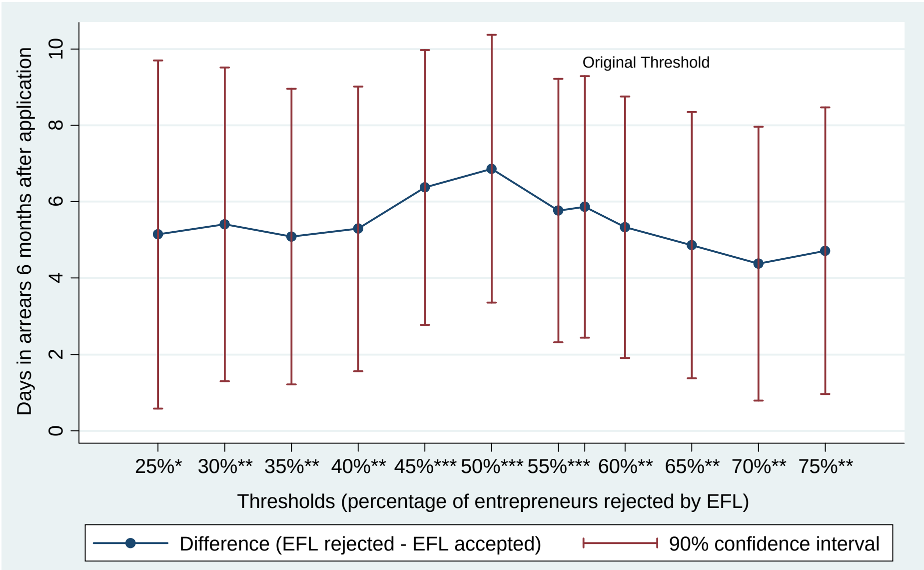
The evidence in table 2 suggests that the EFL tool has the ability to screen out higher risk borrowers from the sample of *banked* entrepreneurs accepted under the traditional method (column 4). Entrepreneurs accepted under the traditional screening method but rejected based on their EFL score have significantly worse repayment behavior for most of our indicators than entrepreneurs accepted under both methods. For example, banked entrepreneurs accepted under the traditional method but rejected based on their EFL score are 8.6 percentage points more likely to have been in arrears by more than 90 days during the 12 months after being screened by the EFL tool, compared to 14.5% of entrepreneurs accepted under both methods.

We do not observe that the EFL tool has the ability to screen out higher risk borrowers for *unbanked* entrepreneurs approved under the traditional method (columns 6). The differences in repayment behavior here are smaller and not statistically different from zero. Moreover, the signs of the estimates do not point consistently in the same direction.

With respect to use of credit, we find that a larger proportion of entrepreneurs rejected based on their EFL score increased their debt one and six months after they were screened by the EFL tool compared to entrepreneurs accepted based on their the EFL score. EFL rejected entrepreneurs are also more likely to obtain a loan from the implementing institution than EFL accepted entrepreneurs. Since both groups were accepted under the traditional method, and if anything entrepreneurs accepted based on their EFL score should be in a better position to get a loan—at least from the implementing institution—these results could be driven by the personality traits that make entrepreneurs less attractive according to the EFL tool. For example, EFL rejected entrepreneurs may be less risk averse and may accept loan offers even under unfavorable conditions, whereas EFL accepted entrepreneurs would turn down unfavorable loan offers.

Since the results in table 2 depend on the arbitrary threshold levels chosen by the implementing institution to accept/reject clients, we run a sensitivity analysis moving the threshold levels between the 25 and 75 percentile (rejecting from 25% up to 75% of screened entrepreneurs, respectively). We use the whole sample of banked and unbanked entrepreneurs to carry out these sensitivity exercises. Figures A1 and A2 in the Appendix show the distribution of each score and the range used for the sensitivity analysis.

Figure 2. Sensitivity analysis for testing hypothesis 1: risk reduction – Moving the EFL score threshold

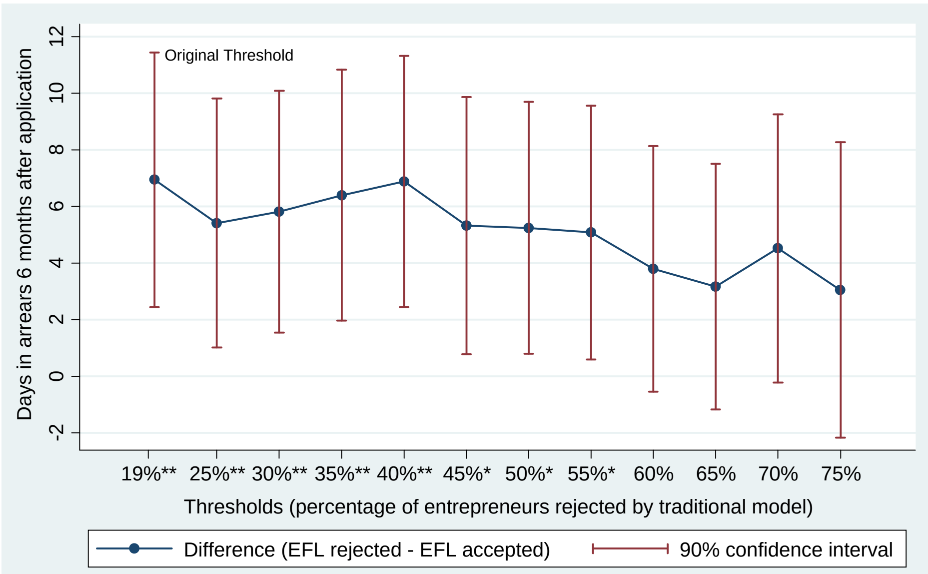


Source: Authors' own calculations
Note: The figure only includes entrepreneurs who were accepted under the traditional screening method.

Figure 2 shows how the difference (between EFL rejected and EFL accepted entrepreneurs) in the average number of days in arrears six months after the EFL tool application varies when moving the EFL score threshold—while keeping the traditional credit score threshold fixed. Entrepreneurs rejected based on their EFL score have a significantly greater number of days in arrears than entrepreneurs accepted based on their EFL score for all hypothetical threshold levels.

