From discouraged borrowers to measuring credit gaps: A methodology based on Enterprise Surveys*

Ozan E. Akbas† Frank Betz‡ Luca Gattini§

This draft: 12 January 2023

Abstract

We define the credit gap as the financing needs of firms that are bankable but discouraged from applying for a loan. A scoring model assesses the creditworthiness of discouraged firms. Credit is assigned based on a rule that models the trade-off between allocating credit to firms that are not creditworthy versus not allocating credit to bankable borrowers. The proposed methodology centers on 35 emerging markets and developing economies and uses the 2018-2020 EBRD-EIB-World Bank Enterprise Survey. We show that on average discouraged firms are less creditworthy than successful applicants. Nonetheless, the share of bankable discouraged firms is large, thus suggesting inefficient credit rationing. The baseline results point at an aggregate credit gap of 7.9% of GDP with significant variation across countries. SMEs account for more than two-thirds of the total, reflecting both their contribution to economic activity and the fact that they are more likely to be credit constrained.

JEL Codes: D22; D45; E51; G21; G32

Keywords: Credit rationing, discouraged borrowers, firm-level data, EMDEs

*The authors would like to thank Till Kadereit for research assistance. Ralph de Haas and Laurent Maurin provided useful comments. The views presented in the paper are those of the authors only and do not necessarily represent those of the European Investment Bank.

†Ozan E. Akbas - Warwick Business School, The University of Warwick, Scarman Road, Coventry CV4 7AL, UK. E-mail: ozan.akbas@warwick.ac.uk

‡Frank Betz - European Investment Bank, 98-100 Boulevard Konrad Adenauer, 2950 Luxembourg. E-mail: f.betz@eib.org

§Luca Gattini - European Investment Bank, 98-100 Boulevard Konrad Adenauer, 2950 Luxembourg. E-mail: l.gattini@eib.org

1 Introduction

Credit rationing arises from information asymmetries between borrowers and lenders, which can lead to moral hazard (Holmstrom and Tirole, 1997) or adverse selection (Stiglitz and Weiss, 1981). Both theoretical mechanisms observe that a higher interest rate reduces the borrower's stake in a project. This in turn constrains the ability of the lender to increase profits by raising interest rates.[1] As a result, credit markets are characterized by an inefficient allocation of resources. To mitigate these market failures, Public Development Banks devote a substantial amount of resources. In the case of EIB Group, SME financing in 2021 accounted for €45bn of the total committed lending volume of €94.9bn.

Quantifying the extent to which companies are able to obtain the finance they need is therefore of first order importance. The literature has developed two approaches to look at credit gaps: (i) a macroeconomic approach; and (ii) methodologies centered on firm-level data. The former approach is also defined as the gap between the credit-to-GDP ratio and its long-term trend (Drehmann and Tsatsaronis, 2014) and is used mainly for macroprudential purposes. Methodologies based on firm-level data pursue a bottom-up approach quantifying credit gaps. This literature frequently exploits surveys, as balance sheet data represent equilibrium outcomes and are not designed to measure excess demand.

Large-scale cross-countries firm surveys such as the EIB Investment Survey (EIBIS), the Survey on the Access to Finance of Enterprises (SAFE) of the ECB, or the EBRD-EIB-World Bank Enterprise Surveys used in this study contain a series of questions that measure the prevalence of financial constraints. However, descriptive accounts of credit rationing do not take into consideration that firms may be constrained for good reasons

[1] The moral hazard explanation emphasizes that higher interest rates may reduce repayments as a result of lower performance, whereas the adverse selection explanation stresses that borrower quality tends to decline as interest rates increase.

(Han et al., 2009), such as poor profitability, a short credit history, or the absence of meaningful financial statements. Providing credit to all rationed firms is unlikely to result in an optimal allocation of resources. This paper therefore seeks to quantify the financing needs of firms that are credit constrained yet bankable or "acceptable" from a credit scoring perspective.

To this end, we develop a methodology tailored to our main data source, the 2018-2020 EBRD-EIB-World Bank Enterprise Survey (ES). Our analysis covers 23,815 firms in 35 economies, largely emergining markets and developing economies, across Central and Eastern Europe (CEE), the Western Balkans (WB), Europe's Eastern Neighbourhood (EN), Europe's Southern Neighbourhood (SN) and Central Asia (CA). Table 1 provides an overview of the countries in our sample. The survey contains a detailed set of questions that measure a firm's ability to access finance. Among firms that need a loan, the survey distinguishes between firms that successfully applied for a loan, firms that had their loan application rejected, and firms that were discouraged from applying for a loan. See Kon and Storey (2003), Freel et al. (2012), Brown et al. (2022) and Mac an Bhaird et al. (2016) for a discussion of discouraged borrowers. Though both rejected applicants and discouraged firms are rationed and therefore credit constrained (Levenson and Willard, 2000), discouraged firms are of particular interest in our case. First, they are empirically much more salient than rejected applicants, as they account for 22.2% of firms in our study, compared to only 1.2% of rejected applicants. Second, a subset of the discouraged firms may well be bankable.

The credit gap in this paper is given by the aggregate financing needs of bankable discouraged firms. To identify the set of bankable discouraged firms we first estimate a scoring model. The scoring model is trained to predict rejections in the sample of applicants. The Enterprise Survey enables us to construct a large set of candidate predictors, which we narrow down using a LASSO-logit with data-driven selection of the penalty parameter. By applying the model out-of-sample we obtain rejection probabilities for the discouraged firms. The scoring model corrects for observable differences between applicants and discouraged firms.

To allocate credit we use a loss function governed by a risk aversion parameter that trades off type I against type II errors, i.e. allocating credit to firms not creditworthy against not allocating credit to creditworthy borrowers. We rely on the loss function, because the probability of rejection does not indicate whether a given discouraged firm should get credit. Credit is allocated based on the rejection probability that minimizes the loss function, such that all firms with a rejection probability below the threshold obtain credit. By tightening the risk aversion parameter we can correct for differences between applicants and discouraged firms that are not picked up by the scoring model. In our baseline specification the rejection rate of discouraged firms is approximately four times the in-sample rejection rate. This suggests that the average discouraged firm is indeed less creditworthy than the average applicant.

The financing needs of the bankable discouraged firms need to be estimated, because the survey does not elicit their preferred volume of credit. We therefore assume that they seek the same amount of credit per worker as the successful applicants in the same economy over the same period. This strategy is feasible as we have information on employment in both discouraged firms and successful applicants. To construct a proxy for the flow of credit to non-financial corporations we exploit aggregate data on credit stocks in combination with information on the maturity distribution of loans available in the Enterprise Survey. The baseline credit gap is therefore given by the flow of credit to non-financial corporation during the reference period of survey multiplied by the ratio of employment in discouraged firms to that of successful applicants. Finally, we offer a complementary perspective by using the fitted values from a projection of the credit gap on a set of macro-financial fundamentals. These include GDP per capita, a measure of institutional quality, a proxy for the business cycle and banking sector characteristics. This measure yields the average credit gap that can be expected given the most important country characteristics.

Our baseline results suggest a credit gap of USD 287bn, or 7.9% of GDP for the countries covered in this study. At USD 100bn, which corresponds to 18.2% of GDP, SN has the highest credit gap, both in absolute terms and relative to GDP. Turkey also has a credit gap of USD 100bn, but that accounts for only 12.8% of GDP. The other regions have comparatively small credit gaps, ranging from 6.6% in EN to 2,4% in WB. Adjusting for macro-financial characteristics compresses the cross-country variation, yielding on average larger gaps in countries with small baseline gaps and vice versa. However, for all regions but SN, the difference between the baseline and the adjusted credit gap amounts to less than 1.5% of GDP. SN has an adjusted credit gap of USD 70bn, which is USD 30bn below the baseline. Our preferred interpretation of this result is that the SN results are subject to greater uncertainty.

As the survey provides information on employment in discouraged firms, we can decompose the credit gap into an SME and a corporate component. The SME component is of particular interest in our context, because they generate a large share of GDP in emerging and developing economies and play an important role in creating sufficient jobs for a growing global work force. In addition, they generate positive externalities through innovation and technology adoption. At the same time, SMEs tend to be more opaque than corporates, and thus more prone to credit rationing. We find that SMEs account for 73% of the overall credit gap in the countries covered in this paper, which amounts to USD 210bn or 5.8% of GDP.

The remainder of the paper is organized as follows: The next section discusses the related literature. Section 3 introduces the data; Section 4 provides a detailed account of the methodology; Section 5 presents the results. Section 6 concerns the macro-financial adjustment. The last section concludes.

2 Literature Review

Measuring credit gaps is an empirical issue. Broadly speaking, two approaches have been deployed in the literature, namely: (i) a macroeconomic approach; and (ii) methodologies centered on firm-level data. The former approach is also defined as the gap between the credit-to-GDP ratio and its long-term trend (Drehmann and Tsatsaronis, 2014). It is employed primarily in macroprudential contexts, such as setting countercyclical capital buffers in the context of Basel III. Methodologies include the one-sided Hodrick-Prescott filter, bandpass methods (Baxter and King, 1999; Christiano and Fitzgerald, 2003), the Kalman filter (Durbin and Koopman, 2012) and structural approaches such as vector error correction modelling (Galán and Mencia, 2018; Lang and Welz, 2018; IMF, 2015).

Methodologies based on firm-level data pursue a bottom-up approach to credit constraints. This literature frequently exploits surveys, as balance sheet data represent equilibrium outcomes and are not designed to measure excess demand. Indeed some surveys identify potential customers that would like to have obtained credit but either were rejected or decided not to apply for a credit line despite needing it. The latter group, typically referred to as discouraged borrowers (Freel et al., 2012; Kon and Storey, 2003; Brown et al., 2022) are of particular interest, as creditworthy firms that decide not to apply for desired external financing (Levenson and Willard, 2000) face a financing gap.

The study by IFC et al. (2017) is closest in scope to our paper, albeit methodologically different. IFC et al. (2017) estimate the financing gap for micro, small and medium-sized enterprises (MSMEs) across developing economies using a potential demand approach.[2] Essentially, IFC et al. (2017) model potential demand for credit by MSMEs and match it with outstanding credit. The average debt-to-sales ratio in ten advanced

[2]See Stein et al. (2013) for a precursor study published by IFC. They posit that an additional USD 2.1tr to USD 2.6tr would be required to meet firms' financing needs.

economies serves as benchmark. Potential demand is derived by assuming that firms in developing countries desire the same debt-to-sales ratio as companies in the benchmark economies. Data on sales and the number of MSMEs in developing countries come from the Enterprise Survey. The study finds that the financing gap for MSMEs totals USD 5.2 trillion, or 19% of GDP on average for a large pool of emerging and developing economies.

