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Abstract

This paper uses a unique dataset where credit rejections experienced by euro area firms are matched with firm and bank characteristics. This allows us to study simultaneously the role that bank weakness and firm weakness had in the credit reduction observed in the euro area during the sovereign debt crisis, and in credit developments characterising the post-crisis recovery. Compared with the existing literature matching borrowers' and lenders' characteristics, our dataset provides a better representation of euro area firms of small and medium size. Our findings suggest that, while firm balance sheet factors have been strong determinants of credit rejections, in the crisis period bank weakness made it harder to obtain external finance for firms located in stressed countries of the euro area.

KEYWORDS: Credit supply, Bank lending, Credit crunch, European sovereign debt crisis.

JEL Classification: E44, F36, G01, G21.

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Non-technical summary

Since the European sovereign debt crisis, we can observe divergent credit developments across the euro area. While bank lending to non-financial corporations located in periphery countries has strongly decreased, bank loans to enterprises based in core countries have increased. Several factors may account for such divergence. On the one hand, credit demand from firms located in the periphery may have been constrained by the lack of new business opportunities or stronger deleveraging needs. On the other hand, these firms may have faced stronger obstacles to accessing external financing. Very different policy implications could be drawn depending on which factors stand behind such divergent credit developments.

Results from the ECB Survey on the Access to Finance of Enterprises (SAFE) provide useful information in this respect. They show that firms located in the periphery demanding a bank loan were more likely to see their loan application rejected in the period that goes from 2010 to 2018. However, looking at SAFE results in isolation does not provide sufficient information to understand whether such more frequent credit rejections were due to a lower creditworthiness of firms, or there were also supply-side weaknesses at play.

Against this background, in this paper we build a unique dataset where information on loan applications from SAFE is matched with firms' and banks' balance sheet information. First, we augment SAFE with firms' balance sheet data from Bureau van Dijk's Orbis-Amadeus databases. This detailed information on firms' characteristics provides appropriate controls to proxy for the health of the firm, including whether it displays an unbalanced leveraged ratio. Second, we further enrich our dataset with information on banks' asset quality, capitalisation, and profitability obtained from Fitch Connect. All in all, this allows us to study whether the stronger financing obstacles faced by firms located in the periphery have been due to being less creditworthy than their peers in core countries, or rather due to confronting banks with a lower ability to grant credit.

We find that firm leverage is strongly associated with a higher probability of credit rejection. However, loan applications have been rejected more often in stressed countries than in core countries, and this gap is not explained fully by differences in firm characteristics. Interaction terms allowing for a different impact of firm characteristics across the two country groups do not show statistical significance.

When we include in our analysis measures of the health of banks, results suggest that periphery-specific bank weakness can explain the higher rejection rates experienced by firms operating in stressed countries. Additionally, we find that in crisis times banks with higher level of non-performing loans (NPLs) seem to lend less even to creditworthy firms, but the effect of the NPL ratio depends on its level. Specifically, at reasonably low levels, a higher NPL ratio might signal the bank use of a more aggressive business model and, as such, be associated with a lower rejection rate. Only at the high levels mostly observed in periphery countries, we find that a higher NPL ratio signals weakness in the bank balance sheet, and thus a limited ability to grant loans even to sound firms.

1 Introduction

Since the European sovereign debt crisis, bank lending to euro area non-financial corporations (NFCs) located in periphery countries has strongly decreased, while bank loans to enterprises based in core countries have increased. In this paper, we examine the determinants of such divergent credit developments across the euro area.

According to economic theory, several explanations may account for the observed differences in credit dynamics across the euro area. On the one hand, it could be that firms located in the periphery may have demanded less credit, e.g. due to a lack of new business opportunities; they could have also experienced stronger deleveraging needs. On the other hand, it could also be that firms operating in the periphery faced stronger obstacles to accessing external financing. Very different policy implications could be drawn depending on which factors stand behind such divergent credit developments.

Results from the ECB Survey on the Access to Finance of Enterprises (SAFE) provide useful information in this respect. They show that firms located in the periphery were more likely to see their bank loan application rejected in the period that goes from 2010 to 2018, compared to their core country peers. SAFE data however do not provide sufficient information to understand whether the observed difference in credit rejections can be fully explained by a lower creditworthiness of firms operating in the periphery, or if there were also supply-side factors at play.

Against this background, in this paper we build a unique dataset where information on credit applications from SAFE is matched with firms' and banks' balance sheet information. Using this database we can examine simultaneously how firm and bank characteristics influenced bank decision to grant credit to firms operating across the euro area. Overall, we find that both firm and bank characteristics matter for the outcome of bank loan applications. In times of crisis, weak banks tend to lend less, even after taking into account firms' creditworthiness. Our results also suggest that bank weakness can explain the higher credit rejection rates experienced by firms operating in stressed countries during the crisis.

We contribute to the literature by building a unique dataset which well represents small and medium-sized enterprises (SMEs) operating in the euro area. A number of papers in the literature study the causes of the credit crunch in the euro area employing the Khwaja and Mian (2008) identification strategy, which requires longitudinal loan level data with different banks lending to the same firm. Acharya et al. (2018) study European syndicated loans. While their dataset covers firms operating in different euro area countries, syndicated loans account for less than 10% of euro area lending and cater mostly to large established corporations. Their findings have therefore little to say on SMEs, which in contrast are well represented in our dataset. From a policy perspective, analysing SMEs' access to bank financing is crucial, both because they account for most of all businesses in Europe and for their strong reliance on bank financing. Other papers apply the Khwaja and Mian (2008) identification strategy to credit registry data matched with bank supervisory information (Jimènez et al. 2012, 2014, 2017, and Bofondi et al. 2018). While their datasets have good coverage of SMEs and very detailed information on the characteristics of each loan granted, they cover firms operating only in one country. Thus, these papers cannot explain differences across countries, which is the main question we address in this paper.

Another crucial feature of our study is that we are able to observe if a firm has applied for a bank loan and the outcome of its loan application. SAFE indeed reports whether firms applied for loans in the previous 6 months and if their credit application was rejected, partially granted or fully granted. Most papers instead, including those based on syndicated loan data as Acharya et al. (2018), do not observe cases in which credit was demanded but not granted. We argue that observing credit rejections, as well as the share of granted credit over the amount requested, is crucial for understanding firms' obstacles to external finance. In this respect, SAFE shows that credit was not fully granted in around 40% of all cases during our sample period (see Table 1). Besides this, suppose in a certain time period a firm borrows more than in the previous period, but its borrowing needs have increased to an even larger extent. In this case, any identification strategy will fail, unless one observes the share of granted credit over the amount requested. Therefore, this information is essential to understand whether this firm is facing stronger obstacles to access external finance.

In addition, our data allows us to observe discouraged borrowers, i.e. firms that did not apply for bank loans as they were fearing a possible rejection. This is an innovation compared to studies using credit registry data such as Jimènez et al. (2012), (2014) and (2017), and Bofondi et al. (2018). While datasets used in these studies include loan application outcomes, discouraged borrowers do not appear, given that these firms did not apply for a loan. However, covering discouraged borrowers is important for the scope of our analysis, given that these borrowers appear to be particularly credit constrained (Ferrando and Mulier 2015).

While there are a few papers that augment SAFE with information on firm and bank characteristics (e.g. Ferrando et al. 2019 and Betz and De Santis 2019), our study constitutes the first attempt to systematically match SAFE data with firms' and banks' financial accounts, which we retrieve from the Bureau Van Dijk (BvD)'s Orbis-Amadeus dataset and Fitch Connect, respectively. Obtaining this information is crucial for the purpose of our analysis, as SAFE neither includes information on firms' financial statements, nor reports the name of the bank(s) to which firms have requested credit. However, banks are known to analyse firms' financial accounts (e.g. firm leverage) when assessing whether to grant them credit. At the same time, whether a credit application will be successful may also depend on bank soundness.

Our results can be summarised as follows. Although we find that firm characteristics seem to have played a prominent role in determining higher rejection rates, they do not fully explain the large difference between core and periphery countries. On the other hand, we find evidence that periphery-specific bank weakness can explain at least part of this difference. Specifically, we find that factors summarising bank weakness affected the probability of experiencing credit rejections more strongly in the periphery than in the core – while we find no evidence for a different impact of firm characteristics across the two country groups.

Turning to the role played by individual bank characteristics, we find that credit rejections are positively and significantly associated with having a relationship with a bank displaying a higher ratio of non-performing loans (NPLs) and a lower level of capitalisation. In line with findings shown in previous studies (see e.g. Jimènez et al. 2017), bank weakness seems to have played a more prominent role during the crisis than in the post-crisis years. Additionally, we find evidence for a non-linear effect of the bank NPL ratio on credit rejections. At reasonably low levels, mostly characterising banks in core countries, a higher NPL ratio does not necessarily indicate bank weakness. It might rather signal the use of a more aggressive business model and, as such, be associated with less credit rejections. On the other hand, at the high levels observed in periphery countries, a higher

NPL ratio most likely signals weak bank balance sheet, and we find it being significantly associated with a lower propensity to grant loans even to sound firms.

Results are robust to different definitions of credit rejection and are not driven by a larger concentration of distressed firms in the periphery. They are also robust to different firm-bank matching criteria applied to those firms reporting multiple bank relationships. Indeed, while in the baseline specification we match firms with their first listed bank (as e.g. in Kalemli-Ozcan et al. 2018 and Ferrando et al. 2019), our findings are robust to the use of random matching, as well as to linking firms to the healthiest bank of those listed.

All in all, this paper contributes to the economic literature by studying euro area credit dynamics during and in the aftermath of the sovereign debt crisis. Thanks to our unique dataset matching credit rejections with firm and bank characteristics, we are able to study the role that firms' and banks' weakness played in the evolution of the access to external finance of euro area firms, including those of small and medium size, during and after the European sovereign debt crisis.

2 Related literature

Few empirical works study loan application outcomes in conjunction with firm and bank characteristics, and they limit their analysis to specific countries only. Bofondi et al. (2018) use Italian credit register data to study the transmission of sovereign stress to Italian banks and their lending during the sovereign debt crisis. Jimènez et al. (2017) use Spanish credit register data of loan applications matched with bank and firm variables. While their analysis is able to distinguish between credit supply and demand, it focuses on Spain and does not cover the European sovereign debt crisis period. Jimènez et al. (2012) and (2014) also use this dataset; the former paper analyses the effects of contractive monetary policy and adverse economic conditions on lending through the bank balance-sheet channel, while the latter identifies the impact of monetary policy on banks' risk-taking in the period preceding the global financial crisis.

Among recent studies using SAFE data, Ferrando et al. (2017) find that firms in stressed countries became more likely to be denied credit, to be credit rationed, and to face higher loan rates in the crisis period. Holton et al. (2014) find that private sector indebtedness has important effects on SMEs' credit access, also underlining a negative impact of a bank balance sheet channel. Both these studies neither control for firm-level leverage ratios nor for bank characteristics. Ferrando and Mulier (2015) study discouraged borrowers in the euro area in the 2010-14 period matching SAFE with Amadeus. They find that firms are more likely to be discouraged in countries where the average interest rate charged by banks is higher. However, given that they do match firms with their banks, they cannot exploit within-country variability in bank characteristics, which is what we do. Ferrando et al. (2019) and Betz and De Santis (2019) augment SAFE with information on firms' and banks' characteristics but focus on a limited time span, as they evaluate the impact of a specific policy such as the announcement of the ECB Outright Monetary Transaction programme (OMTs) or the ECB corporate sector purchase programme. They also focus on firms linked with a much narrower sample of banks than ours, since they limit theyr analysis to banks that are active in the sovereign bond market or participate in syndicated loans – e.g. Ferrando et al. (2019) include information on 126 banks from Bankscope and 25 banks from the EBA stress tests, compared with 826 banks in our sample. Altavilla et al. (2018) use data from a different ECB survey, the Bank

Lending Survey, to study whether borrowers demand less credit from banks with weak balance sheet positions.

