Psychometrics as a Tool to Improve Credit Information

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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 compare 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—that is, those with a credit history. The EFL tool can also allow lenders to offer credit to some unbanked entrepreneurs—that is, those without a credit history—who were rejected based on their traditional credit scores, without increasing the risk of the portfolio. JEL Classification: D82, G21, G32

I. 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.[1] These studies show that SMEs face greater financial constraints than large firms and that these constraints could be one of the factors that limit their growth (Beck, Demirgüç-Kunt, and Maksimovic 2008; Cavallo, Galindo, and Izquierdo 2010; Ibarraran, Maffioli, and Stucchi 2010; Mateev, Poutziouris, and Ivanov 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 lending to them (de la Torre, Pería, and Schmukler 2009).

This paper studies a novel intervention that aims to enhance the information on SMEs useful to potential lenders. A large body of literature has examined the role of information sharing, credit bureaus, and credit scoring in increasing credit to SMEs (see, for example, Berger, Frame, and Miller 2005; Brown, Jappelli, and Pagano 2009; Love and Mylenko 2003; Martinez Peria and Singh 2014). Not all countries, however, have well-developed credit bureaus that gather the level of information needed to build a reliable credit-scoring model. For example, the average credit bureau in Latin America and the Caribbean complies with only half of best practices and covers only 39.3 percent of the adult population (Doing Business Report 2014).

Thus, even though credit scoring can potentially improve 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. 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.

The Entrepreneurial Finance Lab (EFL) has developed an alternative credit information tool that can potentially be used by lenders to better screen loan applicants. This tool uses a psychometric application to predict entrepreneurs' repayment patterns. This study looks at the effectiveness of this tool in reducing the risk of lending to SMEs in the context of a pilot exercise conducted in Peru. The financial institution participating in the study, the fifth-largest commercial bank in Peru, piloted the EFL tool, 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 loan applicants have a traditional 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 traditional 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, 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 used data on formal credit repayment behavior patterns, as collected by the Superintendencia de Banca y Seguros (SBS) in Peru.

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. 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.

Related studies by EFL researchers have shown that entrepreneurs' business profits and repayment behavior patterns are strongly correlated with their personality traits (Klinger, Khwaja, and del Carpio 2013; Klinger, Khwaja, and LaMonte 2013; and 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 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.

II. Background and Analytical Framework

Innovative Screening Methods: The EFL Tool

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). 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.[2]

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 contains psychometric questions developed

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2. Several papers have documented links between personality or intelligence tests and entrepreneurship or business performance (Ciavarella et al. 2004; De Mel, McKemzie and Woodruff 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).

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

		Traditional screening method (TM) decision	
		Accept	Reject
EFL decision	Accept	(1) Accepted 659 entrepreneurs (20.6% unbanked)	(2) Accepted 158 entrepreneurs (10.1% unbanked)
	Reject	(3) Accepted 860 entrepreneurs (25.1% unbanked)	(4) Rejected 209 entrepreneurs (7.2% unbanked)

internally and licensed by third parties relating to individual attitudes, beliefs, integrity, and performance.

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. The EFL credit application used at this time took about 45 minutes to complete (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 application *or* had to be approved under the institution's traditional screening method. Only entrepreneurs who were rejected under both screening methods were not offered a loan (table 1).

Hypotheses

We considered two ways that banks can apply the EFL tool in their credit-risk management and lending decisions and tested two corresponding hypotheses by comparing the repayment patterns 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 poorer loan repayment behavior patterns than entrepreneurs who were accepted under both methods. Looking at table 1, this hypothesis implies that entrepreneurs in quadrant 3 have poorer 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 poorer loan repayment behavior than entrepreneurs who were accepted under the traditional model. In terms of table 1, this hypothesis implies that entrepreneurs in quadrant 2 have no poorer 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 offer credit to applicants they would otherwise have rejected, without increasing the risk of their SME portfolio.

III. Data

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.[3] 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.

We also obtained credit history data from the public credit registry managed by the SBS. All financial institutions subject to credit risk have to provide 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.[4] 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.

To assess loan repayment behavior, we defined three binary variables based on the SBS data, as listed in tables 2 and 3 below. We also used the number of days in arrears 6 and 12 months after applicants were screened by the EFL tool.[5] All variables are described in more detail in appendix table A1. Appendix table A2 provides summary statistics.

IV. Empirical Results

We estimate linear regression models of the following form:

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

3. 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). 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). Appendix 2 shows that the results for testing hypothesis 1 are stronger when using the scores from the EFL Global model v1 than when using the scores from the EFL Africa model v2, but for testing hypothesis 2, both sets of scores give similar results.

4. Entrepreneurs 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.

5. Appendix table A3 shows the correlations between our repayment behavior indicators with the EFL and credit bureau scores. For both scores, a higher value is associated with better repayment behavior.

TABLE 2. Testing Hypothesis 1: Risk Reduction

	Banked + Unbanked		Banked		Unbanked	
	EFL Accepted (1)	Diff§ (2)	EFL Accepted (3)	Diff§ (4)	EFL Accepted (5)	Diff§ (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)
Number of observations	1519		1167		352	

Notes: 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: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Where y_i is a measure of loan repayment behavior, x_i is an indicator defined differently depending on the hypothesis we are testing (as described below), and ε_i is the regression error term. S is the sample of interest; it varies according to the hypothesis we are testing.[6] The estimates reported in tables 2 and 3 correspond to α and β for the specification above.[7]

6. Appendix table A4 reports specifications that control for characteristics of the entrepreneurs and that use Probit, along with Horrace and Oaxaca (2006) tests. The results are robust to using these alternative specifications.

7. Since the estimates 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 of each score. Appendix 3 presents this analysis. The results are overall similar to the ones in the main text.

TABLE 3. Testing Hypothesis 2: Credit to New Borrowers

	Banked + Unbanked		Banked		Unbanked	
	TM Accepted (1)	Diff[§] (2)	TM Accepted (3)	Diff[§] (4)	TM Accepted (5)	Diff[§] (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)
Number of observations	1677		1309		368	

Notes: [§]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: *$p < 0.1$, **$p < 0.05$, ***$p < 0.01$.

Testing Hypothesis 1: Risk Reduction

Table 2 lists our results from testing hypothesis 1: Entrepreneurs who were accepted under the traditional method but rejected based on their EFL score displayed poorer 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 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 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). Banked entrepreneurs accepted under the traditional screening method but rejected based on their EFL score exhibit much poorer 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.

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.

Testing Hypothesis 2: Credit to New Borrowers

Table 3 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 poorer 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 3 shows evidence against hypothesis 2 (column 2). In fact, entrepreneurs rejected under the traditional model and accepted based on their EFL score exhibited poorer 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.

V. CONCLUSIONS

In this paper we detail the use of a psychometric credit application, developed by EFL, to reduce information asymmetries and to better assess credit risk for small businesses. In the context of a pilot exercise conducted by the fifth-largest bank in Peru, we found that the EFL tool can add value to a traditional credit-scoring method in different ways for banked and unbanked entrepreneurs.

For banked entrepreneurs—that is, 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 and can even lead to an increase in the portfolio risk. 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—that is, 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.

Our findings clearly show the importance of information in assessing credit risk and making accurate credit decisions. 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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