Chakraborty and Mallick (2012) estimate the credit gap at firm-level for small businesses based on the National Survey of Small Business Finances for 1988-1989 and 1993 in the US. The authors find that on average credit-constrained small businesses desire 20% more debt. The authors apply an extension of Heckman's correction procedure to adjust for the non-randomness of the sub-sample that is used to estimate firms' demand for debt.

Singh et al. (2016) examine the challenges faced by women entrepreneurs in accessing finance. The work draws on field surveys with 500 female entrepreneurs in Bangladesh, as well as 40 interviews with government organizations and financial institutions. The authors subtract potential demand for external finance from total finance channeled through formal sources. The results reveal a financing gap for women-owned SMEs of around USD 0.77bn, which corresponds to 60.2% of demand by women entrepreneurs in 2015.

Domeher et al. (2017) use surveys to measure the SME financing gap in a low-income setting in Sub-Saharan Africa. Based on data on 1200 SMEs, they provide evidence for credit gaps that vary across sectors, with the agricultural sector being the most credit constrained. Further, their findings reveal low demand among the respondents who had not applied for credit, and suggest that interest rates are a major factor deterring participating in credit markets across all sectors.

Lopez-de Silanes et al. (2018) quantify SME financing gaps for France, Germany, Poland, Netherlands, and Romania. Their financing gap comprises both a credit gap and an equity gap. The ECB SAFE survey is used to estimate the demand for credit. They find credit gaps to be the largest in Poland and the Netherlands, ranging from 5% to 14.7% and 6% to 16.3% of GDP, respectively.

Corrigan et al. (2020) estimate latent credit demand among potential Irish first time home-buyers, discounting for a prudent credit risk assessment.[3] They exploit the Economic Sentiment Monitor Survey to estimate the levels of mortgage credit demand among Irish households, as well as the Irish Survey of Income and Living Conditions. The authors document a gap between acceptable credit demand and supply. They suggest the deployment of targeted public lending instruments to partially alleviate this gap.

3 Data

Firm-level data come from the 2018-2020 wave of the Enterprise Surveys, implemented by the European Investment Bank, the European Bank for Reconstruction and Development and the World Bank Group. Our analysis exploits data on 23,815 firm across 35 economies in Central, Eastern, South-Eastern Europe, Central Asia, the Middle East, and North Africa. Table 1 provides a list of the countries covered in the analysis. To facilitate comparisons across countries and regions, we group them based on geographic proximity. The Enterprise Survey covers a representative sample of an economy's formal, non-agricultural private sector. It includes a broad range of business environment topics, notably access to finance, corruption, infrastructure, crime, competition, investment decisions as well as firm performance. Enterprise Surveys involve face-to-face interviews with business owners and top managers and are designed to represent the

[3]Earlier studies investigating similar issues for households include Cox and Jappelli (1993) and Duca and Rosenthal (1993). Both study the effect of borrowing constraints on consumer liabilities based on the same 1983 Survey of Consumer Finances (SCF). They model desired debt for the group of unconstrained individuals and use the estimated coefficients to evaluate desired debt based on the observed characteristics of the constrained group. Then they assess the extent to which consumer liabilities would increase if constraints were removed.

business environment as experienced by firms. The samples are stratified by size, sector, and geography. Large firms are over-sampled to allow for inference at a reasonable sample size.[4] As the sampling probability differs across firms, we use sampling weights during the aggregation process.

The goal of our analysis is to identify the set of firms that are creditworthy, yet rationed. To this end, we can draw on a detailed set of widely used questions (Popov and Udell, 2012; Gorodnichenko and Schnitzer, 2013) that measure a firm's ability to access finance. Of particular interest are firms that need a loan, but are discouraged from applying (Freel et al., 2012; Kon and Storey, 2003). We start by identifying firms that desire bank loans. These are composed of firms that applied for a loan, i.e. that answer affirmatively to question K16: "Did the establishment apply for any loans or lines of credit in the last fiscal year?". Firms that did not apply are then asked question K17: "What was the main reason the establishment did not apply for any line of credit or loan in the last fiscal year?". Firms that answer "Interest rates are not favorable"; "Collateral requirements are too high"; "Size of loan and maturity are insufficient"; or "Did not think it would be approved" also need a loan, but are discouraged from applying. Discouraged firms are credit-constrained, but they are not the only firms that are credit-constrained. In addition, firms that applied for a loan, but had their loan application rejected are also credit constrained. Table 2 contains definitions of the survey-based variables used in the subsequent analysis.

In total, approximately 38% of firms in the economies covered by the Enterprise Surveys desired bank credit during the last financial year. As Table 3 shows, 16% of firms did actually apply for a loan[5], whereas 22% were discouraged from doing so. The vast majority of credit-constrained firms is discouraged from applying for a loan, as only 1.2% of companies have their loan application rejected. Empirically, rejection do

[4]For more details, see https://www.enterprisesurveys.org/en/methodology.

[5]These firms can have their loan application accepted or rejected

not appear salient, but in our context they are important to gauge the creditworthiness of discouraged firms.

The need for credit and levels of financial intermediation exhibit considerable heterogeneity across countries and regions. A high share of applicants indicates active financial intermediation. A high share of discouraged firms, on the other hand, points to a potentially substantial credit gap. According to Table 3, the share of applicants ranges from 7% in the SN to 27% in WB. This reflects the low application rates in Egypt and the high weight of Egypt in the SN average. The share of discouraged firms ranges from 11% in WB to 36-37% in EN and TUR. The regions differ substantially also in the ratio of applicants to discouraged firms. CEE and WB have the highest ratio, whereas SN has the lowest ratio of applicants to discouraged firms across all countries. This gives a first indication of a potentially large credit gap in SN.

Our methodology links an assessment of the creditworthiness at the firm level to the flow of credit to non-financial corporations. The data on the stock of credit to non-financial corporations come from the Financial Soundness Indicators compiled by the International Monetary Fund (IMF). For CEE countries we use data on NFC credit from the European Central Bank (ECB). In cases where these are not available, we resort to data from the IMF FAS database or to the central bank of the country. Figure 1 plots the level of NFC credit relative to GDP by country and region. With the exceptions of Lebanon and Jordan, the level of NFC credit is well below the euro area average of 41%.[6] To implement our methodology, we need to derive an estimate of the flow of credit to non-financial corporations during the reference period of the survey. To this end, we exploit information on the maturity structure of loans that is available in the 2018-2020 wave of the Enterprise Survey. Specifically, the question BMk10 asks respondents for the original maturity of the last outstanding loan. Figure 2 presents average maturity by country and region, which ranges from 0.8 years in Tunisia to 4.5 years in Albania.

[6] This figure is derived from ECB data for 2019.

Though both countries have a comparable stock of NFC credit of around 21-22% of GDP, the shorter maturity in Tunisia implies that a greater proportion of the credit stock is rolled over, translating into a higher gross flow of credit. As the Enterprise Survey does not cover agriculture, we adjust the stock of NFC credit with the share of value added generated by the industrial and services sector, obtained from the World Bank. To derive an estimate of the credit flow, we link data on the stock of NFC credit with information on the maturity distribution as follows:

$$credit\ flow_{i,t} = st_i\ credit_{i,t-1} + (1 - st_i)\ \frac{credit_{i,t-1}}{maturity_i^{lt}} + \Delta credit_{i,t,t-1} \tag{1}$$

The proportion of loans with an original maturity of one year or less is given by st_i. On average, this applies to around 30% of loans.[7] The stock of credit to non-financial corporations, adjusted for the share of value added in industry and services, is given by $credit_{i,t}$, whereas $maturity_i^{lt}$ denotes the average maturity of long-term loans, i.e. loans with an original maturity exceeding one year. Finally, $\Delta credit_{i,t,t-1}$ represents net credit growth in nominal terms, computed as difference in the stock of two consecutive years.

Our analysis makes also use of selected macro-financial fundamentals. We use data on GDP per capita from the World Economic Outlook database of the IMF. The output gap is defined as the difference between GDP growth in 2018 and the average GDP growth between 2010 and 2019, also based on the IMF WEO database. The political instability/absence of violence dimension of the Worldwide Governance indicators serves as a proxy for institutional quality. Data on the capital adequacy ratio of the banking system, the loan-to-deposit ratio, the ratio of non-performing loans to gross loans and the return on assets likewise come from the Financial Soundness Indicators, and in case they are not available from National Central Banks.

[7] Some countries have a high share of non-response to question BMk10. To account for this, we compute $st_i = (1 - nr_i)st_i^{raw} + nr_i\ st$, where nr_i is the share of non-responses in country i, and st the unconditional sample average. We proceed analogously with $maturity_i^{lt}$.

4 Methodology

The paper derives an estimate of the volume of additional credit that would be required to meet firms' needs, while taking into account their creditworthiness. For example, there is a difference between firm-level financing needs and bankable financing needs: what is profitable for firms to fund with internal resources may not be necessarily profitable for external financiers (i.e. banks). The proposed methodology tries to adjust for this external finance wedge. The Enterprise Survey provides us with an estimate of the share of firms needing a loan. It follows that firms that do not need a loan are not relevant for the analysis.