Among others, Kalemli-Ozcan et al. (2018) stress the importance of taking into account the role played by firm leverage in explaining recent credit dynamics in the euro area. They find that excessive corporate debt accumulated during the boom years can be linked with weak investment in the aftermath of the crisis, and that interacts with weak credit supply from banks. Compared with this paper, we are able to match firm and bank characteristics with credit application rejections. A number of recent papers, including Acharya et al. (2019), Storz et al. (2017), and Schivardi et al. (2018), find that loan 'evergreening' to distressed firms in the euro area periphery has produced capital mis-allocation. However, Schivardi et al. (2018) show that previous studies largely over-estimate the macroeconomic effects of this source of capital mis-allocation.

Our paper also relates to the literature that studies credit supply shocks. A recent contribution by Acharya et al. (2018) applies a version of the Khwaja and Mian (2008) estimator to European syndicated loan data, so as to identify the effect of supply factors by analysing the change in credit granted to the same firm by different banks. However, syndicated loans account for just 10% of euro area lending and cater mostly to large established corporations rather than SMEs. Alternative identification strategies have been proposed by Gilchrist et al. (2018), who estimate supply-induced contractions in the availability of bank credit exploiting the fact that US banks originate loans across multiple local markets. Greenstone et al. (2017) also study US data, obtaining county-level lending shocks thanks to variation in preexisting bank market shares and estimated bank supply-shifts.

In addition, our paper is related to a vast literature that studies the effects of bank asset quality during the crisis, focusing in particular on direct sovereign exposures (see e.g. Acharya and Steffen 2015 and Ongena et al. 2016). Popov and van Horen (2015), Altavilla et al. (2017) and Acharya et al. (2018) find that domestic sovereign exposures amplified the transmission of sovereign stress to banks, so causing a reduction in bank lending to the private sector. Gennaioli et al. (2018) show similar findings analysing a number of sovereign bank episodes that occurred from 1998 to 2012 around the world. On the other hand, Bofondi et al. (2018) find that sovereign portfolio diversification helped little against the transmission of sovereign stress to Italian banks, which reduced lending irrespectively of their direct sovereign exposures. In line with this finding, Corbisiero (2016) and Tabellini (2018) argue that euro area banks may suffer from domestic sovereign stress irrespective of portfolio diversification, being unlikely to survive capital flights and bank runs due to the fear of home sovereign default and a following euro exit. Also in light of these conflicting findings, in our paper we use indicators of bank weakness alternative to direct sovereign exposures.

3 Data and stylised facts

3.1 Data

To study the role of firms' and banks' weakness in credit dynamics during and after the European sovereign debt crisis, we construct a unique dataset matching credit rejections with firm characteristics and bank balance sheet information.

3.1.1 Firm-level characteristics

We obtain data on loan application outcomes (our main variable of interest) from the Survey on the Access to Finance of Enterprises (SAFE), a survey conducted on behalf of the ECB and the European Commission every six months since 2009. The dataset is constructed by randomly selecting NFCs operating in the euro area and neighbouring countries, with the number of firms adjusted to increase the accuracy of the survey across countries, economic activity, and size classes. Sectors covered by the survey include construction, industry, services, and trade within the European Union. As the survey questionnaire was significantly revised at the beginning of 2010, we restrict our analysis starting from wave 3.

While some of the SAFE waves also cover non-euro area countries, we restrict our analysis to firms operating in the euro area only, so as to keep monetary policy constant across countries (Kalemli-Ozcan et al. 2018 and Altavilla et al. 2017).[1] For the same reason, we exclude firms operating in Estonia, Latvia and Lithuania, as these countries joined the euro area only after the starting point of our sample period. Out of this sample, we extract data for firms that reported having applied for bank credit in the preceding six months or not applying because of the fear of a possible rejection ('discouraged firms').

Using the information provided by SAFE, we are able to classify firms according to the outcome of their bank loan applications in the previous 6 months: (i) received all the credit demanded, (ii) received most (i.e. 75% or more) of the credit demanded, (iii) received a limited part (i.e. less than 75%) of the credit demanded, (iv) refused the loan offered as the interest charged was too high, (v) its credit demand was fully rejected, or (vi) did not apply being discouraged. In addition, we extract from SAFE data on firms' perception on their business outlook in terms of profitability, sales and business plan as well on changes in firms' credit history and own capital. We also obtain data on firms' turnover, number of employees, sector of activity, and on the year of establishment.

Given respondents' difficulties in answering on the phone questions related to quantitative accounting elements, SAFE does not collect firms' balance sheet and profit & loss account information. However, such information is crucial for the purpose of our analysis. Banks are indeed known to analyse firms' financial statements when deciding whether to grant credit. Consequently, we augment SAFE with information on firms' financial accounts provided by Bureau van Dijk (BvD)'s Amadeus and Orbis, commercial datasets covering around 21 million companies across Europe and 310 millions companies worldwide, respectively. From these datasets, we extract data on firms' pre-existing leverage, return on asset, investment, and debt servicing capacity. The latter three variables are used in the empirical analysis to identify highly distressed firms, also known in the literature as 'zombie firms' (see e.g. Storz et al. 2017). Data retrieved from Amadeus and Orbis have annual frequency and span back to 2007 to allow for the construction of indicators of firm soundness based on lagged financial variables.

As BvD is able to match around 80% of the firms in SAFE with firms' balance sheet information, we are left with 34,038 firm-wave observations, corresponding to 20,945 firms for the period H1 2010 - H1 2018 (SAFE waves 3 to 19). This relatively limited number of observations is explained by the fact that a large share of the firms in SAFE reported not to have applied for loans in the previous

[1] The smallest euro area countries (Cyprus, Latvia, Lithuania, Luxembourg, Malta, Slovenia and Slovakia) are not systematically included in each wave, but appear at least in one wave per year. However, as they represent less than 3% of the number of employees in the euro area, this should have only a marginal effect on the results for the euro as a whole.

six months as they had sufficient funds. Therefore they are not included in our dataset.

3.1.2 Linking firm-level data with banks' balance sheet information

In addition to firms' financial information, BvD also reports the name of each firm's current bank(s). Such information is available only for a subset of 12 euro area countries, namely: Austria, Cyprus, France, Germany, Greece, Ireland, Luxembourg, Malta, Spain, the Netherlands, Portugal, and Slovenia. Approximately 50% of the firms operating in these countries in our SAFE-Amadeus-Orbis dataset report the name of their current main bank(s), corresponding to 57% of the firm-wave observations. For these firms, we extract data on their banks' relationships from the latest available release of the SAFE-Amadeus-Orbis dataset. Following Giannetti and Ongena (2012), Storz et al. (2017) and Kalemli-Ozcan et al. (2018), we assume that bank-firm relationships do not change over short horizons of time, such as the time-span of our analysis;[2] likewise, in line with Ferrando et al. (2019), we assume that a firm's reported banks correspond to the banks a firm borrows from.

Should a firm report multiple bank relationships, we match it with its first listed bank. Banks are not listed generally in alphabetical order; thus, we assume that the respondent's ordering conveys information on the relevance of its relationship with each of its banks.[3] As a robustness, we also perform a couple of alternative matchings, by randomly assigning to each firm one of the banks indicated or by linking firms with the 'healthiest' bank listed.[4] The latter matching is also motivated by the fact that Altavilla et al. (2018) find that banks soundness is a factor taken into account by firms when selecting whom to borrow from.

Matching firms with banks is not straightforward as Bureau van Dijk's Amadeus and Orbis do not report any additional information on the bank, beside its name. Moreover, bank names are not reported in a consistent manner across firms. For example, while in some instances the full name of the bank (including the geographical location of the local bank branch) is reported, in other cases acronyms are used. At the same time, different banks often have very similar names, making it difficult to use approximate-matching algorithms. As a consequence, we need often to match observations manually to avoid incurring type I errors.

Nevertheless, our matching rate is extremely high: out of the firms that report their banks' name, we are able to successfully match over 98% of our observations.[5] As in Kalemli-Ozcan et al. (2018), unmatched observations often relate to small cooperative banks, for which information is not available in online data platforms. As many firms happen to borrow from the same bank, our dataset includes information of 826 individual banks when considering the first listed bank.[6] From Fitch Connect, we retrieve data on the bank's financial position (e.g. equity, net income, deposits, assets, and liabilities) and asset quality (NPL ratios). Bank level data have annual frequency.

[2] Kalemli-Ozcan et al. (2018) compare the 2015 vintage of Amadeus with that of 2013. Giannetti and Ongena (2012) compare the 2010 vintage of KOMPASS (the original data source of information contained in Amadeus) with that of 2005. Both studies find that bank-firm relationships are extremely sticky over time.

[3] Kalemli-Ozcan et al. (2018) and Ferrando et al. (2019) follow the same approach. Storz et al. (2017) instead match firms with the largest domestic bank reported (in terms of total assets in 2007).

[4] To identify the 'healthiest' bank among those listed, we rank banks in terms of the average NPL ratio in the period 2009-2018 and pick that with the lower NPL ratio.

[5] Using Bankscope, Kalemli-Ozcan et al. (2018) are able to successfully match 87.6% of all the bank name observations. Storz et al. (2017) are able to match 95% of the firms reporting the name if the bank.

[6] When we perform the firm-bank matching by randomly assigning to each firm one of the banks listed, we end up with 971 individual banks. If we match firms with the 'healthiest' bank, we are left with 758 individual banks in our dataset.

Finally, we complement our dataset by including information of country real GDP forecasts (2-years ahead) retrieved from the European Commission's AMECO dataset.

Table 1 reports the descriptive statistics of the main variables used in our empirical specification. The detailed definition of all variables can be found in Table 2 (firm and macro variables) and Table 6 (bank variables).

[Table 1 here]

3.2 Stylised facts

From June 2010 to September 2014, bank loans to NFCs decreased by around 23% in stressed countries but increased by around 4% in the rest of the euro area (Figure 1).

[Figure 1 here]

This difference could be entirely due to a lower demand for loans in the periphery, due to, for instance, a stronger decline in business opportunities. SAFE provides useful information to understand which factors stand behind these dynamics. Figure 2 shows how many SAFE respondents reported to have been totally denied credit, as a percentage of those who reported to have applied for bank loans. The euro area average peaked in the middle of the sovereign debt crisis and has decreased since then. However, cross-country differences are relevant, with Italy and Spain, the two largest economies in the periphery, showing a higher percentage of credit rejections than the rest of the euro area, particularly during the crisis.

[Figure 2 here]

Another interesting stylised fact is shown in Figure 3. Besides those that got denied credit, a relevant share of firms reported not to have even applied for loans, because of being discouraged. Again, periphery countries display larger shares of discouraged firms compared to the rest of the euro area; and such shares tend to decline, overall, in the years following the sovereign debt crisis.

[Figure 3 here]

Figure 2 and Figure 3 show that the lower aggregate lending in the periphery during the crisis was not entirely due to a lower demand. At least part of the difference, indeed, was due to firms being more often denied credit. However, a difference in the financial soundness of firms applying for loans could still be the main or the only reason explaining diverging credit dynamics across euro area countries. Such consideration underlines the importance of controlling for appropriate firm characteristics, which we obtain thanks to matching SAFE with Amadeus.

