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Does Bank Efficiency Influence the Cost of Credit?

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Abstract

Using a large sample of firms from nine European countries, this study examines the relationship between bank efficiency and the cost of credit for borrowing firms. We hypothesize that bank efficiency – the ability of banks to operate at lower costs – is associated with lower loan rates and thus lower cost of credit. Combining firm-level and bank-level data, we find support for this prediction. The effect of bank efficiency on the cost of credit varies with firm and bank size. Bank efficiency reduces the cost of credit for SMEs, but does not exert a significant influence for either micro companies or large firms. Furthermore, the effect is driven by large banks, where improvements in bank efficiency tend to be strongly associated with lower cost of credit. We also find that lower bank competition facilitates the transmission of greater bank efficiency to lower cost of credit. Overall, our results indicate that measures that increase bank efficiency can foster access to credit.

JEL Codes: G21, L11.
Keywords: bank efficiency, cost of credit.

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1. Introduction

Cost efficiency of banks is a broad measure of bank performance that has frequently been utilized in empirical banking literature over the last two decades. It measures the ability of a bank to operate at lower cost by comparing its cost structure to that of a best-practice bank. A vast literature on bank efficiency has focused on measuring the level and determinants of bank efficiency around the world,[2] with the goal of improving the performance of financial institutions.[3]

Surprisingly, while the determinants of bank efficiency have been systematically explored, the consequences of bank efficiency have received much less attention. Exceptions are papers focusing on the impact of bank efficiency on financial stability (for example, Berger and DeYoung, 1997; Roman et al., 2016), economic growth (Lucchetti, Papi and Zazzaro, 2001; Hasan, Koetter and Wedow, 2009) and the transmission of monetary policy (Havranek, Irsova and Lesanovska, 2016). One important omission from this list is the effect of bank efficiency on the cost of credit. This omission is rather surprising, because economic theory naturally predicts that a greater ability of banks to operate at a lower marginal cost should be associated with lower "prices" – lower loan rates – and thus lower cost of credit. If correct, this argument would imply that a key instrument for facilitating firms' access to credit is to improve bank efficiency.

This paper aims to fill a gap in the literature by investigating how bank efficiency affects the cost of credit in nine Western European countries. A major challenge in analyzing this impact is obtaining firm-level information on lending banks so that efficiency at the bank level and cost of credit at the firm level can be linked. The last wave of the Amadeus database provides such information, allowing us to identify which banks lend to each borrowing firm. Thus, we can combine firm-level data from the Amadeus database with bank-level data from the Bankscope database to build a large sample of 240,000 firms from nine European countries.

[2] See, for instance, Berger, Hasan and Zhou (2009) on China, Fuji, Managi and Matousek (2014) on India, and Goddard, Molyneux and Williams (2014) on Latin America.
[3] For instance, Altunbas, Evans and Molyneux (2001) and Bonin, Hasan and Wachtel (2005) focus on the effects of ownership structure, Berger and Bonaccorsi di Patti (2006) on the role of capital structure, and Barth et al. (2013) on the impact of bank regulation.

To perform our investigation, we model cost of credit as a function of bank efficiency and a set of firm- and country-specific control variables. We measure bank efficiency with a stochastic frontier approach commonly used in works on the banking industry (such as Lensink, Meesters and Naaborg, 2008; Berger, Hasan and Zhou, 2009). We use different specifications of the stochastic frontier approach designed for a cross-country analysis, by testing the influence of country-specific variables and controlling for the environmental conditions in the frontier. We also investigate whether the effect of bank efficiency on the cost of credit is contingent on firm size, bank competition, and bank size, and perform several checks to examine the robustness of our results to different specifications of key variables and sub-samples.

We face two key challenges in our investigation. First, while we can identify the lending banks for each firm, we do not have information on the share of each bank in the loans to the company. Therefore, we must assign each bank an equal weight in its importance for a firm. This is a limitation, but we address it by conducting additional estimations on the sub-sample of firms that use only one bank, for which therefore this problem does not exist. One-bank firms represent about 40% of the sample and thus provide a large enough sample to perform alternative estimations.

Second, measuring the cost of credit at firm level is difficult. Information on individual loans can be found in credit registries but is limited to single-country datasets, or it can be obtained for large loans in a cross-country framework. These data sources are problematic if one wishes, as we do, to analyze the cost of credit in a number of countries for a wide spectrum of firm size. To overcome these challenges, we therefore measure the cost of credit by calculating the ratio of interest expenses to total bank debt using firm-level data. This indicator, measuring the implicit interest rate charged by banks, has also been used by Carbo-Valverde, Rodriguez-Fernandez and Udell (2009) and Fungacova, Shamshur and Weill (2017).

Our paper contributes to two debates in the literature. Firstly, we augment the vast literature on bank efficiency by investigating the impact of the cost efficiency of banks on the cost of credit for firms. Secondly, we improve our understanding of how bank behavior shapes access to credit. Several studies have investigated how bank competition and concentration influence access to credit (for example, Beck, Demirgüc-Kunt and

Maksimovic, 2004); our work departs significantly from the existing empirical literature by focusing on the role of bank efficiency.

This work has important implications. From a normative perspective, the finding that greater efficiency reduces cost of credit provides support for policies aimed at improving bank efficiency. From a positive perspective, our findings help to explain differences observed in the cost of credit across European countries. Our results also suggest that convergence in cost efficiency across European countries would facilitate convergence in the cost of credit for firms.

The paper proceeds as follows: Section 2 presents the data; Section 3 explains the efficiency scores and the econometric model; Section 4 reports the results; and Section 5 concludes.

2. Data

To study whether bank efficiency affects the cost of credit for firms, both firm-level data and bank-level data need to be collected. The firm-level data come from the Amadeus database provided by Bureau van Dijk, which contains comprehensive financial information on public and private companies across Europe. The vast majority of firms in Amadeus report unconsolidated financial statements; consolidated statements are provided mainly by large companies only. In our dataset, we use unconsolidated financial statements, to avoid double counting firms and subsidiaries or operations abroad, and exclude firms that report only consolidated statements. We exclude firms operating in the financial intermediation sector and insurance industries (NACE codes 64–66), because they have a different liability structure and cannot be similarly taken into account in our investigation explaining the cost of credit.

The bank-level data used to compute bank efficiency come from the Bankscope database. We further match bank-level information to firm-level information by taking advantage of the recent Amadeus update, which includes information about lending banks for each firm. We link both databases by carefully checking the identity of lending banks and matching it to banks available in Bankscope.

We focus on nine 'old' EU member countries for our investigation, since they represent a consistent sample of developed countries without the specific characteristics of the more recent EU members. The newer EU countries are former or still transitioning economies with specific populations of firms and particular banking sector features, for example a substantial market share of foreign banks, which can both raise the cost of and impede access to credit.

Firm-level information on the lending banks is available for nine old EU countries: Austria, France, Germany, Greece, Ireland, the Netherlands, Portugal, Spain, and the United Kingdom. We have a cross-section of firms for 2015, since information on the lending banks is only available for the last wave of Amadeus.

The key firm-level variable is *Cost of credit.* It is defined as the difference between the ratio of financial expenses divided by bank debt and the country's nominal short-term interest rate, where bank debt is the sum of short-term bank debt ("loans") and long-term bank debt ("long-term debt"). This measure of the implicit interest rate, which accords with Carbo-Valverde, Rodriguez-Fernandez and Udell (2009),[4] has been used to measure cost of credit by Fungacova, Shamshur and Weill (2017). It captures the cost of credit well, because the vast majority of our sample consists of micro and small enterprises that lack access to non-bank funding sources, so their financial expenses are mainly loan expenses.