4.1 Scoring Model

Firms that do need a loan fall in two categories: applicants and discouraged firms. While funding might be available for SMEs, pricing, maturity and collateral requirements might not meet the firms' needs (Freel et al., 2012; Rostamkalaei et al., 2020). A naive approach could consist of allocating credit to all discouraged firms. However rejections are a natural outcome in a credit selection and screening assessment. Accordingly, also loans to some applicants were denied by the banking sectors. Moreover, it is likely that discouraged firms differ from applicants along a range of dimensions. To screen discouraged firms we propose a scoring model. The goal of the scoring model is to provide an assessment of the creditworthiness of discouraged firms (Ferrando and Mulier, 2022).[8] The Enterprise Survey provides a large set of candidate predictors which we narrow down using the LASSO (Tibshirani, 1996), specifically a LASSO-Logit (Friedman et al., 2010). The LASSO performs variable selection and regularization to

[8] Ferrando and Mulier (2022) explores the creditworthiness of discouraged firms for euro area countries, making use of the SAFE survey - European Central Bank. It contains a somewhat different set of information on discouraged borrowers compared to the Enterprise Survey employed in our study. As a result our approach is methodologically different from the one offered by Ferrando and Mulier (2022) but it is conceptually similar.

avoid overfitting and improve prediction accuracy. The LASSO augments the likelihood function of the logit with a penalty term given by the sum of the absolute value of the regression coefficients.

$$\widehat{\boldsymbol{\beta}}_{LASSO}(\lambda) = \arg\min \left\{-\ell_{LOGIT}(\beta_0, \boldsymbol{\beta}) + \lambda \, ||\boldsymbol{\beta}||_1\right\} \tag{2}$$

In line with Abadie and Kasy (2019), which highlights the importance of using data-driven procedures to select penalty parameters, we apply 5-fold cross-validation to obtain the penalty term λ. The scoring model is estimated on the sample of applicants. We obtain the final regression coefficients by fitting a regular logit augmented by country and sector fixed effects with the covariates selected by LASSO. To arrive at the rejection probabilities we apply the final model to the sample of discouraged firms.

4.2 Allocating Credit

The next step is to devise a mechanism that allocates credit to discouraged firms. The scoring model yields a probability of rejection for each discouraged firm, but that in itself does not indicate whether the firm should obtain credit. Following Betz et al. (2014), we employ a loss function that incorporates banks' risk-aversion given by the parameter μ to obtain a threshold probability $\tilde{p}$ that determines the allocation, such that credit will be allocated only to firms with a rejection probability below the threshold.

$$L(\mu, \tilde{p}) = \mu \frac{FN}{TP + FN} P(rejected) + (1 - \mu) \frac{FP}{FP + TN} P(\neg rejected) \quad \mu, \tilde{p} \in [0; 1] \tag{3}$$

The problem is framed such that banks seek to identify firms that are not creditworthy. A company that is not creditworthy and classified accordingly is referred to as a true positive (TP). Analogously, a firm that is creditworthy and classified accordingly is a true negative (TN). Two types of errors can occur: First, high quality firms can be classified as not creditworthy, a false positive (FP) or type I error. Second, low quality firms can be classified as creditworthy, a false negative(FN) or type II error. Thus $\frac{FN}{TP+FN}$ yields the ratio of low quality companies obtaining credit relative to the total number of low quality firms. Conversely, $\frac{FP}{FP+TN}$ gives the ratio of high quality firms not obtaining credit relative to the total number of high quality firms. The loss function is an average of the two error rates, weighted by the relative importance of high and low quality firms in the training sample and the banks' preferences for committing either type I or type II errors, as represented by the risk aversion parameter μ. Banking sectors with a high μ are more concerned about allocating credit to low quality firms and can therefore be considered conservative. A low μ, on the other hand, identifies banking sectors that care more about not serving enough firms and can thus be viewed as aggressive.

4.3 Aggregation

So far, the analysis has focused on the individual firm. The next step is to aggregate the experiences of the individual firms to obtain an aggregate credit gap. To this end, we propose the following definition:

$$credit\ gap_i = \sum_{j \in discouraged} w_{ij}\ \mathbb{1}(\widehat{approved_{ij}})\ \widehat{volume}_{ij} \tag{4}$$

where w_{ij} is the survey weight of firm j in country i. The indicator function $\mathbb{1}(\widehat{approved_{ij}}) = 1$ if and only if the probability of rejection is below the threshold probability, i.e. $\hat{p}_{ij} < \tilde{p}$. The term $\widehat{volume}_{ij}$ indicates the desired loan volume of the discouraged firms.

The Enterprise Survey does not ask discouraged firms for the loan amount that they would desire in case they could obtain a loan. As the likelihood of approval, this quantity is unknown and therefore needs to be approximated. To obtain a proxy, we assume that discouraged firms desire the same volume of credit per worker as the successful applicants. This strategy is feasible, as we have information on employment in both discouraged firms and successful applicants. Moreover, the Enterprise Survey asks respondents with an outstanding loan for the total balance at the time of the interview. Unfortunately, this variable has many missing values. We therefore use the aggregate volume of credit to non-financial corporations scaled by the total employment of successful applicants.

This yields the following expression for the credit gap in country i:

$$credit\ gap_i = credit\ flow_i \frac{\sum_{j \in discouraged} w_{ij}\ \mathbb{1}(\widehat{approved}_{ij})\ emp_{ij}}{\sum_{k \in applied} w_{ik}\ \mathbb{1}(approved_{ik})\ emp_{ik}} \tag{5}$$

where emp_{ij} is the full-time equivalent employment of firm j in country i and $credit\ flow_i$ is defined in Equation 1. As Equation 5 shows, the credit gap is increasing in the total employment of discouraged firms that according to the scoring model would be eligible for credit in case they had applied. Conversely, the credit gap is decreasing in the total employment of successful loan applicants. Perhaps counter-intuitively, the credit gap is increasing in the total credit flow. This follows from linking the desired credit volume of discouraged firms to what could be referred to as a measure of leverage in successful applicants. At this stage, it is straightforward to decompose the credit gap into an SME and a corporate component:

$$credit\ gap_i^{SME} = credit\ flow_i \frac{\sum_{j \in discouraged} w_{ij}\ \mathbb{1}(\widehat{approved}_{ij})\ \mathbb{1}(SME_{ij})\ emp_{ij}}{\sum_{k \in applied} w_{ik}\ \mathbb{1}(approved_{ik})\ emp_{ik}} \tag{6}$$

5 Results

5.1 Scoring Model

The objective of the scoring model is to identify a set of predictors for firms that applied for a loan and to use it out of sample to discriminate among discouraged firms, thus discerning their creditworthiness.

In principle, we are able to generate a large number of candidate predictors from the Enterprise Survey. However, the sample is restricted to the applicant firms. Moreover, owing to missing observations of individual variables the training sample shrinks as the number of regressors increases. We therefore apply the LASSO procedure to a model with 51 regressors, which leaves us with 3468 observations. Table 2 provides definitions of the variables selected by LASSO. To economize on space Table 2 omits the candidate variables that do not enter the final model.[9] All predictors are binary variables; lack of financial statement information is a limitation of the Enterprise Surveys. Table 4 presents the corresponding summary statistics for both applicants and the discouraged firms.

LASSO selects 18 regressors of the 51 entering the model. Table 5 shows the results of the post-LASSO logit. Not all of the variables have significant coefficients, but this is not the selection criterion. In general, however, coefficients do have the expected sign. For instance, firms that own property which can be used as collateral are significantly less likely to have their loan application rejected. Firms that expect their sales to decrease, on the other hand, are more likely to face a rejection. Though some of the variable may be considered endogenous, it is important to note that the goal of the exercise is prediction, not to uncover the true parameter values.[10]

[9]Definitions of the variables that do not survive the LASSO are available from the authors on request.

[10]For the prediction exercise, the scoring model has been augmented by country and sector fixed effects. Empirically, it makes little difference, if the country and sector fixed affects are subject to the LASSO model selection procedure or not.

It appears that the scoring model is able to distinguish between successful and rejected applicants. Figure 3 presents the distributions of the probability of a rejected loan application for firms whose loan application has been approved and for firms whose loan application has been rejected. Firms with an approved loan application have an average probability of rejection of 6.7%, compared to 19.9% for firms with a rejected loan application. Though the latter figure may appear low at first glance, it follows from the low frequency of rejections in the training data.

As expected, discouraged firms have on average a higher model-implied probability of rejection than firms with an approved loan application. Figure 4 presents the results of the out-of-sample prediction for discouraged firms. The average probability of rejection for discouraged firms equals 15.3%, which is more than twice as high than the 6.7% of approved applicants. This suggests that, based on observables, discouraged firms are on average less creditworthy than successful applicants. Table 4 provides insights as to why this is the case. In general, discouraged firms have on average readings of variables that are positively associated with access to finance. For instance, among the discouraged firms around 54% are small, compared to 34% of applicants. Likewise, only 19% of discouraged firms have an internationally recognized quality certificate, compared to 34% of applicants. 49% of applicant firms have audited accounts whilst only 36% of discouraged firms have their accounts audited.

5.2 Allocating Credit

The next step is to allocate credit. To this end, we evaluate the loss function for a given level of risk aversion μ over a grid of candidate thresholds $\tilde{p} \in [0, 0.01, 0.02, ..., 1]$. Table 6 presents results of this exercise for $\mu \in [0.75; 0.95]$. Column $\tilde{p}$ presents the threshold probability associated with the given level of μ. As expected, the threshold probability declines as banks become more conservative. The column labelled *Rejections* shows the proportion of actual loan applicants that had their application rejected. This is a property of the training sample and therefore independent of the model outcomes. However, it is still useful as a benchmark for the in-sample rejection rates generated by the model. Column *Predictions in-sample* yields the share of firms in the training sample of the scoring model that would have had their loan application rejected, given the threshold probability. As banks become more conservative, the in-sample rejection rate increases. Column *Predictions out-of-sample* yields the share of discouraged firms that would have had their loan application rejected conditional on the threshold probability. The on average lower creditworthiness of discouraged firms shows up in predicted rejection rates that at any given level of risk aversion are consistently higher than those predicted for the training sample of actual applicants.

Different values of the risk aversion parameter result in different credit allocations. A priori, it appears reasonable to assume a risk aversion parameter that generates an in-sample predicted rejection rate that is close to the actual rejection rate of 7.8%. This applies to both $\mu \in [0.75; 0.79]$ which generate a predicted rejection rate of 5% and to $\mu \in [0.80; 0.84]$, which results in a rejection rate of 12%. To further discriminate between the two allocations it is important to note that the scoring model does not correct for unobservable differences between applicants and non-applicants. It is likely that discouraged firms are weaker than applicants also in dimensions that are unobservable to the analyst. Such differences may include, for instance, the quality of the marginal investment opportunity. Against this background, it appears preferable to be more risk averse and choose the allocation with the lower threshold probability. At a threshold probability of $\tilde{p} = 0.18$, 31.7% of discouraged firms are denied credit. This implies that 68.3% of discouraged firms should have obtained a bank loan if they had applied for one. This suggests that in our sample self-rationing is rather inefficient, consistent with the results in Wernli and Dietrich (2022) for the Swiss credit market.