Moving towards examining facts related to bank weakness, Figure 4 shows the median ratio of non-performing loans to total gross loans of banks operating in selected euro area countries, and in the euro area as a whole.

[Figure 4 here]

During the crisis and its aftermath, banks in stressed countries registered much larger NPL ratios – one of the several proxies that, following the literature (e.g. Storz et al. 2017), we use below to measure bank soundness – compared to banks in the rest of the euro area. This suggests to further explore the role played by bank weakness, and underlines the importance of an empirical specification that can examine loan rejections not only in conjunction with firm characteristics, but also with measures of bank soundness.

4 Empirical analysis

We analyse a number of empirical models that can be broadly summarised according to the following specification:

$$\begin{aligned} \text{Credit rejection}_i = \beta_0 + \beta_1 \text{ Periphery}_i + \beta_2 \text{ Firm leverage}_i + \sum_{j=3}^{n+2} \beta_j \text{ Firm characteristics}_i \\ + \sum_{l=n+3}^{m+n+2} \beta_l \text{ Bank characteristics}_i + \sum_{z=m+n+3}^{m+n+r+2} \beta_z \text{ Other control variables}_i + \varepsilon_i \end{aligned} \tag{1}$$

In our baseline specification, the dependent variable 'Credit rejection' equals 1 if the firm reported (i) to have applied for bank loans in the previous six months but got nothing, or (ii) to have applied but only got a limited part (i.e. strictly less than 75%) of its demand, or (ii) not to have applied being discouraged,[7] or (iv) to have refused credit because it was offered at a too high cost. It equals 0 if the firm reported (i) to have applied for bank credit and got everything, or (ii) to have applied and got most (i.e. 75% or more) of its demand. We analyse below the robustness of results to a more agnostic specification of the dependent variable following an ordered probit model.

'Periphery' is a dummy variable assuming value 1 if the firm applying for the loan operates in a stressed country and 0 otherwise. Following the sovereign debt crisis literature (see e.g. Altavilla et al. 2017), we classify as periphery countries Cyprus, Greece, Ireland, Italy, Portugal, Slovenia, and Spain; the core countries are Austria, Belgium, Finland, France, Germany, Luxembourg, Malta, the Netherlands, and Slovakia. 'Firm characteristics' is a vector of n characteristics of the firm j, 'Bank characteristics' is a vector of m characteristics of the bank that the firm j reports being its main bank. Other control variables include wave dummies, which control for shifts across semesters due, for instance, to monetary policy, gobal factors, or euro area-level business cycle dynamics; and yearly GDP growth forecasts for the country where firm i operates, which control for the country-specific business cycle.

It is important to note that our regressions are not run at the loan level, i.e. we do not match a firm and a bank to each single loan application. Our dependent variable refers instead to the overall outcome of bank loan applications submitted by each firm during the past semester. Subsequently, this outcome is matched with the bank that each firm reports being its main bank.[8]

SAFE includes some panel structure, but only for a limited number of firms. Each of these panellist firms, moreover, are not interviewed systematically, i.e. they appear only in a small subset of the survey waves. This makes the panel structure not only small in size and possibly poorly representative, but also heavily unbalanced. For this reason, the models analysed in this paper are estimated as pooled cross section.

[7] Ferrando and Mulier (2015) estimate that the majority of discouraged borrowers would be unable to get a loan if they would apply.

[8] If the firm reports multiple bank relationship, we use a number of different matching criteria. See Section 4.2 for more details.

The dependent variable ‘credit rejection’ in Equation 1 is a vector of dimension $1 \times g$, where g is the number of realisation of the dependent variable in our sample. A certain realisation of ‘credit rejection,’ say i, corresponds to a certain firm, say j, that experiences or not credit rejection at a certain time, say t; values assumed by each of the independent variables will then refer to values associated to the firm j at time t.[9] Time t refers to the semester of realisation of ‘credit rejection.’ The value of ‘Firm leverage’ associated to a realisation of ‘credit rejection’ in semester t refers to $t - s$, where $s = 1$ semester, if the realisation of the dependent variable is observed in the first half of the year; and $s = 2$ semesters, if the realisation is observed in the second half of the year.[10]

As SAFE is semiannual, while Amadeus-Orbis and FitchConnect are annual, we need to make an assumption on how to treat a firm possibly appearing twice in a year, to avoid counting twice the same value of an annual variable. We include data of the first semester if the firm reported the same outcome in both semesters, and data of the semester of credit rejection otherwise.

We split the sample period in ‘crisis’ and ‘post-crisis’ in a number of model specifications. The ‘crisis’ period includes SAFE waves from 3 (covering the semester March-September 2010) to 11 (April-September 2014), while the ‘post-crisis’ period includes waves from 12 (October 2014-March 2015) to 19 (April 2018-September 2018). Choosing the starting point of the post-sovereign debt crisis period is obviously subject to a risk of arbitrariness. We choose the second half of 2014 given that, starting from this semester, both Spanish and Italian 10-year sovereign bonds have yielded below 3% and displayed spreads below 200 basis points compared to German sovereign bonds of the same maturity.

4.1 The role of firm characteristics

In this section, we investigate whether the higher credit rejection rates observed in the periphery can be entirely explained by differences in the creditworthiness of the firms in the two country groups. In this first set of regressions the main variables of interest are ‘Periphery’ and ‘firm leverage,’ where the latter is measured as the ratio between total debt and total assets. Firm characteristics we control for also include the firm’s size in terms of number of its employees, its turnover, industry (at the one-digit level, i.e. distinguishing between industry, services, construction, and trade) and age (i.e. the number of years since the firm was established). Regressions also include firms’ own assessment on a number of factors that are directly related to the ability of a firm to obtain external finance; namely, the firm business outlook, its own capital, and its credit history.[11]

4.1.1 The baseline empirical model

The first two columns of Table 2 show results from the linear probability model and the probit model estimated for the full sample period, from March 2010 to September 2018. Both the main variables of interest, ‘Periphery’ and ‘firm leverage,’ are estimated to have a significant impact on

[9] The use of a pooled cross section implies that, if a firm is interviewed more than once, each observation is treated as a separate event.The issue of potential bias due to autocorrelation is discussed in Section 4.1.

[10] We regress credit rejections of the lagged value of firm leverage given that this is the information possibly available to banks receiving loan applications.

[11] To limit the risk of incurring bias due to measurement error, we exclude those firms reporting zero or negative total liabilities, as well as zero or negative total assets. Additionally, we exclude firms with a total debt to total assets ratio greater than 3. Such values, besides being at risk of measurement errors, only characterise firms which are well above the 99th percentile of our distribution.

the probability of credit rejection. Being located in a stressed country and being more leveraged are both associated with a higher probability of credit rejection.

[Table 2 here]

Other firm characteristics are also significantly associated with credit rejections and display the expected sign. Firms that report a deteriorated business outlook, own capital and credit history experience higher probability of credit rejection. Having a smaller turnover, a lower number of employees, and being established more recently, are associated with a higher probability of credit rejection. Moreover, firms operating in industry and construction are estimated to be more likely to experience credit rejections compared to firms operating in services (the omitted sector in the regressions).

Turning to macroeconomic indicators, the positive and significant coefficient of GDP growth forecast suggests that operating in a country with a better growth outlook is associated with a higher probability of credit rejection. While being counterintuitive, this can be explained by a 'mean reversion' components of GDP forecasts. If the estimated potential growth of GDP is not correctly revised, the more realised growth is below its estimated potential, the more forecasts tend to overstate recovery in the near- to the medium-term ahead.[12] At the same time, all regressions estimate that an improvement in the firm-specific business outlook is significantly associated with a smaller probability of experiencing credit rejections.

When we interact 'Firm leverage' with the crisis years, we do not find a statistically significant change in the role played by 'firm leverage.' In contrast, we find a significant, more strongly negative impact of 'Periphery' on the access to finance during the crisis. In columns (3) to (6) we allow the coefficients of all variables to change from crisis to post-crisis, re-estimating the linear probability and the probit model separately for the crisis and the post-crisis period. Results are confirmed, including the one of a stronger difference between core and periphery during the crisis years. Importantly, estimated average marginal effects from the probit models strongly confirm results of the linear probability models, also in terms of the economic significance of 'periphery.' Both models estimate that, else equal, being located in a stressed country of the euro area increases the probability that a firm will experience credit rejection by 17% during the crisis period, and by 10% (or by 11%, according to the linear probability model) in the post-crisis period.[13]

Interestingly, we find no significant change in the impact of firm leverage on the likelihood of credit rejections across the two country groups (see the insignificant interaction terms between 'Firm leverage' and 'Periphery'). In other words, the impact that the leverage ratio has on the chance of experiencing a credit rejection is not significantly different in stressed countries compared to non-stressed ones, while the coefficient of 'Periphery' remains strongly significant.

To allow for a better interpretation of the economic significance of the coefficients, Figure 5 shows the adjusted predictions at representative values that firm leverage assumes over the whole range of its values, computed from the probit model for both the crisis and the post-crisis period. During the

[12]We use GDP growth forecasts instead of contemporaneous GDP growth because of endogeneity concerns. However, replacing forecasts with realised growth rates leaves results unchanged; and, as expected, a higher realised growth rate is found to be significantly associated with a lower probability of credit rejections.

[13]In the probit regressions the AMEs of 'Periphery' are estimated from, 'Periphery' is interacted with leverage. While the presence of an interaction term can in principle affect the computation of AMEs, here it does not constitute a problem because such interaction term is insignificantly different from zero. To check that, we re-estimated the AME of 'Periphery' in regressions without such interaction but otherwise identical to the one in the fourth and the sixth columns of Table 2, finding results basically unchanged.

crisis, moving from the 10th to the 90th percentile of the distribution of firm leverage, is estimated to increase the probability of credit rejection by about 30%. The result is very similar for the post-crisis period, while the curve is shifted down.

[Figure 5 here]

Additionally, adjusted predictions shown in Figure 6 allow us to estimate how the probability of credit rejections vary with respect to two dimensions: first, whether the firm is located in a stressed country, and second, across different levels of firm leverage. Operating in a stressed country is associated with a substantially higher probability of being denied credit, at *any level* of firm leverage in both periods. However, such difference substantially attenuates in the post-crisis period.

[Figure 6 here]

SAFE collects random samples from a large population of firms at each wave independently of each other. Therefore, autocorrelation should not be an issue in the use of a pooled cross section. However, independent sampling does not hold within the subset of firms appearing in more than one wave (i.e. 'panellist' firms), and autocorrelation might still occur among them. For instance, we might have a firm that is discouraged due to a past rejection, and include both events in our sample without accounting for their serial correlation. To take into account this source of potential bias, we run regressions on a restricted sample that includes 'panellist' firms only the first time they are sampled in SAFE, i.e. only the time they were randomly selected. Results are reported in Table 8 in the Appendix and strongly confirm those shown in Table 2, both in terms of statistical and economic significance.

4.1.2 Regressing credit rejections wave by wave

In addition to splitting the sample into crisis and post-crisis period, we also estimate the same linear probability model as in in Table 2 separately for each wave of SAFE. Figure 7 shows how coefficients and confidence intervals of 'Firm leverage' and 'Periphery' vary over time. [14]

[Figure 7 here]

In line with the findings discussed above, results show that both the statistical and the economic significance of firm leverage remains broadly constant across semesters. On the other hand, the coefficient of 'Periphery' varies substantially, peaking in 2012 and then reducing, in a rather consistent manner. This suggests that, as periphery countries' perceived risks are sufficiently attenuating, credit rejections seem to be due relatively less to country-specific stress factors, and relatively more to factors related to firm characteristics.

