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Quantifying Credit Gaps Using Survey Data on Discouraged Borrowers [*]

Ozan E. Akbas[†] Frank Betz[‡] Luca Gattini[§]

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Abstract

The credit gap in this study is given by the financing needs of firms that are bankable but discouraged from applying for a loan. To quantify the credit gap, we combine a scoring model that assesses the creditworthiness of discouraged firms with a credit allocation rule. Our study covers 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, suggesting inefficient credit rationing. The baseline results point to an aggregate credit gap of 8.4% 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

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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. As a result, credit markets are characterized by rationing and more generally, an inefficient allocation of resources. To mitigate these market failures, Public Development Banks devote a substantial amount of resources. For instance, SME financing in 2021 accounted for €45bn of the total committed lending volume of €94.9bn for the European Investment Bank (EIB) Group. Quantifying the extent to which companies are able to obtain the finance they need is thus of first-order importance.

To this end, this paper proposes a methodology that quantifies excess demand in corporate credit markets from the bottom up, with a focus on discouraged borrowers operating. According to Levenson and Willard (2000) and Kon and Storey (2003), discouraged borrowers are creditworthy firms in need of external finance that nevertheless do not apply for a loan because they expect to be rejected and face high application costs.[1] Our methodology allows for some discouraged borrowers to be rationed for good reasons (Han et al., 2009). Providing credit to all discouraged firms is unlikely to result in an optimal allocation of resources. This paper, therefore, seeks to quantify the financing needs of firms that are discouraged from applying yet *bankable* from a credit scoring perspective.

Our methodology employs the 2018-2020 EIB-EBRD-WBG Enterprise Surveys (ES) as the main data source. Our analysis covers 23,815 firms in 35 high and middle-income economies across Europe, Asia, the Middle East and North Africa. The survey contains

[1]Studies of credit rationing among firms (Stiglitz and Weiss, 1981; Berger and Udell, 1992; Banerjee and Duflo, 2014; Berg, 2018) frequently focus on firms that apply for a loan.

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. Both rejected applicants and discouraged firms are rationed and therefore credit constrained. However, empirically discouraged borrowers are much more salient than rejected applicants, as they account for 22.2% of firms in our sample, compared to only 1.2% of rejected applicants.

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 a 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.

The rejection probabilities do not directly indicate whether a given discouraged firm should get credit. So, we allocate credit by setting a threshold in the distribution of rejection probabilities that replicates the observed rejection rate in the sample of applicants. Discouraged firms with a rejection probability below this threshold obtain credit. We find that the rejection rate of discouraged firms is close to three times the in-sample rejection rate. This suggests that the average discouraged firm is less creditworthy than the average applicant. At the same time, about 77% of discouraged firms would have seen their loan application approved if they were to apply for a loan, thus indicating inefficient credit rationing.

The financing needs of the bankable discouraged firms need to be estimated because the survey does not elicit their preferred volume of credit. Therefore, we 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. The baseline credit gap is therefore given by the flow of credit to non-financial corporations during the reference period of the survey multiplied by the ratio of employment in discouraged firms to that of successful applicants.

Our baseline results suggest a credit gap of 8.4% of GDP or USD 306bn for the countries covered in this study. 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 workforce. 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 6.2% of GDP or USD 225bn.

We subject the baseline result to a series of robustness checks. Specifically, we derive 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. Adjusting for macro-financial characteristics compresses cross-country variation, yielding on average larger gaps in countries with small baseline gaps and vice versa. A substantial deviation between the baseline and the adjusted credit gap indicates that the results are subject to greater uncertainty. In addition, we develop an alternative allocation regime that does not depend on a rejection threshold. The results largely replicate the baseline estimate. Finally, we study the sensitivity of our results to unobserved differences between applicants and discouraged firms by allocating credit based on the assumption that the actual rejection probabilities are 25% higher than the model-implied probabilities. This yields a marginally smaller credit gap of 8% of GDP, which amounts to 94% of the baseline.

This paper contributes to the literature on credit gaps. The literature has developed two approaches, each with its own purpose: (i) a macroeconomic approach, and (ii) methodologies based on firm-level data. The former is employed primarily in macroprudential contexts, such as setting countercyclical capital buffers in the context of Basel III (Drehmann and Tsatsaronis, 2014; Lang and Welz, 2018). The latter takes a bottom-up approach to quantifying structural excess demand for credit, mainly in a developing country or emerging market context.

The bottom-up approach frequently exploits surveys, as balance sheet data represent equilibrium outcomes and are not designed to measure excess demand. Contributions include Chakraborty and Mallick (2012); Domeher et al. (2017); Lopez-de Silanes et al. (2018); Cole and Sokolyk (2016) and Corrigan et al. (2020). The closest in scope to our paper is IFC et al. (2017). They use the credit intensity of SMEs in ten advanced benchmark economies to derive potential demand by SMEs in emerging and developing countries and find a financing gap for SMEs totalling USD 5.2 trillion, or 19% of GDP on average for a large pool of emerging and developing economies. Our paper is different in that it draws on the credit intensity of successful applicants to derive the potential demand of bankable discouraged firms located in the same country.

To quantify excess demand for credit, our paper draws on the literature on discouraged borrowers. Levenson and Willard (2000) and Kon and Storey (2003) argue that there can exist good firms in need of external finance, *discouraged borrowers*, that choose not to apply for a loan due to high applications costs or fear of rejection. Our paper is thus related to studies by Brown et al. (2011); Mac an Bhaird et al. (2016); Cole and Sokolyk (2016); Rostamkalaei et al. (2020); Brown et al. (2022) and Ferrando and Mulier (2022) in that it identifies the financing needs of discouraged borrowers that are bankable from a credit scoring perspective. Banks may seek to address these needs when improvements in monetary and economic conditions allow for an expansion of aggregate credit (Ruckes, 2004; Dell'Ariccia and Marquez, 2006).

The remainder of the paper is organized as follows: Section 2 introduces the data; Section 3 provides an account of the methodology; Section 4 presents the results. Section 5 concerns the robustness and sensitivity checks. The last section concludes.

2 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 firms 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 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.[2] 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

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

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.

In total, approximately 38% of firms in the economies covered by the Enterprise Surveys desired bank credit during the last financial year. As Table 2 shows, 16% of firms did actually apply for a loan[3], whereas 22% were discouraged from doing so. The vast majority of credit-constrained firms are discouraged from applying for a loan, as only 1.2% of companies have their loan application rejected. Empirically, rejections do 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 2, 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

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

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 Non-financial Corporate (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% (derived from the 2019 ECB data). 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 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. 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.