The prevalence of predicted rejections varies considerably across countries and regions. According to Figure 5, the share of predicted rejections is particularly high in EN, followed by CA. The EN average is driven by Ukraine and to a lesser extent Moldova.[11] In CA, Mongolia has by some margin the highest rates of predicted rejections. The predicted rejections offset the high share of discouraged firms, especially in EN. Conversely, TUR and WB have particularly low shares of predicted rejections. In these cases, the scoring model in conjunction with the allocation rule considers most discouraged firms bankable.

5.3 Baseline credit gap

Our baseline results suggest an aggregate credit gap of USD 287bn, or 7.9% of GDP for the countries covered in this study. Table 7 presents the estimates by country and region. At USD 100bn, which corresponds to 18.2% of the regional GDP, SN has the highest credit gap, both in absolute terms and relative to GDP. The regional aggregate is driven by large credit gaps in Egypt (USD 44bn) and Morocco (USD 30bn). Relative to GDP, Jordan and Lebanon also have large credit gaps of 23.9% and 19.9%, respectively. This appears counterintuitive, given the large stock of credit to non-financial corporations in both countries (see Figure 1). However, in the case of Lebanon the survey was implemented at a period in the second half of 2019, when the crisis affecting Lebanon intensified, resulting in a high share of discouraged companies. Turkey also has a credit gap of USD 100bn, but that accounts for only 12.8% of GDP. Turkey is similar to Lebanon in that it has a fairly developed financial system, as reflected in a comparatively high share of credit to GDP. At the same time, macroeconomic conditions were deteriorating while the survey was in the field. The other regions have comparatively small credit gaps, ranging from 6.6% in EN to 2.4% in WB. Reasons are different. In the EN and, to a certain extent, in the CA regions the lower credit gap is determined by high implied

[11]To note that these estimates refer to the period prior to the Russian invasion of Ukraine. Nonetheless, these countries suffered banking sector crises (due to different causes) between 2014 and 2016. This can affect the results whereby banking sectors were more reluctant to extend credit in the period following the banking sector crises.

rejection rates trimming significantly the elevated levels of firms' discouragement. Also the observed credit flows are somewhat lower than in other regions.

SMEs account for 73% of the overall credit gap in the countries covered in this paper. Columns (3) and (4) of Table 7 provide detailed results on the SME credit gap, which we estimate at USD 210bn or 5.8% of GDP. At 13.4%, SN has the highest SME credit gap relative to GDP, whereas Turkey has the highest gap in nominal terms (USD 80bn). Column 5 of Table 7 yields the percentage of the total credit gap that is due to SMEs. In all regions with the exception of EN, SMEs account for more than 60% of the credit gap. This reflects both their contribution to economic activity and the fact that they are more likely to be credit constrained. The lower gap on SMEs in the EN region may underscore the still significant presence of large corporate organisations legacy of the Soviet Era. It is not a surprise that the regional aggregate is largely driven by Belarus and Ukraine, whilst Moldova, Gerogia and Azerbaijan are more in line with the other regional aggregates.

At 5.8% of GDP, our SME credit gap is much smaller than the 19% estimated by IFC et al. (2017). This reflects differences in methodology. They use the credit intensity of MSMEs in ten advanced benchmark economies to derive potential demand by MSMEs in emerging and developing countries.[12] But these levels of credit can only be sustained in an advanced economy context, characterized by the corresponding institutions and high levels of physical and human capital. Our study, by contrast, draws on the credit intensity of successful applicants to derive the potential demand of bankable discouraged firms located in the same country. By construction, these firms face the same operating environment as the benchmark firms. It is therefore not surprising that adding the credit gap of 7.9% of GDP to the stock of outstanding credit of 22% of GDP amounts to less than the euro area average of 41% of GDP.

[12] In addition, they impute - via a regression approach - the observable aggregate quantities of the MSMEs stock of credit for those countries where data were not available.

5.4 Sensitivity analysis

Next, we examine the sensitivity of the baseline results with regard to the choice of the risk aversion parameter. The baseline specification assumes a risk aversion parameter of 0.8. In view of adverse selection concerns, there is no point in considering a risk aversion parameter that yields in-sample rejection probabilities lower than the unconditional sample average of 7.8%. This rules out all risk aversion parameters smaller than 0.8. There is, however, merit in studying how the credit gaps changes if banks are assumed to be more risk averse, i.e. more concerned about extending credit to firms that are not creditworthy.

Table 8 presents results for a corresponding increase in the risk aversion parameter of 5pp and 10pp, respectively. At the aggregate level, a 5pp increase in risk aversion results in a credit gap of 7.3% of GDP. This corresponds to 92% of the baseline credit gap of 7.9% of GDP. Turkey stands out in that the credit gap responds barely to the increase in risk aversion. This could indicate that credit constraints in Turkey are not driven by observable borrower characteristics. CA is interesting in that the 5pp increase in risk aversion results in a 25% decline of the credit gap. In absolute terms, however, the decline amounts to only 0.7pp, and therefore the sharp relative decline mainly reflects the low baseline credit gap.

The results respond more strongly to a 10pp increase in risk aversion. At the aggregate level, the credit gap declines to 5.2% of GDP, which corresponds to 65% of the baseline. The average decline, however, masks considerable heterogeneity at the regional level. Again, Turkey and CA are on opposite ends of the spectrum. While in Turkey, the credit gap amounts to 92% of the baseline even at 10pp higher risk aversion, the CA credit gap declines to only 24% of the baseline. Yet, a 10pp increase in the risk aversion parameter implies that banks would reject 34.3% of their loan applicants (see Table 6 - predictions in-sample), which does not appear that plausible in view of a 7.8% rejection rate for the actual loan applications.

6 Adjusting for Macro-Financial Fundamentals

A drawback of the approach outlined so far is that is tends to indicate large credit gaps in countries that experience a downturn following years of buoyant credit growth. As a result of rapid credit growth, such countries will have a comparatively high share of outstanding credit relative to GDP. In a downturn, a relatively high share of companies will be discouraged from applying for a loan. To mitigate this issue, we propose a complementary perspective to the credit gap shown in Equation 5, derived from a projection of the credit gap on a set of macro-financial variables. In a simple way, this step combines our survey-based method with elements of the macroeconomic approach. The result is the credit gap that we can expect given the country's macro-financial conditions. We refer to this metric as adjusted credit gap.

To implement this approach, we need to identify a set of variables that are associated with the volume of credit that an economy can sustain over the medium to long-term. Specifically, we consider the following variables: (i) Log GDP per capita. Higher GDP per capita can be viewed as a short-cut for a better contracting environment. Economies with a higher GDP per capita should support a greater volume of credit. (ii) Output gap. Here, the rationale is that the flow of credit is typically pro-cyclical, and that a positive output gap should be associated with a smaller credit gap. (iii) Political instability. The idea is that political instability is inimical to the provision of credit. Everything else equal, countries suffering from political instability are likely to support a smaller volume of credit. (iv) Capital adequacy ratio. Well capitalized banks could support a greater volume of credit. (v) Loan-to-deposit ratio. A high loan-to-deposit ratio may indicate lack of funding and thus be associated with a smaller volume of credit. (vi) Non-performing loan ratio. A high non-performing loan ratio may indicate poor banking practices but also a risky operating environment, both of which would be associated with a smaller volume of credit. (vi) Return on assets. Everything else equal, a higher return on assets suggests profitable lending opportunities, and therefore a greater volume of credit.

The goal of the exercise is to obtain predictions of the adjusted credit gap. Therefore, we are not interested in the parameter estimates per se. Ex-ante, we are ignorant as to the relative importance of the individual variables, and thus turn again to LASSO for help with model selection. Given that the distribution of the credit gap variable is by construction non-negative, we are applying the LASSO to a Poisson regression. Table 9 presents the corresponding regression results. Column (1) has results for the full model and Column (2) for the specification preferred by LASSO based on cross-validation with five folds. LASSO retains three of the seven covariates that enter the full model: the measure of the output gap, the political instability index, and the capital adequacy ratio of the banking system. The variables have the expected sign. A positive output gap, a more stable political environment, and higher capital ratios are all associated with smaller credit gaps. Empirically, The Pseudo R^2 indicates an in-sample fit that is similar to the full model.

The macro-financial adjustment yields comparable results to the baseline credit gap for all regions but SN. As Table 10 shows, the aggregate adjusted credit gap amounts to USD 247bn, which is USD 39bn smaller than the baseline credit gap. At the regional level, the difference between the baseline and the adjusted credit gap amounts to less than 1.5% of GDP. The exception is SN, with an adjusted credit gap of USD 70bn, which is USD 30bn smaller than the baseline. Figure 7 provides visual evidence on how the baseline and the adjusted credit gap are correlated at the country level. For countries that are located above the 45 degree line, the adjusted credit gap exceeds the baseline and vice versa. Most countries with a small baseline gap also have a small adjusted credit gap, albeit one that is slightly larger. The degree of dispersion around the 45 degree line increases along with the baseline credit gap. Most countries with a high baseline credit gap have a smaller adjusted credit gap. This applies in particular to Jordan, Bulgaria, and to a lesser extent Egypt. This is expected, as the regression compresses cross-country variation. On the other hand, for Tunisia and Palestine the adjustment yields a considerably higher credit gap than the baseline.

Figure 8 presents visual evidence on the range of credit gap estimates at the country and regional level. Wider bands indicate that the estimates are surrounded by a greater degree of uncertainty. This concerns the majority of SN economies, but also Bulgaria.

7 Conclusion

This paper proposes a methodology to quantify credit gaps based on firm-level data. Having an idea of the size of the potential credit gaps can inform the design of policy measures that seek to reduce them. We define the credit gap as the financing needs of firms that are discouraged from applying for a loan yet bankable according to our methodology.

To identify the set of bankable discouraged firms we combine a scoring model with a credit allocation rule. The scoring model provides an assessment of the creditworthiness of the discouraged firms. The credit allocation rule models the trade-off between allocating credit to firms that are not creditworthy versus not allocating credit to bankable borrowers. The financing needs of the bankable discouraged firms are derived by assuming that they desire the same amount of credit per worker as the successful applicants.