4.1.3 Refining the definition of credit rejection: Ordered probit

In this section, we exploit the richness of of our dependent variable using an ordered probit model (McKelvey and Zavoina 1975).[15] We classify the dependent variable in four categories, ordered

[14] Complete estimates are included in Table 9 in the Appendix.

[15] While preserving the ordering of responses, the ordered probit makes no assumptions about the interval distances between them. OLS estimates, in contrast, would assume equal distance when dealing with more than two outcomes – which is not appropriate in this setting.

according to whether the firm applied for bank credit and (i) got everything, (ii) got most of it (i.e. 75% or more), (iii) got only a limited part of it (i.e. strictly less than 75%), or (iv) got nothing. We exclude firms discouraged from applying, as well as those which refused credit because of its cost, so as to be rigorous about the ordering of responses.[16]

Table 3 broadly confirms the results discussed above. Being more leveraged and being located in a stressed country are estimated to significantly increase the chances of experiencing a worse credit application outcome.

[Table 3 here]

All else equal, firms in the periphery are estimated to be 9% more likely to be totally denied credit, 10% more likely to face a partial rejection, but 19% less likely to obtain their entire demand than their peers based in core countries during the crisis period. In line with previous results, significant differences remain, but decreased in magnitude, in the post-crisis period – where periphery firms are still estimated to be 5% more likely to be totally denied credit, 7% more likely to face a partial rejection, and 11% less likely to obtain their entire demand.

4.1.4 Controlling for distressed firms

A number of recent papers, including Acharya et al. (2019), Storz et al. (2017), and Schivardi et al. (2018), argue that a substantial amount of distressed (or "zombie") firms have emerged in periphery countries following the crisis; and that granting credit to these firms has generated capital misallocation.[17]

To avoid interpreting credit rejections to distressed firms as obstacles to external finance, regressions shown in Table 4 include a dummy variable, 'Distressed firm,' constructed in line with the aforementioned literature.[18] Specifically, 'Distressed firm' assumes value 1 if, for at least two consecutive years, the firm reported negative return on asset, negative net investment, and a EBITDA-to-total financial debt ratio smaller than 5%.

[Table 4 here]

Table 4 shows that, as expected, distressed firms face a higher probability of credit rejections. This notwithstanding, findings strongly confirm those in Table 2. Being located in a stressed country of the euro area is estimated to increase the probability of credit rejection by the exact same percentage, i.e. 17% during the crisis and 10% (or 11%, according to the linear probability model) in the post-crisis years. The probit model still estimates that moving from the 10th to the 90th percentile of the distribution of firm leverage increases the probability of credit rejection by about 30% during the crisis. Similar results are found for the post-crisis years, but with a downward-shifted probability curve (Figure 8).

[Figure 8 here]

Most importantly, we check whether a larger concentration of distressed firms in the periphery can explain the higher rejection rates in such countries, interacting 'Periphery' with 'Distressed firm',

[16] Obviously this choice comes at the expense of a reduction in the sample size.
[17] It is less clear whether this has had large or negligible aggregate effects. Acharya et al. (2019) and Storz et al. (2017) argue in favour of the first hypothesis; Schivardi et al. (2018) find that their estimates are flawed.
[18] See Storz et al. 2017.

as well as with 'Firm leverage'. Both interaction terms, however, show no statistical significance; while the coefficients of 'Periphery' remain strongly significant and unchanged compared to Table 2. In other words, a relevant part of the higher rejection rates observed in the periphery remains unexplained even taking into account this additional source of firm weakness.

4.2 Accounting for the role played by bank weakness

The findings discussed so far suggest that the financial soundness of firms demanding loans goes a long way in explaining credit rejections. Other characteristics related, for instance, to the firm-specific business outlook, the size, both in terms of turnover and number of employees, the age and the sector are also significantly associated with the likelihood of obtaining the requested credit.

In spite of the explanatory power of such variables, however, our findings suggest that the higher rejection rates that firms located in the euro area periphery have experienced since the sovereign debt crisis are not entirely due to firm-specific factors. This leads us to investigate further the role that bank weakness might have played, as well as its possible determinants.

To do so, we augment the empirical model by including variables that can identify the soundness of banks in our sample. As our dataset includes a number of small and non-listed banks, market-based measures, such as CDS spreads, are often either not available or insufficiently accurate. Thus, we use instead bank balance sheet information we obtain from the Fitch Connect database. Using the variable in Amadeus-Orbis where firms report their main bank(s), we match firms with their banks, and study how the probability that a firm will be denied credit depends on variables indicating the soundness of its bank.

Firm-bank matching is available only for a subset of the euro area countries in our sample, namely: Austria, France, Germany, Luxembourg, Malta, and the Netherlands (core countries); and Cyprus, Greece, Ireland, Spain, Portugal, and Slovenia (periphery countries). Before studying the role played by bank characteristics, it is therefore important to verify that our smaller sample remains representative of the larger one we used in the models described in Section 4.1.

Table 5 shows results from linear probability models separately estimated for the following different samples: (1) the full SAFE-Amadeus sample analysed in Section 4.1; (2) the smaller sample obtained excluding observations from the four countries where no firm reports its bank(s) in Amadeus (namely, Belgium, Finland, Italy, and Slovakia); and (3) the even smaller sample limited only to observations where both firms report their bank(s) and Fitch Connect provides values for all the bank characteristics we include in the subsequent regressions. In column (4) of Table 5 we show the results obtained by re-estimating the model for the same sample as in (3), but this time also including bank variables in the regression.

[Table 5 here]

Results in columns (2) and (3) are very comparable to those obtained in the full sample (column 1). However, when we include bank characteristics (column 4), the estimated difference in the credit rejection rate between periphery and core countries decreases and becomes insignificantly different from zero in the post-crisis period. This different result is not explained by a change in the sample: the models (3) and (4) are estimated on the same sample and use the same regressors, apart from bank variables. In other words, once we control for bank weakness – possibly a lasting consequence of the sovereign debt crisis shock that hit particularly periphery banks – we find no evidence of an unexplained difference in credit rejection rates across the two country groups in the post-crisis years. This is a first sign of how linking credit rejections to bank characteristics can be important, when one analyses euro area credit dynamics since the sovereign debt crisis.

4.2.1 The role of bank characteristics

The firm-bank matching performed in the baseline specification follows the approach undertaken by e.g. Kalemli-Ozcan et al. 2018 and Ferrando et al. 2019; namely, we match each firm that reports multiple bank relationships with its first listed bank.[19] All the results discussed in this section, however, are tested against two alternative firm-bank matching criteria (see details below).

Following the recent literature focusing on the role of weakness of euro area banks (see e.g. Schivardi et al. 2018 and Storz et al. 2017), we proxy for the soundness of a bank by including the following variables. Bank capitalisation, measured as the ratio between a bank's equity and its total assets; bank NPLs ratio, corresponding to the share of the bank's non-performing loans over its total gross loans; bank return on assets (ROA), equal to net income over total assets; bank Z-score, computed as the ROA plus equity-to-assets ratio, divided by the standard deviation of ROA over the sample period of a bank; bank maturity mismatch, corresponding to the difference between total deposits and liquid assets, divided by the bank's total assets. Furthermore, we control for the bank size, expressed as the logarithm of the bank's average total assets over the sample period.

In Table 6 we start by adding to the linear specification analysed in Table 2 one bank variable at a time (columns 1 to 5), also including an interaction term with 'crisis.' Each of these variables is estimated to be significantly associated with credit rejections. Having a relationship with a bank whose NPL ratio is higher, is associated with a higher probability of credit rejection. Being linked to a better capitalised bank also seems to marginally reduce the chance of facing a credit rejection during the crisis, but shows the opposite sign in the post-crisis years – which might suggest better capitalised banks have switched to tougher standards for granting credit. Both the z-score and the ROA, which provide different measures of the profitability of a bank, show the expected negative relationship with credit rejections. A higher value of the bank maturity mismatch might signal balance sheet liquidity risks; its estimated association with higher rejection rates in the post-crisis years seems consistent with this interpretation. On the other hand, a higher value of this indicator might be mainly due to a larger reliance of the bank on costumer deposits, generally considered as a stable source of funding; this might explain its small negative relationship with credit rejections during the crisis period.

[Table 6 here]

When we re-estimate the model including all bank characteristics (columns 6 and 7), the only variable retaining its significance unchanged is the bank NPL ratio. This is not surprising, given the primary role the literature assigns to NPLs as a proxy for bank weakness (see e.g. Schivardi et al. 2018). We find again that having a relationship with a bank whose NPL ratio is higher, is significantly associated with a higher probability of experiencing credit rejections, both in the crisis and in the

[19] This criterion is preferred because generally banks are not listed in alphabetic order, so the ordering can convey relevant information about the relative importance of the relationships the firm has with the banks reported.

post-crisis years. This finding is confirmed when we re-estimate the model splitting the sample period across the crisis and the post-crisis period. Results also support the hypothesis of a role played by bank capitalisation, in this case with evidence being limited only to the crisis period, and with the coefficient displaying the expected sign. Namely, having a relationship with a better capitalised bank results being significantly associated with a lower probability of credit rejection. Evidence relative to bank maturity mismatch remains mixed, consistent with the above mentioned hypothesis that a greater value of this indicator may be prone to different interpretations.

We test the robustness of these findings to alternative firm-bank matching criteria. First, we match each firm reporting multiple bank relationships with a random bank among those it has listed (Table 10). Second, we match firms reporting multiple bank relationships with their healthiest bank, i.e. the bank displaying the lowest average NPL ratio over the sample period (Table 11). The latter robustness test is the most severe we can employ against our finding that banks with a higher NPL ratio are more likely to reject credit applications. Previous findings are confirmed, which shows that they do not depend on the approach followed in the baseline.

4.2.2 Bank weakness and credit rejections: Core vs. periphery countries

In Table 7 we check whether the impact of bank characteristics differs across euro area core and periphery countries. We estimate the same regressions as in columns (8) to (11) of Table 6, but also including an interaction term with 'Periphery' for each of the five bank characteristics introduced above.

[Table 7 here]

In Section 4.1, we found no evidence for a different impact of firm characteristics on credit rejections across the two country groups. On the other hand, Table 7 shows that both the NPL ratio and the maturity mismatch of banks significantly interact with periphery, suggesting that periphery-specific bank weakness can help to explain the higher rejection rates experienced by firms operating in stressed countries.

The heterogeneity in the impact of the bank NPL ratio across the two country groups is particularly interesting. During the crisis, being associated to a bank with a higher NPL ratio is estimated to increase the probability of credit rejections in the periphery, while the opposite holds in core countries. These contrasting findings are robust to using the random matching criterion (columns 8 to 11 of Table 10).[20]

The very different distribution of the bank NPL ratio across the two country groups seems to be the main driver of this apparently puzzling result. During the crisis, the median core countries' bank in our sample displayed a NPL ratio of about 5%, a 10th percentile of just above 2%, and a 90th percentile of around 7.5%. During the same time period, the median NPL ratio for periphery banks was instead 15%, the 10th percentile was equal to 4% and the 90th was as high as 45%.

In the light of such different distributions, we may interpret a higher NPL ratio in core countries' banks as a signal of a more aggressive business model, possibly implying granting more loans, rather

[20] Concerning the match with the healthiest bank, regressions still show a negative coefficient of NPL for core countries, but not significantly different from zero. On the other hand, they fully support the the finding that being associated to a bank with a higher NPL ratio in the periphery is estimated to significantly increase the probability of credit rejections. See columns (8) to (11) of Table 11.

than as an indicator of substantial weakness in the bank balance sheet. On the other hand, NPL ratios of well above 10% characterised the majority of banks in the periphery; at such high levels, a higher NPL ratio could rather signal bank weakness and, as such, a limited ability to grant loans even to sound firms. Therefore, the apparently contrasting results in periphery and core countries could be due to a non-linear effect of the NPL ratio on the probability of credit rejections.

