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Psychometrics as a Tool to Improve Screening and Access to Credit[1]

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October 20, 2015

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 debt accrual and repayment behavior patterns across entrepreneurs who were offered a loan based on the traditional credit-scoring method versus 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.

JEL Classification: D82, G21, G32
Keywords: Asymmetric information, psychometric tests, credit risk, access to credit.

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1. Introduction

Given the important role that small and medium enterprises (SMEs) play 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, Demirgüç-Kunt, and Maksimovic, 2008; Cavallo et al., 2010; Ibarraran, Maffioli, and Stucchi, 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, and as a result, financial institutions have difficulties assessing the risk of loaning to them (de la Torre, Martínez Pería, and Schmukler 2009).

This paper studies a novel intervention that aims to enhance the amount and type of information on SMEs useful to potential lenders. A large body of 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, not all countries have credit bureaus, because of coordination problems between lenders; and where bureaus exist, the information they provide may be limited, for legal and institutional reasons. Meanwhile, loan applicants with bureau-supplied information are often 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.

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. This study looks at the effectiveness of this tool in reducing the risk of loaning to SMEs, as well as in expanding

[5] Numerous studies have documented the important role played by small and medium enterprises (SMEs) in the process of industrialization and economic development (Liedholm, 2002; Beck, Demirguc-Kunt, and Levine, 2005; Beck and Demirguc-Kunt, 2006; Ayyagari, Beck, and Demirguc-Kunt, 2007; Nichter and Goldmark, 2009; Liedholm and Mead, 2013). In many countries, such firms employ the majority of the workforce (Ayyagari et al., 2007; Haltiwanger and Krizan, 1999; Hijzen, 2010; Ibsen and Westergaard-Nielsen, 2011; Haltiwanger, Jarwin, and Miranda, 2013). In Latin America, 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.

access to credit for small firms, in the context of a pilot exercise conducted in Peru. The financial institution participating in the trial, the fifth-largest commercial bank in Peru, piloted the EFL tool starting in March 2012, with the goal of expanding its 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 bank were offered a loan.

Peru has several private credit bureaus that, together, cover 100 percent of the adult population. Thus, all applicants for bank loans have a credit score. But for individuals who have not previously taken out a loan from a formal financial institution, this score is based primarily on demographic information rather than actual credit history. For the purposes of this study, these individuals are referred to as "unbanked." Applicants with credit scores in an acceptable range (as defined by the implementing institution) were offered a loan even if their EFL score was below the threshold.

This setup allowed the researchers to test two possible uses of the EFL tool: (i) as a secondary screening mechanism for entrepreneurs accepted under the traditional credit-scoring method,[6] 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 tested whether the EFL tool could increase access to credit for unbanked borrowers whose traditional credit score might not provide sufficient information to banks.

We used monthly data on formal credit usage and repayment behavior patterns, as 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 portfolio risk for "banked" entrepreneurs (i.e., those who have taken out loans from a formal financial institution) when it is used to complement traditional credit scores. Banked applicants accepted under the traditional credit-scoring method but rejected based on their EFL score are 8.6 percentage points more likely to have been in arrears for more than 90 days during the 12 months after being screened by the EFL

[6] We use "traditional screening process," "traditional method," "traditional model," and "traditional credit-scoring method" interchangeably to refer to the conventional screening process used by the bank to evaluate credit risk based on the traditional credit score.

tool, compared to 14.5 percent of entrepreneurs who are accepted using both methods. We did 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 found that the EFL tool can be used to extend credit to some unbanked entrepreneurs who were rejected based on their traditional credit scores, 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 unbanked entrepreneurs' access to credit, we compared the credit use of loan applicants with an EFL score just below and above the threshold set by the implementing institution. We found evidence that those above the threshold are more likely to receive loans (most often from the implementing institution) than those below the threshold.

Our paper contributes to studies of the relationship between individual characteristics (i.e., 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 found that entrepreneurs' business profits and repayment behavior patterns are strongly correlated with their individual personality traits. Similarly, Klinger, Khwaja, and LaMonte (2013) and Klinger et al. (2013) studied the repayment behavior of entrepreneurs in Peru and Argentina, respectively, and compared these with patterns in other countries in which they applied the same psychometric tool. Their results show that despite differences in the distribution of personality traits, the dimensions that are related to business performance and credit risk are common across countries (Klinger et al., 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 with a traditional credit-scoring method. Our paper is the first external study examining the predictive power of psychometric credit scoring; that is, it uses independently collected data on repayment behavior patterns and is not coauthored 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 participating 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—limited access to reliable information needed to assess their growth potential and risk profiles, and difficulties gathering that information at a low cost—banks in the United States have shifted their focus away from business operations and toward 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, 2007; Berger and Udell, 2006).[7]

In the United States, the wide adoption of credit scoring has led to an increase in the credit extended to SMEs; an increase in lending to relatively opaque, risky businesses; an increase in lending to low-income areas, and to areas outside the banks' local markets; and an increase in loan maturities (Berger, Frame, and Miller, 2005). Not all countries, however, have well-developed credit bureaus that gather the level of information on SMEs and consumers needed to build a reliable credit-scoring model. The average credit bureau in Latin America and the Caribbean complies with only half of best practices, as defined by the World Bank in its Doing Business Report, and covers only 39.3 percent of the adult population (Doing Business Report 2014). Credit bureau coverage is even lower in many other world regions (with the notable exception of the high-income countries in the Organisation for Economic Co-operation and Development, OECD).