Our baseline results suggest a credit gap of USD 287bn, or 7.9% of GDP for the countries covered in this study. SMEs account for 73% of the overall credit gap in the countries covered in this paper, which amounts to 5.8% of GDP. This reflects both their contribution to economic activity and the fact that they are more likely to be credit constrained. The macro-financial adjustment yields comparable results to the baseline credit gap for most regions, with an overall credit gap among all countries of 6.8%.

The stock of NFC credit to GDP for the 35 countries equals approximately 22% on average between 2018 and 2020. Eliminating the credit gap would bring the overall stock of NFC credit to roughly 29-30% of regional GDP. Thus even with the credit gap closed the volume of credit remains well below the euro area average. This could reflect the on average lower levels of economic and financial development in the countries studied (Beck et al., 2006; Love, 2003) as well as limitations of the overall institutional framework (Demirgüç-Kunt and Maksimovic, 1998; Beck et al., 2005).

Closing the credit gaps requires a multi-year perspective and efforts from multiple actors, and the findings provide support for a set of possible interventions. Larger gaps, above all in the SME segment, call for long-term funding support and an efficient interest rate pass-through to firms. Risk sharing products can help decrease banks' risk aversion and ease the collateral requirements imposed on firms. Finally yet importantly, strengthening financial literacy (Cowling and Sclip, 2022) and improving the information environment (Bertrand and Mazza, 2022) can increase the acceptability of assets and reduce firms' discouragement.

References

Abadie, A. and M. Kasy (2019). Choosing among regularized estimators in empirical economics: The risk of machine learning. *Review of Economics and Statistics 101*(5), 743–762.

Baxter, M. and R. G. King (1999). Measuring business cycles: approximate band-pass filters for economic time series. *Review of Economics and Statistics 81*(4), 575–593.

Beck, T., A. Demirgüç-Kunt, L. Laeven, and V. Maksimovic (2006). The determinants of financing obstacles. *Journal of International Money and Finance 25*(6), 932–952.

Beck, T., A. Demirgüç-Kunt, and V. Maksimovic (2005). Financial and legal constraints to growth: does firm size matter? *Journal of Finance 60*(1), 137–177.

Bertrand, J. and P. Mazza (2022). Borrowers' discouragement and creditor information. *International Review of Law and Economics 72*.

Betz, F., S. Oprică, T. A. Peltonen, and P. Sarlin (2014). Predicting distress in European banks. *Journal of Banking & Finance 45*, 225–241.

Brown, R., J. M. Liñares-Zegarra, and J. O. Wilson (2022). Innovation and borrower discouragement in SMEs. *Small Business Economics 59*, 1489–1517.

Chakraborty, A. and R. Mallick (2012). Credit gap in small businesses: Some new evidence. *International Journal of Business 17*(1), 66–80.

Christiano, L. J. and T. J. Fitzgerald (2003). The band pass filter. *International Economic Review 44*(2), 435–465.

Corrigan, E., C. O'Toole, and R. Slaymaker (2020). Credit demand in the Irish mortgage market: What is the gap and could public lending help? *ESRI Working Paper No. 671*.

Cowling, M. and A. Sclip (2022). Dynamic discouraged borrowers. *British Journal of Management*.

Cox, D. and T. Jappelli (1993). The effect of borrowing constraints on consumer liabilities. *Journal of Money, Credit and Banking 25*(2), 197–213.

Demirgüç-Kunt, A. and V. Maksimovic (1998). Law, finance, and firm growth. *Journal of Finance 53*(6), 2107–2137.

Domeher, D., G. Musah, and N. Hassan (2017). Inter-sectoral differences in the SME financing gap: Evidence from selected sectors in Ghana. *Journal of African Business 18*(2), 194–220.

Drehmann, M. and K. Tsatsaronis (2014). The credit-to-GDP gap and countercyclical capital buffers: questions and answers. *BIS Quarterly Review*.

Duca, J. V. and S. S. Rosenthal (1993). Borrowing constraints, household debt, and racial discrimination in loan markets. *Journal of Financial Intermediation 3*(1), 77–103.

Durbin, J. and S. J. Koopman (2012). *Time series analysis by state space methods*. Oxford: Oxford University Press.

Ferrando, A. and K. Mulier (2022). The real effects of credit constraints: Evidence from discouraged borrowers. *Journal of Corporate Finance 73*.

Freel, M., S. Carter, S. Tagg, and C. Mason (2012). The latent demand for bank debt: characterizing "discouraged borrowers". *Small Business Economics 38*(4), 399–418.

Friedman, J., T. Hastie, and R. Tibshirani (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software 33*(1), 1.

Galán, J. and J. Mencia (2018). Empirical assessment of alternative structural methods for identifying cyclical systemic risk in Europe. *Banco de Espana Working Paper No. 1825*.

Gorodnichenko, Y. and M. Schnitzer (2013). Financial constraints and innovation: Why poor countries don't catch up. *Journal of the European Economic Association 11*(5), 1115–1152.

Han, L., S. Fraser, and D. J. Storey (2009). Are good or bad borrowers discouraged from applying for loans? evidence from US small business credit markets. *Journal of Banking and Finance 33*(2), 415–424.

Holmstrom, B. and J. Tirole (1997). Financial intermediation, loanable funds, and the real sector. *Quarterly Journal of Economics 112*(3), 663–691.

IFC, World Bank, and SME Finance Forum (2017). MSME finance gap: assessment of the shortfalls and opportunities in financing small, micro and medium enterprises in emerging markets. *IFC Study*.

IMF (2015). Central, Eastern, and Southeastern Europe: Mind the credit gap. *IMF Regional Economic Issues*.

Kon, Y. and D. J. Storey (2003). A theory of discouraged borrowers. *Small Business Economics 21*(1), 37–49.

Lang, J. H. and P. Welz (2018). Semi-structural credit gap estimation. *ECB Working Paper No. 2194*.

Levenson, A. R. and K. L. Willard (2000). Do firms get the financing they want? Measuring credit rationing experienced by small businesses in the U.S. *Small Business Economics 14*, 83–94.

Lopez-de Silanes, F., J. McCahery, D. Schoenmaker, and D. Stanisic (2018). Estimating the financing gaps of SMEs. *Journal of Corporate Finance Research 12*(2), 1–54.

Love, I. (2003). Financial development and financing constraints: international evidence from the structural investment model. *Review of Financial Studies 16*(3), 765–791.

Mac an Bhaird, C., J. Sanchez Vidal, and B. Luceyc (2016). Discouraged borrowers: Evidence for eurozone SMEs. *Journal of International Financial Markets, Institutions and Money 44*, 46–55.

Popov, A. and G. F. Udell (2012). Cross-border banking, credit access, and the financial crisis. *Journal of International Economics 87*(1), 147–161.

Rostamkalaei, A., M. Nitani, and A. Riding (2020). Borrower discouragement: the role of informal turndowns. *Small Business Economics 54*, 173–188.

Singh, S., R. Asrani, and A. Ramaswamy (2016). Study on mapping the market potential and accelerating finance for women entrepreneurs in Bangladesh. *IFC Working Paper*.

Stein, P., O. P. Ardic, and M. Hommes (2013). Closing the credit gap for formal and informal micro, small, and medium enterprises. *IFC Study*.

Stiglitz, J. E. and A. Weiss (1981). Credit rationing in markets with imperfect information. *American Economic Review 71*(3), 393–410.

Tibshirani, R. (1996). Regression shrinkage and selection via the Lasso. *Journal of the Royal Statistical Society: Series B (Methodological) 58*(1), 267–288.

Wernli, R. and A. Dietrich (2022). Only the brave: improving self-rationing efficiency among discouraged swiss SMEs. *Small Business Economics 59*, 977–1003.

Figures and Tables

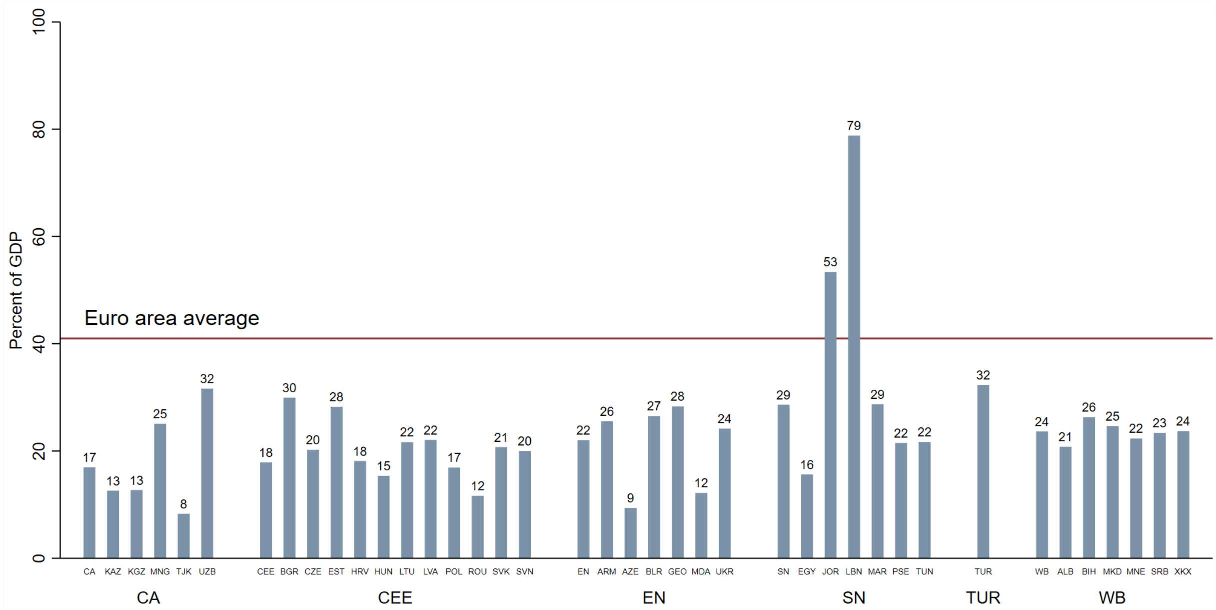

Figure 1: Credit to non-financial corporations.