We consider two firm-level control variables taken from the literature. The first is *Firm size*, measured as the log of total assets, as firms of different size can differ in their financing patterns. The second is *Tangibility*, defined as the ratio of tangible fixed assets to total assets. A greater share of tangible fixed assets that could serve as collateral can contribute to easier access to credit.

To check whether the impact of bank efficiency on the cost of credit is influenced by firm size, we separately consider micro firms (that is, firms with fewer than ten employees or a turnover or total assets of less than 2 million euros), small and medium-sized firms (either fewer than 250 employees or a turnover of less than 50 million euros

[4] Carbo-Valverde, Rodriguez-Fernandez and Udell (2009) compute the loan interest spread as the difference between the ratio of loan expenses to bank loans outstanding and the interbank interest rate.

or balance sheet total of less than 43 million euros), and large firms.[5] Micro firms (30 %), and small and medium-sized firms (67 %) together represent 97 % of the entire sample.

We consider four country-specific control variables. We control for banking development, with *Private credit* defined as the ratio of private credit by deposit money banks and other financial institutions to GDP, collected from the Global Financial Development Database. *GDP per capita* and *Inflation* take into account macroeconomic conditions and are both extracted from the World Development Indicators. *Rule of law* measures institutional quality and comes from the Worldwide Governance Indicators.

After excluding observations for which firm-level information or the identity of the lending bank(s) are not available, we have a sample of 377,925 firm-bank observations for about 240,000 firms. Descriptive statistics of all variables are presented in Table 1. Table 2 reports the number of banks per firm in the sample. The vast majority of firms use only a few banks: 40.6% of firms have only one bank, while 82.05% of firms have no more than three banks. The definitions of all variables are provided in the Appendix.

3. Methodology

3.1 Bank efficiency

Cost efficiency measures the difference between a bank's actual cost and its optimal cost for producing the same bundle of outputs. This difference then provides information on inefficiencies in the production process and on the optimality of the chosen mix of inputs. To estimate cost efficiency scores, we use a stochastic frontier approach, a technique that has been widely used in studies on banking efficiency (for example, Bonin, Hasan and Wachtel, 2005; Berger, Hasan and Zhou, 2009). It decomposes the distance from the efficiency frontier into an inefficiency term and a random error, which represents random disturbances reflecting luck or measurement errors. We assume a normal distribution for the random error and a half-normal distribution for the inefficiency term. Following Jondrow et al. (1982), bank-specific estimates of inefficiency terms can then be calculated using the distribution of the inefficiency term

[5] This classification is employed by the European Commission. For further details see http://ec.europa.eu/eurostat/web/structural-business-statistics/structural-business-statistics/sme

conditional on the estimate of the composite error term (namely, the sum of the inefficiency term and the random error).

We adopt the intermediation approach for the specification of banking inputs and outputs. This approach assumes that the bank collects deposits to transform them into loans with capital and labor. We consider two outputs in the cost function: loans and investment assets. We also employ three input prices. The price of funds is calculated as the interest rate paid on borrowed funds, the price of labor is defined as personnel expenses divided by total assets, and the price of physical capital is calculated as the ratio of other operating expenses to fixed assets. Total cost is the sum of the costs incurred for borrowed funds, labor, and physical capital. We employ the commonly-used translog form to model the cost frontier of banks. The cost frontier model we estimate is then formulated as follows:

$$\begin{aligned}\ln\left(\frac{TC}{w_3}\right) &= \beta_0 + \sum_m \alpha_m \ln y_m + \sum_n \beta_n \ln\left(\frac{w_n}{w_3}\right) + \frac{1}{2}\sum_m\sum_j \alpha_{mj} \ln y_m \ln y_j \\ &+ \frac{1}{2}\sum_n\sum_k \beta_{nk} \ln\left(\frac{w_n}{w_3}\right)\ln\left(\frac{w_k}{w_3}\right) + \sum_n\sum_m \gamma_{nm} \ln\left(\frac{w_n}{w_3}\right)\ln y_m \\ &+ u + v\end{aligned} \tag{1}$$

where TC is total cost, y_m is the m^{th} bank's output (m = 1, 2), w_n is the n^{th} input price (n = 1, 2), w_3 is the price of borrowed funds, u the inefficiency term, and v the random error. For simplicity of presentation, the indices for each bank have been dropped. Homogeneity conditions are imposed by normalizing total costs, price of labor and price of physical capital, by the price of borrowed funds.

Given the cross-country nature of our sample, the inclusion of country-level variables in the frontier function could be important. Many cross-country studies on bank efficiency have estimated a common frontier, pooling all banks without including country-level variables (for example, Casu and Girardone, 2006; Fiordelisi, Marques-Ibanez and Molyneux, 2011). However, Lozano-Vivas, Pastor and Pastor (2002) have pointed out that the omission of country-level variables in the estimation of the frontier leads to a misinterpretation of the cross-country differences in efficiency. These can be attributed to differences in managerial performance, but they can also result from variations in environmental characteristics. For instance, a bank may benefit from a greater income per capita in a country, which would contribute to higher bank outputs for exogenous reasons. Consequently, they conclude that estimating a common frontier without considering environmental conditions "is not able to compare the different banking systems on an equal footing" (Lozano-Vivas, Pastor and Pastor, 2002, p.73).

Therefore, a number of cross-country works on bank efficiency have followed this paper by including country-level variables in the estimation of the frontier, to provide a relevant analysis of cross-country differences in efficiency in Europe (for example, Lensink, Meesters and Naaborg, 2008; Hasan, Koetter and Wedow, 2009).

In our study, we focus on the relationship between bank efficiency and the cost of credit and, therefore, are not primarily interested in the causes of inefficiencies. Our hypothesis is that a more efficient bank can provide cheaper loans to its customers, irrespective of whether that efficiency is related to better managerial performance or better environment. Nonetheless, the frequent inclusion of country-level variables in the estimation of efficiency frontiers motivates us to test different specifications, so that we assess the sensitivity of our findings to this choice.

We therefore estimate efficiency scores using three alternative specifications for the cost frontier. Firstly, we estimate a common frontier without country-level variables. With this specification, efficiency scores measure the cost performance of each bank to a common frontier for all countries, and do not account for the environmental differences across countries. Secondly, we estimate a common frontier including country fixed effects to control for cross-country differences. Thirdly, a common frontier is estimated with country-level variables. We consider four country-level variables that have been used in former works estimating common frontiers with environmental variables (for example, Lozano-Vivas, Pastor and Pastor, 2002; Hasan, Koetter and Wedow, 2009). These are the same country-level variables included in some of our regressions explaining cost of credit. With both the latter specifications, efficiency scores measure the cost performance of each bank relative to a common frontier for all countries, taking into account environmental differences across countries.

The descriptive statistics for the three types of efficiency scores are reported for the full sample in Table 1. We observe that average bank efficiencies are of the same order of magnitude, with respectively 73.8%, 75.7%, and 74.5% for the frontiers without country controls, with country fixed effects, and with country control variables. Rank-order correlations among the different cost efficiency measures are positive and statistically significant. Specifically, the correlation coefficients range from 0.8964 to 0.9837 and are all significant at the 1% level. Given the high rank-order correlation among the cost efficiency measures, we only report the estimations employing the efficiency scores based on the frontier with country control variables. The only exception is our main estimations, where we use all three cost efficiency measures to ensure the robustness of our results across cost efficiency score specifications.