Thus, even though credit scoring represents a potential solution to the problem of improving SMEs' access to credit, it can take many years to pass legislation that will lead to improvements in the quality and depth of information recorded by credit bureaus as well as in the

[7] 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 et al., 2005).

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 credit 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 by employers in the selection of personnel, and the results show 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). This is especially true when the applicant is matched with the competencies required to do the job. These tests, in combination, are better able to predict overall job performance than a review of the candidate's job experience, level of education, employment interview results, peer ratings, and reference checks (Schmidt and Hunter, 1998).

Using psychometric tests to screen out SME owners whose repayment behavior may increase the lender's risk, however, is a departure from the typical uses of such tests. Operating on the assumption that there is a trait or set of traits that characterize low- versus high-risk loan applicants, the psychometrician's task is to identify those 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 developed a psychometric credit-scoring tool by first quantifying the individual 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 characteristics were put in three categories: personality, intelligence, and integrity (Klinger, Khwaja, and del Carpio, 2013). EFL researchers initially 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).

The EFL 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. 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.[8]

After identifying questions that could potentially predict credit risk and trying out a first prototype of their tool, the EFL researchers 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 traditional credit scores. It contains psychometric questions developed internally and licensed by third parties relating to individual 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 the 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 to SMEs. Entrepreneurs 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.[9] The EFL credit application used at this time took 45 minutes to complete, on average (the current version takes 25 minutes). To be approved for a loan, the entrepreneur either had to score above the threshold (defined by the institution) on the EFL credit application *or* had to be approved under the institution's conventional screening method based on traditional credit scores.[10] Only entrepreneurs who were rejected under both screening methods were not offered a loan (Table 1).

[8] 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, McLiesh, and Shleifer, 2007; Zhao and Seibert, 2006). To date, the only evidence on integrity and willingness to repay loans comes from EFL itself (Klinger, Khwaja, and del Carpio, 2013). 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).

[9] The implementing institution is the fifth-largest commercial bank in Peru in terms of its assets, the balance of its loan portfolio, and total deposits taken (Superintendencia de Banca, Seguros y AFP, Balance Sheets at December 2014). In 2013, the International Finance Corporation (IFC) acquired 12.67 percent of the institution's shares.

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

All applicants had a credit score from one of Peru's private credit bureaus, which the implementing institution uses in their conventional 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 Table 1, not all entrepreneurs who were offered a loan from the implementing institution accepted. Some applicants secured loans with other financial institutions. For example, our data suggest that 51.6 percent of unbanked entrepreneurs who were approved got a loan from a formal institution (including the participating institution), but only 23.6 percent got a loan from the implementing institution. According to the personnel of the bank in question, some unbanked entrepreneurs used approval letters provided by the institution to secure other loans that were disbursed faster or had different conditions.

Table 1. Credit Decisions Based on the EFL Score and Traditional Credit Score

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">Traditional credit-scoring method (TM) decision</td></tr>
<tr><td>Accept</td><td>Reject</td></tr>
<tr><td rowspan="2">EFL decision</td><td>Accept</td><td>(1) Accepted
659 entrepreneurs
(20.6% unbanked)
(23.5% got loan from the implementing institution)</td><td>(2) Accepted
158 entrepreneurs
(10.1% unbanked)
(24.7% got loan from the implementing institution)</td></tr>
<tr><td>Reject</td><td>(3) Accepted
860 entrepreneurs
(25.1% unbanked)
(29.3% got loan from the implementing institution)</td><td>(4) Rejected
209 entrepreneurs
(7.2% unbanked)
(0% got loan from the implementing institution)</td></tr>
</table>

Source: Authors' own compilation.

2.3 Hypotheses

We considered two ways that banks can apply the EFL tool in their credit-risk management and lending decisions. We tested two corresponding hypotheses by comparing the repayment behavior of the different groups listed in Table 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 patterns than entrepreneurs who were accepted under both methods.[11] Looking at Table 1, this hypothesis implies that entrepreneurs in quadrant 3 have worse repayment patterns than entrepreneurs in quadrant 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.[12] In terms of Table 1, this hypothesis implies that entrepreneurs in quadrant 2 have no worse repayment patterns than do entrepreneurs in quadrants 1 and 3. If this hypothesis is true, banks can rely on the EFL tool to help them extend credit to applicants they would otherwise have rejected, without increasing the risk of their SME portfolio.

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

To what extent can using the EFL tool provide access to loans for unbanked entrepreneurs without a credit history? To address this question, we tested a third hypothesis.