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.[4] 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 the 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.

[4] 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 $maturity_i^{lt}$.

3 Methodology

3.1 Allocating Credit to Discouraged Firms

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. The Enterprise Survey identifies the firms needing a loan. Firms that do not need a loan are not relevant for the analysis. Firms that do need a loan fall into two categories: applicants and discouraged firms. Loan applications are subject to a screening mechanism, and as a result also fall into two categories depending on whether they are approved or rejected.

To identify the set of bankable discouraged firms we first estimate a scoring model. The scoring model is predicated on the following, stylized sequential screening mechanism for $P(rejected_j|applied_j = 1)$, which is the probability for firm j of seeing its loan application rejected conditional on having applied for a loan. At time t_0, the financial institution sets its risk appetite, taking into account profitability targets, risk policies, strategic planning, as well as its cost structure, notably its cost of capital. This set of parameters determines a threshold probability of default PD^*, above which a bank rejects loan applications. Firm j decides to apply for a loan at time t_1. If firm j applies, a bank assesses firm j's riskiness via the measurement of firm j's probability of default PD_j at time t_2. At time t_3, firm j's loan application is rejected or accepted depending on whether PD_j exceeds the selection threshold PD^*.

$$P(rejected_j|applied_j) = 1 - P(approved_j|applied_j) = P(PD_j \leq PD^*|applied_j) \qquad (2)$$

We do not have information on the probability of default of firms. However, the Enterprise Survey contains detailed information on firms' ability to access finance, including the outcome of loan applications. Our analysis therefore focuses on whether the loan application is approved or rejected, bearing in mind the link to the default probability shown in Equation 2.

The Enterprise Survey provides a large set of candidate predictors to estimate a scoring model for $P(rejected_j|applied_j)$. We narrow down and select the predictors using the Lasso (Tibshirani, 1996), specifically a Lasso-Logit (Friedman et al., 2010). The Lasso performs variable selection and regularization to avoid overfitting and to 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:

$$\widehat{\boldsymbol{\beta}}_{LASSO}(\lambda) = \arg\min \left\{-\ell_{LOGIT}(\beta_0, \boldsymbol{\beta}) + \lambda\,||\boldsymbol{\beta}||_1\right\} \tag{3}$$

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.

The goal of the scoring model is to provide an assessment of the creditworthiness of discouraged firms. To this end, we employ the scoring model out of sample to obtain rejection probabilities for the discouraged firms. However, a predicted rejection probability does not directly indicate whether a firm would obtain credit or not. To allocate credit, we need to set a threshold probability above which a firm is rejected. We resort to the observable information for applicant firms. Specifically, the threshold level $\tilde{p}$ follows from the percentile of the rejection probability distribution that replicates the observed rejection rate in the sample of applicants.

$$\tilde{p} = F_p^{-1}(1 - \overline{rejected}) \tag{4}$$

As a result, discouraged firms with a predicted rejection probability below this threshold obtain credit.

3.2 From Firm-Level Data to Country-Level Aggregates

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

$$credit\ gap_i = \sum_{j \in discouraged} w_{ij}\ \mathbb{1}(\widehat{approved}_{ij})\ \widehat{volume}_{ij} \tag{5}$$

where w_{ij} is the survey weight of firm j in country i. The indicator function $\mathbb{1}(\widehat{approved}_{ij})$ equals one if and only if the probability of rejection is below the threshold probability $\tilde{p}$. 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:

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

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 6 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:

$$credit\ gap_i^{SME} = credit\ flow_i \frac{\sum_{j \in discouraged} w_{ij}\ \mathbb{1}(\widehat{approved}_{ij})\ \mathbb{1}(SME_{ij})\ emp_{ij}}{\sum_{k \in applied} w_{ik}\ \mathbb{1}(approved_{ik})\ emp_{ik}} \tag{7}$$

4 Results

The objective of the scoring model described in section 3.1 is to identify a set of predictors for firms that applied for a loan and to use it out of sample to assess the creditworthiness of discouraged firms.

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. Therefore, we apply the Lasso procedure to a model with 51 regressors. Table 3 provides definitions of the variables selected by Lasso and omits the candidate variables that do not enter the final model.[5] Table 4 presents the corresponding summary statistics for both the applicants and the discouraged firms.

Choosing a good value for the penalty term λ is crucial because it controls the amount of regularization, i.e. how much to shrink the coefficients. In line with Abadie and Kasy (2019), which highlights the importance of using data-driven procedures to select penalty parameters, we initially apply 5-fold cross-validation to obtain the penalty

[5]Definitions of the variables that do not survive the Lasso are available from the authors on request. All predictors are binary variables; lack of financial statement information is a limitation of the Enterprise Surveys.

term λ. Under 5-fold cross-validation, the Lasso selects 18 of the 51 regressors entering the model. However, our variable selection isn't too sensitive to alternative approaches to pick a penalty term, i.e. using information criteria. Table 5 summarizes the variables selected by Lasso using these different approaches. Variable selection under the Akaike information criterion (AIC) yields the same 18 regressors as with 5-fold cross-validation. Not surprisingly, fewer variables are selected under the Bayesian information criterion (BIC) due to its heavy penalty on model complexity. Finally, we lose two regressors if we use a 10-fold cross-validation.

Table 6 shows the results of the post-Lasso logit with these 18 regressors. 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 that 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 variables may be considered endogenous, it is important to note that the goal of the exercise is prediction, not to uncover the true parameter values.[6]

It appears that the scoring model is able to distinguish between successful and rejected applicants. Figure 3A and Figure 3B present 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.

Discouraged firms have on average a higher model-implied probability of rejection than firms with an approved loan application. Figure 3C presents the results of the

[6]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 effects are subject to the Lasso model selection procedure or not.

out-of-sample prediction for discouraged firms. The average probability of rejection for discouraged firms equals 15.2%, which is more than twice as high as 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. On average, discouraged firms have readings of variables that are negatively 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.