Table 3 presents the mean efficiency scores by country, while Table 4 reports the efficiency scores by bank size and by bank ownership.

3.2 Econometric specifications

To analyze the relationship between bank efficiency and cost of credit, we run regressions of cost of credit on the efficiency score and a set of control variables:

$$y_{ij} = \alpha + \beta X_{ij} + \gamma Z_j + Efficiency_{ij} + \varepsilon_{ij}, \quad (2)$$

where y_{ij} is the cost of bank credit for firm *i* in country *j*; *X* is a set of firm-specific variables (*Firm size, Tangibility*); *Z* is a set of country-level variables (*Private credit, Rule of law, GDP per capita, Inflation*); *Efficiency* is the measure of bank efficiency, and ε is a random error term. We also include industry fixed effects in the estimations to control for the influence of the industry on the cost of credit. We estimate the equation (2) by including either country fixed effects or a set of country-level variables, so that we test the robustness of our findings to different specifications.

The endogeneity problem is greatly reduced in our setting for the empirical investigation since bank efficiency is computed at the bank level, while cost of credit is firm-level information obtained from a different data source. It is therefore unlikely that the cost of credit can exert an impact on bank efficiency. Nonetheless, we later test whether our results could be driven by potential endogeneity.

4. Results

4.1 Main estimations

Table 5 reports the results of the main estimations. We consider six different specifications based on the choice of the efficiency frontier and the inclusion of country control variables or country fixed effects.

We find that *Bank efficiency* is negatively related to the cost of credit. The estimated coefficient is significant in four specifications out of six tested. Therefore, our main conclusion is that bank efficiency has a negative influence on cost of credit. In other words, our findings support the view that higher bank efficiency is associated with the lower cost of credit. This is in line with the idea that the benefits of banks' ability to minimize costs are transferred to borrowers through the cost of credit. Thus, our findings are of particular importance to policymakers who aim to design policies improving access to credit. Specifically, fostering bank efficiency could play an important role in the financing of the economy as a whole.

The estimated coefficients of the firm-level control variables have the expected sign. *Size* is negatively related to cost of credit, which is consistent with the view that larger firms enjoy lower credit costs. Furthermore, *Tangibility* is negative, as the greater tangibility of assets provides more collateral and therefore contributes to reducing the cost of credit. When including country-level control variables, we point out that both *Private Credit* and *GDP per capita* have a negative impact on the cost of credit. These findings accord with the view that greater financial and economic development is associated with lower cost of credit, due to lower information asymmetries (Godlewski and Weill, 2011). *Rule of law* is positive, which contrasts with the expectation that a better institutional framework would reduce the cost of credit, while *Inflation* is negative. It must however be stressed that our sample is a cross-section of firms from nine countries. As such, country-level variables intend to control for the influence of the country-specific environment on the cost of credit, but should not be used to draw general conclusions on the relation between country variables and the cost of credit.

4.2 Estimations by firm size

Our main results show that bank efficiency exerts a negative influence on the cost of credit. We further investigate whether the effect of bank efficiency on the cost of credit varies with the size of a firm. This issue is of utmost interest, since small firms are particularly affected by limited access to credit and have been shown to suffer the most from higher loan rates charged by banks.[6] We therefore investigate whether higher bank efficiency is associated with the lower cost of credit for all types of firms.

We re-estimate our regressions by considering separately the following groups of firms: micro companies, SMEs, and large companies. The results are reported in Table 6. Overall the results on the relationship between bank efficiency and cost of credit are consistent across the tested efficiency frontiers.[7]

We find that bank efficiency is not significant for micro enterprises and for large companies. However, bank efficiency is significantly negative for SMEs in one of the two specifications tested. We therefore support the view that the negative impact of bank efficiency on cost of credit is only observed for SMEs, while no relation can be found either for micro enterprises or for large companies.

The implications of these results are then straightforward. Greater bank efficiency can be beneficial for SMEs. It does not seem to facilitate access to credit through lower costs for micro enterprises or large companies. While large firms can rely on other sources of financing, the design of policies to enhance bank efficiency would not foster access to credit for all firms suffering from high loan rates. Still, we show that greater bank efficiency can facilitate access to credit for SMEs, even if micro enterprises do not benefit from this.

4.3 The effect of competition

We demonstrate that higher bank efficiency benefits firms by reducing their borrowing costs. This transmission of bank efficiency into credit costs could potentially be affected by competition in the banking sector. Building on the competition literature,

[6] Based on a survey on managers mostly from small companies, Beck et al. (2006, p.938) show that "high interest rates" is the main financing obstacle for firms all around the world.

[7] While we only report the results for the cost efficiency with country variables, the results using the alternative cost efficiency specifications (with no country controls and country fixed effects) are available upon request.

we consider how competition moderates the relationship between bank efficiency and the cost of credit.

There are two opposing views concerning the relationship between bank competition and cost of credit – the market power hypothesis and the information hypothesis. The market power hypothesis suggests that greater bank competition would lead to lower loan rates (Sapienza, 2002; Kim et al., 2005; Degryse and Ongena, 2005). As more efficient banks have lower costs than their less efficient competitors, they would be able to offer lower loan rates to borrowing firms than less efficient banks under this hypothesis.

In contrast, the information hypothesis stresses the importance of collecting soft information about borrowing firms. Greater bank competition decreases bank incentives to invest in soft information and consequently increases the cost of credit for firms (Petersen and Rajan, 1995; Fungacova, Shamshur and Weill, 2017). More efficient banks, it is argued, have a comparative advantage in technologies like relationship lending that are based primarily on extracting value from soft information (Berger, 2007). Therefore, under the information hypothesis, higher competition would cause a disadvantage in relationship lending for more efficient banks and force them to charge higher loan rates compared to less efficient banks.

We use the Lerner index to measure bank competition. The advantage of using this measure is that it directly quantifies the competitive behavior of each bank without inferring it from indirect proxies such as market share. The Lerner index is defined as the difference between price and marginal cost, divided by price. Following Carbo-Valverde, Rodriguez-Fernandez and Udell (2009), price is the average price of bank production (proxied by total assets) and is defined as the ratio of total revenues to total assets. The marginal cost is estimated on the basis of a translog cost function with one output (total assets) and the same three input prices (price of labor, price of physical capital, and price of borrowed funds) used for the estimation of cost efficiency scores.

We estimate the Lerner index for each bank for five years and then use the five-year average as a measure of bank competition. This is in line with Beck, Demirgüc-Kunt and Maksimovic (2004) and Claessens and Laeven (2005) among others, who also adopt average measures of bank competition. In our case, this approach also allows us to reduce the potential correlation between the Lerner index and bank efficiency. The correlation coefficients for the Lerner index averaged over five years and the three efficiency measures range from 0.15 to 0.18.[8]

The effect of bank competition on the cost of credit is captured by including the Lerner index and the interaction term between the Lerner index and bank efficiency in our main specifications. The coefficient for the Lerner index represents the direct effect of competition on the cost of credit. The coefficient for the interaction term shows how the relationship between bank efficiency and the cost of credit is moderated by competition. We present the results in columns (1) and (2) of Table 7. As the estimated direct effect of the Lerner index on the cost of credit is positive and significant, higher competition is associated with the lower cost of credit. The total effect of the competition on the cost of credit, however, is the sum of the coefficient for the *Lerner index* and the coefficient for the interaction term *Bank efficiency* × *Lerner index,* multiplied by the value of *Bank efficiency*. Thus, the overall effect of the Lerner index on the cost of credit is positive when efficiency is low but it decreases gradually as bank efficiency increases. Then, the overall impact of the Lerner index on the cost of credit is negative when bank efficiency exceeds 65.5% and 70.2%, depending on the specification. The mean value of bank efficiency scores, for comparison, is 74.5%. We thus conclude that a higher Lerner index (lower competition) increases the cost of credit when bank efficiency is low, but reduces the cost of credit when bank efficiency is high. Therefore, the information hypothesis dominates for efficient banks, while the market power hypothesis dominates for inefficient banks.