In figure 3, we examine how the average number of days in arrears six months after being screened by the EFL tool changes when moving the traditional credit score threshold while keeping the EFL score threshold fixed. The implementing institution had set the traditional credit score threshold quite low (at the 19th percentile), but the results in figure 3 suggest that the EFL tool is still able to screen out higher risk borrowers when the traditional credit score threshold is set more conservatively—up to the 55th percentile. However, for even higher values of the traditional credit score threshold (i.e. above the 55th percentile), the difference in average number of days in arrears between EFL accepted and EFL rejected entrepreneurs is not statistically significant.

Figure 3. Sensitivity analysis for testing hypothesis 1: risk reduction – Moving the traditional credit score threshold



Source: Authors' own calculations
Note: The figure only includes entrepreneurs who were accepted under the traditional screening method.

4.2 Testing hypothesis 2: Credit to new borrowers

Table 3 reports the results for testing hypothesis 2: Entrepreneurs who were rejected under the traditional model but accepted based on their EFL score do not display worse loan repayment behavior than entrepreneurs who were accepted under the traditional model. Each couple of columns presents regressions of the outcome variables on a dummy variable equal to one if the entrepreneur was rejected under the traditional model and accepted based on their EFL score and equal to zero if the entrepreneur was accepted under the traditional model. The first column presents the constant coefficient—the average for entrepreneurs accepted under the traditional method—while the second column presents the dummy variable coefficient—difference between entrepreneurs rejected under the traditional model and accepted based on their EFL score and entrepreneurs accepted under the traditional model.

Table 3 shows evidence against hypothesis 2 (column 2). In fact, entrepreneurs rejected under the traditional model and accepted based their EFL score show worse loan repayment behavior than those accepted under the traditional method. These results seem to be driven by banked entrepreneurs and suggest that the traditional screening method—which incorporates, for banked entrepreneurs, valuable information about their past repayment behavior—is a powerful tool to screen out high credit risk (column 4).

The differences in loan repayment behavior for unbanked entrepreneurs are smaller and not statistically different from zero (column 6). Moreover, the size of the coefficients is small compared to the coefficients for banked entrepreneurs. Our results thus suggest that the EFL tool can be used to offer loans to unbanked applicants who are rejected under the traditional method without increasing the risk of the loan portfolio. However, this finding does not hold for banked applicants (from whom the traditional method includes credit scores that are more informative than for unbanked applicants).

Table 3. Testing hypothesis 2: Credit to new borrowers

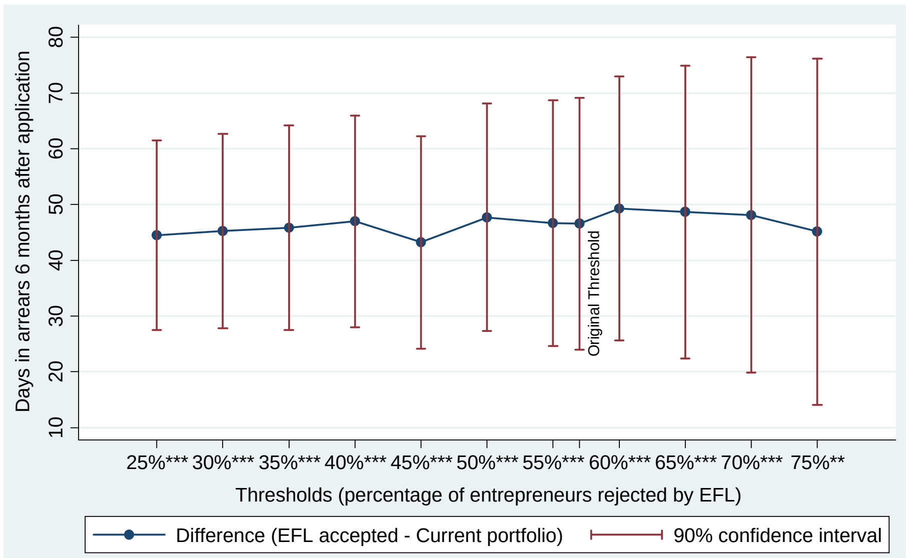
	Banked + Unbanked		Banked		Unbanked	
	TM Accepted	Diff §	TM Accepted	Diff §	TM Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.295***	0.311***	0.293***	0.323***	0.305***	0.140
	(0.013)	(0.042)	(0.013)	(0.044)	(0.036)	(0.170)
More than 90 days in arrears at SBS (12 months after app.)	0.145***	0.161***	0.147***	0.171***	0.130***	-0.005
	(0.010)	(0.043)	(0.011)	(0.045)	(0.028)	(0.121)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.194***	0.221***	0.193***	0.244***	0.202***	-0.036
	(0.011)	(0.041)	(0.012)	(0.043)	(0.030)	(0.112)
Number of days in arrears (6 months after app.)	16.711***	44.742***	16.596***	46.828***	17.482***	23.435
	(1.073)	(9.061)	(1.153)	(9.754)	(2.947)	(18.646)
Number of days in arrears (12 months after app.)	31.892***	59.108***	32.690***	62.909***	26.640***	4.582
	(1.914)	(12.627)	(2.093)	(13.476)	(4.578)	(13.510)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.501***	-0.020	0.544***	-0.079*	0.358***	0.267**
	(0.013)	(0.042)	(0.015)	(0.044)	(0.026)	(0.124)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.579***	-0.060	0.620***	-0.120***	0.440***	0.247**
	(0.013)	(0.042)	(0.014)	(0.044)	(0.027)	(0.119)
Classification at SBS (12 months after app.)	0.885***	0.090***	0.999***	0.001	0.506***	0.244**
	(0.008)	(0.015)	(0.001)	(0.001)	(0.027)	(0.112)
Loan from implementing institution	0.268***	-0.021	0.280***	-0.055	0.227***	0.210*
	(0.011)	(0.036)	(0.013)	(0.037)	(0.022)	(0.126)
Number of observations	1677		1309		368	

Source: Authors' own calculations

Note: § Difference between entrepreneurs rejected under the traditional model and accepted based on the EFL score and entrepreneurs accepted under the traditional model. Ordinary least squares estimates. Outcome variables are for loans from all formal financial institutions, i.e. not limited to the implementing institution unless stated otherwise. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