The probit estimation, which allows for non-linearities, helps to verify the consistency of this hypothesis. Again, an interaction term allows for a different impact of the NPL ratio on credit rejections in periphery versus core countries. Figure 9 shows the adjusted prediction at representative values of the NPL ratio in the crisis period. Estimates confirm the hypothesis of a non-linear impact of the bank NPL ratio on the probability of credit rejection. For values below 10%, both in periphery and in core countries, a higher NPL ratio is estimated to be associated with a lower probability of credit rejection; by contrast, once the NPL ratio exceeds levels above 15%, its relationship with the probability of credit rejections clearly switches to the opposite sign.

[Figure 9 here]

[Figure 10 here]

In the post-crisis period, the NPL ratio is no longer estimated to be a significant determinant of credit rejections when the sample is spit in the two country groups.[21] As such, Figure 10 does not show a similar pattern as the one found for the NPL ratio in the crisis period.

5 Conclusion

This paper studies the role that firms' and banks' weakness played in the evolution of the access to external finance of euro area firms, with a particular focus on firms of small and medium size, during and after the European sovereign debt crisis. To do so, we build a unique dataset where information on loan applications from SAFE are matched with firms' and banks' balance sheet information, obtained from Amadeus-Orbis and Fitch Connect respectively.

We find that, while firm characteristics, and leverage in particular, are strongly associated with the probability of experiencing credit rejections, they leave unexplained a relevant part of the observed difference across periphery and core countries, even taking into account the incidence of firm distress in the periphery. On the other hand, our findings suggest that periphery-specific bank weakness is able to explain at least part of this difference. We also find evidence for a non-linear effect of the bank NPL ratio. Only beyond a certain level, a higher NPL ratio signals weakness in the bank balance sheet; at such higher levels, we find that it implies a lower ability to grant loans even to sound firms.

We show that our results are robust to a number of different model specifications, definitions of credit rejections, as well as firm-bank matching criteria.

[21] A less significant role of supply-side factors in the post-crisis years is consistent e.g. with Jimènez et al. (2017), who analyse credit developments in the Spanish economy in the pre-crisis against the crisis period (2002 to mid-2007 versus mid-2007 to mid-2010), and find that while demand-side components continuously matter for obtaining credit, supply-side factors only play a role during the crisis.

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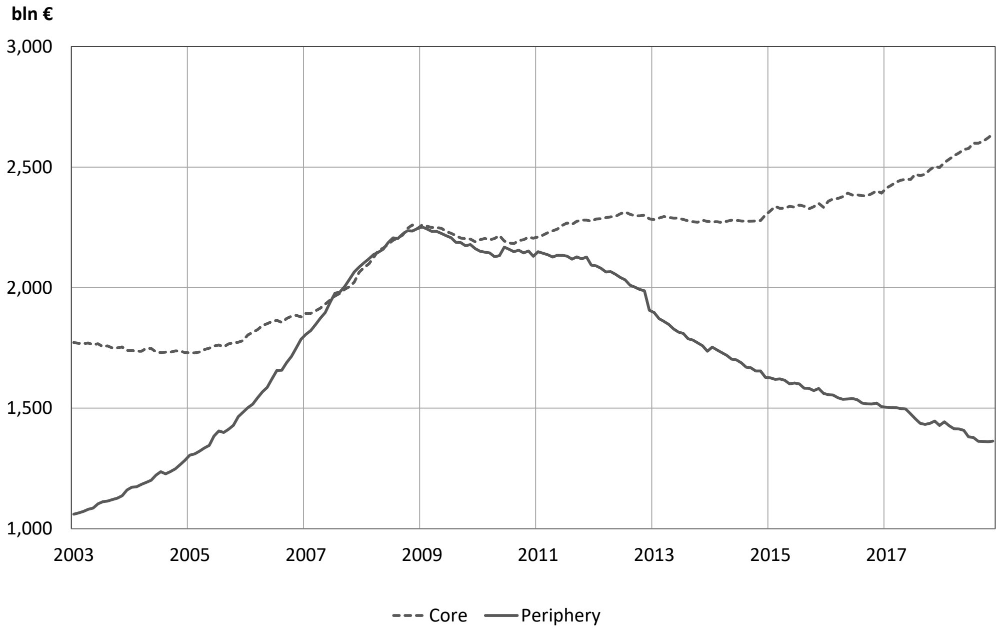
6 Figures and tables

Table 1: Descriptive statistics

	Obs.	Data Source	Type	5pc	25pc	Median	Mean	75pc	95pc
Firms									
Firms' access to finance									
Credit rejection	34,038	SAFE	Dummy	-	-	-	0.318	-	-
Discouraged	34,038	SAFE	Dummy	-	-	-	0.166	-	-
Totally rejected	34,038	SAFE	Dummy	-	-	-	0.068	-	-
Obtained a limited part of it	34,038	SAFE	Dummy	-	-	-	0.070	-	-
Cost too high	34,038	SAFE	Dummy	-	-	-	0.014	-	-
Obtained most of it	34,038	SAFE	Dummy	-	-	-	0.067	-	-
Obtained everything	34,038	SAFE	Dummy	-	-	-	0.615	-	-
Firm soundness									
Distressed firm	19,221	Amadeus-Orbis	Dummy	-	-	-	0.030	-	-
Leverage	27,146	Amadeus-Orbis	Continous	0.277	0.54	0.708	0.715	0.864	1.127
Outlook deteriorated	33,407	SAFE	Dummy	-	-	-	0.261	-	-
Capital deteriorated	33,780	SAFE	Dummy	-	-	-	0.182	-	-
Credit history deteriorated	33,461	SAFE	Dummy	-	-	-	0.173	-	-
Further firm characteristics									
Sector: industry	34,038	SAFE	Dummy	-	-	-	0.325	-	-
Sector: construction	34,038	SAFE	Dummy	-	-	-	0.108	-	-
Sector: trade	34,038	SAFE	Dummy	-	-	-	0.248	-	-
Sector: services	34,038	SAFE	Dummy	-	-	-	0.319	-	-
Employees: 1 to 9	34,038	SAFE	Dummy	-	-	-	0.248	-	-
Employees: 10 to 49	34,038	SAFE	Dummy	-	-	-	0.326	-	-
Employees: 50 to 249	34,038	SAFE	Dummy	-	-	-	0.310	-	-
Employees: above 250	34,038	SAFE	Dummy	-	-	-	0.116	-	-
Turnover: up to 2mln	33,617	SAFE	Dummy	-	-	-	0.378	-	-
Turnover: 2 to 10 mln	33,617	SAFE	Dummy	-	-	-	0.283	-	-
Turnover: 10 to 50 mln	33,617	SAFE	Dummy	-	-	-	0.223	-	-
Turnover: above 2mln	33,617	SAFE	Dummy	-	-	-	0.115	-	-
Firm age	33,579	SAFE	Dummy	-	-	-	0.052	-	-
Banks									
Bank soundeness indicators									
NPL ratio	11,534	Fitch Connect	Continous	1.800	3.430	5.660	11.094	12.290	44.890
Capitalisation	12,617	Fitch Connect	Continous	3.429	4.922	6.475	7.537	9.047	14.024
ROA	12,497	Fitch Connect	Continous	-1.92	0.070	0.290	0.190	0.500	1.200
Z-score	12,476	Fitch Connect	Continous	-1.152	0.364	1.671	2.789	3.712	10.632
Maturity mismatch	12,737	Fitch Connect	Continous	0.045	0.412	0.584	0.526	0.709	0.803
Further banks' characteristics									
Total assests (ln)	13,414	Fitch Connect	Continous	6.719	9.567	11.205	10.998	12.402	14.102
Macro indicators									
GDP forecast 2-yrs ahead	34,038	AMECO	Continous	0.800	1.400	1.700	1.714	2.000	3.000

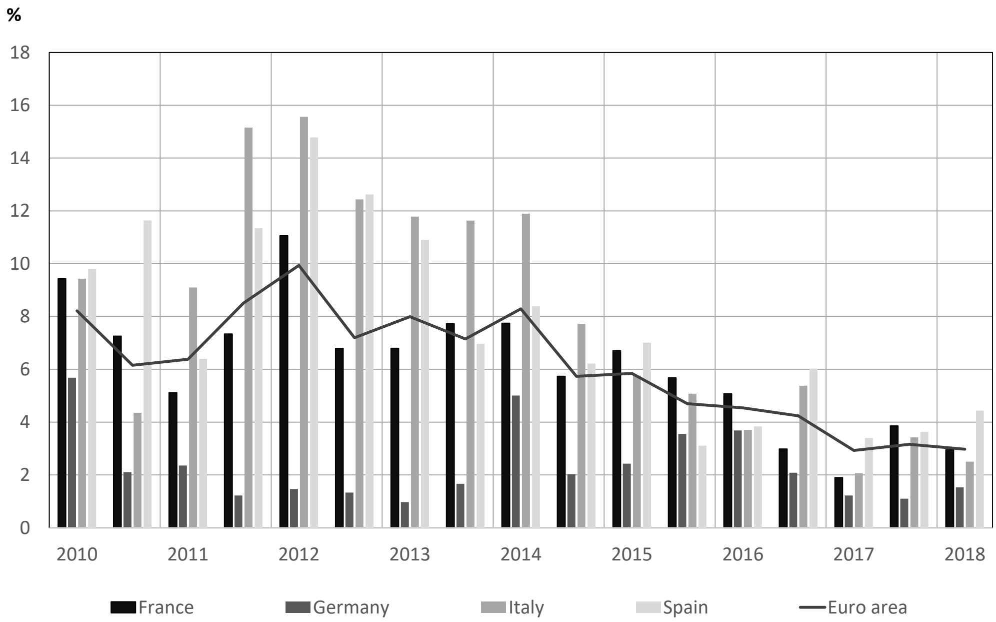
Notes: This table shows number of observations, data sources, type, and summary statistics (i.e. mean, 5th, 25th, 50th, 75th and 95th percentiles) for each variable included in the empirical models estimated in this paper, as distributed in our sample. All variables obtained from SAFE and AMECO databases are semiannual, while those obtained from Amadeus-Orbis and Fitch Connect are annual.