4.4 Estimations by bank size

Our main estimations indicate that greater bank efficiency contributes to a lower cost of credit. Thus, clients of more cost-efficient banks benefit from their lower costs through cheaper loans. However, the literature has widely debated the optimal bank size. Recent studies demonstrate the potentially detrimental influence of banks that are too large for financial stability (Vinals et al., 2013; Laeven, Ratnovski and Tong, 2014). We

[8] As a robustness check, we have performed estimations using the Lerner index for the current year. Our results hold. These results are available upon request.

therefore investigate whether the transmission of bank efficiency to loan pricing varies by bank size.

There are various reasons why banks of different sizes may differ in terms of transmission of their cost to loan prices. Firstly, banks of different sizes serve different clienteles. Berger et al. (2005) and Berger, Bouwman and Kim (2017) show that large banks grant fewer loans to small businesses. They tend to specialize in lending to larger companies because they can use “hard”, quantitative information obtained from audited financial statements. Small banks, instead, have a comparative advantage in lending to small companies by utilizing “soft”, qualitative information gathered over the course of a relationship established with a small business. Secondly, large banks also differ from small banks in terms of their business model. As pointed out by Laeven, Ratnovski and Tong (2014), a greater size allows large banks to have a broader range of activities resulting in greater diversification. Large banks can consequently focus on a different set of activities to small banks.

To test empirically whether the effect of bank efficiency on the cost of credit differs for large and small banks, we create a dummy variable *Large bank*, which is equal to one if a bank belongs to the top 25% of banks in terms of assets and zero otherwise. We include this variable and the interaction term *Bank efficiency* × *Large bank* in the estimations. The interaction term captures the impact of bank size on the relationship between bank efficiency and cost of credit. We report the results in columns (3) and (4) of Table 7. We observe that the interaction term *Bank efficiency* × *Large bank* is negative in all estimations and significant in the specification with country-specific control variables.

We therefore provide evidence that the impact of bank efficiency on the cost of credit is influenced by bank size. Specifically, higher efficiency in large banks contributes more to lower credit costs than higher efficiency in small banks. From a policy perspective, this conclusion suggests that gains in efficiency in large banks provide more benefits in terms of reduced cost of credit than those in small banks. As a consequence, authorities should particularly encourage efforts to improve efficiency in large banks.

4.5 Estimations by bank ownership

The diversity of ownership structure is an important characteristic of the European banking industry. While commercial banks generally dominate the market in Europe, a non-negligible market share also belongs to cooperative and savings banks in France, Germany and Spain. Banks of different types are likely to have different business models that could affect the relationship between bank efficiency and the cost of credit. For example, Altunbas, Evans and Molyneux (2001) have demonstrated that bank efficiency can be influenced by bank ownership in Europe.

We therefore investigate whether the relationship between bank efficiency and the cost of credit is moderated by bank ownership. We differentiate between five types of banks: (*i*) commercial banks, (*ii*) cooperative banks, (*iii*) savings banks, (*iv*) bank holdings and holding companies, and (*v*) other banks category that captures all the remaining bank types in our sample. Respectively, we introduce five dummy variables for each bank type. The main specification is then augmented to include all bank type dummy variables and their interactions with *Bank efficiency* in the estimations. The interaction terms capture the relationship between bank efficiency and the cost of credit for each type of bank relative to the omitted – other banks – category.

The results are reported in columns (5) and (6) in Table 7. The evidence is mixed. On the one hand, ownership dummy variables and their interactions terms with bank efficiency are not significant in the estimation without country-specific control variables. On the other hand, we observe positive and significant coefficients for commercial banks and cooperative banks in the estimation with country-specific control variables. This latter estimation therefore provides some support to the view that the negative impact of bank efficiency on cost of credit would be less strong for commercial banks and cooperative banks than for the other types of banks.

4.6 Robustness tests

We examine the robustness of our findings in several ways.

One-bank firms. We redo the estimations on the sub-sample of firms that use only one bank. A potential criticism of our investigation concerns the absence of information on the breakdown of loans by bank for each firm. As a consequence, we consider all the banks providing loans to a firm and look at the impact of their efficiency levels on the cost of credit of the firm. The composition of the sample, however, is such that the vast majority of firms maintain relationships with a rather small number of banks, which reduces this potential problem.

We can, however, allow for a clean identification, at the cost of reducing the sample size, by performing the estimations only for firms with one bank. These firms represent about 40% of the observations in our sample, so they provide a sample large enough to generate relevant estimations. These estimations are displayed in columns (1) and (2) of Table 8. We observe a significantly negative coefficient for bank efficiency in all estimations, meaning that greater bank efficiency is associated with the lower credit costs for firms. These results are not only consistent with the results obtained on the full sample, but also, as expected, stronger – the estimated coefficient is negative and significant in both specifications.

Alternative measure for the cost of credit. Following Fungacova, Shamshur and Weill (2017), we redefine the cost of credit as interest paid divided by total debt, since information on interest paid is available in the Amadeus database for a large number of firms. The results are reported in columns (3) and (4) of Table 8. We still observe that the estimated coefficient of bank efficiency is negative and significant in the specification with country fixed effects. Therefore, these results generally align with our main estimations and thus provide additional support for our key finding.

Sample composition. We perform the estimations excluding France and Spain. As approximately 70% of firms are located in these countries, one might wonder if our findings still hold when we exclude firms from these countries. The two first columns of Table 9 display these estimations. We note that the coefficient on bank efficiency is negative and significant in all estimations. Therefore, our selection of countries does not drive the main results.

Profit efficiency. In our analysis we use cost efficiency as our main measure of bank efficiency. This choice accords with the tested hypothesis, according to which a greater ability of banks to operate with lower costs should be associated with lower banking prices, including lower cost of credit. However several studies on bank efficiency have also pointed out the importance of profit efficiency, which is a broader concept that combines cost efficiency and revenue efficiency (e.g., Berger and Mester, 1997; Berger, Hasan and Zhou, 2009). To be profit efficient a bank must be able to produce with the minimal costs (cost efficient) and with the maximal revenues (revenue efficient). A bank can therefore be cost efficient but not profit efficient, if it has high cost efficiency but low revenue efficiency. Berger and Mester (1997, p.930) provide two reasons why banks can have low cost efficiency and high profit efficiency: "firms with low cost efficiency tend to have high revenue efficiency that offsets it. This could occur because of competitive pressures if, for example, firms with highly valued product mixes or high revenue efficiency feel less market discipline to control their costs (…) An alternative explanation is that much of what are measured as cost inefficiencies are actually unmeasured differences in product quality that required additional costs to create."