Hypothesis 3: Banking the unbanked. Unbanked entrepreneurs who were accepted based on their EFL score were more likely to get a loan than unbanked entrepreneurs who were rejected based on their EFL score. Looking back at Table 1, this hypothesis implies that unbanked clients in quadrants 1 and 2 are more likely to be offered a loan after being screened by the EFL tool than unbanked clients in quadrants 3 and 4. Since clients in these two groups are likely to have very different characteristics, we also restrict the sample here to the unbanked

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[11] To test this hypothesis for banked entrepreneurs we can use 1,167 observations, which allows us to detect a difference of 5.3 percentage points between groups; for unbanked entrepreneurs we can only use 352 observations, which allow us to detect a difference of 13.7 percentage points between groups. In both cases the calculations were conducted at an 80 percent power and a 95 percent confidence level for the binary indicators with the incidence closest to 50 percent.

[12] To test this hypothesis for banked entrepreneurs we can use 1,309 observations, which allows us to detect a difference of 8.8 percentage points between groups; for unbanked entrepreneurs we can only use 368 observations, which allows us to detect a difference of 29.5 percentage points between groups. In both cases the calculations were conducted at an 80 percent power and 95 percent confidence level for the binary indicator with the incidence closest to 50 percent.

entrepreneurs who scored near the EFL threshold defined by the implementing institution, so as to compare clients with similar characteristics.

3. Data, Descriptive Statistics, and Methodology

3.1 Data Sources

We obtained data collected by an EFL questionnaire that the implementing bank administered to 1,993 loan applicants 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 the applicant's age, gender, marital status, business sales, and sector of activity.[13]

The EFL scores used for the pilot were initially generated by a model built with data pooled across various African countries where EFL had tested its credit-scoring model (EFL Africa model v2).[14] Once the current implementing bank generated enough observations, 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.

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

[13] The questionnaire administered by EFL also gathered data on entrepreneurs' years of education, number of dependents, family history of entrepreneurship, and psychological profile, as well as the age of their business, number of businesses started, business assets, etc. Because this information is used to calculate the score, EFL restricted our access to it.

[14] Using pooled data has the advantage of improving predictive power because the samples involved are larger, 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. (2013) find that traits explaining loan defaults 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 overfitting issues. EFL therefore uses an adaptive model—a Bayesian hierarchical logit model—which assumes that the behavior of covariates varies 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 the data available for a particular country and segment (tailored model); the more data are 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 obtained 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 the maximum number of days in arrears (across all financial institutions), total debt, and classifies debtors in one of five status categories: normal, with potential payment problems, poor payment, doubtful payment, and loss.[15] Only banked entrepreneurs appear in the public credit registry data. About 76 percent of the entrepreneurs in our sample were banked at the time they were screened by the EFL tool.

Table 2. 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 calculations.
Note: The table displays averages of the variables in each group.

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

Table 2 lists descriptive statistics for the four possible scenarios described in Table 1, separating banked and unbanked entrepreneurs.

3.2 Repayment Behavior and Access to Credit Indicators

To assess loan repayment behavior, we used the status of the entrepreneur at various intervals in the public credit registry managed by the SBS.[16]

We defined several variables to assess entrepreneurs' repayment behavior: a binary variable equal to one if, 12 months after being screened by the EFL tool, their classification was poorer than "normal," and zero if their classification was "normal"; and 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 zero if it was less than 90 days during the same period. We also used the total number of days in arrears 6 and 12 months after applicants were screened by the EFL tool.

We examined the use of credit as well. The SBS data do not specify which financial institution has issued entrepreneurs a loan—they only report the total amount of debt each month. We thus used 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 used a binary variable equal to one if the person had any classification in the SBS's credit bureau 12 months after being screened by the EFL tool, and zero if the person does not have any classification (i.e., does not have credit from a formal financial institution subject to credit risk).

Table A2 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.

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[16] The public credit bureau managed by the SBS receives the classification given to the entrepreneurs by the various financial institutions with which they maintain 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.

3.3 Methodology

We estimate linear regression models of the following form:

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

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 his or her EFL score and accepted under the traditional screening method, and equal to zero if the entrepreneur was accepted based on both his or her EFL score and the traditional screening method; ε_i is the regression error term. S is the sample of interest; it varies according to the hypothesis we are testing.

The estimates reported in Tables 3–7 correspond to α and β for the specification above. Table A3 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 A3 also lists 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 3 lists our results from testing hypothesis 1: Entrepreneurs who were accepted under the traditional method but rejected based on their EFL score displayed worse loan repayment behavior than entrepreneurs who were accepted under both methods. The sample in Table 3 includes only entrepreneurs who were accepted under the traditional method. Each pair of columns presents regressions of our outcome variables on a dummy variable equal to one if the entrepreneur was rejected based on an 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).

The evidence in Table 3 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). Banked entrepreneurs accepted under the traditional screening method but rejected based on their EFL score exhibit significantly worse repayment behavior patterns across 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 percent of entrepreneurs accepted under both methods.