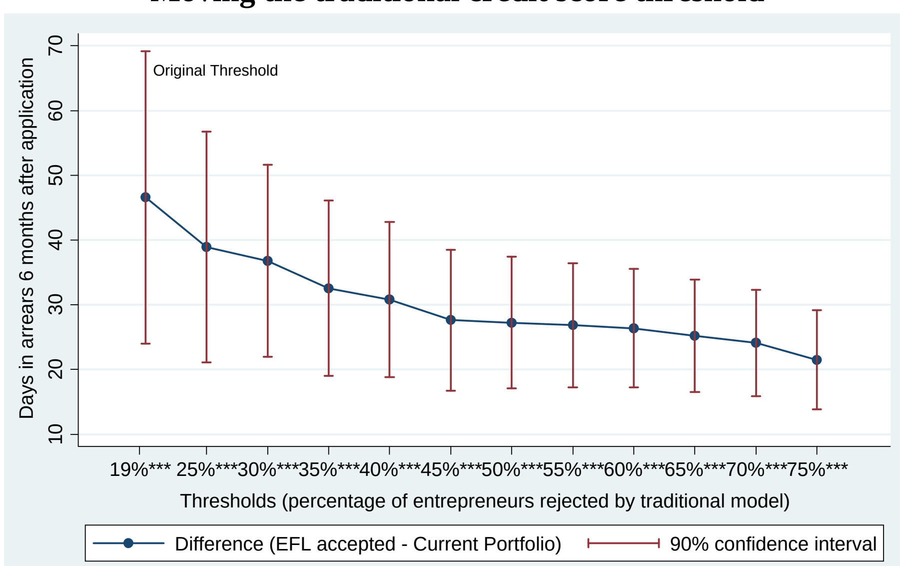
We also find that a larger proportion of unbanked entrepreneurs rejected under the traditional method and accepted based on their EFL score become banked —an increase of 24.4 percentage points with respect to entrepreneurs accepted under the traditional method. This increase seems to be driven by the implementing institution and its decision to offer loans to applicants who passed the EFL credit application (the size of the increase in the probability of having any loan—24.4 percentage points—is similar to the size of the increase in the probability of having a loan from the implementing institution—21 percentage points).

Figure 4. Sensitivity analysis for testing hypothesis 2: credit to new borrowers – Moving the EFL score threshold



Source: Authors' own calculations

Figure 5. Sensitivity analysis for testing hypothesis 2: credit to new borrowers – Moving the traditional credit score threshold



Source: Authors' own calculations

We now examine how robust these results are to changes in the acceptance/rejection thresholds. Figure 4 shows that increasing the EFL score threshold does not noticeably improve loan repayment behavior for entrepreneurs rejected under the traditional method and accepted based on their EFL score (figure 4)—compared to entrepreneurs accepted under the traditional method. The sensitivity analysis thus confirms that the EFL tool has limited power to sift low risk entrepreneurs from a pool of entrepreneurs who have been rejected based on information about their past repayment behavior (banked entrepreneurs).

Figure 5 shows the sensitivity analysis for testing hypothesis 2 when varying the traditional credit score threshold. With a higher threshold, the pool of entrepreneurs that can undergo secondary screening with the EFL tool increases. The difference in loan repayment behavior across the current portfolio and entrepreneurs added through EFL screening becomes smaller as the traditional credit score threshold increases. However, it is still positive and statistically significant.

4.3 Testing hypothesis 3: Banking the unbanked

Table 4 reports the results for testing hypothesis 3: Unbanked entrepreneurs who were accepted by the EFL tool have a greater probability of getting a loan than unbanked entrepreneurs who were rejected by the EFL tool. Each couple of columns presents regressions of the outcome variables on a dummy variable equal to one if the *unbanked* entrepreneur was rejected based on their EFL score and equal to zero if the *unbanked* entrepreneur was accepted based on their EFL score. For each exercise in table 4 the first column presents the constant coefficient—the average for entrepreneurs accepted based on their EFL score—while the second column presents the dummy variable coefficient—the difference between entrepreneurs rejected based on their EFL score and accepted based on their EFL score.

The first two columns contain the estimates for the whole sample of unbanked entrepreneurs controlling for the EFL score; columns 3-4 contain the estimates for the whole sample of unbanked entrepreneurs controlling for cubic polynomial of the EFL score; columns 5-6 contain the estimates for the sample of unbanked entrepreneurs around the threshold chosen by the implementing institution—a 10% bandwidth around the threshold—controlling for the EFL score; and columns 7-8 contain the estimates for the sample of unbanked entrepreneurs around the threshold chosen by the implementing institution—a 5% bandwidth around the threshold—controlling for the EFL score.

If hypothesis 3 is true, a larger fraction of unbanked entrepreneurs accepted by the EFL tool should have been able to get a loan, mainly via the implementing institution, than unbanked entrepreneurs rejected by EFL. Table 4 shows evidence supporting this hypothesis (columns 4, 6, and 8). In the sample close to the threshold, which is likely to contain entrepreneurs with similar characteristics on each side of the threshold, unbanked entrepreneurs rejected by the EFL tool are less likely to get a loan from the implementing institution and are less likely to become banked.[16]

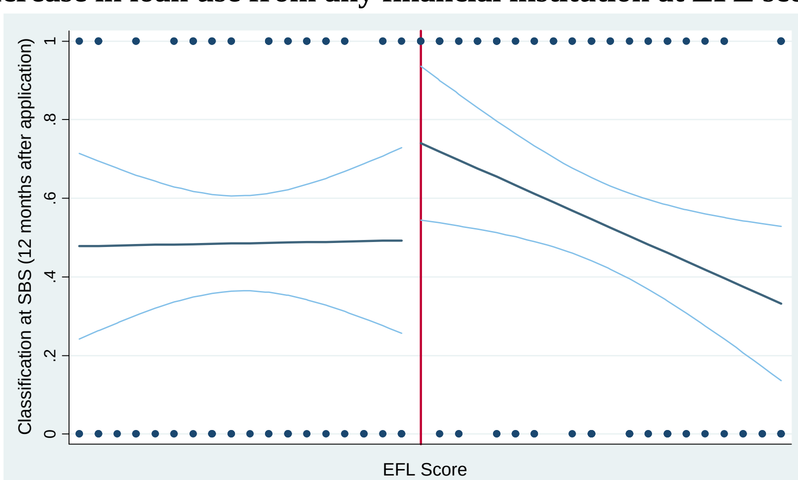
Table 4. Testing hypothesis 3: Banking the unbanked