To test whether the focus on profit efficiency would have different implications for the cost of credit, we first compute profit efficiency scores. We consider an alternative profit frontier following Berger, Hasan and Zhou (2009). This frontier model is similar to the cost frontier (see equation 1) with one change for the dependent variable. The dependent variable in this case is the profit (measured by net income) normalized by borrowed funds. As the minimum value of profit in the sample is negative, we add its absolute value and the unity to each observation to avoid taking a natural logarithm of negative number. We then estimate the alternative profit frontier including country level control variables since it is our preferred specification for cost efficiency scores.

We find that the mean profit efficiency score is 0.793 (to be compared with 0.745 for the mean cost efficiency score). We compute the Spearman rank order correlation between cost efficiency and profit efficiency scores: the correlation is -0.2634 and is significant at the 1% level. In line with Berger and Mester (1997), cost efficiency and profit efficiency scores are negatively correlated.

We then estimate the relation between profit efficiency and the cost of credit in the last two columns of Table 9. We observe that profit efficiency is negative and significant in both estimations. Hence profit efficiency, similarly to cost efficiency, is negatively related to the cost of credit.

Endogeneity. A potential concern is that bank risk strategies could be driving our main result. For example, a very risk-averse bank that specializes in lending to low-risk firms will have lower loan loss expenses and may appear to be more cost efficient than the typical bank. It will charge lower interest rates because it is lending to clients with low default risks. To address this concern, we need to observe whether banks with two different levels of cost efficiency are lending to the same firm at different rates. Our data, however, does not allow for such a level of granularity.

To strengthen a casual interpretation of our results, we opt for a matching analysis that allows us to compare the cost of credit of matched firms borrowing from high and low efficiency banks. For clean identification we focus on one-bank firms only. First, we split our sample into two groups by efficiency level. The top 10% of banks (high efficiency) form the treated group and the bottom 10% of banks (low efficiency) form the control group. Using a nearest neighbor matching algorithm, we find similar pairs of firms borrowing from banks in different efficiency groups and then compare their cost of credit.

Formally, let $D = 1$ if the firm borrows from a high efficiency bank and $D = 0$ if the firm borrows from a low efficiency bank. Similarly, Y_1 is the cost of credit for a firm that borrows from a high efficiency bank and Y_0 is the cost of credit for a firm that borrows from a bank in a low efficiency group. Then an observed firm's cost of credit is equal to

$$Y = DY_1 + (1 - D)\, Y_0 \tag{3}$$

The difference in the cost of credit could be attributed to the treatment effect when a firm is borrowing simultaneously from high and low efficiency banks, and defined as

$$\Delta Y = Y_1 - Y_0 \tag{4}$$

We only observe a firm either borrowing from the high efficiency bank (treatment group) or from the low efficiency bank (control group). To define the best approximation of the difference, we use the exact matching on industry (2-digit NACE) and conduct a nearest neighbor matching procedure that accounts for the similar set of firm-specific characteristics. We assume that banks consider firms' asset structure when setting interest rates. Specifically, we match firms on their size and tangibility.[9] Table 10 Panel A presents the results of the matching analysis. The average effect on the treatment group is about -0.009 (standard error 0.002). It is highly statistically significant and robust across all bank efficiency measures. The sign and size of the estimated effect is also very close to our main estimation results reported in Table 5.

We further assess the quality of the matching by comparing the distribution of baseline covariates between treatment and control groups in the matched sample (Austin 2009, 2011). Summary statistics for matched and unmatched samples is reported in Panel B of Table 10. Comparability of firms borrowing from high and low efficiency banks is assessed using standardized differences.[10] The summary statistics appear to indicate a good balance. Matching has significantly diminished systematic differences in means. For example, in the unmatched sample the absolute standardized difference for firm size is 0.683, while in the matched sample it is close to zero (0.002). Overall, balance is achieved for all covariates as they are lying within a 10% window, which has been used in the literature as the definition of a negligible difference (Austin, 2009). We further look at the diagnostic box plots (Figure 1) and the kernel density plots (Figure 2). All the plots using the matched data appear to be balanced.

5. Conclusion

In this paper we examine the impact of bank efficiency on the cost of credit. We combine firm-level data with bank-level data so that we can identify the level of efficiency of the banks lending money to each firm. We then perform estimations on a large sample of 240,000 companies from nine European countries.

Our key finding is that higher bank efficiency is associated with lower cost of credit. Therefore, we support the view that banks' effectiveness in minimizing costs is transferred to borrowing firms through lower costs of credit. This conclusion is robust

[9] Note that when matching on more than one continuous covariate, the nearest-neighbor matching estimator is biased. We therefore use Abadie and Imbens' (2006, 2011) procedure to correct for this bias.
[10] The advantage of looking at the standardized difference is that, unlike *t*-tests commonly used to assess balancing, the standardized difference is not influenced by sample size (Rosenbaum and Rubin, 1985; Austin 2009).

using the alternative definition of the cost of credit, the alternative specifications of the frontier, the country sample composition, the set of control variables, and the restriction of the sample to one-bank firms.

We also observe that the impact of bank efficiency on cost of credit differs with the size of the firm. Thus, bank efficiency diminishes the cost of credit only for SMEs. The relationship between bank efficiency and the cost of credit is also negative, but not significant for micro companies and large companies. The negative effect of bank efficiency on the cost of credit is mediated by the Lerner index – lower bank competition facilitates the transfer of greater bank efficiency to lower cost of credit. Finally, we find that greater cost efficiency is transmitted to lower cost of credit mainly by large banks.

The normative implications of our findings are that taking measures to enhance the efficiency of banks, and in particular of large banks, could reduce the cost of credit for firms. Therefore, implementing policies to improve bank efficiency should facilitate access to credit. Literature on bank efficiency has identified a large set of determinants, including bank ownership and capital structure. Using these determinants, authorities can design policies enhancing bank efficiency so as to foster access to credit and thus improve the financing of the economy as a whole.

From a positive perspective, our work can help to understand the cross-country differences in the cost of credit. It demonstrates that bank efficiency is one of the important determinants of the cost of credit and as such should be taken into account alongside the degree of competition or the development of banking markets.

In addition to these implications, our results are of importance for researchers, since they provide a major reason to investigate the level and the determinants of bank efficiency. Our research is an initial step towards understanding the effects of bank efficiency on the cost of credit. Further work is needed to check the relevance of our results with alternative datasets, in particular in emerging and developing countries, where companies suffer the most from the high cost of credit.

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Table 1.
Descriptive statistics

This table provides descriptive statistics for the variables used in the estimations. Firm size is the log of total assets in thousand USD. GDP per capita is in USD. The remaining variables are ratios. Definitions of all variables are provided in the Appendix.

	Obs.	Mean	Std. Dev.	Min	Max
Firm-level variables					
Firm size	377 925	0.808	1.616	-5.036	5.048
Tangibility	377 925	0.258	0.238	0.000	0.975
Cost of credit	377 925	0.069	0.083	0.000	0.619
Country-level variables					
Private credit	377 925	113.6	14.4	77.5	134.7
Rule of law	377 925	1.104	0.337	0.242	1.935
GDP per capita	377 925	32 301	7 462	21 969	51 258
Inflation	377 925	-0.197	0.504	-1.736	0.897
Bank-level variables					
Bank (cost) efficiency					
No country controls	377 925	0.738	0.071	0.135	0.969
Country fixed effects	377 925	0.757	0.072	0.141	0.970
Country-level controls	377 593	0.745	0.074	0.133	0.969
Profit efficiency	377 950	0.793	0.125	0.000	0.989
Lerner index	372 087	-0.011	0.294	-1.221	1.792

Table 2.
Number of banks per firm

This table provides descriptive statistics for the number of banks used by firms. Definitions of variables are provided in the Appendix.