Table 3. 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	

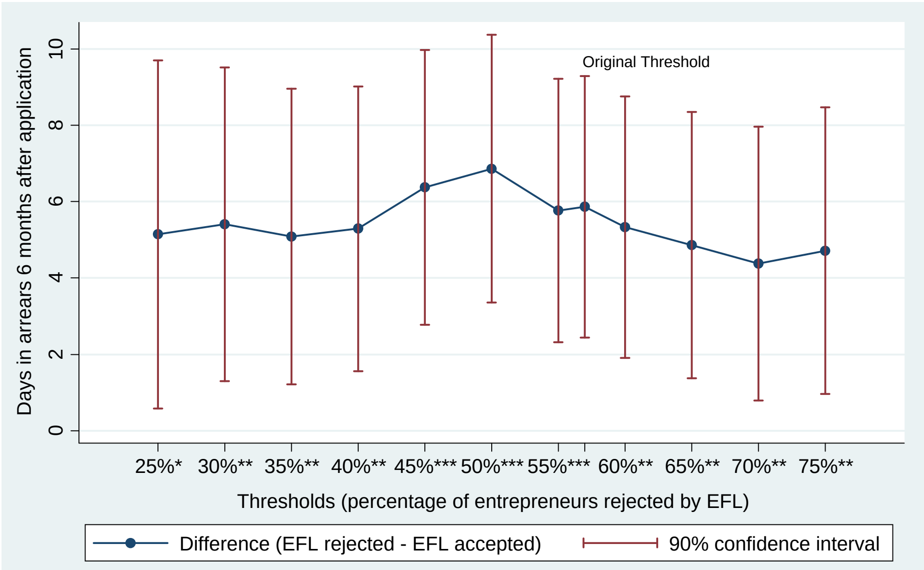
Source: Authors' own calculations.
Note: The sample includes all entrepreneurs accepted under the traditional method.
§ Difference between entrepreneurs rejected and accepted based on their EFL score. Ordinary least squares estimates. Outcome variables are for loans from all formal financial institutions,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

We did not observe that the EFL tool had the ability to screen out higher-risk borrowers for *unbanked* entrepreneurs approved under the traditional method (column 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 the use of credit, we found that a larger proportion of entrepreneurs who were rejected based on their EFL score increased their debt one and six months after they were screened by the EFL tool compared with entrepreneurs who were accepted based on their EFL score. EFL-rejected entrepreneurs were 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 with a high 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 be more likely to turn down unfavorable loan offers.

Since the results in Table 3 depend on the arbitrary threshold levels chosen by the implementing institution to accept/reject clients, we ran a sensitivity analysis moving the threshold levels between the 25th and 75th percentile (rejecting from 25 percent up to 75 percent of screened entrepreneurs, respectively). We used the whole sample of banked and unbanked entrepreneurs to carry out these sensitivity exercises. Figures A1 and A2 in the Appendix illustrate the distribution of each score and the range used for the sensitivity analysis.

Figure 1. Sensitivity Analysis for Testing Hypothesis 1: Risk Reduction—Moving the EFL Score Threshold

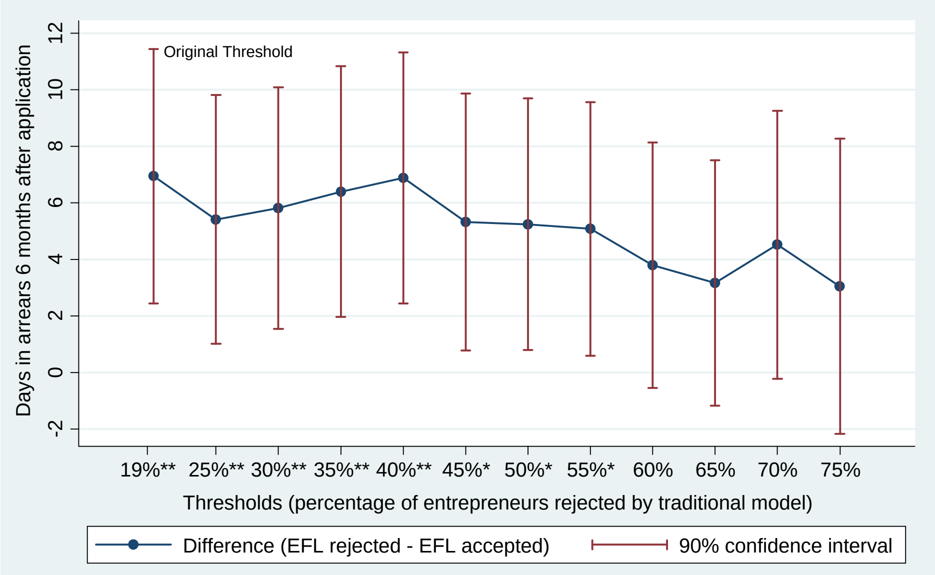


Source: Authors' own calculations.
Note: The figure includes only entrepreneurs who were accepted under the traditional screening method. It illustrates the difference in the number of days in arrears between entrepreneurs rejected based on an EFL score and accepted under the traditional model versus entrepreneurs accepted under both methods.
***, **, * indicate that the difference is statistically significant at the 1%, 5%, and 10% level, respectively.

Figure 1 illustrates 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 who were 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 2, 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 2 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 2. Sensitivity Analysis for Testing Hypothesis 1: Risk Reduction—Moving the Traditional Credit Score Threshold



Source: Authors' own calculations.