The next step is to allocate credit. Figure 4 documents the steps of our credit allocation mechanism. The rejection rate for the applicant firms in the sample is 7.8%, which amounts to an approval rate of 92.2%. As shown in Figure 4A, this approval rate is matched in the cumulative distribution of the predicted rejection probabilities for the applicant firms. The 92$^{\text{nd}}$ percentile of the distribution corresponds to a rejection threshold of 22.9%. We apply this rejection threshold to the distribution of the predicted rejection probabilities for the discouraged firms. As a result, we allocate credit to discouraged firms with a rejection probability below the threshold (see Figure 4B). We find that conditional on the rejection threshold, 77.2% of the discouraged firms would have had their loan application approved. Thus, the discouraged firms are on average less creditworthy than the applicant firms. If they were to apply to a loan, they would face a rejection rate close to three times higher than firms that actually applied for a loan. At the same time, the majority of discouraged firms would have their loan application accepted, had they applied for a loan. The scoring model considers them comparable to successful applicants, which is in line with the results in Ferrando and Mulier (2022).

We apply the aggregation method presented in section 3.2 to the firm-level credit allocation obtained so far. Our baseline results suggest an aggregate credit gap of

USD 306bn or 8.4% of GDP for the countries covered in this study. Table 7 presents the estimates by country and region. At USD 103.3bn, which corresponds to 18.9% of 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 45.9bn) and Morocco (USD 30bn). Relative to GDP, Jordan and Lebanon also have large credit gaps of 24.3% and 21.6%, respectively. This appears counter-intuitive, 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 during 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 101bn, but that accounts for only 13% 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 7.5% in EN to 2.5% in WB, for different reasons. In EN and, to a certain extent, CA the on average lower credit gaps are the result of high implied rejection rates that significantly shrink the set of discouraged firms. Moreover, the 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 224bn or 6.2% of GDP. At 13.9%, SN has the highest SME credit gap relative to GDP, whereas Turkey has the highest gap in nominal terms (USD 81.8bn). 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, Georgia and Azerbaijan are more in line with the other regional aggregates.

At 6.2% 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.[7] 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 8.4% of GDP to the stock of outstanding credit of 22% of GDP amounts to less than the euro area average of 41% of GDP.

5 Robustness and Sensitivity

5.1 Adjusting for Macro-Financial Fundamentals

A drawback of the approach outlined so far is that it 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 6, derived from a projection of the credit gap on a set of macro-financial variables. In a simple way, this

[7] 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.

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 the 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. [8] Specifically, we consider the following variables: (i) Log GDP per capita. Higher GDP per capita can be viewed as a shortcut 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 a 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 variable selection. Given that the distribution of the credit gap variable is by construction non-negative, we are applying the Lasso to a Poisson regression.

[8] Previous studies linking macro-financial fundamentals to the level of firms' discouragement in the economy (e.g. Mol-Gómez-Vázquez et al., 2022; Mol-Gómez-Vázquez et al., 2019) also inform the choice of candidate variables to the extent possible given the large set of emerging and developing markets covered in our study.

Table 8 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 9 shows, the aggregate adjusted credit gap amounts to USD 266bn, which is USD 40bn smaller than the baseline credit gap. At the regional level, the difference between the baseline and the adjusted credit gap amounts to 1.1% of GDP. The exception is SN, with an adjusted credit gap of USD 73.7bn, which is almost USD 30bn smaller than the baseline. Column 3 of Table 9 provides evidence on how the baseline and the adjusted credit gap compare at the country and regional levels. On average, countries with a small baseline gap as a percentage of GDP also have a small adjusted credit gap, albeit one that is slightly larger. For some countries with a baseline credit gap that is close to zero, such as the Czech Republic and Slovenia, the adjustment results in an eleven-fold increase in the credit gap, though the difference is limited in terms of GDP. On the other hand, countries with a high baseline credit gap have on average a smaller adjusted credit gap. This applies in particular to Jordan, Bulgaria, and to a lesser extent Egypt and Ukraine. This is expected, as the regression compresses cross-country variation. On the other hand, for Tunisia and Palestine, two countries with a sizeable credit gap to begin with, the adjustment yields a further increase in the credit gap of 11.4 p.p. and 7.9 p.p., respectively.

5.2 Proportional Allocation Mechanism

Allocating credit based on a rejection threshold that corresponds to a threshold probability of default mimics the behaviour of banks. One may object that the way in which we derive the rejection threshold is somewhat arbitrary. This subsection develops an alternative allocation mechanism that does not require a rejection threshold. As the goal of this exercise is to derive a credit gap at the level of the economy, we assume an allocation of credit in proportion to the approval probability of the individual firm. This yields the following expression for the credit gap in country i:

$$credit\ gap_i = credit\ flow_i \frac{\sum_{j \in discouraged} w_{ij}\ \mathbb{P}(\widehat{approved_{ij}})\ emp_{ij}}{\sum_{k \in applied} w_{ik}\ \mathbb{1}(approved_{ik})\ emp_{ik}} \tag{8}$$

Whereas the baseline approach fully meets the needs of firms with a rejection probability below the threshold, and fully rations those with a rejection probability above, Equation 8 rations all firms in accordance with their rejection probability. Thus, a firm with a rejection probability of 1% obtains 99% of the desired credit whereas a firm with a rejection probability of 10% receives only 90% of the desired credit. This works, because we are dealing with a sample of firms that represent a large number of firms in the economy as indicated by the sampling weight w_{ij}. Thus, for a sample firm that represents 20 firms in the economy and has a rejection probability of 10%, 2 firms in the economy would be denied credit, whereas 18 would have their loan application approved.

Proportional allocation yields a marginally larger total credit gap of 8.7% of GDP or USD 316bn, compared to a baseline of 8.4% or USD 306bn (see Table 10). At the country level, the difference is biggest in Jordan, where the credit gap increases by USD 4.6bn or 10.8p.p. Apparently, the Jordanian sample has a relatively large share of companies with rejection probabilities exceeding the threshold. These firms are fully rationed under the baseline methodology but have their demands partially met under proportional allocation. Other countries with sizeable differences include Slovakia and North Macedonia where proportional allocation yields a credit gap that is 4.1 p.p. and 3.3 p.p. higher than the baseline. Differences between the baseline and proportional allocation tend to average out at the regional level where samples are larger. For instance, for CEE, SN, TUR, and WB the difference between both methods is less than 0.5 p.p. of GDP.

5.3 Unobserved Differences between Applicants and Discouraged Firms

So far, the analysis has assumed that the scoring model captures all relevant differences between applicants and discouraged firms. The analysis is predicated on the existence of information asymmetries between borrowers and lenders. A fortiori, this applies to us as analysts. Figure 3 illustrate that in terms of observables discouraged firms have on average worse credit risks than applicants. It is also likely that they are worse in ways that are unobservable to us. Jiménez et al. (2018) demonstrate empirically the importance of unobservable risk factors during a credit crunch.