Banks	Frequency	Percent	Cumulative percent
1	153 438	40.6	40.60
2	84 921	22.47	63.07
3	71 713	18.98	82.05
4	36 615	9.69	91.73
5	18 740	4.96	96.69
6	8 052	2.13	98.82
7	2 854	0.76	99.58
8	1 027	0.27	99.85
9	387	0.1	99.95
10	138	0.04	99.99
11	40	0.01	100
Total	377 925	100	

Table 3.
Bank efficiency scores and sample composition by country

This table provides the descriptive statistics for the efficiency scores estimated with a cross-country stochastic frontier with country variables and the number of observations, banks, and firms by country.

	Country-level variables		Obs.	Banks	Firms
	Mean	Std dev.			
Austria	0.751	0.084	3 696	238	2 143
Germany	0.759	0.108	18 281	1 257	9 474
Spain	0.765	0.062	183 401	180	94 933
France	0.731	0.065	79 815	214	79 815
United Kingdom	0.792	0.113	12 229	52	12 188
Greece	0.590	0.029	14 848	10	6 556
Ireland	0.828	0.111	1 674	23	1 673
Netherlands	0.610	0.134	235	17	182
Portugal	0.727	0.042	65 420	115	33 699

Table 4.
Bank efficiency scores by size and ownership

This table presents the descriptive statistics for the efficiency scores estimated with a cross-country stochastic frontier with country variables. A bank is classified as Large bank if it belongs to the top 25% of banks in terms of total assets, otherwise it is classified as Small bank. Size classes are quantiles in total assets. Commercial bank, Cooperative bank, Bank holdings, Savings bank denote the respective bank ownership types.

	Obs.	Mean	Std. dev.
		By size	
Small bank	289 665	0.751	0.072
Large bank	89 934	0.727	0.080
Size class 1st quantile	94 160	0.759	0.044
Size class 2nd quantile	95 839	0.705	0.067
Size class 3rd quantile	99 666	0.787	0.060
Size class 4th quantile	89 934	0.727	0.083
		By ownership	
Commercial banks	283 211	0.745	0.077
Cooperative banks	45 120	0.750	0.036
Bank holdings	10 239	0.787	0.022
Savings banks	30 094	0.738	0.061
Other banks	10 935	0.702	0.135

Table 5.
Main estimations

This table presents the results of OLS regressions examining the relation between cost of credit and bank efficiency. Definitions of variables are provided in the Appendix. Standard errors (in brackets) are robust to arbitrary heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable = Cost of credit					
	No country controls		Country FEs		Country-level controls	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank efficiency	-0.009***	-0.003	-0.011***	-0.006***	-0.009***	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Firm size	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.046***	-0.044***	-0.046***	-0.044***	-0.046***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Private credit		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Rule of law		0.019***		0.019***		0.020***
		(0.002)		(0.002)		(0.002)
GDP per capita		-0.000***		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Inflation		-0.026***		-0.026***		-0.026***
		(0.001)		(0.001)		(0.001)
Constant	0.079***	0.111***	0.080***	0.112***	0.082***	0.109***
	(0.008)	(0.010)	(0.008)	(0.010)	(0.010)	(0.010)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No
R^2	0.038	0.036	0.038	0.036	0.038	0.036
N	379,599	377,925	379,599	377,925	377,950	377,593

Table 6.
Estimations by firm size

This table presents the results of OLS regressions examining the relation between cost of credit and bank efficiency. Efficiency scores are estimated with a cross-country stochastic frontier with country variables. Definitions of variables are provided in the Appendix. Standard errors (in brackets) are robust to arbitrary heteroskedasticity *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable = *Cost of credit*					
	Micro		SME		Large	
	(1)	(2)	(3)	(4)	(5)	(6)
Bank efficiency	-0.007	-0.004	-0.008***	0.002	-0.011	-0.011
	(0.004)	(0.004)	(0.003)	(0.002)	(0.011)	(0.010)
Firm size	-0.006***	-0.006***	-0.002***	-0.001***	0.004***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Tangibility	-0.043***	-0.043***	-0.047***	-0.045***	-0.048***	-0.050***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.004)
Private credit		-0.000		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Rule of law		0.032***		0.022***		-0.032***
		(0.012)		(0.002)		(0.008)
GDP per capita		-0.000		-0.000***		0.000***
		(0.000)		(0.000)		(0.000)
Inflation		-0.034***		-0.027***		-0.005
		(0.005)		(0.001)		(0.004)
Constant	0.027	0.000	0.079***	0.115***	0.218***	0.254***
	(0.018)	(0.022)	(0.011)	(0.011)	(0.010)	(0.013)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No
R^2	0.046	0.046	0.037	0.036	0.080	0.076
N	112,460	112,425	252,753	252,449	12,737	12,719

Table 7.
Moderating effects of bank competition, bank size and bank ownership

This table presents the results of OLS regressions examining the relation between cost of credit and bank efficiency. Efficiency scores are estimated with a cross-country stochastic frontier with country variables. The Lerner index is defined as the difference between price and marginal cost divided by price. Large bank is a dummy variable equal to one if the bank belongs to the top 25% of banks in terms of total assets and zero otherwise. Commercial bank, Cooperative bank, Bank holding, Savings bank are dummy variables equal to one if the bank belongs to this ownership type and zero otherwise. Definitions of variables are provided in the Appendix. Standard errors (in brackets) are robust to arbitrary heteroskedasticity. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable = Cost of credit					
	The impact of competition		The impact of bank size		The impact of bank ownership	
	(1)	(2)	(3)	(3)	(5)	(6)
Bank efficiency	-0.008**	-0.0002	-0.004	0.014***	-0.007	-0.017***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)	(0.006)
Lerner index	0.019**	0.040**				
	(0.005)	(0.005)				
Bank efficiency × Lerner index	-0.029**	-0.057**				
	(0.006)	(0.006)				
Bank efficiency × Large bank			-0.004	-0.030***		
			(0.005)	(0.005)		
Large bank			0.004	0.024***		
			(0.004)	(0.004)		
Bank efficiency× Commercial bank					0.003	0.025***
					(0.006)	(0.006)
Bank efficiency× Cooperative bank					-0.001	0.020*
					(0.012)	(0.012)
Bank efficiency× Bank holding					0.044	0.015
					(0.039)	(0.039)
Bank efficiency× Savings bank					-0.016	0.005
					(0.010)	(0.010)
Commercial bank					-0.000	-0.016***
					(0.005)	(0.004)
Cooperative bank					-0.006	-0.024***
					(0.009)	(0.009)
Bank holding					-0.036	-0.013
					(0.030)	(0.031)
Savings bank					0.009	-0.005
					(0.007)	(0.007)
Firm size	-0.002**	-0.002**	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Tangibility	-0.045**	-0.043**	-0.046***	-0.044***	-0.046***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Private credit		-0.001**		-0.001***		-0.001***
		(0.000)		(0.000)		(0.000)
Rule of law		0.025**		0.027***		0.018***
		(0.002)		(0.002)		(0.002)
GDP per capita		-0.000**		-0.000***		-0.000***
		(0.000)		(0.000)		(0.000)
Inflation		-0.030**		-0.030***		-0.025***
		(0.001)		(0.001)		(0.001)
Constant	0.085**	0.131**	0.078***	0.106***	0.065***	0.135***
	(0.002)	(0.003)	(0.011)	(0.010)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No	Yes	No
R^2	0.036	0.035	0.038	0.037	0.039	0.038
N	370,438	370,081	377,950	377,593	377,949	377,592