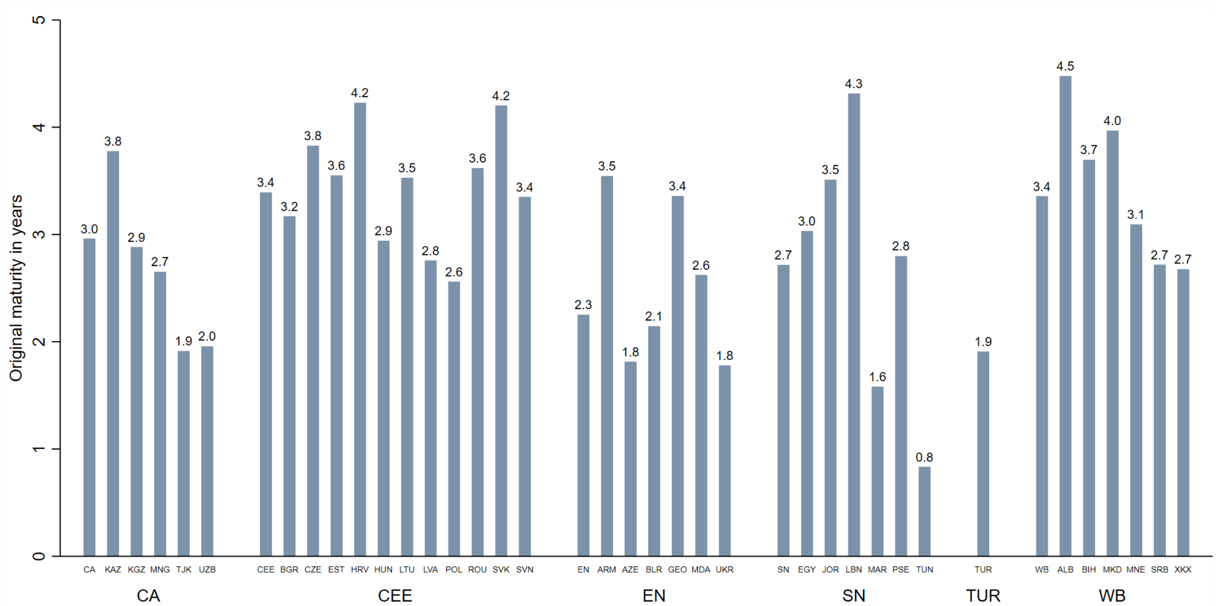

Figure 2: Average original maturity of loans in years.

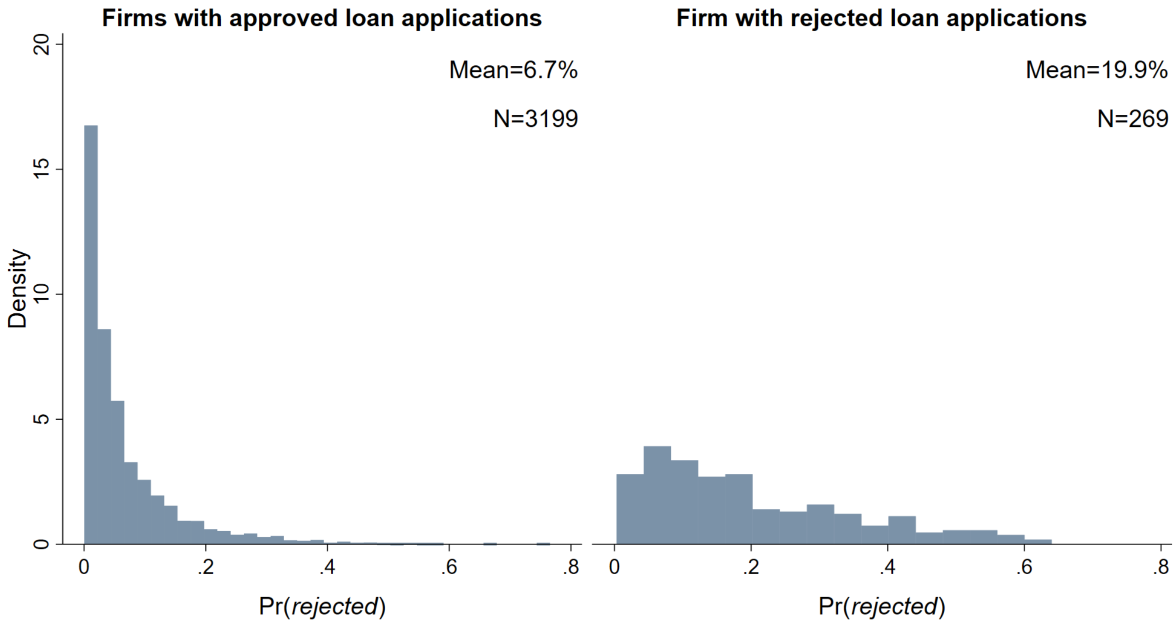

Figure 3: Probability of rejection for loan applicants.

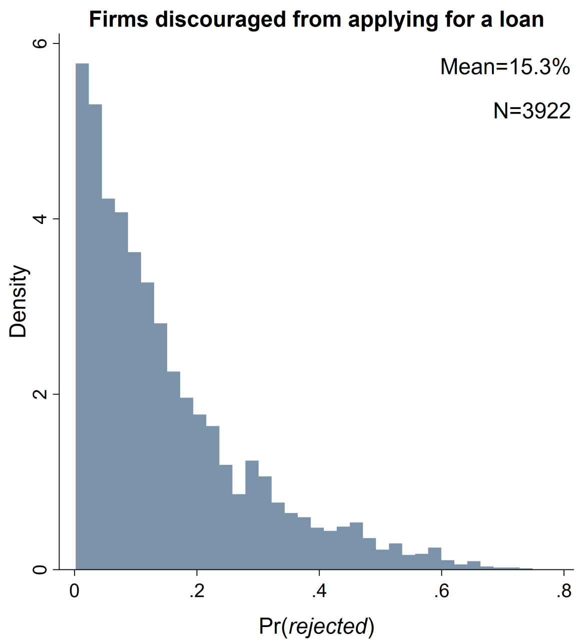

Figure 4: Probability of rejection for firms discouraged from applying for a loan.

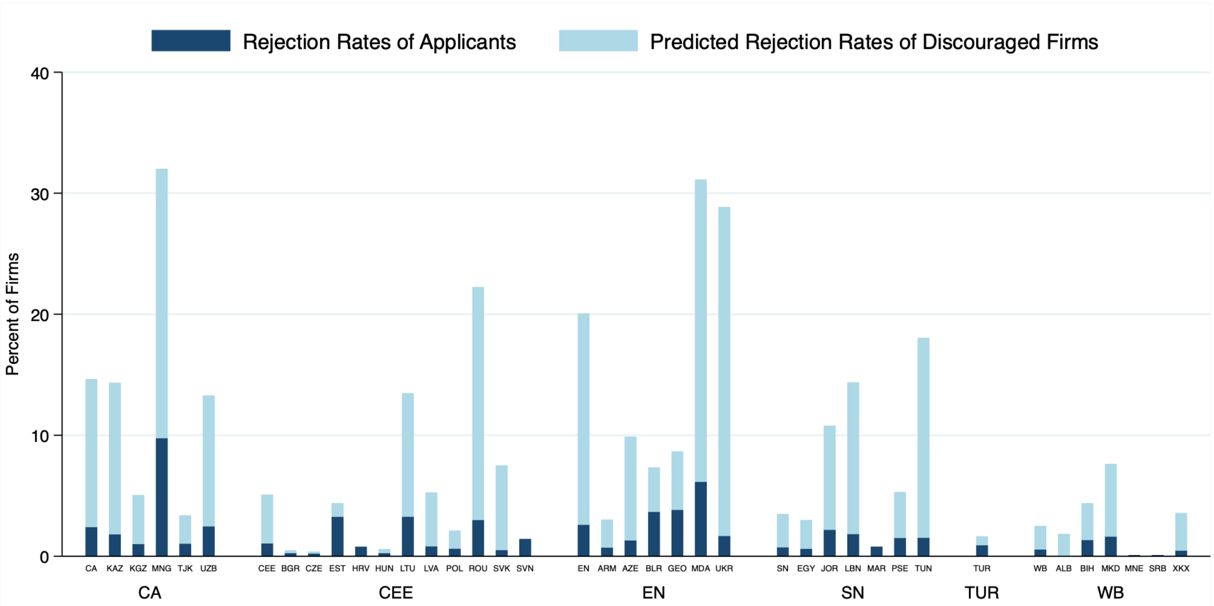

Figure 5: Rejection rates of applicants and predicted rejection rates for discouraged firms.

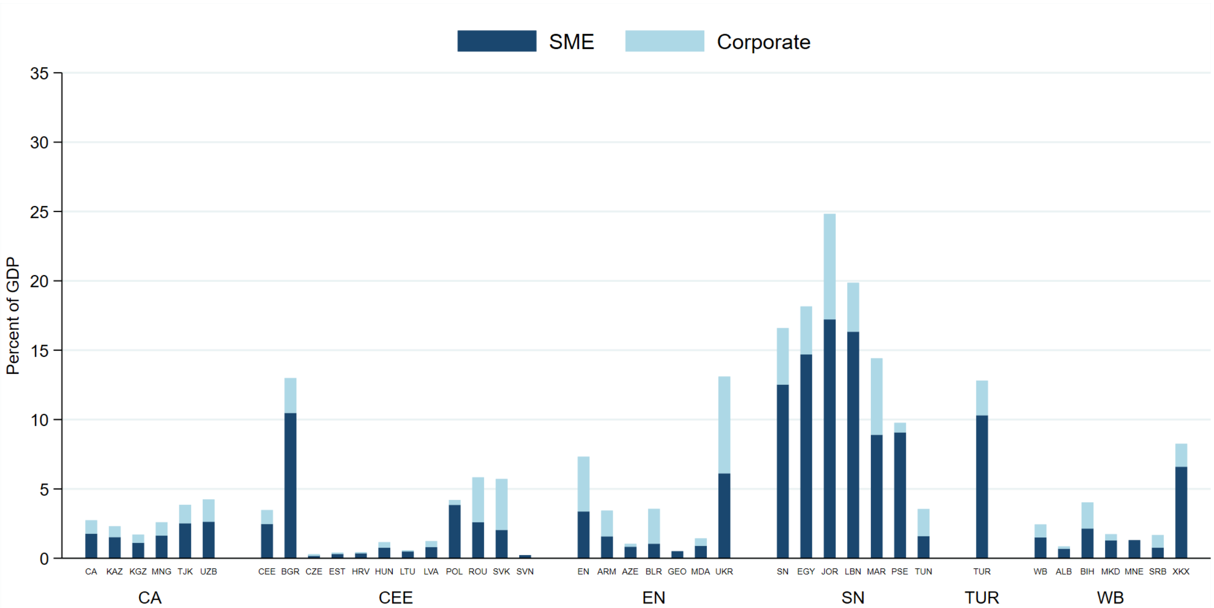

Figure 6: Credit gap, decomposed into SME and corporate borrowers.