Figure 1: Bank loans to domestic firms in the euro area



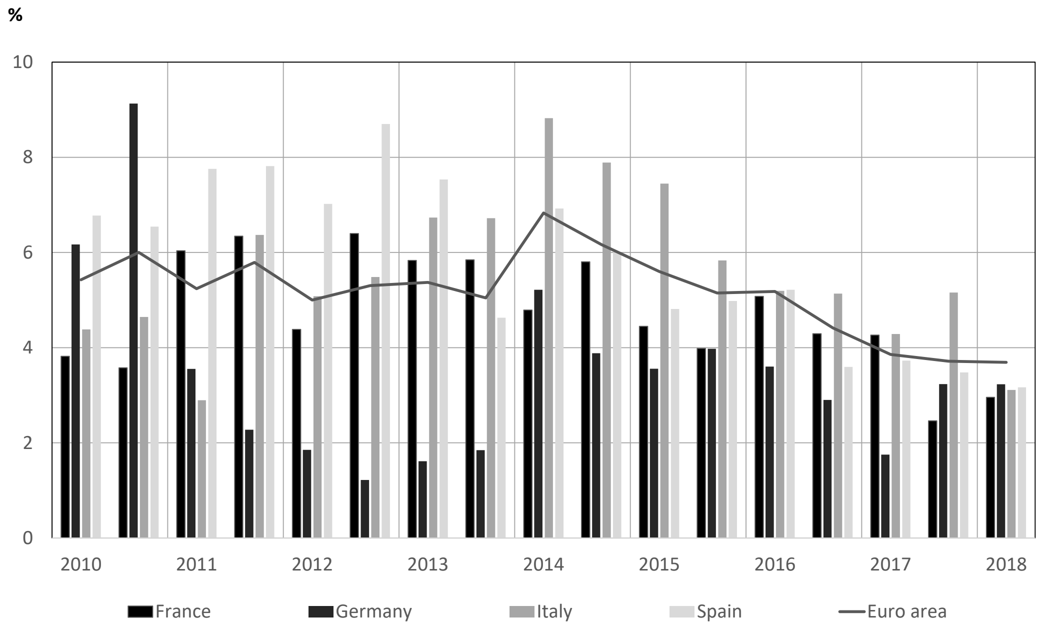
Notes: This figure shows monthly outstanding amounts of bank loans to domestic non financial corporations (NFC) in the euro area. Core: Austria, Belgium, Finland, France, Germany, Luxembourg, Malta, the Netherlands, and Slovakia. Periphery: Cyprus, Greece, Ireland, Italy, Portugal, Slovenia, and Spain. Data source: ECB SDW.

Figure 2: SAFE – Firms that applied for bank loans but got rejected



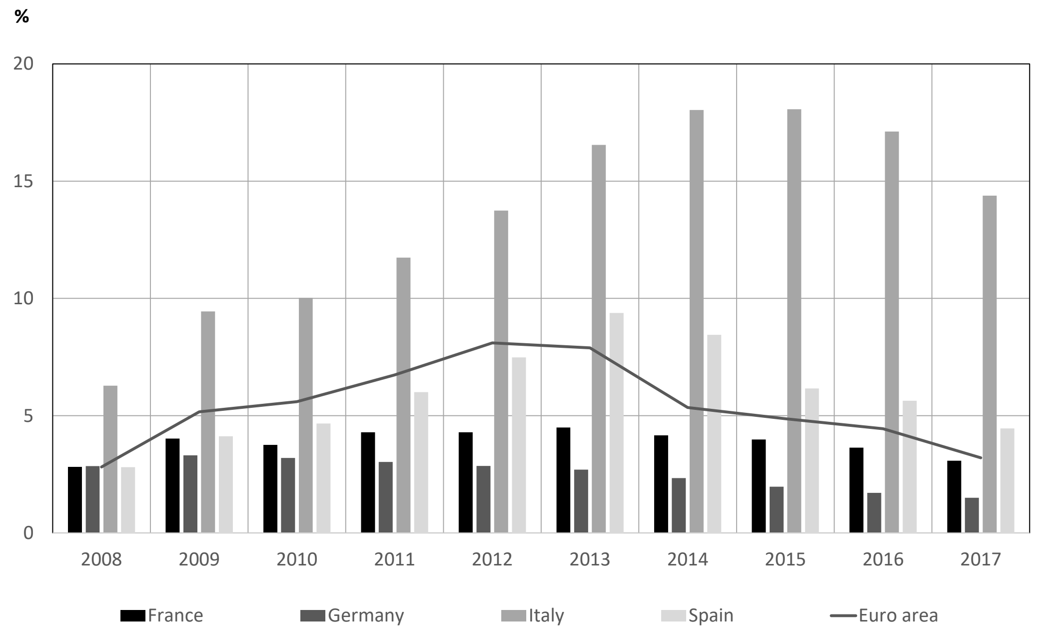
Notes: This figure shows how many SAFE respondents reported a total credit rejection over the past six months, as a percentage of those who reported to have applied for bank loans. 'Euro area' refers to euro area-19 (changing composition). Data source: SAFE, ECB and European Commission.

Figure 3: SAFE – Firms that did not apply for bank loans being discouraged



Notes: This figure shows how many SAFE respondents reported not to have applied for bank loans over the past six months because of being discouraged, as a percentage of total respondents. 'Euro area' refers to euro area-19 (changing composition). Data source: SAFE, ECB and European Commission.

Figure 4: Bank soundness – NPL ratio



Notes: This figure shows the median non-performing loans to total gross loans ratio of banks in a country. Bank nonperforming loans to total gross loans are the value of nonperforming loans divided by the total value of the loan portfolio (including nonperforming loans before the deduction of specific loan-loss provisions). 'Euro area' refers to euro area-19 (changing composition). Data source: International Monetary Fund, Global Financial Stability Report.

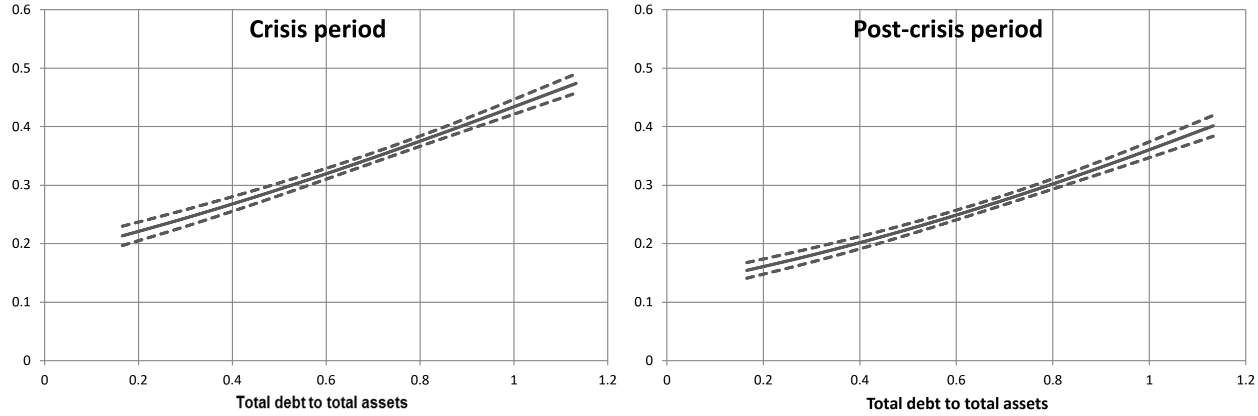
Table 2: Credit rejection and firm characteristics

	Full sample		Crisis period		Post-crisis period	
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Credit rejection$_t$	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.10***	0.35***	0.17***	0.57***	0.11***	0.46***
	(0.01)	(0.03)	(0.02)	(0.08)	(0.02)	(0.08)
			AME:	0.17***	AME:	0.10***
				(0.01)		(0.01)
Firm leverage$_{t-s}$	0.29***	0.95***	0.28***	0.88***	0.29***	1.01***
	(0.01)	(0.05)	(0.02)	(0.07)	(0.02)	(0.07)
Periphery $\times$ Crisis$_t$	0.08***	0.20***				
	(0.01)	(0.04)				
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	-0.02	-0.10				
	(0.02)	(0.07)				
Periphery $\times$ Firm leverage$_{t-s}$			0.01	-0.04	-0.01	-0.17
			(0.03)	(0.10)	(0.03)	(0.11)
Business outlook deteriorated$_t$	0.07***	0.22***	0.06***	0.18***	0.09***	0.29***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.04)
Own capital deteriorated$_t$	0.14***	0.42***	0.14***	0.40***	0.15***	0.46***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)
Credit history deteriorated$_t$	0.15***	0.42***	0.13***	0.38***	0.16***	0.48***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.04)
Other firm characteristics						
Size$_t$ – 1 to 9 employees	0.09***	0.27***	0.07***	0.20***	0.11***	0.37***
	(0.02)	(0.05)	(0.02)	(0.07)	(0.02)	(0.08)
Size$_t$ – 10 to 49 employees	0.03**	0.10**	0.01	0.02	0.05***	0.20***
	(0.01)	(0.05)	(0.02)	(0.06)	(0.02)	(0.07)
Size$_t$ – 50 to 249 employees	0.01	0.02	-0.00	-0.02	0.02	0.08
	(0.01)	(0.04)	(0.02)	(0.06)	(0.01)	(0.06)
Turnover$_t$ – up to €2mn	0.14***	0.49***	0.14***	0.43***	0.14***	0.54***
	(0.01)	(0.05)	(0.02)	(0.07)	(0.02)	(0.08)
Turnover$_t$ – €2mn to €10mn	0.08***	0.32***	0.09***	0.30***	0.07***	0.33***
	(0.01)	(0.05)	(0.02)	(0.06)	(0.02)	(0.07)
Turnover$_t$ – €10mn to €50mn	0.03**	0.13***	0.03*	0.12**	0.02	0.14**
	(0.01)	(0.04)	(0.02)	(0.06)	(0.01)	(0.06)
Sector$_t$ – Industry	0.02***	0.07***	0.02*	0.06*	0.03**	0.09**
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.04)
Sector$_t$ – Construction	0.05***	0.14***	0.05***	0.16***	0.04***	0.13***
	(0.01)	(0.03)	(0.02)	(0.05)	(0.01)	(0.05)
Sector$_t$ – Trade	-0.01	-0.03	0.00	-0.00	-0.01	-0.05
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.04)
Age$_t$ – Young	0.07***	0.20***	0.05***	0.16***	0.10***	0.30***
	(0.02)	(0.05)	(0.02)	(0.06)	(0.03)	(0.09)
Other control variables						
2y-ahead GDP growth forecast$_t$	0.07***	0.22***	0.06***	0.17***	0.08***	0.26***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	21,625	21,625	11,136	11,136	10,489	10,489
R^2	0.19		0.17		0.20	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

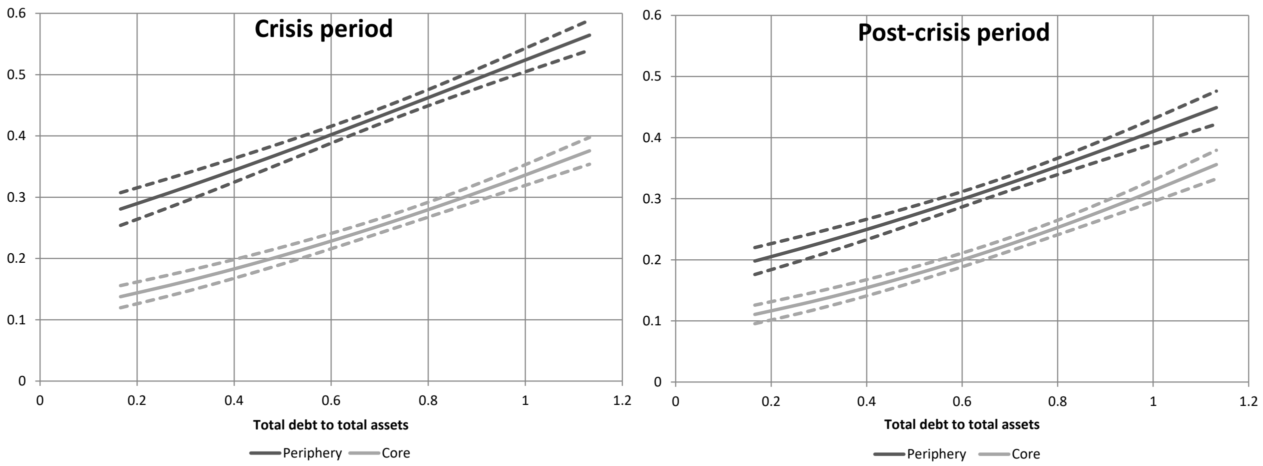
Notes: "Credit rejection" equals 1 if the firm applied for bank credit but got totally rejected, got a limited part of it ($< 75\%$), refused the credit because it was offered at a too high cost, or did not apply being discouraged; it equals 0 if the firm obtained the credit demanded fully or mostly ($\geq 75\%$). For firms interviewed twice in a year, we include the first semester if they reported the same outcome, and the semester of credit rejection otherwise. Firm leverage is the total debt-to-total assets ratio, as reported at the end of the calendar year preceding the semester of realisation of 'credit rejection'. Periphery equals 1 if the firm is located in a stressed country and 0 otherwise. Estimated average marginal effects (AMEs) of periphery are included; AMEs obtained from a regression excluding the periphery-leverage interaction coincide after rounding. Business outlook deteriorated, own capital deteriorated and credit history deteriorated equal 0 if firms reported improvement or no change. The omitted firm size is 250 employees or above; the omitted firm turnover is above €50mn; and the omitted sector is services. "Age: Young" equals 1 if the firm was established within the last 5 years and 0 otherwise. The crisis period includes waves from 3 to 11 (Mar-10 to Sep-14), the post-crisis one waves from 12 to 19 (Oct-14 to Sep-18). All regressions include 2-year ahead GDP growth forecasts of the country where the firm operates and wave dummies.