Table 8.
Robustness checks 1/2

This table presents the results of OLS regressions examining the relation between cost of credit and bank efficiency. Efficiency scores are estimated with a cross-country stochastic frontier with country variables. Estimations (1) and (2) are performed on the subsample of firms with only one bank. Specifications (3) and (4) employ an alternative measure for the cost of credit that is the ratio of interest paid to total debt. Definitions of variables are provided in the Appendix. Standard errors (in brackets) are robust to arbitrary heteroskedasticity *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable = Cost of credit			
	One-bank relationship firms only		Alternative measure of cost of credit	
Bank efficiency	-0.009***	-0.006*	-0.005***	0.002
	(0.003)	(0.003)	(0.002)	(0.002)
Firm size	-0.000**	-0.000*	-0.004***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.046***	-0.045***	-0.031***	-0.029***
	(0.001)	(0.001)	(0.000)	(0.000)
Private credit		-0.000***		-0.001***
		(0.000)		(0.000)
Rule of law		0.001		0.051***
		(0.004)		(0.001)
GDP per capita		-0.000		-0.000***
		(0.000)		(0.000)
Inflation		-0.016***		-0.036***
		(0.002)		(0.001)
Constant	0.082***	0.116***	0.070***	0.129***
	(0.011)	(0.011)	(0.010)	(0.010)
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No
R^2	0.030	0.029	0.042	0.041
N	153,465	153,109	371,593	371,240

Table 9.
Robustness checks 2/2

This table presents the results of OLS regressions examining the relation between cost of credit and bank efficiency. Efficiency scores are estimated with a cross-country stochastic frontier with country variables. Estimations (1) and (2) are performed on the sample excluding France and Spain, both countries together representing 70% of observations. Specifications (3) and (4) employ an alternative efficiency measure, specifically, profit efficiency. Definitions of variables are provided in the Appendix. Standard errors (in brackets) are robust to arbitrary heteroskedasticity *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively.

	Dependent variable = Cost of credit			
	Without France and Spain		Profit efficiency	
Bank efficiency	-0.008**	-0.013***		
	(0.004)	(0.004)		
Profit efficiency			-0.013***	-0.004***
			(0.001)	(0.001)
Firm size	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Tangibility	-0.035***	-0.035***	-0.048***	-0.044***
	(0.001)	(0.001)	(0.001)	(0.001)
Private credit		-0.001***		-0.000***
		(0.000)		(0.000)
Rule of law		0.013***		0.016***
		(0.005)		(0.002)
GDP per capita		-0.000		-0.000***
		(0.000)		(0.000)
Inflation		-0.021***		-0.025***
		(0.002)		(0.001)
Constant	0.060***	0.132***	0.076***	0.113***
	(0.022)	(0.011)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	No	Yes	No
R^2	0.074	0.073	0.029	0.036
N	114,743	114,386	377,949	377,592

Table 10.

Nearest Neighbor Matching: Bank Efficiency and Cost of Credit

The table reports the results for the nearest neighbor matching procedure using one-bank firms. We split the sample by bank efficiency level. The top 10% of banks (high efficiency) form the treated group and the bottom 10% of banks (low efficiency) form the control group. We then analyze the effect of borrowing from high efficiency banks on the cost of credit of firms by estimating the Average Treatment Effect on Treated (ATT). Panel A presents matching results and Panel B provides a covariate balance summary. Variable definitions are provided in the Appendix. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels respectively.

Panel A. Nearest Neighbor Matching

	Outcome variable = *Cost of Credit* (Average Treatment Effect on Treated)		
	No country controls	Country fixed effects	Country-level controls
Difference (Treated - Control)	-0.0091***	-0.0087***	-0.0097***
	(0.002)	(0.002)	(0.002)

Panel B. Covariate Balance Summary

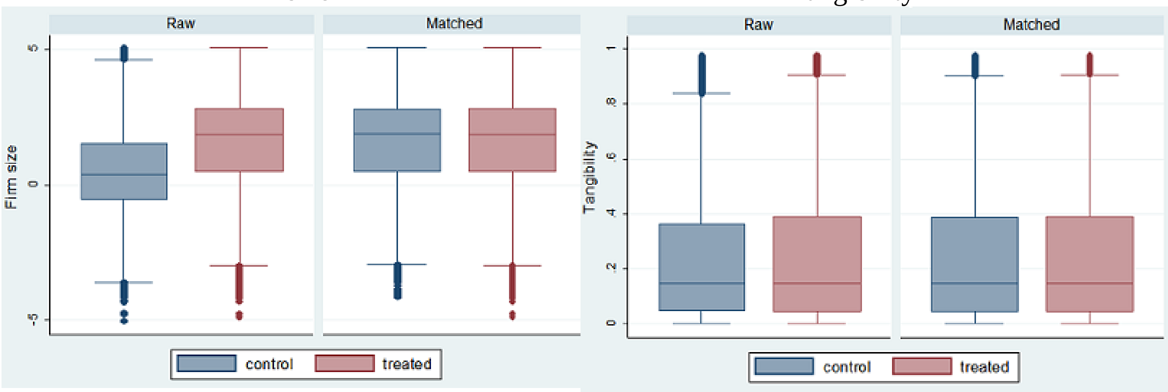
	Standardized differences		Variance ratio	
	Raw	Matched	Raw	Matched
No county controls				
Firm Size	0.683	0.002	1.163	1.022
Tangibility	0.064	0.005	1.229	1.015
Country fixed effects				
Firm Size	0.493	0.003	1.085	1.019
Tangibility	0.335	0.006	1.547	1.016
Country-level controls				
Firm Size	0.417	0.002	1.167	1.025
Tangibility	0.188	0.007	1.316	1.020

Figure 1.

Box plots of the unmatched and matched data.