Note: The figure includes only entrepreneurs who were accepted under the traditional screening method. It illustrates the difference in the number of days in arrears between entrepreneurs rejected based on an EFL score and accepted under the traditional model versus entrepreneurs accepted under both methods.

***, **, * indicate that the difference is statistically significant at the 1%, 5%, and 10% level, respectively.

4.2 Testing Hypothesis 2: Credit to New Borrowers

Table 4 presents the results of testing hypothesis 2: Entrepreneurs who were rejected under the traditional model but accepted based on their EFL score did not display worse loan repayment behavior than entrepreneurs who were accepted under the traditional model. Each pair 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 the 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 (the difference between entrepreneurs rejected under the traditional model and accepted based on their EFL score and entrepreneurs accepted under the traditional model).

Table 4. 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	

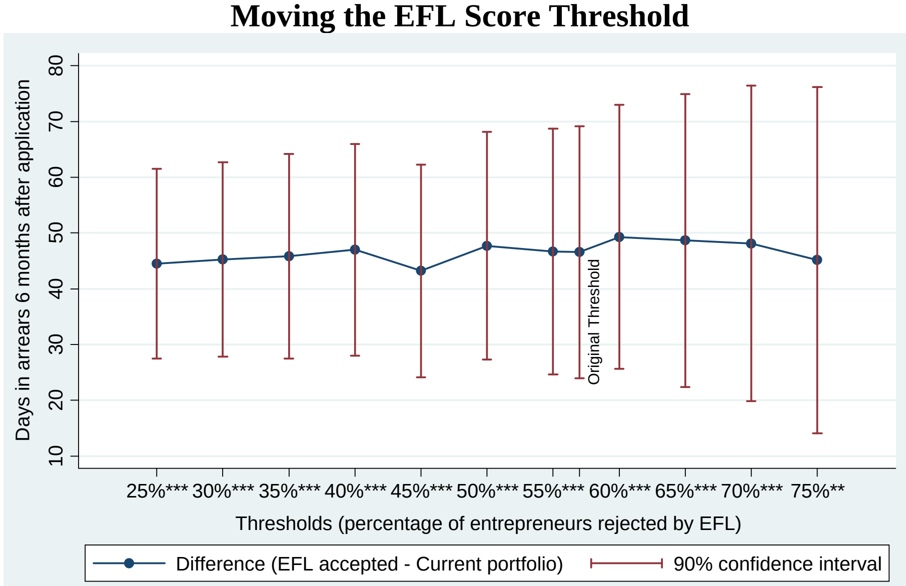
Source: Authors' own calculations.

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 parentheses: * p<0.1, ** p<0.05, ***p<0.01.

Table 4 shows evidence against hypothesis 2 (column 2). In fact, entrepreneurs rejected under the traditional model and accepted based on their EFL score exhibited 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, for banked entrepreneurs, incorporates valuable information about their past repayment behavior—is a powerful tool to screen out high-risk applicants (column 4).

The differences in the loan repayment behavior patterns of 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 (whose credit scores are generally more informative than those of unbanked applicants).

Figure 3. Sensitivity Analysis for Testing Hypothesis 2: Credit to New Borrowers—Moving the EFL Score Threshold



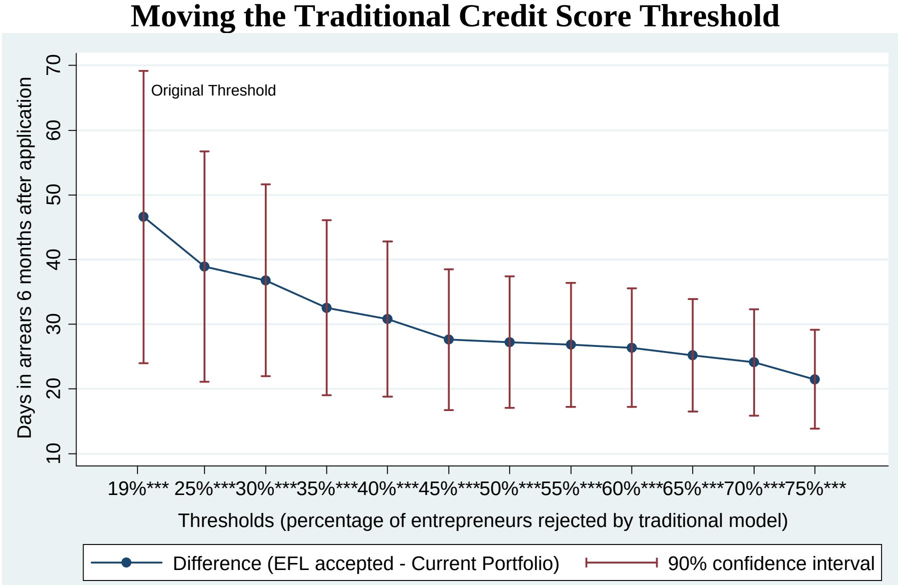
Source: Authors' own calculations.
Note: The figure illustrates the difference in the number of days in arrears between entrepreneurs rejected under the traditional model but accepted based on their EFL score versus entrepreneurs accepted by the traditional model.
***, **, * indicate that the difference is statistically significant at the 1%, 5%, and 10% level, respectively.