Figure 5: Probit – Adjusted predictions of 'Firm leverage'



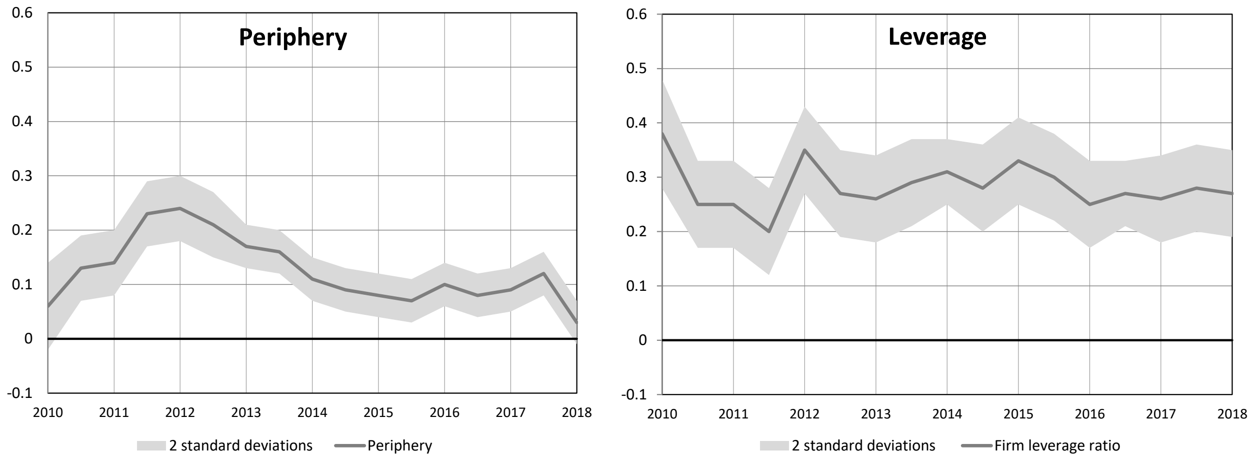
Notes: This figure shows the adjusted predictions at representative values and confidence bands (± 2 standard deviations) of firm leverage in terms of the probability of experiencing credit rejections (shown in decimals on the vertical axis). Adjusted predictions are derived from the probit model in Table 2. The left panel refers to the crisis period, while the right panel to the post-crisis period.

Figure 6: Probit – Credit rejections and 'Periphery' over levels of 'Firm leverage'



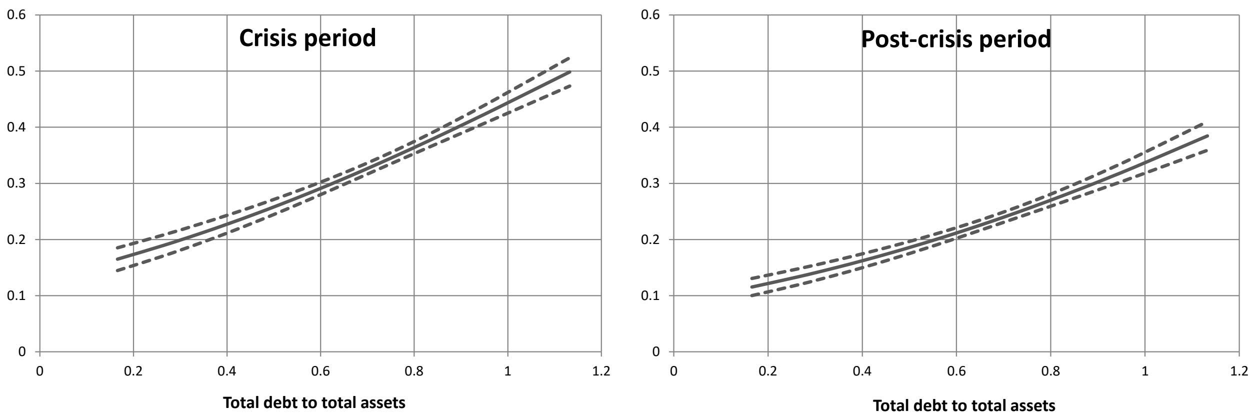
Notes: This figure shows the estimated impact of 'Periphery' on the probability of credit rejections (shown in decimals on the vertical axis), over the percentiles of the distribution of 'Firm leverage', both in the crisis (left panel) and in the post-crisis period (right panel). Adjusted predictions and confidence bands (± 2 standard deviations) are derived from the probit model in Table 2.

Figure 7: ‘Periphery’ and ‘Firm leverage’ across waves



Notes: This figure shows how coefficients and confidence bands (±2 standard deviations) of the variables Periphery (left panel), and Firm leverage (right panel), vary across regressions separately run for each wave of the SAFE in the sample. Coefficients and standard deviations are derived from the linear probability models in Table 9.

Figure 8: Probit with ‘Distressed firm’ – Adjusted predictions of ‘Firm leverage’



Notes: This figure shows the adjusted predictions at representative values and confidence bands (±2 standard deviations) of firm leverage in terms of the probability of experiencing credit rejections (shown in decimals on the vertical axis). Adjusted predictions are derived from the probit model in Table 4, which also includes Distressed firm. The left panel refers to the crisis period, while the right panel to the post-crisis period.

Table 3: Ordered probit model

	Ordered probit		
Dependent variable:	(1)	(2)	(3)
Ordered credit application outcome$_t$	Full sample	Crisis	Post-crisis
Periphery	0.43***	0.62***	0.42***
	(0.03)	(0.03)	(0.03)
Periphery $\times$ Crisis$_t$	0.21***		
	(0.04)		
Firm leverage$_{t-s}$	0.86***	0.81***	0.85***
	(0.06)	(0.06)	(0.06)
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	-0.07		
	(0.08)		
Cut-1	2.44***	2.15***	2.26***
	(0.08)	(0.10)	(0.10)
Cut-2	2.76***	2.47***	2.58***
	(0.08)	(0.10)	(0.10)
Cut-3	3.32***	3.07***	3.08***
	(0.08)	(0.10)	(0.10)
Firm characteristics	Business outlook$_t$, Own capital$_t$, Credit history$_t$ Size$_t$, Turnover$_t$, Sector$_t$, Age$_t$		
Other controls	GDP growth forecast$_t$, Wave dummies		
Observations	17,903	9,118	8,785

	AMEs of 'Periphery'	
Credit application outcome$_t$	Crisis	Post-crisis
Totally rejected	0.09***	0.05***
	(0.00)	(0.00)
Obtained a limited part of it ($< 75\%$)	0.07***	0.04***
	(0.00)	(0.00)
Obtained most of it ($\geq 75\%$)	0.03***	0.03***
	(0.00)	(0.00)
Obtained everything	-0.19***	-0.11***
	(0.01)	(0.01)

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: The the dependent variable is composed of four categories, ordered according to whether the firm applied for bank credit and (1) got everything, (2) got most of it (i.e. 75% or more), (3) got only a limited part of it (i.e. strictly less than 75%), or (4) got nothing. Independent variables are defined as in Table 2.

Table 4: Credit rejection and firm characteristics – Distressed firms

	Full sample		Crisis period		Post-crisis period	
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Credit rejection$_t$	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.11***	0.41***	0.19***	0.80***	0.10***	0.57***
	(0.01)	(0.04)	(0.03)	(0.12)	(0.03)	(0.12)
			AME:	0.17***	AME:	0.11***
				(0.01)		(0.01)
Firm leverage$_{t-s}$	0.31***	1.10***	0.38***	1.36***	0.30***	1.22***
	(0.02)	(0.08)	(0.03)	(0.13)	(0.03)	(0.12)
Distressed firm$_t$	0.21***	0.60***	0.16***	0.44**	0.17***	0.48**
	(0.03)	(0.11)	(0.06)	(0.19)	(0.06)	(0.20)
			AME:	0.14***	AME:	0.17***
				(0.03)		(0.04)
Periphery × Crisis$_t$	0.07***	0.17***				
	(0.01)	(0.05)				
Periphery × Firm leverage$_{t-s}$			-0.02	-0.32*	0.01	-0.22
			(0.04)	(0.16)	(0.04)	(0.16)
Periphery × Distressed firm$_t$			-0.02	-0.02	0.05	0.13
			(0.07)	(0.22)	(0.07)	(0.24)
Business outlook deteriorated$_t$	0.07***	0.21***	0.06***	0.17***	0.08***	0.29***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.05)
Own capital deteriorated$_t$	0.14***	0.42***	0.13***	0.39***	0.16***	0.50***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.06)
Credit history deteriorated$_t$	0.15***	0.45***	0.15***	0.42***	0.16***	0.49***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.05)
Other firm characteristics						
Size$_t$ – 1 to 9 employees	0.07***	0.19***	0.03	0.07	0.10***	0.34***
	(0.02)	(0.06)	(0.03)	(0.09)	(0.02)	(0.09)
Size$_t$ – 10 to 49 employees	0.00	0.00	-0.02	-0.08	0.03	0.11
	(0.01)	(0.05)	(0.02)	(0.08)	(0.02)	(0.08)
Size$_t$ – 50 to 249 employees	0.00	-0.01	-0.02	-0.06	0.02	0.07
	(0.01)	(0.05)	(0.02)	(0.06)	(0.01)	(0.07)
Turnover$_t$ – up to €2mn	0.13***	0.48***	0.14***	0.47***	0.12***	0.48***
	(0.02)	(0.06)	(0.02)	(0.08)	(0.02)	(0.09)
Turnover$_t$ – €2mn to €10mn	0.09***	0.34***	0.10***	0.35***	0.07***	0.32***
	(0.01)	(0.05)	(0.02)	(0.07)	(0.02)	(0.08)
Turnover$_t$ – €10mn to €50mn	0.03**	0.14***	0.03*	0.13*	0.02	0.14*
	(0.01)	(0.05)	(0.02)	(0.07)	(0.01)	(0.07)
Sector$_t$ – Industry	0.04***	0.13***	0.04***	0.13***	0.03***	0.13***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.04)
Sector$_t$ – Construction	0.06***	0.18***	0.06***	0.18***	0.05***	0.20***
	(0.01)	(0.04)	(0.02)	(0.06)	(0.02)	(0.06)
Sector$_t$ – Trade	0.01	0.01	0.01	0.03	0.00	0.01
	(0.01)	(0.03)	(0.01)	(0.05)	(0.01)	(0.05)
Age$_t$ – Young	0.07***	0.21***	0.04	0.13	0.11**	0.35**
	(0.03)	(0.08)	(0.03)	(0.09)	(0.05)	(0.14)
Other control variables						
2y-ahead GDP growth forecast$_t$	0.06***	0.21***	0.05***	0.15***	0.07***	0.25***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.03)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,156	15,156	7,780	7,780	7,376	7,376
R^2	0.20		0.19		0.19	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: This table includes results from regressions including a dummy variable, distressed firm, which equals 1 if, for at least two consecutive years, the firm registered at the same time negative return on asset, negative net investment, and EBITDA-to-total financial debt ratio smaller than 5%; distressed firm equals 0 otherwise. The dependent variable and the other independent variables are defined as in Table 2.