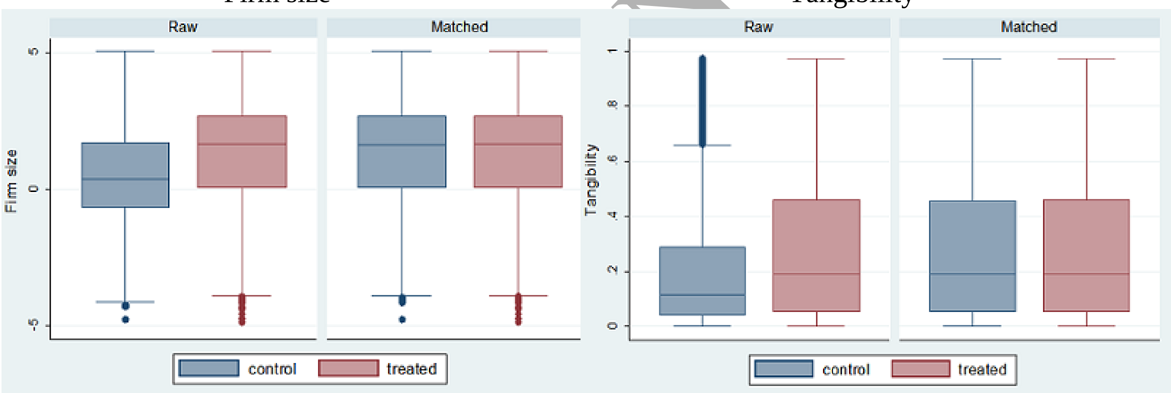
No country controls

Firm size Tangibility



Country fixed effects

Firm size Tangibility



Country-level controls

Firm size Tangibility

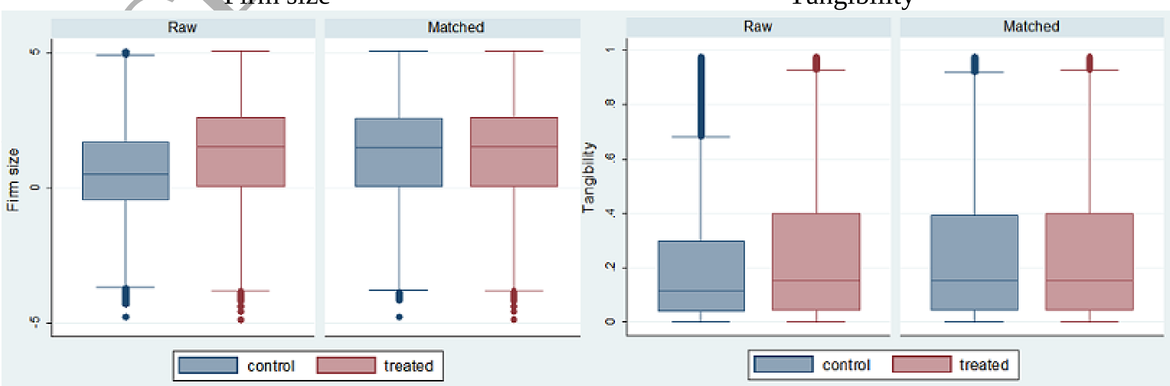
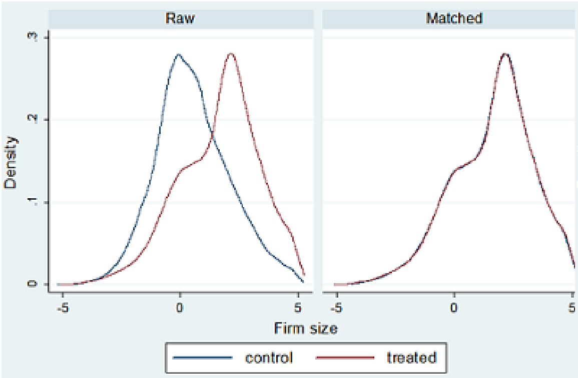


Figure 2.

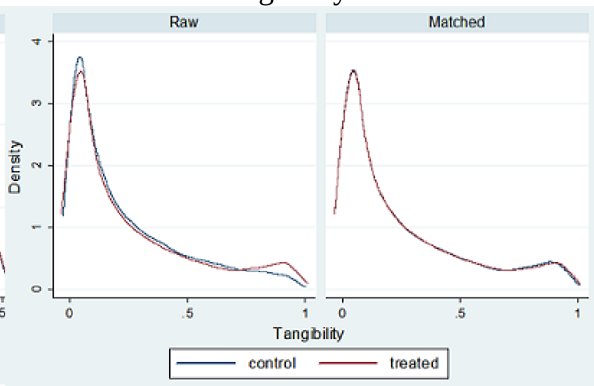
The kernel density plots using the unmatched and matched data.

No country controls

Firm size

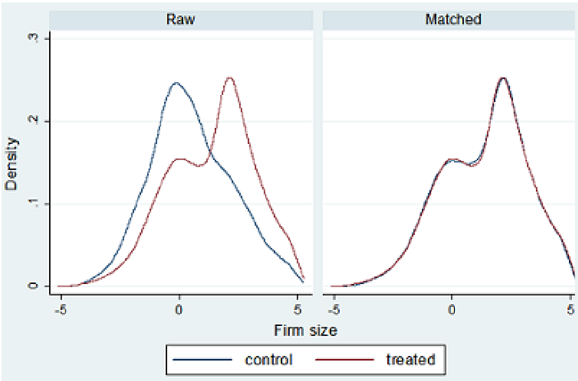


Tangibility

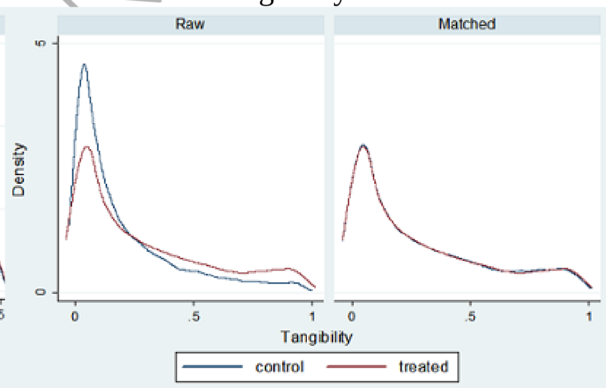


Country fixed effects

Firm size

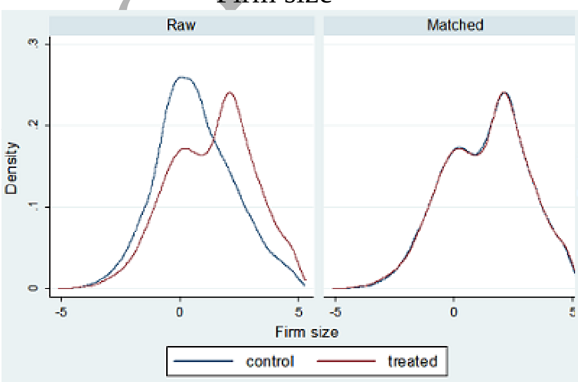


Tangibility

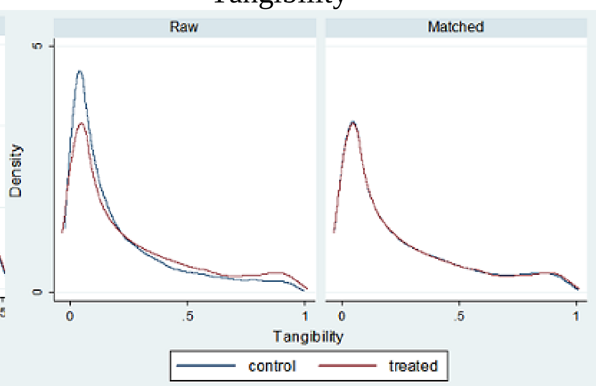


Country-level controls

Firm size



Tangibility



Appendix

Variable	Definition
Bank efficiency	Cost efficiency score. Source: own computation.
Profit efficiency	Profit efficiency score. Score: own computation.
Firm size	= log(total assets). Source: Amadeus.
Tangibility	= tangible fixed assets /total assets. Source: Amadeus.
Cost of credit	= (financial expenses /total debt) – country nominal short-term interest rate. Source: Amadeus and SDW.
Lerner index	Lerner index is defined as the difference between price and marginal cost divided by price. Source: own computation.
Private credit	Private credit by deposit money banks to GDP. Source: Global Financial Development Database, World Bank.
Rule of law	This variable captures the extent to which agents have confidence in the rule of law and how well they expect members of society to abide by the rules. In particular, it looks at the perceptions about the quality of enforcement of contract law and property rights, as well as the behavior of the police and the courts, and the frequency of crime and violence. Source: Worldwide Governance Indicators, World Bank.
GDP per capita	GDP per capita in USD. Source: World Development Indicators, World Bank.
Inflation	Consumer Price index growth rate. Source: World Development Indicators, World Bank