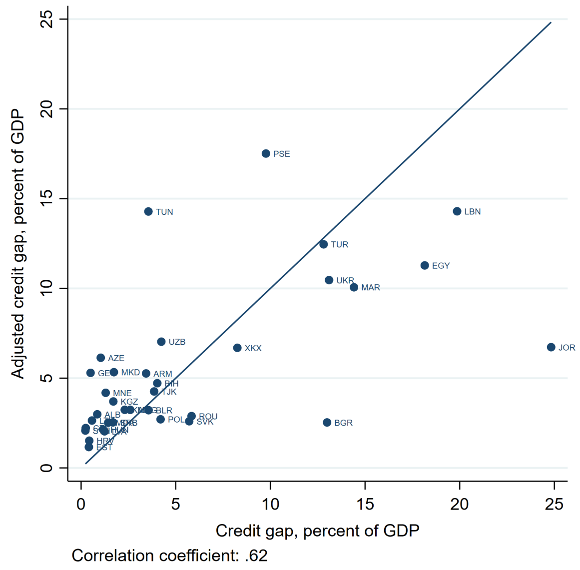

Figure 7: The credit gap and the credit gap adjusted for fundamentals.

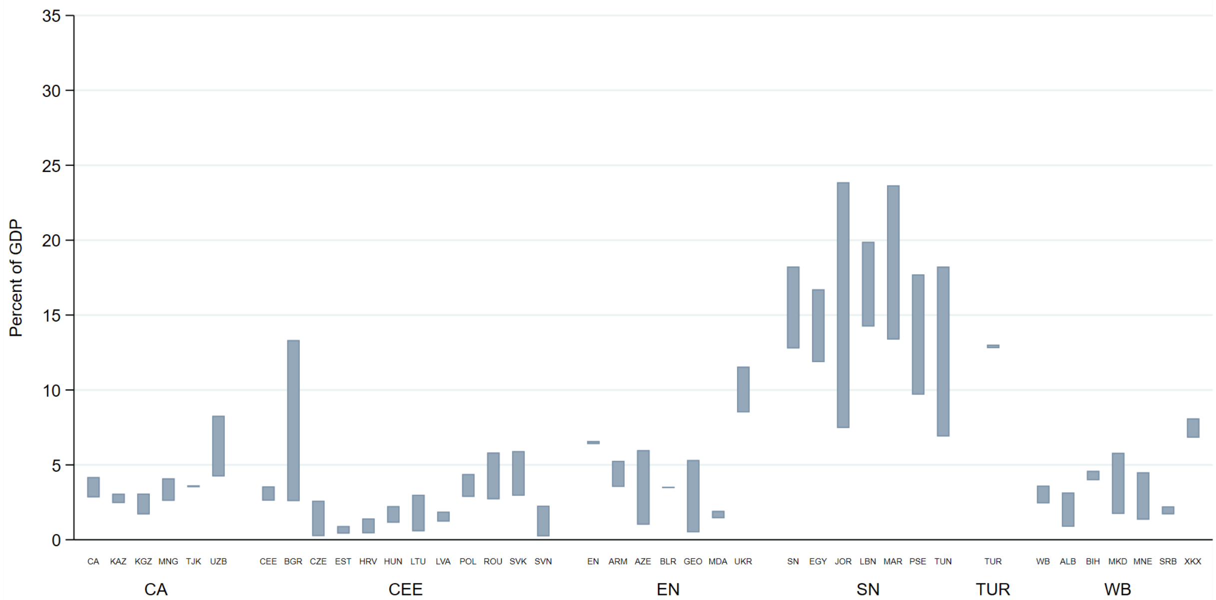

Figure 8: Range of credit gap estimates by country.

Table 1: Definition of Country Groupings

Country Group		Country	ISO Code
Central Asia	CA	Kazakhstan	KAZ
		Kyrgyz Republic	KGZ
		Mongolia	MNG
		Tajikistan	TJK
		Uzbekistan	UZB
Central and Eastern Europe	CEE	Bulgaria	BGR
		Croatia	HRV
		Czech Republic	CZE
		Estonia	EST
		Hungary	HUN
		Latvia	LVA
		Lithuania	LTU
		Poland	POL
		Romania	ROU
		Slovakia	SVK
		Slovenia	SLN
Eastern Neighbourhood	EN	Armenia	ARM
		Azerbaijan	AZE
		Belarus	BLR
		Georgia	GEO
		Moldova	MDA
		Ukraine	UKR
Southern Neighbourhood	SN	Egypt	EGY
		Jordan	JOR
		Lebanon	LBN
		Morocco	MAR
		Palestine	PSE
		Tunisia	TUN
Western Balkans	WB	Albania	ALB
		Bosnia and Herzegovina	BIH
		Kosovo	XKX
		Montenegro	MNE
		North Macedonia	MKD
		Serbia	SRB

Owing to its size, Turkey constitutes its own entity.

Table 2: Variable Definitions - Enterprise Survey

VARIABLE	DEFINITION
Applied	Indicator equal to 1 if the firm applied for a loan during the last financial year
Discouraged	Indicator equal to 1 if the firm did not apply for a loan during the last financial year because of high interest rates, stringent collateral requirements, complex application procedures, insufficient volume and maturity, or they expected to loan application to be rejected
Rejected	Indicator equal to 1 if the firm applied for a loan and the loan application was rejected
Publicly listed	Indicator equal to 1 if the firms is listed on a stock exchange
Legal status - Other	Indicator equal to 1 if the firm in not listed, not a limited liability company, not a sole proprietorship, not a partnership and not a limtited partnership
Business strategy	Indicator equal to 1 if the company has a formal, written business strategy
Supervisory board	Indicator equal to 1 if the firm has a supervisory board
0-5 years old	Indicator equal to 1 if the firm is less than five years old
Certificate	Indicator equal to 1 if the company has an internationally recognized quality certification
Website	Indicator equal to 1 if the company has a website
Expected total sales decrease	Indicator equal to 1 if the firm expected total sales to decrease
Owns building	Indicator equal to 1 if the firm owns the building it occupies
Invested: fixed assets	Indicator equal to 1 if the firm invested in fixed assets during the previous financial year
Leased: fixed assets	Indicator equal to 1 if the company leased fixed assets during the previous financial year
Bank account	Indicator equal to 1 if the company has a checking or savings account
Overdraft facility	Indicator equal to 1 if the company has access to an overdraft facility
Audited	Indicator equal to 1 if the company has audited financial statements
Import license application	Indicator equal to 1 if the firms has submitted an application to obtain an import license
Operating license application	Indicator equal to 1 if the firms has submitted an application to obtain an operating license
Small firm	Indicator equal to 1 if the firm has less than 20 employees
Exporter	Indicator equal to 1 if the firm exports more than 10% of sales

Table 3: Need for Loans

	NEED	APPLIED	REJECTED	DISCOURAGED
	[% of firms]	[% of firms]	[% of firms]	[% of firms]
CA	36.6	14.3	2.4	22.3
KAZ	32.1	9.7	1.8	22.3
KGZ	27.0	15.3	1.0	11.7
MNG	82.2	44.2	9.8	38.0
TJK	31.1	11.6	1.0	19.4
UZB	38.7	19.0	2.5	19.7
CEE	32.5	19.4	1.1	13.1
BGR	34.6	12.7	0.3	21.9
CZE	28.9	25.9	0.2	3.0
EST	29.9	26.2	3.3	3.7
HRV	29.3	24.8	0.8	4.5
HUN	30.5	23.7	0.3	6.8
LTU	32.9	21.0	3.3	12.0
LVA	32.2	22.8	0.8	9.4
POL	26.7	13.3	0.6	13.4
ROU	48.9	14.3	3.0	34.6
SVK	26.9	13.4	0.5	13.5
SVN	34.2	32.3	1.4	1.9
EN	57.6	21.4	2.6	36.2
ARM	60.6	27.2	0.7	33.4
AZE	31.8	13.5	1.3	18.3
BLR	49.0	30.6	3.7	18.4
GEO	40.6	31.3	3.8	9.3
MDA	54.0	19.0	6.1	35.0
UKR	65.1	15.7	1.7	49.5
SN	29.8	6.7	0.7	23.1
EGY	26.1	4.1	0.6	22.0
JOR	30.8	13.0	2.2	17.8
LBN	53.6	25.7	1.8	27.9
MAR	45.8	15.3	0.8	30.4
PSE	24.1	11.5	1.5	12.6
TUN	59.5	23.8	1.5	35.7
TUR	60.5	23.5	0.9	37.0
WB	37.8	26.8	0.6	10.9
ALB	23.6	18.3	0.0	5.3
BIH	38.7	26.2	1.3	12.6
MKD	36.0	19.9	1.6	16.1
MNE	47.7	24.8	0.1	22.9
SRB	45.2	36.2	0.1	8.9
XKX	29.7	13.5	0.5	16.1
TOTAL	38.2	16.0	1.2	22.2

Table 4: Summary Statistics - Enterprise Survey

	Applicants		Discouraged firms	
	Mean	SD	Mean	SD
Publicly listed	0.07	0.26	0.06	0.23
Legal status - Other	0.02	0.15	0.04	0.20
Business strategy	0.50	0.50	0.39	0.49
Supervisory board	0.37	0.48	0.32	0.47
0-5 years old	0.09	0.29	0.09	0.28
Certificate	0.34	0.47	0.19	0.39
Website	0.71	0.46	0.52	0.50
Expected total sales decrease	0.16	0.36	0.20	0.40
Owns building	0.73	0.44	0.68	0.47
Invested: fixed assets	0.59	0.49	0.25	0.43
Leased: fixed assets	0.31	0.46	0.12	0.33
Bank account	0.95	0.22	0.88	0.33
Overdraft facility	0.53	0.50	0.32	0.47
Audited	0.49	0.50	0.36	0.48
Import license application	0.10	0.31	0.06	0.23
Operating license application	0.16	0.37	0.10	0.30
Small firm	0.34	0.47	0.54	0.50
Exporter	0.30	0.46	0.14	0.35

Table 5: Model Selected by Lasso Logit Based on Five-Fold Cross-Validation

VARIABLE	REJECTED
LS - Public	0.485
	(0.312)
Legal Status - Other	-0.400
	(0.590)
Business Strategy	0.075
	(0.155)
Supervisory Board	0.137
	(0.180)
0-5 Years	0.470**
	(0.202)
Certificate	-0.345*
	(0.201)
Website	-0.097
	(0.159)
Expected Total Sales Decrease	0.654***
	(0.181)
Owns Building	-0.595***
	(0.153)
Invested: Fixed Assets	-0.710***
	(0.153)
Leased: Fixed Assets	-0.274
	(0.191)
Bank Account	0.291
	(0.289)
Overdraft Facility	-1.138***
	(0.188)
Audited	-0.155
	(0.169)
Import License Application	-0.877**
	(0.366)
Operating License Application	0.252
	(0.189)
Small Firm	0.657***
	(0.161)
Exporter	-0.100
	(0.200)
N	3468

Logistic regression with country and sector fixed effects. Dependent variable: Loan application rejected. T-statistics in parentheses. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$.