	Unbanked controlling for EFL score (linear)		Unbanked controlling for EFL score (cubic)		Unbanked around threshold c. EFL Score (L)		Unbanked around threshold c. EFL Score (L)	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Classification worse than "Normal" at SBS (12 months after app.)	0.083	0.066	13.540	0.137	6.558	-0.152	29.014***	-0.579**
	(0.463)	(0.111)	(15.408)	(0.140)	(4.302)	(0.218)	(8.295)	(0.268)
More than 90 days in arrears at SBS (12 months after app.)	-0.307	0.067	1.459	0.109	3.921	-0.043	17.712**	-0.333
	(0.371)	(0.092)	(10.618)	(0.121)	(4.183)	(0.208)	(8.694)	(0.264)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.035	0.041	-5.035	0.095	3.568	-0.033	20.177**	-0.344
	(0.380)	(0.090)	(11.718)	(0.115)	(3.448)	(0.185)	(7.684)	(0.237)
Number of days in arrears (6 months after app.)	1.569	-4.600	803.217	-0.342	385.706	-10.543	2125.491**	-38.955
	(42.459)	(10.963)	(960.001)	(13.428)	(479.816)	(22.999)	(1007.860)	(28.910)
Number of days in arrears (12 months after app.)	-37.539	19.936	1814.216	28.114	698.722	-0.294	2781.396**	-35.253
	(74.901)	(17.510)	(1556.089)	(21.085)	(830.049)	(40.158)	(1279.509)	(46.964)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.349	0.042	-12.214	-0.079	3.682	-0.182	12.332	-0.331
	(0.319)	(0.077)	(9.999)	(0.094)	(2.875)	(0.159)	(7.858)	(0.221)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.935***	-0.025	-9.897	-0.147	4.908*	-0.262	12.311	-0.360
	(0.334)	(0.079)	(10.334)	(0.097)	(2.874)	(0.159)	(8.121)	(0.223)
Classification at SBS (12 months after app.)	1.569***	-0.082	7.281	-0.160*	5.963**	-0.305**	19.767**	-0.568***
	(0.324)	(0.079)	(9.085)	(0.094)	(2.854)	(0.153)	(7.529)	(0.197)
Loan from implementing institution	0.613**	-0.065	-20.681***	-0.179**	3.217	-0.259**	11.565	-0.441**
	(0.273)	(0.064)	(7.580)	(0.079)	(2.277)	(0.130)	(6.947)	(0.179)
Number of observations	394		394		150		76	

Source: Authors' own calculations

Note: § Difference between entrepreneurs rejected by the EFL tool and entrepreneur accepted by the EFL tool. Ordinary least squares estimates. Outcome variables are for loans from all formal financial institutions, i.e. not limited to the implementing institution unless stated otherwise. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

Figure 6. Increase in loan use from any financial institution at EFL score threshold



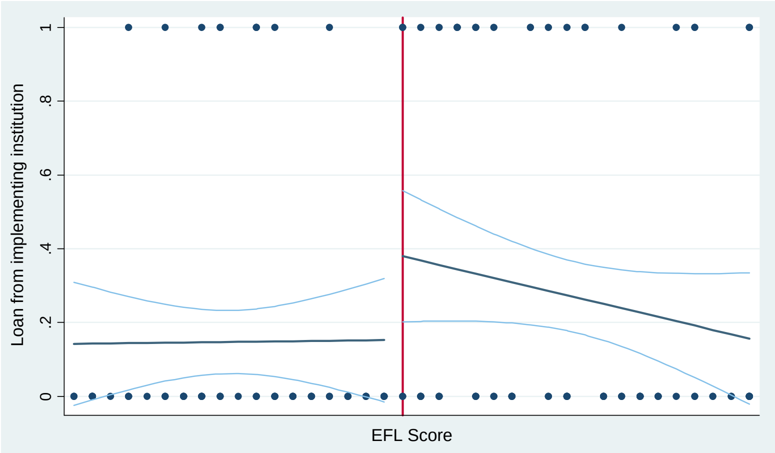
Source: Authors' own calculations

Note: The figure shows the predicted values from a linear regression of the indicator variable for having a classification at SBS (12 months after application) on the EFL score, run separately on each side of the cutoff, along with the 95% confidence intervals.

[16] The results in table A3 in the Appendix illustrate that most of the baseline characteristics we observe for the entrepreneurs in our sample are not statistically different around the EFL score threshold.

Figures 6 and 7 show the results corresponding to column 6. The negative slope for the regressions to the right of the threshold—entrepreneurs accepted by EFL—is consistent with the results observed in table 2: higher EFL scores may be correlated with personality traits that make these entrepreneurs more attractive according to the EFL tool; they may have been accepted because they are more risk averse and less prone to take debt at unfavorable conditions (lower credit risk).

Figure 7. Increase in loan use from implementing institution at EFL threshold



Source: Authors' own calculations
Note: The figure shows the predicted values from a linear regression of the indicator variable for having a loan from the implementing institution on the EFL score, run separately on each side of the cutoff, along with the 95% confidence intervals.

5. Updating EFL scores

In this section we use the updated EFL scores and threshold level (from the EFL Global model v1). After updating the scores, 49% of entrepreneurs who were initially rejected based on their EFL score would have been accepted had their initial answers been weighted using the parameters of the new model; similarly, 30% of entrepreneurs who were initially accepted based on their EFL score would have been rejected had their initial answers been weighted using the parameters of the new model.[17]

We limit our sample to entrepreneurs who did not take a loan from the implementing institution since the new, tailored model was estimated using data generated from repayment behavior for the implementing institution loans. All of our outcome variables in this section are thus based on

[17] The rejection rate for the old model is 53.2% while the rejection rate for the new model is 41.4%.

loans from other financial intuitions.[18] For comparability, tables A4 and A5 in the appendix replicate our previous results when using the old, EFL Africa model v2 (from tables 2 and 3), but limiting the sample to entrepreneurs who did not take a loan from the implementing institution.