This subsection therefore examines the sensitivity of the results to unobserved risk factors. Specifically, we assume that the true rejection probabilities are 25% higher than the model outcomes. Figure 5 illustrates how the distribution of rejection probabilities changes when they are scaled by a factor of 1.25. Some firms that under the baseline specification are located to the left of the rejection threshold move to the right and thus will be denied credit. As a result, the approval rate drops from 77.2% under the baseline to 69.4%.

Table 11 shows that the total credit gap declines marginally to 8% of GDP or USD 298bn, which amounts to 94% of the baseline. In most economies, the credit gap shrinks by less than 20%. One exception is Lithuania, where the credit gap drops to 0.6% of GDP, which corresponds to only 53% of the baseline. On the other hand, in nine economies the credit gap is not sensitive at all to scaling the rejection probabilities. In the end, it appears that the limited sensitivity of the results can be attributed to the limited probability mass around the rejection threshold.

Figure 6 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. Jordan stands out with estimates ranging from 8% to 35% of GDP. This pattern may reflect data quality issues with this particular survey. At the regional level, SN has both the highest credit gap and the widest dispersion of estimates. This suggests that the estimates be taken with a pinch of salt. On the other hand, there are many countries with a fairly narrow range of estimates. These are mainly those with a comparatively low baseline credit gap.

6 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 and allocate them credit we estimate a scoring model, trained to predict rejections in the sample of loan applicants. The model is deployed out-of-sample to obtain rejection probabilities for the discouraged firms. Credit is allocated by inferring a threshold in the distribution of rejection probabilities of discouraged firms that corresponds to the observable applicants' rejection rate.

We find that discouraged firms have a close to three times higher rejection rate than the applicant firms and thus are on average less creditworthy. At the same time, roughly 77% of the discouraged firms would have had their loan application approved. This points to inefficient credit rationing. 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 306bn or 8.4% 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 6.2% of GDP. This reflects both their contribution to economic activity and the fact that they are more likely to be credit-constrained. Adjusting for macro-financial factors yields comparable results to the baseline credit gap for most regions, with an overall credit gap among all countries of 7.3%.

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 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.

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Figures and Tables

TABLE 1: DEFINITION OF COUNTRY GROUPINGS

This table shows the countries and their groupings covered in this paper. Owing to its size, Turkey constitutes its own entity.

COUNTRY GROUP		COUNTRY	ISO
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

Table 2: Need for Loans

This table shows the profile of the firm population in the Enterprise Surveys. Column 1 reports the share of firms that have stated they are in need of a loan. Column 2 reports the share of firms that have stated they applied for a loan. Column 3 reports the share of firms that have stated they had their loan application rejected. Column 4 reports the share of firms that have stated they were discouraged from applying for a loan. Regional results are highlighted in gray.

	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 3: VARIABLE DEFINITIONS - ENTERPRISE SURVEY

This table provides the definitions of the variables selected by Lasso under 5-fold cross-validation.

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
Legal Status - Public	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 limited 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	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 4: SUMMARY STATISTICS - ENTERPRISE SURVEY

This table reports the mean and the standard deviation of the 18 variables selected by Lasso under 5-fold cross-validation for the applicant firms and for the discouraged firms.

	APPLICANT		DISCOURAGED	
	MEAN	SD	MEAN	SD
Legal Status - Public	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	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: COMPARISON OF DIFFERENT PENALTY SELECTION APPROACHES

This table shows the variables selected by Lasso using different approaches for selecting the optimal penalty parameter λ. Column 1 reports the variable selection under 5-fold cross-validation, the preferred approach in this paper, as reference. Columns 2 and 3 report the variables selected when Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to select λ, respectively. Column 4 reports the variables under the approach with a 10-fold cross-validation.

	5-CV	AIC	BIC	10-CV
Legal Status - Public	✓	✓	✗	✗
Legal Status - Other	✓	✓	✗	✓
Business Strategy	✓	✓	✗	✗
Supervisory Board	✓	✓	✗	✓
0-5 Years	✓	✓	✓	✓
Certificate	✓	✓	✓	✓
Website	✓	✓	✓	✓
Expected Total Sales Decrease	✓	✓	✓	✓
Owns Building	✓	✓	✓	✓
Invested: Fixed Assets	✓	✓	✓	✓
Leased: Fixed Assets	✓	✓	✓	✓
Bank Account	✓	✓	✗	✓
Overdraft Facility	✓	✓	✓	✓
Audited	✓	✓	✗	✓
Import License Application	✓	✓	✓	✓
Operating License Application	✓	✓	✓	✓
Small Firm	✓	✓	✓	✓
Exporter	✓	✓	✗	✓

TABLE 6: MODEL SELECTED BY LASSO LOGIT UNDER 5-FOLD CROSS-VALIDATION

This table reports the post-Lasso logistic regression with country and sector fixed effects. The variables are selected by Lasso. Dependent variable is the loan applications rejected. *t*-Statistics are in parentheses. * p < 10%, ** p < 5%, *** p < 1%.

VARIABLE	REJECTED
Legal Status - 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

TABLE 7: BASELINE CREDIT GAP ESTIMATES

This table reports the baseline credit gap estimates. Columns 1 and 2 report the total credit gap in percent of GDP and in million US dollars, respectively. Columns 3 and 4 report the SME credit gap in percent of GDP and in million US dollars, respectively. Column 5 shows the share of the SME credit gap in the total credit gap. Regional results are highlighted in gray.