We also found that a larger proportion of unbanked entrepreneurs who were rejected based on their traditional credit score and accepted based on their EFL score took out loans—an increase of 24.4 percentage points over entrepreneurs whose traditional credit scores were deemed acceptable. 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).

We now examine how robust these results are in light of changes to the acceptance/rejection thresholds. Figure 3 shows that increasing the EFL score threshold does not noticeably improve the loan repayment behavior of entrepreneurs who were rejected under the traditional method and accepted based on their EFL score—compared with 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 their past repayment behavior (banked entrepreneurs).

Figure 4 illustrates 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 the EFL screening process becomes smaller as the traditional credit score threshold increases. However, it is still positive and statistically significant.

Figure 4. Sensitivity Analysis for Testing Hypothesis 2: Credit to New Borrowers—Moving the Traditional Credit Score Threshold



Source: Authors' own calculations.
Note: The figure illustrates the difference in the number of days in arrears between entrepreneurs rejected under the traditional model but accepted based on their EFL score versus entrepreneurs accepted by the traditional model.
***, **, * indicate that the difference is statistically significant at the 1%, 5%, and 10% level, respectively.

4.3 Testing Hypothesis 3: Banking the Unbanked

Table 5 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 pair of columns presents regressions of the outcome variables on a dummy variable equal to one if the unbanked entrepreneur was rejected based on the EFL score, and equal to zero if the unbanked entrepreneur was accepted based on the EFL score. For each exercise in Table 5 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 the EFL score and accepted based on the EFL score).

Table 5. Testing Hypothesis 3: Banking the Unbanked

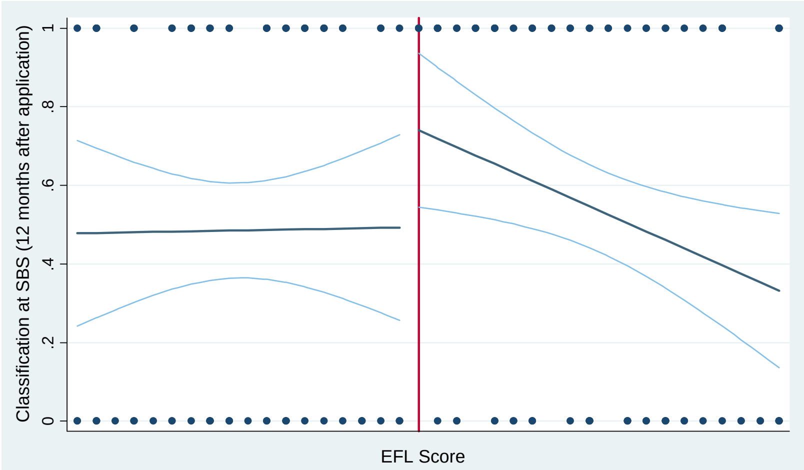
	Unbanked controlling for EFL score (linear)		Unbanked controlling for EFL score (cubic)		Unbanked around threshold c. EFL Score (L)		Unbanked around threshold c. EFL Score (L)	
	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §	EFL Accepted	Diff §
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Classification 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 parentheses: * p<0.1, ** p<0.05, ***p<0.01.

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

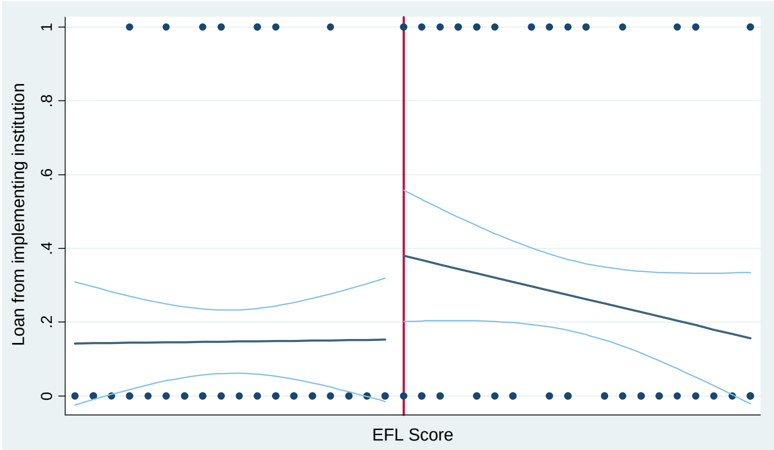
controlling for the EFL score; and columns 7 and 8 contain the estimates for the sample of unbanked entrepreneurs around the threshold chosen by the implementing institution—a 5 percent bandwidth around the threshold—controlling for the EFL score.

Figure 5. 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 percent confidence intervals.

Figure 6. 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 percent confidence intervals.

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 from the implementing institution, than unbanked entrepreneurs rejected by EFL. Table 5 lists 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 or any other financial institution.[17]

Figures 5 and 6 illustrate 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 3: 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 under unfavorable conditions (and thus a lower credit risk).