Table 5 displays the results for testing hypothesis 1 with the updated EFL scores. The ability to screen out high default risk using the new, EFL Global model v1 is higher compared to the old, EFL Africa model v2. For example, among entrepreneurs accepted under the traditional model, those who would have been rejected using the new EFL score were 11.7 percentage points more likely to have a classification worse than "Normal" at SBS 12 months after being screened by the EFL tool than those who would have been accepted using the new EFL score. The same difference is only 5.2 percentage points when using the old EFL score (as shown in table A4). Similar improvements are present throughout our indicators of repayment behavior.

Table 5. Using updated EFL scores to test hypothesis 1: Risk reduction

	Banked + Unbanked		Banked		Unbanked	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.229***	0.117***	0.234***	0.121***	0.178***	0.101
	(0.019)	(0.032)	(0.020)	(0.034)	(0.058)	(0.090)
More than 90 days in arrears at SBS (12 months after app.)	0.104***	0.063**	0.107***	0.068**	0.075*	0.047
	(0.014)	(0.026)	(0.015)	(0.028)	(0.042)	(0.067)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.143***	0.099***	0.146***	0.107***	0.120**	0.054
	(0.015)	(0.027)	(0.016)	(0.030)	(0.046)	(0.073)
Number of days in arrears (6 months after app.)	12.256***	10.863***	12.466***	10.479***	10.222**	14.225
	(1.514)	(2.999)	(1.592)	(3.208)	(4.951)	(8.552)
Number of days in arrears (12 months after app.)	23.420***	12.519***	23.995***	13.204**	18.234**	9.948
	(2.732)	(4.799)	(2.898)	(5.204)	(8.161)	(12.498)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.348***	0.035	0.412***	0.014	0.147***	0.115**
	(0.019)	(0.031)	(0.023)	(0.036)	(0.029)	(0.052)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.486***	0.024	0.556***	0.012	0.267***	0.079
	(0.020)	(0.032)	(0.023)	(0.036)	(0.036)	(0.059)
Classification at SBS (12 months after app.)	0.839***	0.012	1.000***	-0.003	0.333***	0.097
	(0.015)	(0.023)	(0.000)	(0.003)	(0.039)	(0.062)
Loan from implementing institution	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Number of observations	1040		783		257	

Source: Authors' own calculations

Note: The sample includes all entrepreneurs accepted under the traditional method who did not take a loan from the implementing institution. § Difference between entrepreneurs rejected and accepted based on their updated EFL score (from the EFL Global model v1). Ordinary least squares estimates. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

Table 6 shows our results for testing hypothesis 2 with scores from the new model. The ability to select entrepreneurs with low credit risk from the pool of entrepreneurs rejected under the

[18] Loan repayment behavior is highly correlated across entrepreneurs who have a loan from the implementing institution and those who have a loan from other financial intuitions. For example, the correlation between a dummy variable equal to one if the entrepreneur was ever 90 days in arrears or more during the implementing institution loan tenure and zero otherwise and a similar dummy variable generated for 90 days in arrears or more during the same period for any loan in the formal financial system is 0.71.

traditional method is quite similar across the new model and the old model. For example, under the new model, entrepreneurs rejected under the traditional model and accepted based on their EFL score are 38.1 percentage points more likely to have a classification worse than "normal" at the SBS than entrepreneurs accepted under the traditional model. Under the old model the size of this difference is 35.8 percentage points.

Table 6. Using updated EFL scores to test hypothesis 2: Credit to new borrowers

	Banked + Unbanked		Banked		Unbanked	
	TM Accepted	Diff §	TM Accepted	Diff §	TM Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.279***	0.381***	0.283***	0.386***	0.245***	0.155
	(0.015)	(0.041)	(0.016)	(0.042)	(0.044)	(0.226)
More than 90 days in arrears at SBS (12 months after app.)	0.130***	0.245***	0.131***	0.261***	0.121***	-0.121***
	(0.012)	(0.047)	(0.012)	(0.049)	(0.035)	(0.035)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.182***	0.273***	0.185***	0.292***	0.160***	-0.160***
	(0.013)	(0.042)	(0.013)	(0.043)	(0.036)	(0.036)
Number of days in arrears (6 months after app.)	16.233***	49.248***	16.227***	50.021***	16.283***	33.717
	(1.317)	(9.735)	(1.400)	(10.098)	(3.897)	(31.687)
Number of days in arrears (12 months after app.)	28.559***	72.406***	28.840***	75.691***	26.485***	-4.685
	(2.196)	(14.080)	(2.347)	(14.623)	(6.276)	(13.758)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.369***	0.011	0.423***	-0.053	0.202***	0.353**
	(0.014)	(0.041)	(0.017)	(0.043)	(0.024)	(0.168)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.510***	-0.092**	0.573***	-0.163***	0.316***	0.239
	(0.015)	(0.042)	(0.017)	(0.044)	(0.028)	(0.169)
Classification at SBS (12 months after app.)	0.850***	0.138***	0.999***	0.001	0.390***	0.388***
	(0.011)	(0.014)	(0.001)	(0.001)	(0.030)	(0.142)
Loan from implementing institution	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Number of observations	1270		989		366	

Source: Authors' own calculations

Note: § Difference between entrepreneurs that would have been rejected under the traditional model and accepted based on their updated EFL score and entrepreneurs accepted under the traditional model (only for entrepreneurs who did not take a loan from the implementing institution). Ordinary least squares estimates. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

6. Conclusions

In this paper we study the use of a psychometric credit application to reduce information asymmetries and to better assess credit risk and extend credit to small businesses. The psychometric credit application was developed by EFL with the goal of identifying traits that characterize low and high credit risk entrepreneurs, traits that make it possible to select the entrepreneurs who are able to 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 the fifth largest bank in Peru, we find that the EFL's too can add value to a traditional credit scoring method in different ways for banked and unbanked entrepreneurs. For *banked* entrepreneurs, i.e. those with a credit history, the EFL tool can be used a secondary screening mechanism to reduce the risk of the portfolio risk. However, when used as a tool to rescue potential low-risk applicants among a pool of *banked* entrepreneurs with negative credit histories who have been rejected using the traditional credit scoring method, the EFL tool has limited power and can even lead to an increase in the portfolio risk. These results are robust to variations of the threshold chosen to distinguish between accepted and rejected loan applicants. That is, with respect to portfolio risk, the EFL tool does not do well at replacing credit history information, but it does well at complementing this information.