	CREDIT GAP		SME CREDIT GAP		
	[% GDP]	[MILLION USD]	[% GDP]	[MILLION USD]	[% BASELINE]
CA	3.4	8,914	2.3	6,030	68
KAZ	2.9	5,175	2.0	3,503	68
KGZ	1.9	155	1.2	97	62
MNG	3.2	427	2.1	283	66
TJK	3.7	288	2.5	191	66
UZB	5.5	2,869	3.7	1,956	68
CEE	4.2	68,627	3.0	48,594	71
BGR	13.4	8,890	10.8	7,175	81
CZE	0.3	627	0.2	547	87
EST	0.5	148	0.4	117	79
HRV	0.4	268	0.4	222	83
HUN	1.2	1,872	0.8	1,239	66
LTU	1.1	575	1.0	528	92
LVA	1.5	508	1.0	358	71
POL	5.1	29,890	4.7	27,699	93
ROU	6.8	16,402	3.3	7,988	49
SVK	8.8	9,326	2.5	2,599	28
SVN	0.2	123	0.2	123	100
EN	7.5	21,034	3.7	10,256	49
ARM	3.6	443	1.6	205	46
AZE	1.1	539	0.9	442	82
BLR	3.6	2,183	1.1	665	30
GEO	0.6	101	0.6	101	100
MDA	1.8	203	1.2	138	68
UKR	13.4	17,564	6.6	8,705	50
SN	18.9	103,337	13.9	76,120	74
EGY	17.4	45,911	14.2	37,246	81
JOR	24.5	10,513	17.1	7,334	70
LBN	21.6	11,852	18.1	9,911	84
MAR	23.7	30,134	14.6	18,605	62
PSE	10.8	1,751	9.3	1,521	87
TUN	7.4	3,175	3.5	1,502	47
TUR	13.0	101,321	10.5	81,823	81
WB	2.5	2,852	1.6	1,752	61
ALB	0.9	131	0.7	106	81
BIH	4.3	874	2.3	455	52
MKD	2.1	264	1.6	208	79
MNE	1.3	74	1.3	74	100
SRB	1.7	862	0.8	394	46
XKX	8.2	647	6.5	515	80
TOTAL	8.4	306,086	6.2	224,575	73

TABLE 8: ADJUSTING FOR MACRO-FINANCIAL FUNDAMENTALS

This table reports Poisson regressions with robust standard errors. Dependent variable is the credit gap. Column 1 presents the full model without a Lasso penalty. Column 2 presents the model with variables selected by Lasso based on 5-fold cross-validation. *t*-Statistics are in parentheses. * p < 10%, ** p < 5%, *** p < 1%.

	FULL MODEL	POST SELECTION
Log GDP Per Capita	0.075	
	(0.179)	
Output Gap	-0.180*	-0.131**
	(0.107)	(0.066)
Political Stability (WGI)	-0.325	-0.412**
	(0.274)	(0.182)
Capital Adequacy Ratio	-0.123***	-0.116***
	(0.046)	(0.041)
Loan-to-Deposit Ratio	0.000	
	(0.005)	
Non-Performing Loan Ratio	0.012	
	(0.015)	
Return on Assets	-0.020	
	(0.203)	
Constant	3.173*	3.722***
	(1.698)	(0.769)
Pseudo R2	0.332	0.326

TABLE 9: CREDIT GAP ADJUSTED FOR MACRO-FINANCIAL FUNDAMENTALS

This table reports the adjusted credit gaps, derived from a projection of the credit gap on a set of macro-financial variables selected by Lasso. Column 1 reports the results in percent of GDP. Column 2 reports the results in million US dollars. Columns 3 and 4 report this adjusted credit gap estimate as percentage of the baseline credit gap estimate and its percentage point difference from the baseline credit gap estimate. Regional results are highlighted in gray.

	CREDIT GAP (MACRO-FINANCIAL ADJUSTMENT)			
	[% GDP]	[MILLION USD]	[% OF BASELINE]	[± PP. FROM BASELINE]
CA	4.6	12,077	135	1.2
KAZ	3.5	6,207	120	0.6
KGZ	3.5	289	186	1.6
MNG	4.5	594	139	1.3
TJK	4.0	310	108	0.3
UZB	8.9	4,677	163	3.4
CEE	2.9	48,058	70	-1.3
BGR	2.9	1,929	22	-10.5
CZE	2.9	7,238	1155	2.7
EST	1.1	333	224	0.6
HRV	1.6	1,021	381	1.2
HUN	2.5	4,056	217	1.4
LTU	3.3	1,798	313	2.3
LVA	2.1	739	146	0.7
POL	3.2	18,760	63	-1.9
ROU	3.0	7,343	45	-3.8
SVK	3.3	3,459	37	-5.5
SVN	2.6	1,383	1127	2.3
EN	7.0	19,431	92	-0.6
ARM	5.8	720	162	2.2
AZE	6.5	3,085	572	5.4
BLR	3.8	2,300	105	0.2
GEO	5.8	1,028	1017	5.3
MDA	2.2	251	123	0.4
UKR	9.2	12,047	69	-4.2
SN	13.5	73,703	71	-5.4
EGY	12.6	33,028	72	-4.9
JOR	8.1	3,462	33	-16.4
LBN	15.2	8,336	70	-6.4
MAR	14.0	17,790	59	-9.8
PSE	18.7	3,048	174	8.0
TUN	18.8	8,039	253	11.4
TUR	13.9	108,410	107	0.9
WB	4.0	4,490	157	1.5
ALB	3.5	531	405	2.6
BIH	5.1	1,022	117	0.7
MKD	6.3	802	304	4.2
MNE	4.9	272	368	3.6
SRB	2.5	1,280	149	0.8
XKX	7.4	583	90	-0.8
TOTAL	7.3	266,169	87	-1.1

TABLE 10: CREDIT GAP RESULTING FROM PROPORTIONAL CREDIT ALLOCATION

This table reports the credit gaps resulting from a credit allocation where each firm gets credit proportional to their rejection probabilities, i.e. every firm gets rationed. Column 1 reports the results in percent of GDP. Column 2 reports the results in million US dollars. Columns 3 and 4 report this proportional credit gap estimate as percentage of the baseline credit gap estimate and its percentage point difference from the baseline credit gap estimate. Regional results are highlighted in gray.

	CREDIT GAP (PROPORTIONAL CREDIT ALLOCATION)			
	[% GDP]	[MILLION USD]	[% OF BASELINE]	[± PP. FROM BASELINE]
CA	4.5	11,759	132	1.1
KAZ	4.3	7,641	148	1.4
KGZ	2.0	169	109	0.2
MNG	3.5	468	109	0.3
TJK	3.7	288	100	0.0
UZB	6.1	3,193	111	0.6
CEE	4.4	73,042	106	0.3
BGR	12.9	8,576	96	-0.5
CZE	0.2	591	94	0.0
EST	0.5	147	99	0.0
HRV	0.4	258	96	0.0
HUN	1.1	1,795	96	-0.1
LTU	2.3	1,246	217	1.3
LVA	1.6	552	109	0.1
POL	4.7	27,458	92	-0.4
ROU	7.7	18,603	113	0.9
SVK	13.0	13,698	147	4.1
SVN	0.2	119	97	0.0
EN	8.9	24,736	118	1.3
ARM	3.4	420	95	-0.2
AZE	1.2	585	109	0.1
BLR	3.5	2,127	97	-0.1
GEO	0.8	148	147	0.3
MDA	5.1	577	284	3.3
UKR	15.9	20,878	119	2.5
SN	19.4	106,280	103	0.5
EGY	16.5	43,400	95	-1.0
JOR	35.3	15,174	144	10.9
LBN	23.4	12,828	108	1.8
MAR	22.5	28,649	95	-1.2
PSE	10.9	1,781	102	0.2
TUN	10.4	4,449	140	3.0
TUR	12.5	97,738	96	-0.5
WB	2.5	2,851	100	0.0
ALB	0.9	129	99	0.0
BIH	4.2	853	98	0.1
MKD	2.2	282	107	0.1
MNE	1.3	72	97	0.0
SRB	1.7	847	98	0.0
XKX	8.5	669	103	0.3
TOTAL	8.7	316,405	103	0.3