5. Updating EFL Scores

In this section we review the data using the updated EFL scores and threshold level (from the EFL Global model v1). After updating the scores, 49 percent 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 percent 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.[18]

We limited 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 in relation to loans from the implementing institution. All of our outcome variables in this section are thus based on loans from other financial institutions.[19] For comparison, Tables A4 and A5 in the Appendix replicate our previous results when using the old, EFL Africa model v2 (from Tables 3 and 4) but limiting the sample to entrepreneurs who did not take a loan from the implementing institution.

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[17] The results in Table A4 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.

[18] The rejection rate for the old model is 53.2 percent, while the rejection rate for the new model is 41.4 percent.

[19] 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.

Table 6. 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 parentheses: * p<0.1, ** p<0.05, ***p<0.01.

Table 7. 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 parentheses: * p<0.1, ** p<0.05, ***p<0.01.

Table 6 displays the results of 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 the EFL screening than those who would have been accepted using the new EFL score. The difference between these same groups was only 5.2 percentage points when using the old EFL score (as shown in Table A5). Similar improvements are present throughout our indicators of repayment behavior.

Table 7 lists 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 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.

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 the credit risk posed by loan recipients, traits that make it possible to select loan applicants (in this case, 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 found that the EFL's tool 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 as a secondary screening mechanism to reduce the portfolio risk. But for banked entrepreneurs with negative credit histories who have been rejected using the traditional credit-scoring method, the EFL tool has limited power to rescue potential low-risk applicants and can even lead to an increase in the portfolio risk. These results are robust in light of variations in the threshold chosen to distinguish between accepted and rejected loan applicants. That is, with respect to portfolio risk, the EFL tool does not successfully replace credit history information, but it does well at complementing this information.

For unbanked entrepreneurs—i.e., those with no formal 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 found evidence that the EFL tool increases unbanked entrepreneurs' access to credit.

Our findings clearly show the importance of information in assessing credit risk, making accurate credit decisions, and expanding credit supply. They highlight the power of traditional screening methods, based mainly on applicants' 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, including data from retailers and utility companies in addition to banks and financial institutions, and allowing 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 credit-scoring models and increase credit markets' confidence in their credit scores, even for entrepreneurs who have not previously borrowed from 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. Variable Definitions

Variables	Description
EFL score (old model)	Score generated using the EFL Africa model v2 (data pooled across various African countries)
EFL score (new model)	Score generated using the EFL Global model v1 (first to incorporate non-African data)
Sales	Value of sales reported by the entrepreneurs at the time of the application
Debt-to-sales ratio	Debt-to-sales ratio estimated using data reported by the entrepreneur and data from the SBS
Age	Age of the entrepreneur at the time of the application
Female	Dummy that equals 1 if entrepreneur is female
Marital status	As reported by the entrepreneurs at the time of the application
Divorced	Dummy that equals 1 if applicant is divorced
Living with partner	Dummy that equals 1 if applicant is living with a partner
Married	Dummy that equals 1 if applicant is married
Separated	Dummy that equals 1 if applicant is separated
Single	Dummy that equals 1 if applicant is single
Widowed	Dummy that equals 1 if applicant is widowed
Business sector	As reported by the entrepreneurs at the time of the application
Agriculture	Dummy that equals 1 if applicant operates in the sector “agriculture”
Commerce	Dummy that equals 1 if applicant operates in the sector “commerce”
Other services	Dummy that equals 1 if applicant operates in the sector “other services”
Manufacturing	Dummy that equals 1 if applicant operates in the sector “manufacturing”
Classified as “normal” at the SBS	Dummy that equals 1 if applicant was classified as “normal” (less than 9 days in arrears) at the SBS, 1 month before being screened by the EFL tool
Classification worse than “normal” at SBS (12 months after EFL application)	Dummy that equals 1 if applicant was classified worse than “normal” (9 or more days in arrears) at the SBS, 12 months after being screened by the EFL tool; and 0 otherwise
More than 90 days in arrears at SBS (12 months after EFL application)	Dummy that equals 1 if number of days in arrears exceeds 90 days, 12 months after being screened by the EFL tool
More than 90 days in arrears at SBS (during next 12 months following app.)	Dummy that equals 1 if number of days in arrears exceeds 90 days, at any time during the 12 months following the screening by the EFL tool
Number of days in arrears (6 months after app.)	Total number of days in arrears 6 months after being screened by the EFL tool
Number of days in arrears (12 months after app.)	Total number of days in arrears 12 months after being screened by the EFL tool
Increase in debt at SBS (1 month after test wrt 1 month before app.)	Dummy that equals 1 if an increase in the total amount of debt was detected 1 month after being screened by the EFL tool (compared to 1 month before the screening)
Increase in debt at SBS (6 months after test wrt 1 month before app.)	Dummy that equals 1 if an increase in the total amount of debt was detected 6 months after being screened by the EFL tool (compared to 1 month before the screening)
Classification at SBS (12 months after app.)	Dummy that equals 1 if applicant has any classification at the SBS 12 months after being screened by the EFL tool
Loan from implementing institution	Dummy that equals 1 if applicant received a loan from the implementing institution

Table A2. 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 parentheses: * p<0.1, ** p<0.05, *** p<0.01.