For *unbanked* entrepreneurs, i.e. those without a credit history, our results suggest that the EFL tool can be used to make additional loans to applicants rejected based on the traditional screening method without increasing portfolio risk. In line with these results, we also find evidence that the EFL tool increases access to credit for unbanked entrepreneurs.

Our findings clearly show the importance of information for assessing credit risk, making accurate credit decisions, and expanding credit supply. They highlight the power of traditional screening methods, based mainly on the entrepreneur's credit history, to screen out loan applicants with poor loan repayment behavior. Increasing the quality of the information that credit bureaus can access, for example data from retailers and utility companies in addition to banks and financial institutions, as well as positive information (payment history on accounts in good standing) in addition to negative information (late payments, number and amount of defaults and arrears, and bankruptcies), could improve the ability to produce better credit scoring models and to increase credit markets' confidence in their credit scores, even for entrepreneurs without previous experience with formal financial institutions. In the meantime, EFL offers a practical solution to financial institutions in countries where well developed credit bureaus are in the process of consolidation.

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Appendix

Table A1. Predictive power of EFL and credit bureau score

	Banked + Unbanked		Banked + Unbanked		Banked + Unbanked		
	Constant	EFL Score†	Constant	Trad. Score†	Constant	Trad. Score†	EFL Score†
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Classification worse than "Normal" at SBS (12 months after app.)	0.545***	-0.052*	0.835***	-0.080***	0.905***	-0.080***	-0.019
	(0.122)	(0.031)	(0.044)	(0.006)	(0.118)	(0.007)	(0.030)
More than 90 days in arrears at SBS (12 months after app.)	0.367***	-0.053**	0.474***	-0.050***	0.609***	-0.049***	-0.036
	(0.102)	(0.026)	(0.049)	(0.007)	(0.104)	(0.007)	(0.026)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.582***	-0.095***	0.532***	-0.051***	0.814***	-0.050***	-0.076***
	(0.107)	(0.027)	(0.045)	(0.006)	(0.107)	(0.007)	(0.027)
Number of days in arrears (6 months after app.)	45.262***	-5.616	87.001***	-10.256***	99.026***	-10.211***	-3.210
	(16.599)	(4.354)	(11.526)	(1.649)	(16.265)	(1.672)	(4.173)
Number of days in arrears (12 months after app.)	67.428***	-6.934	134.086***	-15.035***	143.856***	-14.990***	-2.614
	(25.139)	(6.491)	(15.607)	(2.217)	(25.350)	(2.246)	(6.246)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.785***	-0.079**	0.463***	0.003	0.763***	0.005	-0.081**
	(0.121)	(0.031)	(0.048)	(0.007)	(0.126)	(0.007)	(0.031)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.910***	-0.089***	0.409***	0.026***	0.779***	0.028***	-0.100***
	(0.120)	(0.031)	(0.047)	(0.007)	(0.124)	(0.007)	(0.031)
Classification at SBS (12 months after app.)	1.050***	-0.038**	0.977***	-0.012***	1.101***	-0.011***	-0.034*
	(0.069)	(0.018)	(0.018)	(0.003)	(0.070)	(0.003)	(0.018)
Loan from implementing institution	0.510***	-0.069**	0.183***	0.010*	0.454***	0.012**	-0.073***
	(0.105)	(0.027)	(0.035)	(0.005)	(0.103)	(0.006)	(0.027)
Number of observations	1087		1087		1087		

Source: Authors' own calculations

Note: § Correlations estimated using Ordinary Least Squares (LPM)—outcomes regressed on EFL and traditional credit score. † Original scores rescaled for presentation purposes. Outcome variables are for loans from all formal financial institutions, i.e. not limited to the implementing institution unless stated otherwise. Robust Standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

Table A2. Alternative specifications (with controls and Probit)

	Hypothesis 1				Hypothesis 2				Hypothesis 3 (Around Threshold)			
	LPM Diff § (1)	Probit Diff § (2)	ρ	Pr ∉[0,1]	LPM Diff § (3)	Probit Diff § (4)	ρ	Pr ∉[0,1]	LPM Diff § (7)	Probit Diff § (8)	ρ	Pr ∉[0,1]
Classification worse than "Normal" at SBS (12 months after app.)	0.004	0.004	0.997	0.001	0.320***	0.305***	0.998	0.000	0.059	0.048	0.960	0.074
	(0.027)	(0.027)			(0.043)	(0.041)			(0.157)	(0.074)		
More than 90 days in arrears at SBS (12 months after app.)	0.029	0.029	0.994	0.003	0.164***	0.136***	0.994	0.003	0.146	0.113	0.975	0.145
	(0.022)	(0.022)			(0.044)	(0.031)			(0.130)	(0.121)		
More than 90 days in arrears at SBS (during next 12 months following app.)	0.056**	0.057**	0.993	0.003	0.232***	0.202***	0.994	0.003	0.142	0.135	0.975	0.104
	(0.023)	(0.023)			(0.042)	(0.032)			(0.123)	(0.116)		
Number of days in arrears (6 months after app.)	5.996***				45.607***				25.726			
	(2.197)				(9.205)				(18.400)			
Number of days in arrears (12 months after app.)	9.035**				59.047***				52.417*			
	(4.064)				(12.882)				(30.671)			
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.070**	0.073**	0.994	0.001	-0.050	-0.052	0.995	0.001	-0.068	-0.078	0.94	0.027
	(0.028)	(0.029)			(0.042)	(0.043)			(0.101)	(0.100)		
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.105***	0.107***	0.999	0.000	-0.085**	-0.087**	0.999	0.000	-0.130	-0.126	0.9	0.027
	(0.028)	(0.028)			(0.042)	(0.042)			(0.097)	(0.099)		
Classification at SBS (12 months after app.)	0.014	0.014	0.958	0.007	0.081***	0.120***	0.963	0.017	-0.107	-0.104	0.78	0.020
	(0.017)	(0.017)			(0.015)	(0.036)			(0.102)	(0.098)		
Loan from implementing institution	0.081***	0.079***	0.994	0.007	-0.055	-0.053	0.996	0.005	-0.173**	-0.202**	0.984	0.073
	(0.026)	(0.026)			(0.037)	(0.039)			(0.081)	(0.091)		
Number of observations		1519				1677				150		

Source: Authors' own calculations

Note: The sample includes both banked and unbanked entrepreneurs. § Differences according to hypotheses and estimated using Ordinary Least Squares (LPM) and marginal effects at the mean values (Probit). All specifications include the following controls: potential client's age, gender, and marital status; business sales (self-reported); and sector of activity. Outcome variables are for loans from all formal financial institutions, i.e. not limited to the implementing institution unless stated otherwise. Robust Standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01. ρ: Correlation between the linear probability model and the probit predicted probabilities. Pr∉[0,1]: proportion of the predicted probabilities based on the linear probability model that fall outside the unit interval.