TABLE 11: CREDIT GAP UNDER UNOBSERVED DIFFERENCES

This table presents the sensitivity of the baseline credit gap estimates to unobserved differences between the applicants and the discouraged firms. Columns 1 and 2 report the credit gap under the assumption that the true rejection probability is 25% higher than the estimated rejection probability. Column 3 shows the credit gap accounting for unobserved differences relative to the baseline credit gap. Column 4 reports the percentage point difference from the baseline credit gap estimate. Regional results are highlighted in gray.

	CREDIT GAP (UNOBSERVED DIFFERENCES)			
	[% GDP]	[MILLION USD]	[% OF BASELINE]	[± PP. FROM BASELINE]
CA	2.9	7,502	84	-0.5
KAZ	2.5	4,456	86	-0.4
KGZ	1.7	140	90	-0.2
MNG	2.7	360	84	-0.5
TJK	3.6	278	97	-0.1
UZB	4.3	2,268	79	-1.1
CEE	3.7	60,435	88	-0.5
BGR	13.3	8,852	100	-0.1
CZE	0.3	627	100	0.0
EST	0.4	125	84	-0.1
HRV	0.4	268	100	0.0
HUN	1.2	1,864	100	0.0
LTU	0.6	306	53	-0.5
LVA	1.2	419	82	-0.3
POL	4.4	26,079	87	-0.7
ROU	5.9	14,155	86	-0.9
SVK	7.2	7,618	82	-1.6
SVN	0.2	123	100	0.0
EN	6.6	18,499	88	-0.9
ARM	3.5	441	99	0.0
AZE	1.0	475	88	-0.1
BLR	3.6	2,136	98	-0.1
GEO	0.5	96	95	0.0
MDA	1.4	162	79	-0.4
UKR	11.6	15,190	86	-1.8
SN	18.3	100,053	97	-0.6
EGY	16.8	44,115	96	-0.7
JOR	23.9	10,271	98	-0.6
LBN	20.0	10,954	92	-1.6
MAR	23.7	30,134	100	0.0
PSE	9.7	1,577	90	-1.1
TUN	7.0	3,003	95	-0.4
TUR	12.8	99,722	98	-0.2
WB	2.4	2,740	96	-0.1
ALB	0.9	131	100	0.0
BIH	4.0	814	93	-0.3
MKD	1.7	220	83	-0.4
MNE	1.3	74	100	0.0
SRB	1.7	862	100	0.0
XKX	8.1	639	99	-0.1
TOTAL	8.0	288,951	94	-0.5

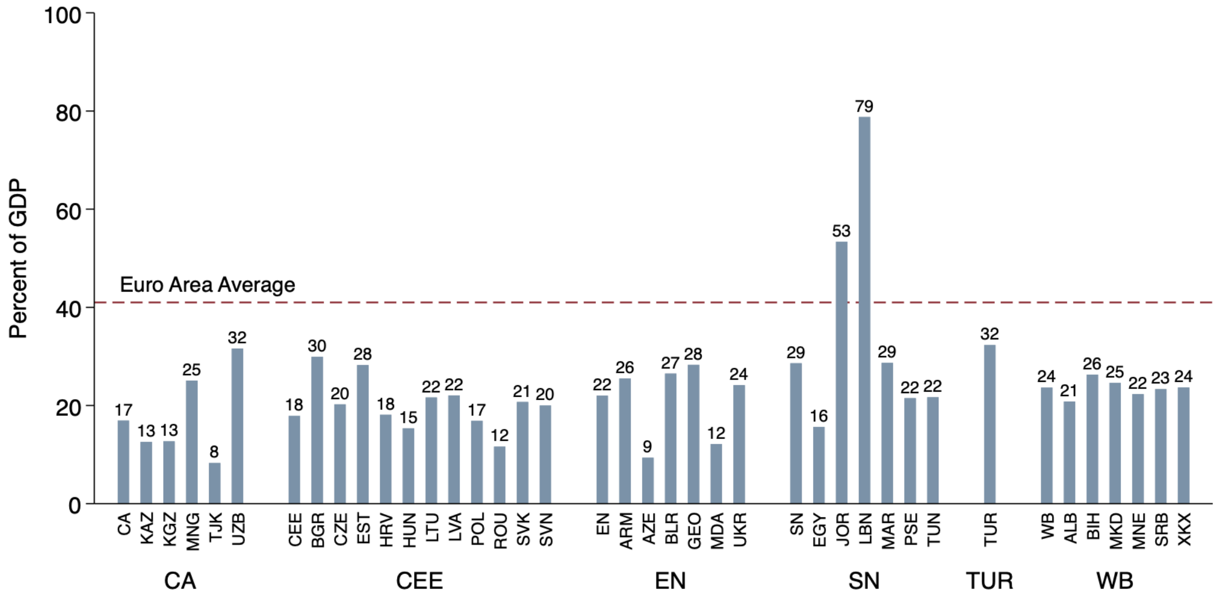


FIGURE 1: CREDIT TO NON-FINANCIAL CORPORATIONS

This figure plots the credit to non-financial corporations (NFC) relative to GDP for each country and region in our sample. The data primarily come from the International Monetary Fund's (IMF) the Financial Soundness Indicators (FSI) and the European Central Bank (ECB); when these resources are not available for a country we resort to the IMF's the Financial Access Survey (FAS) and the local central banks. The stock of NFC credit is adjusted by the share of value added in the industrial and services sectors, which is obtained from the World Bank (WB). The red line indicates the Euro area average of NFC credit to GDP.