Table A3. 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 parentheses: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. 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 A4. 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	

Source: Authors' own calculations.

Table A5. 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 parentheses: * p<0.1, ** p<0.05, *** p<0.01.

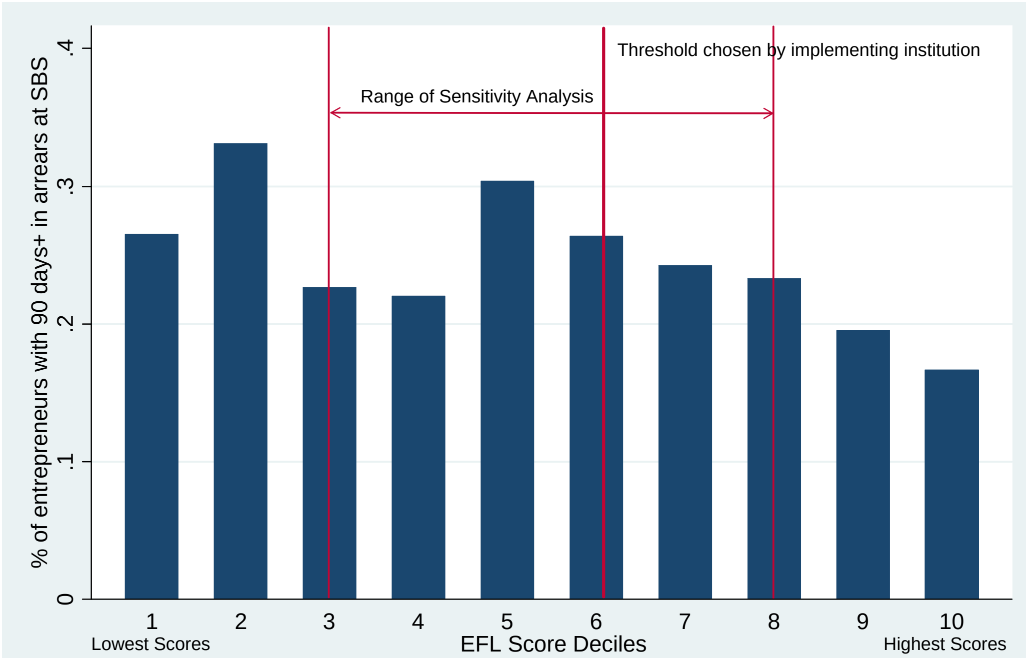
Table A6. Using Original EFL Scores to Test Hypothesis 2: Credit to New Borrowers (Reduced Sample)

	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.

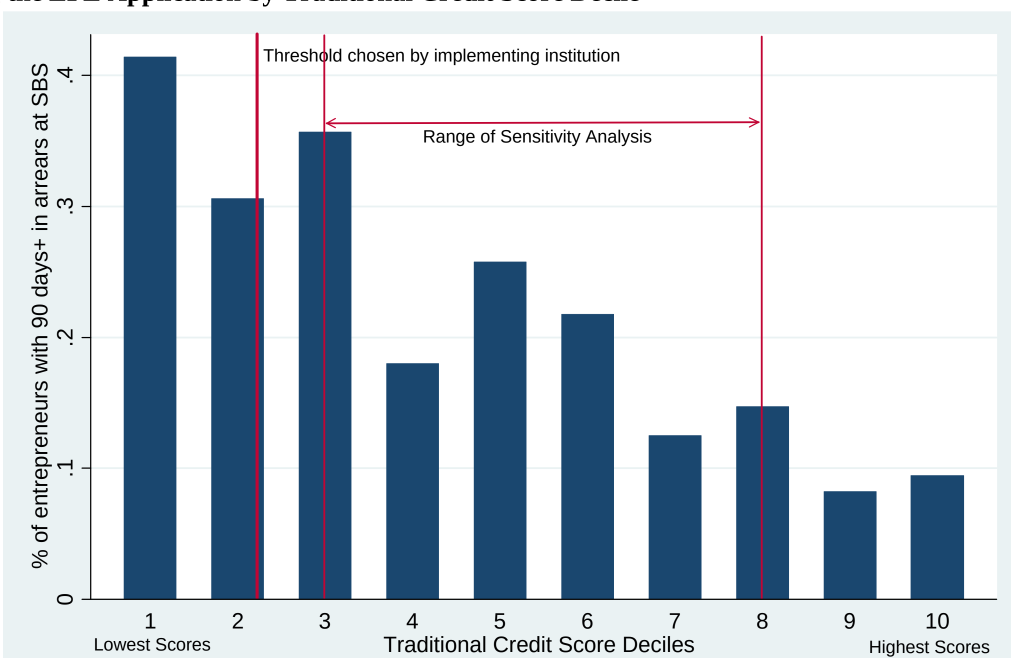
Note: § Difference between entrepreneurs that would have been rejected under the traditional model and accepted based on their updated EFL score and entrepreneurs accepted under the traditional model (only for entrepreneurs who did not take a loan from the implementing institution). Ordinary least squares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