Table A3. Hypothesis 3: Banking the unbanked - Entrepreneurs' baseline characteristics around EFL score threshold

	Unbanked controlling for EFL score (linear)		Unbanked controlling for EFL score (cubic)		Unbanked around threshold c. EFL Score (L)		Unbanked around threshold c. EFL Score (L)	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age	27.026***	-6.624***	-771.827***	-6.450***	-87.659*	0.003	-245.264	3.496
	(5.856)	(1.491)	(166.786)	(1.715)	(50.710)	(2.633)	(151.064)	(3.718)
Female	0.108	0.085	-1.191	0.049	1.932	-0.061	-1.012	-0.006
	(0.334)	(0.080)	(10.035)	(0.097)	(2.967)	(0.161)	(8.184)	(0.229)
log_sales	9.408***	-0.385**	-88.058***	-0.568***	4.221	-0.224	12.367	-0.450
	(0.641)	(0.166)	(18.666)	(0.185)	(5.320)	(0.307)	(14.089)	(0.407)
Married	-0.225	-0.096	1.327	-0.095	0.666	-0.138	3.304	-0.215
	(0.258)	(0.070)	(6.795)	(0.087)	(2.729)	(0.152)	(8.402)	(0.227)
Single	0.693**	0.185**	-4.855	0.118	4.113	-0.001	0.142	0.118
	(0.311)	(0.075)	(9.137)	(0.092)	(2.789)	(0.156)	(8.423)	(0.227)
Commerce	1.915***	-0.293***	-1.912	-0.262***	3.669	-0.291**	2.030	-0.237
	(0.257)	(0.068)	(8.963)	(0.080)	(2.391)	(0.125)	(5.450)	(0.168)
Other services	-0.877***	0.212***	1.971	0.203***	-2.848	0.240**	-2.338	0.253*
	(0.190)	(0.056)	(5.284)	(0.064)	(1.936)	(0.107)	(4.628)	(0.147)
Manufacturing	-0.020	0.073	1.495	0.056	0.179	0.051	1.308	-0.016
	(0.194)	(0.047)	(7.285)	(0.055)	(1.681)	(0.079)	(3.023)	(0.089)
Number of observations	394		394		150		76	

Table A4. Using original EFL scores to test hypothesis 1: Risk reduction (reduced sample)

	Banked + Unbanked		Banked		Unbanked	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.250***	0.052*	0.255***	0.053*	0.194***	0.075
	(0.021)	(0.030)	(0.022)	(0.031)	(0.072)	(0.090)
More than 90 days in arrears at SBS (12 months after app.)	0.106***	0.044*	0.107***	0.047*	0.103*	0.026
	(0.016)	(0.023)	(0.017)	(0.025)	(0.057)	(0.072)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.130***	0.095***	0.129***	0.105***	0.143**	0.026
	(0.016)	(0.025)	(0.017)	(0.026)	(0.060)	(0.075)
Number of days in arrears (6 months after app.)	12.080***	7.482***	10.975***	9.639***	23.970***	-11.987
	(1.587)	(2.545)	(1.547)	(2.688)	(8.226)	(9.088)
Number of days in arrears (12 months after app.)	23.385***	9.474**	23.760***	9.582**	19.529**	10.486
	(2.769)	(4.297)	(2.936)	(4.621)	(8.083)	(11.728)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.345***	0.043	0.400***	0.043	0.147***	0.092*
	(0.021)	(0.029)	(0.025)	(0.034)	(0.034)	(0.048)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.468***	0.076**	0.519***	0.101***	0.284***	0.053
	(0.022)	(0.030)	(0.025)	(0.034)	(0.043)	(0.057)
Classification at SBS (12 months after app.)	0.853***	-0.006	1.000***	-0.002	0.321***	0.114*
	(0.016)	(0.022)	(0.000)	(0.002)	(0.045)	(0.059)
Loan from implementing institution	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Number of observations	1112		840		272	

Source: Authors' own calculations

Note: The sample includes all entrepreneurs accepted under the traditional method who did not take a loan from the implementing institution. § Difference between entrepreneurs rejected and accepted based on their EFL score (from the EFL Africa model v2). Ordinary least squares estimates. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