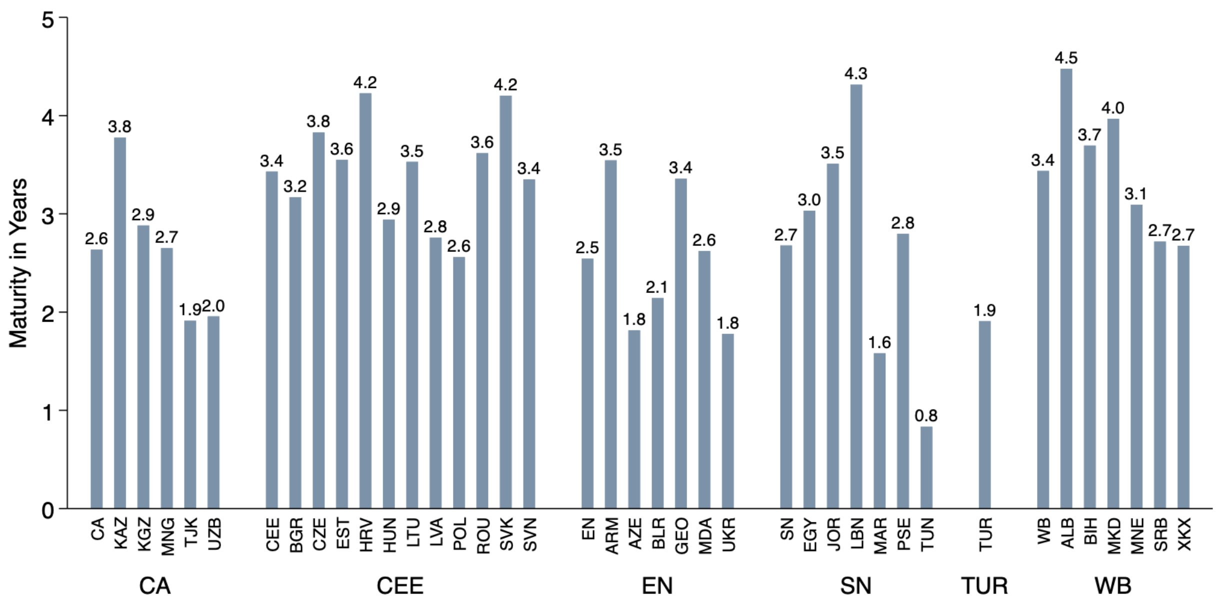
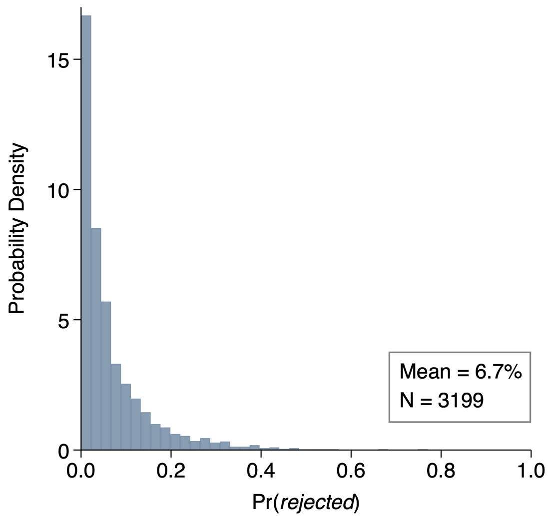
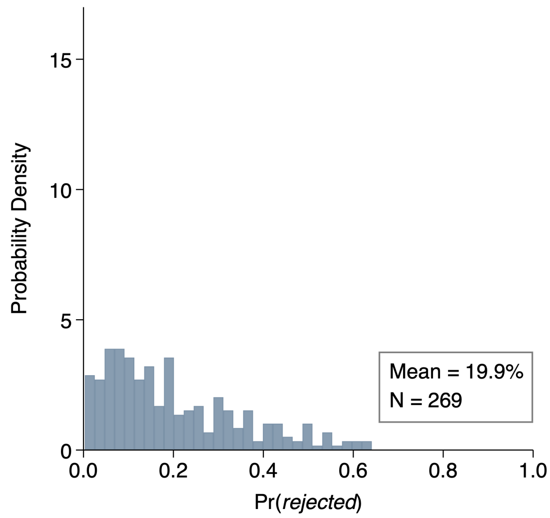


FIGURE 2: AVERAGE ORIGINAL MATURITY OF LOANS

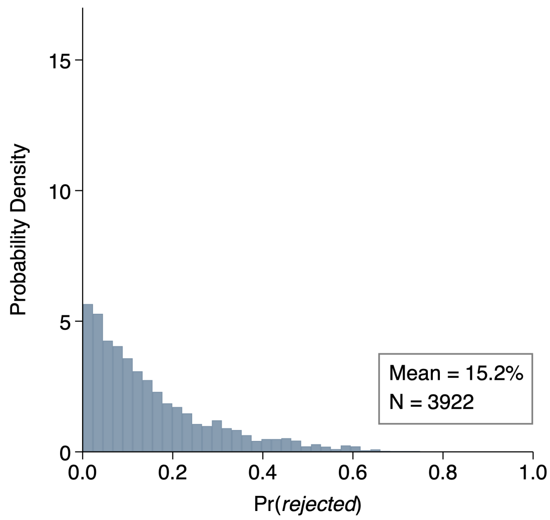
This figure shows the average maturity in years of the last outstanding loan for firms in the sample. The data come from firms' responses to Q.BMk10 in the 2018-2020 wave of the Enterprise Surveys.