Table 6: Risk Aversion

μ	$\tilde{p}$	TN	FN	FP	TP	Rejections	Predicted rejections	
							in-sample	out-of-sample
0.75	0.29	3099	197	100	72	7.8	5.0	16.0
0.76	0.29	3099	197	100	72	7.8	5.0	16.0
0.77	0.29	3099	197	100	72	7.8	5.0	16.0
0.78	0.29	3099	197	100	72	7.8	5.0	16.0
0.79	0.29	3099	197	100	72	7.8	5.0	16.0
0.80	0.18	2906	146	293	123	7.8	12.0	31.7
0.81	0.18	2906	146	293	123	7.8	12.0	31.7
0.82	0.18	2906	146	293	123	7.8	12.0	31.7
0.83	0.18	2906	146	293	123	7.8	12.0	31.7
0.84	0.18	2906	146	293	123	7.8	12.0	31.7
0.85	0.14	2769	121	430	148	7.8	16.7	40.7
0.86	0.13	2708	111	491	158	7.8	18.7	44.0
0.87	0.13	2708	111	491	158	7.8	18.7	44.0
0.88	0.13	2708	111	491	158	7.8	18.7	44.0
0.89	0.13	2708	111	491	158	7.8	18.7	44.0
0.90	0.07	2222	56	977	213	7.8	34.3	65.6
0.91	0.07	2222	56	977	213	7.8	34.3	65.6
0.92	0.07	2222	56	977	213	7.8	34.3	65.6
0.93	0.07	2222	56	977	213	7.8	34.3	65.6
0.94	0.07	2222	56	977	213	7.8	34.3	65.6
0.95	0.04	1687	24	1512	245	7.8	50.7	78.1

The risk aversion parameter μ denotes the relative weight of type I and type II errors in the loss function. The threshold probability $\tilde{p}$ is the probability of rejection that minimizes the loss function for a given level of the risk aversion parameter μ. Firms with a probability of rejection above the threshold will not receive credit. TN - true negatives, FN - false negatives, FP - false positives, TP - true positives. Rejections shows the proportion of firms that had their loan application rejected. Predictions in-sample yields the share of firms in the training sample of the scoring model that would have had their loan applications rejected, given the threshold probability. Predictions out-of-sample yields the share of discouraged firms that would have had their loan application rejected conditional on the threshold probability.

Table 7: Credit Gap Estimates

	Credit Gap		SME Credit Gap		
	[% GDP]	[Million USD]	[% GDP]	[Million USD]	[% Total Gap]
CA	2.8	7,389	1.8	4,778	65
KAZ	2.5	4,401	1.6	2,909	66
KGZ	1.7	140	1.1	91	65
MNG	2.6	343	1.6	215	63
TJK	3.6	278	2.3	182	65
UZB	4.2	2,227	2.6	1,380	62
CEE	3.6	58,659	2.5	41,954	72
BGR	13.3	8,852	10.7	7,139	81
CZE	0.2	603	0.2	524	87
EST	0.4	125	0.3	94	75
HRV	0.4	268	0.4	222	83
HUN	1.1	1,833	0.7	1,200	65
LTU	0.6	306	0.5	259	85
LVA	1.2	419	0.8	269	64
POL	4.4	25,813	4.0	23,634	92
ROU	5.8	14,062	2.6	6,250	44
SVK	5.9	6,256	2.1	2,242	36
SVN	0.2	123	0.2	123	100
EN	6.6	18,410	3.0	8,458	46
ARM	3.5	440	1.6	202	46
AZE	1.0	475	0.8	381	80
BLR	3.5	2,119	1.0	622	29
GEO	0.5	87	0.5	87	100
MDA	1.4	162	0.9	101	63
UKR	11.6	15,128	5.4	7,065	47
SN	18.2	99,838	13.4	73,087	73
EGY	16.7	44,000	13.5	35,603	81
JOR	23.9	10,262	16.6	7,116	69
LBN	19.9	10,921	16.4	8,980	82
MAR	23.7	30,134	14.6	18,605	62
PSE	9.7	1,577	9.0	1,465	93
TUN	6.9	2,944	3.1	1,317	45
TUR	12.8	99,722	10.3	80,250	80
WB	2.4	2,728	1.5	1,675	61
ALB	0.9	131	0.7	106	81
BIH	4.0	802	2.1	427	53
MKD	1.7	220	1.3	164	75
MNE	1.3	74	1.3	74	100
SRB	1.7	862	0.8	394	46
XKX	8.1	639	6.5	510	80
TOTAL	7.9	286,746	5.8	210,201	73

Table 8: Sensitivity of Credit Gap Estimates to Risk Aversion Parameter

	%GDP			%BASE	
RISK AVERSION	BASE	+5PP.	+10PP.	+5PP.	+10PP.
CA	2.8	2.1	0.7	75	24
KAZ	2.5	1.6	0.5	65	19
KGZ	1.7	1.6	0.7	95	43
MNG	2.6	2.0	1.2	77	46
TJK	3.6	3.4	2.5	94	69
UZB	4.2	3.9	1.0	92	24
CEE	3.6	3.1	2.0	87	55
BGR	13.3	13.0	12.6	98	94
CZE	0.2	0.2	0.2	100	75
EST	0.4	0.3	0.3	75	70
HRV	0.4	0.4	0.4	100	96
HUN	1.1	1.1	1.0	93	87
LTU	0.6	0.5	.	82	.
LVA	1.2	0.8	0.2	68	20
POL	4.4	4.1	2.0	94	46
ROU	5.8	4.5	2.4	77	41
SVK	5.9	4.1	3.3	68	55
SVN	0.2	0.2	0.2	100	99
EN	6.6	5.8	3.0	88	46
ARM	3.5	3.4	2.3	96	66
AZE	1.0	0.9	0.5	90	51
BLR	3.5	3.4	3.0	97	86
GEO	0.5	0.5	0.1	98	19
MDA	1.4	1.4	0.4	94	27
UKR	11.6	9.9	4.7	86	40
SN	18.2	16.3	9.3	90	51
EGY	16.7	15.8	7.8	94	46
JOR	23.9	13.9	5.0	58	21
LBN	19.9	15.0	6.6	75	33
MAR	23.7	23.6	17.5	100	74
PSE	9.7	8.8	7.4	91	78
TUN	6.9	4.9	2.4	72	34
TUR	12.8	12.7	11.7	99	92
WB	2.4	2.3	2.0	94	83
ALB	0.9	0.9	0.9	100	100
BIH	4.0	3.6	3.1	91	78
MKD	1.7	1.4	1.1	84	66
MNE	1.3	1.3	1.2	100	93
SRB	1.7	1.7	1.6	100	95
XKX	8.1	7.3	6.0	91	74
TOTAL	7.9	7.3	5.2	92	65

This table presents the sensitivity of the baseline credit gap estimates to the risk aversion parameter used in the scoring model. We report the baseline credit gap estimates, and the estimates under 5 pp. and 10 pp. higher bank risk aversion, respectively, as a percent of GDP. We further report the latter two estimates as a percent of the baseline credit gap estimates (100%).

Table 9: Adjusting for Macro-Financial Fundamentals

	FULL MODEL	POST SELECTION
Log GDP per capita	0.016	
	(0.200)	
Output gap	-0.151	-0.144**
	(0.143)	(0.069)
Political stability (WGI)	-0.276	-0.303*
	(0.410)	(0.180)
Capital adequacy ratio	-0.118**	-0.116**
	(0.052)	(0.048)
Loan-to-deposit ratio	-0.003	
	(0.006)	
Non-performing loan ratio	-0.001	
	(0.021)	
Return on assets	0.010	
	(0.205)	
Constant	4.415**	4.492***
	(1.995)	(0.889)
Pseudo R2	0.330	0.327

Poisson regression with robust standard errors. Column (2) presents results for variables selected by LASSO based on cross-validation with five folds. Dependent variable: Total credit gap. T-statistics in parentheses. * p < 10%, ** p < 5%, *** p < 1%.

Table 10: Adjusted Credit Gap

	ADJUSTED CREDIT GAP	
	[% GDP]	[MILLION USD]
CA	4.2	10,951
KAZ	3.1	5,521
KGZ	3.1	255
MNG	4.1	542
TJK	3.6	276
UZB	8.3	4,356
CEE	2.6	42,946
BGR	2.6	1,716
CZE	2.6	6,490
EST	0.9	281
HRV	1.4	886
HUN	2.2	3,612
LTU	3.0	1,616
LVA	1.9	648
POL	2.9	16,829
ROU	2.7	6,524
SVK	2.9	3,108
SVN	2.3	1,235
EN	6.4	17,840
ARM	5.3	657
AZE	6.0	2,819
BLR	3.5	2,078
GEO	5.3	937
MDA	1.9	217
UKR	8.5	11,132
SN	12.8	69,916
EGY	11.9	31,210
JOR	7.5	3,209
LBN	14.2	7,814
MAR	13.4	17,016
PSE	17.7	2,884
TUN	18.2	7,784
TUR	13.0	101,607
WB	3.6	4,058
ALB	3.2	478
BIH	4.6	929
MKD	5.8	737
MNE	4.5	248
SRB	2.2	1,129
XKX	6.8	537
TOTAL	6.8	247,318