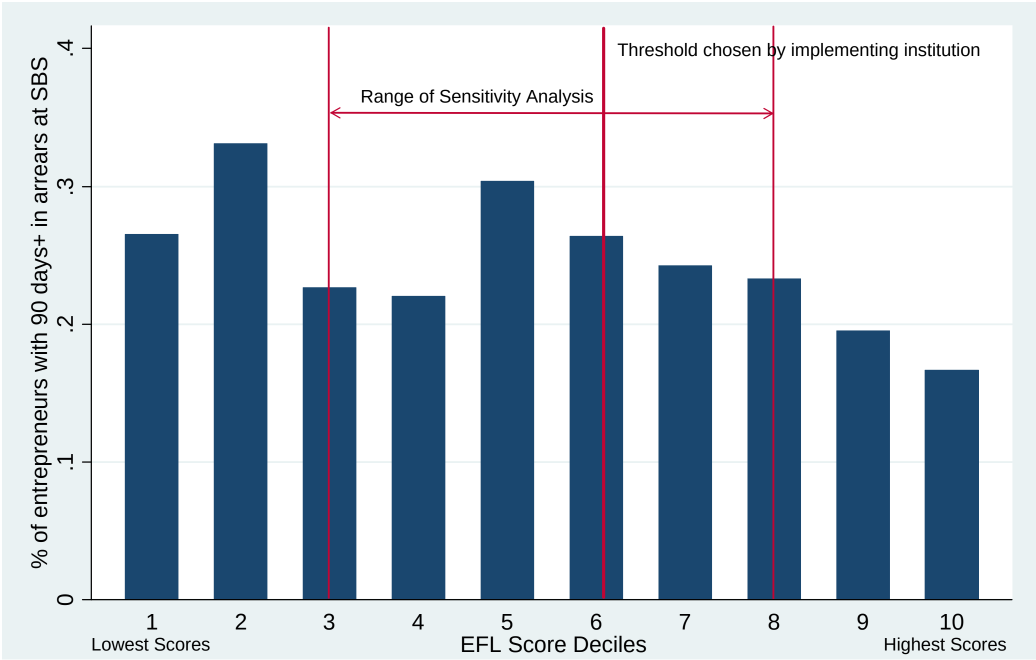
Table A5. Using original EFL scores to test hypothesis 2: Credit to new borrowers (reduced sample)

	Banked + Unbanked		Banked		Unbanked	
	TM Accepted	Diff §	TM Accepted	Diff §	TM Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)
Classification worse than "Normal" at SBS (12 months after app.)	0.279***	0.358***	0.283***	0.368***	0.245***	0.005
	(0.015)	(0.048)	(0.016)	(0.049)	(0.044)	(0.223)
More than 90 days in arrears at SBS (12 months after app.)	0.130***	0.207***	0.131***	0.222***	0.121***	-0.121***
	(0.012)	(0.052)	(0.012)	(0.054)	(0.035)	(0.035)
More than 90 days in arrears at SBS (during next 12 months following app.)	0.182***	0.284***	0.185***	0.306***	0.160***	-0.160***
	(0.013)	(0.048)	(0.013)	(0.050)	(0.036)	(0.036)
Number of days in arrears (6 months after app.)	16.233***	58.277***	16.227***	59.666***	16.283***	32.517
	(1.317)	(12.005)	(1.400)	(12.496)	(3.898)	(35.616)
Number of days in arrears (12 months after app.)	28.559***	72.708***	28.840***	76.590***	26.485***	-14.735
	(2.197)	(16.390)	(2.347)	(17.022)	(6.277)	(12.040)
Increase in debt at SBS (1 month after test wrt 1 month before app.)	0.369***	-0.007	0.423***	-0.068	0.202***	0.242
	(0.014)	(0.046)	(0.017)	(0.049)	(0.024)	(0.168)
Increase in debt at SBS (6 month after test wrt 1 month before app.)	0.510***	-0.098**	0.573***	-0.164***	0.316***	0.128
	(0.015)	(0.048)	(0.017)	(0.050)	(0.028)	(0.169)
Classification at SBS (12 months after app.)	0.850***	0.125***	0.999***	0.001	0.390***	0.277*
	(0.011)	(0.018)	(0.001)	(0.001)	(0.030)	(0.160)
Loan from implementing institution	0.000	0.000	0.000	0.000	0.000	0.000
	(.)	(.)	(.)	(.)	(.)	(.)
Number of observations	1231		950		281	

Source: Authors' own calculations

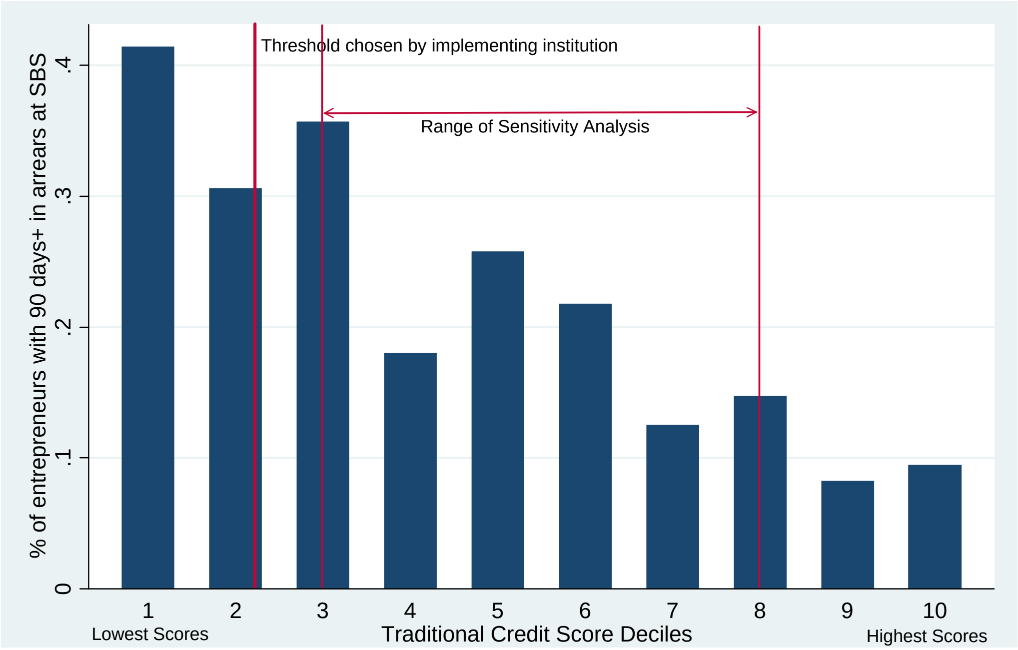
Note: § Difference between entrepreneurs that would have been rejected under the traditional model and accepted based on their updated EFL score and entrepreneurs accepted under the traditional model (only for entrepreneurs who did not take a loan from the implementing institution). Ordinary least squares estimates. Robust standard errors in parenthesis: * p<0.1, ** p<0.05, ***p<0.01.

Figure A1. Percentage of Entrepreneurs with more than 90 days in Arrears at the SBS during the 12 months following the EFL application by EFL Score Decile



Source: Authors' own calculations

Figure A2. Percentage of Entrepreneurs with more than 90 days in Arrears at the SBS during the 12 months following the EFL application by Traditional Credit Score Decile



Source: Authors' own calculations