(A) APPROVED APPLICANTS



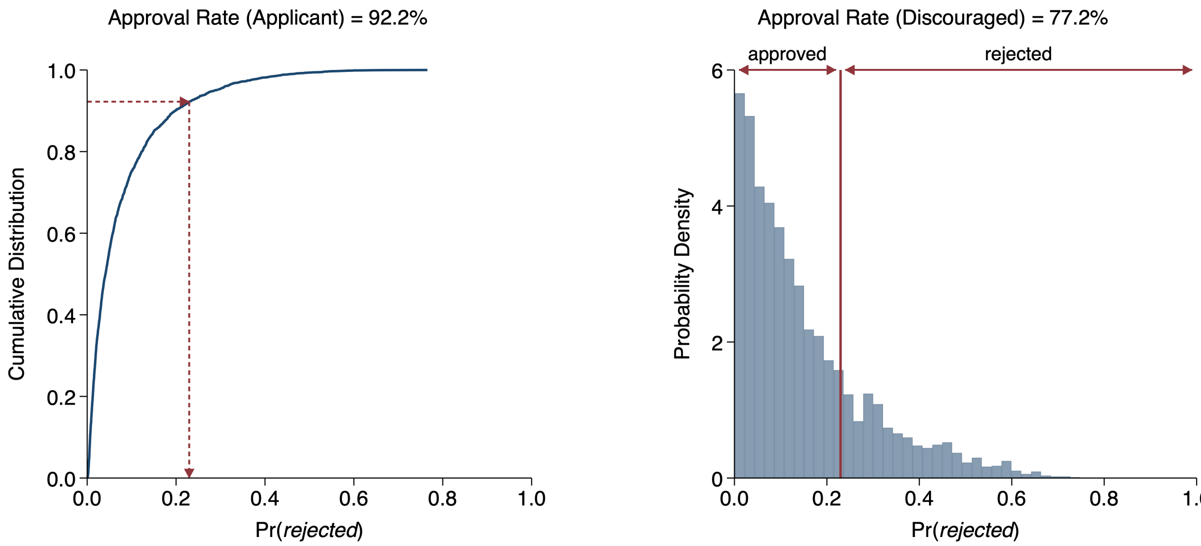
(B) REJECTED APPLICANTS



(C) DISCOURAGED FIRMS

FIGURE 3: PREDICTED REJECTION PROBABILITIES

This figure shows the distributions of firms' rejection probabilities. Panels A and B present the rejection probabilities in-sample for firms whose loan applications were approved and rejected, respectively. Panel C presents the rejection probabilities out-of-sample for firms that were discouraged from applying for a loan. In each panel, we report the mean rejection probability and the number of observations in the distribution.



(A) **(B)**

Figure 4: Credit Allocation Mechanism

This figure shows how the rejection threshold is determined and then used to allocate credit to discouraged firms. Panel A shows how the rejection threshold is inferred by matching the share of rejections in the sample of applicant firms. Panel B shows how a discouraged firm with an estimated rejection probability below the inferred rejection threshold gets credit.

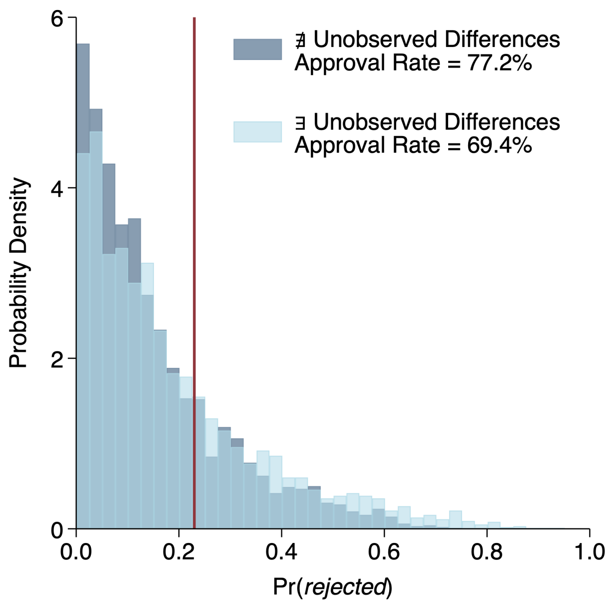


Figure 5: Unobserved Difference Between The Applicant and The Discouraged Firms

This figure shows the effect of unobserved differences between the applicant and the discouraged firms. The baseline distribution with dark blue assumes there are no unobserved differences. The light blue distribution scales the baseline distribution assuming that the true rejection probability is 25% higher than the estimated rejection probability. The red line depicts the threshold probability. We further report the estimated approval rates of discouraged firms in both cases.

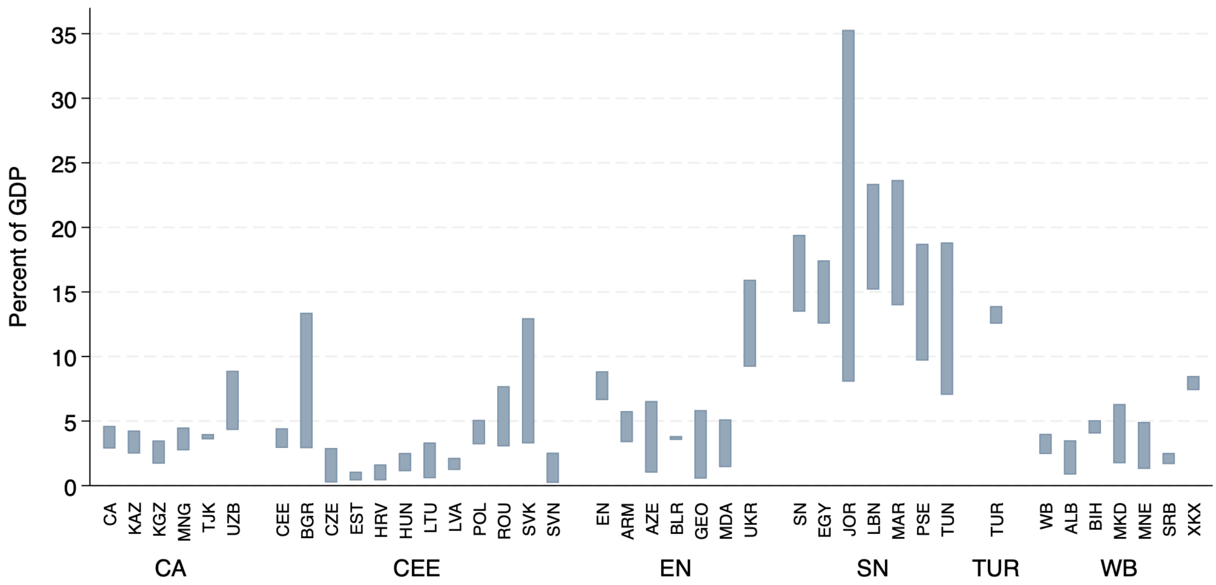


FIGURE 6: RANGE OF CREDIT GAP ESTIMATES

This figure shows the range of credit gap estimates for each country and region in the sample. We report the minimum and the maximum among the different credit gap estimates: baseline, baseline adjusted for macro-financial fundamentals, baseline adjusted for unobserved differences, proportional credit allocation.

Quantifying credit gaps using survey data on discouraged borrowers

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