Table 5: Comparison across the different samples

	Linear probability model			
Dependent variable:	(1)	(2)	(3)	(4)
Credit rejection$_t$	16 countries	12 countries	12 countries with banks	12 countries with banks
Periphery	0.10***	0.08***	0.07**	0.03
	(0.01)	(0.01)	(0.03)	(0.03)
Periphery $\times$ Crisis$_t$	0.08***	0.09***	0.11***	0.09***
	(0.01)	(0.01)	(0.02)	(0.02)
Firm leverage$_{t-s}$	0.29***	0.30***	0.34***	0.35***
	(0.01)	(0.02)	(0.03)	(0.03)
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	–0.02	-0.05**	-0.09**	-0.09**
	(0.02)	(0.02)	(0.04)	(0.04)
Business outlook deteriorated$_t$	0.07***	0.07***	0.05***	0.04***
	(0.01)	(0.01)	(0.01)	(0.01)
Own capital deteriorated$_t$	0.14***	0.14***	0.18***	0.16***
	(0.01)	(0.01)	(0.02)	(0.02)
Credit history deteriorated$_t$	0.15***	0.14***	0.16***	0.16***
	(0.01)	(0.01)	(0.02)	(0.02)
Size$_t$ – 1 to 9 employees	0.09***	0.11***	0.12***	0.11***
	(0.02)	(0.02)	(0.03)	(0.03)
Size$_t$ – 10 to 49 employees	0.03**	0.05***	0.06***	0.06***
	(0.01)	(0.02)	(0.02)	(0.02)
Size$_t$ – 50 to 249 employees	0.01	0.01	0.01	0.02
	(0.01)	(0.01)	(0.02)	(0.02)
Turnover$_t$ – up to €2mn	0.14***	0.16***	0.19***	0.20***
	(0.01)	(0.02)	(0.02)	(0.02)
Turnover$_t$ – €2mn to €10mn	0.08***	0.09***	0.09***	0.09***
	(0.01)	(0.02)	(0.02)	(0.02)
Turnover$_t$ – €10mn to €50mn	0.03**	0.03**	0.03*	0.03*
	(0.01)	(0.01)	(0.02)	(0.02)
Sector$_t$ – Industry	0.02***	0.03***	0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
Sector$_t$ – Construction	0.05***	0.04***	0.02	0.02
	(0.01)	(0.01)	(0.02)	(0.02)
Sector$_t$ – Trade	-0.01	-0.02*	-0.02	-0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Age$_t$ – Young	0.07***	0.06***	-0.01	-0.01
	(0.02)	(0.02)	(0.04)	(0.04)
Bank variables$_t$	No	No	No	Yes
2y-ahead GDP growth forecast$_t$	0.07***	0.08***	0.08***	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Wave dummies	Yes	Yes	Yes	Yes
Observations	21,625	14,997	7,474	7,474
R^2	0.19	0.20	0.22	0.23

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: Firm-bank matching is available only for a subset of the euro area countries in our sample, namely: Austria, Cyprus, France, Germany, Greece, Ireland, Luxembourg, Malta, Spain, the Netherlands, Portugal, and Slovenia. This table includes results from regression separately run for the following different samples: (1) the full sample used in Section 4.1, (2) a sample obtained excluding observations from countries where no firm reports its bank(s), (3) the sample limited only to those firms reporting their bank(s), and (4) the same sample limited to firms reporting their bank(s), but this time also including bank variables in the regression. Dependent and independent variables are defined as in Table 2.

Table 6: Credit rejection and bank characteristics

	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Crisis period		Post-crisis period	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Credit rejection$_t$	LPM	LPM	LPM	LPM	LPM	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.009	0.049***	0.053***	0.062***	0.048***	-0.007	0.011	0.140***	0.457***	-0.015	-0.020
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.017)	(0.061)	(0.022)	(0.074)	(0.017)	(0.064)
								AME:	0.141***	AME:	-0.005
Periphery $\times$ Crisis$_t$	0.120***	0.124***	0.121***	0.114***	0.128***	0.142***	0.430***				
	(0.024)	(0.019)	(0.021)	(0.019)	(0.019)	(0.027)	(0.095)				
Firm leverage$_{t-s}$	0.334***	0.319***	0.327***	0.323***	0.317***	0.336***	1.157***	0.247***	0.793***	0.334***	1.158***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.089)	(0.028)	(0.099)	(0.023)	(0.090)
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	-0.083**	-0.079**	-0.089***	-0.084**	-0.079**	-0.089**	-0.368***				
	(0.035)	(0.033)	(0.033)	(0.033)	(0.033)	(0.035)	(0.134)				
Bank NPL ratio$_t$	0.006***					0.005***	0.017***	0.006***	0.018***	0.005***	0.015***
	(0.001)					(0.001)	(0.002)	(0.001)	(0.004)	(0.001)	(0.002)
Bank NPL ratio$_t$ $\times$ Crisis$_t$	-0.002*					-0.001	-0.002				
	(0.001)					(0.001)	(0.004)				
Bank Capitalisation$_t$		0.009***				0.002	0.008	-0.006**	-0.019*	0.003	0.011
		(0.002)				(0.002)	(0.008)	(0.003)	(0.010)	(0.002)	(0.008)
Bank Capitalisation$_t$ $\times$ Crisis$_t$		-0.010***				-0.007**	-0.025**				
		(0.003)				(0.003)	(0.012)				
Bank Z-score$_t$			-0.004***			-0.003	-0.010	0.002	0.005	-0.003	-0.010
			(0.002)			(0.002)	(0.007)	(0.002)	(0.008)	(0.002)	(0.007)
Bank Z-score$_t$ $\times$ Crisis$_t$			0.004			0.005	0.016				
			(0.002)			(0.003)	(0.011)				
Bank ROA$_t$				-0.045***		-0.006	-0.021	0.001	0.006	-0.007	-0.022
				(0.008)		(0.010)	(0.034)	(0.007)	(0.019)	(0.010)	(0.035)
Bank ROA$_t$ $\times$ Crisis$_t$				0.041***		0.006	0.021				
				(0.010)		(0.012)	(0.039)				
Bank maturity mismatch$_t$					0.110***	0.054	0.195	-0.088*	-0.275	0.087**	0.317*
					(0.032)	(0.038)	(0.145)	(0.053)	(0.182)	(0.041)	(0.164)
Bank maturity mismatch$_t$ $\times$ Crisis$_t$					-0.114***	-0.096**	-0.336*				
					(0.039)	(0.048)	(0.183)				
Bank size	0.012***	0.017***	0.011***	0.012***	0.018***	0.012***	0.043***	0.003	0.015	0.018***	0.064***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.015)	(0.007)	(0.022)	(0.005)	(0.019)
Control variables	Firms: Business outlook$_t$, Own capital$_t$, Credit history$_t$, Size$_t$, Turnover$_t$, Sector$_t$, and Age$_t$; 2y-ahead GDP growth forecast$_t$; Wave dummies.										
Observations	7,669	8,353	8,263	8,275	8,437	7,474	7,474	2,969	2,969	4,505	4,505
R^2	0.23	0.22	0.22	0.22	0.21	0.24		0.22		0.24	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: 'Bank capitalisation' is measured as the ratio between a bank's equity and its total assets. 'Bank NPLs ratio' corresponds to the share of the bank's non-performing loans divided by its total gross loans. 'Bank ROA' is the bank return on assets, equal to net income over total assets. 'Bank z-score' is computed as the ROA plus equity-to-assets ratio, divided by the standard deviation of bank ROA over the sample period. 'Bank maturity mismatch' is the is the difference between total deposits and liquid assets divided by total assets. 'Bank size' is the logarithm of the bank's average total assets over the sample size. The dependent variable and the remaining independent variables are defined as in Table 2.

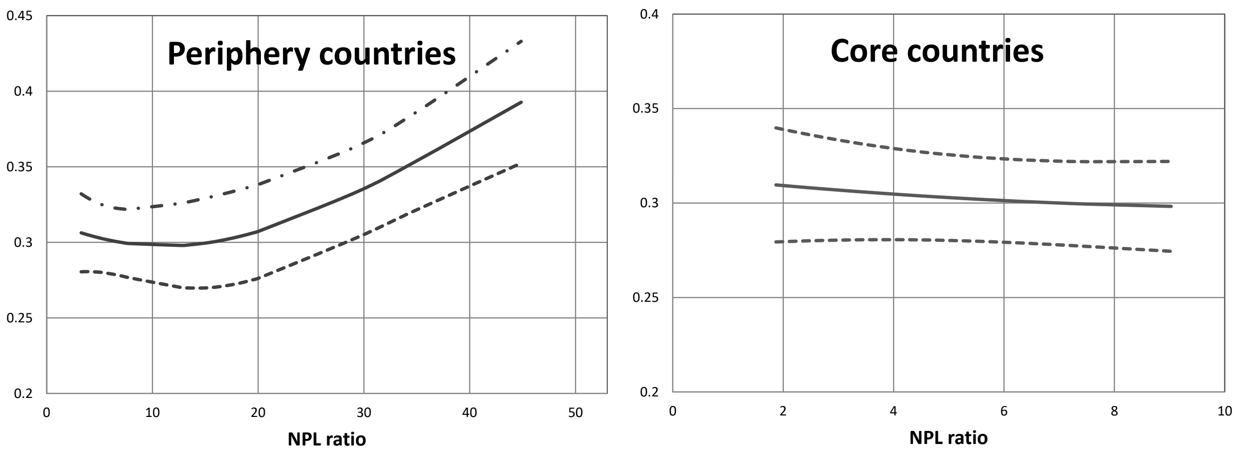
Table 7: Bank characteristics interacted with Periphery

Dependent variable: Credit rejection$_t$	Crisis period (1) LPM	(2) Probit	Post-crisis period (3) LPM	(4) Probit
Periphery	0.140**	0.329	-0.116*	-0.445*
	(0.065)	(0.222)	(0.069)	(0.244)
Firm leverage$_{t-s}$	0.242***	0.779***	0.333***	1.160***
	(0.028)	(0.100)	(0.023)	(0.090)
Bank NPL ratio$_t$	-0.013***	-0.056***	-0.002	-0.009
	(0.005)	(0.021)	(0.003)	(0.014)
Bank NPL ratio$_t$ $\times$ Periphery	0.021***	0.080***	0.006*	0.023
	(0.005)	(0.021)	(0.004)	(0.015)
Bank Capitalisation$_t$	-0.010*	-0.034	0.003	0.012
	(0.006)	(0.022)	(0.004)	(0.014)
Bank Capitalisation$_t$ $\times$ Periphery	0.004	0.017	0.001	0.003
	(0.006)	(0.024)	(0.004)	(0.017)
Bank Z-score$_t$	-0.000	0.000	-0.002	-0.006
	(0.003)	(0.009)	(0.002)	(0.008)
Bank Z-score$_t$ $\times$ Periphery	-0.006	-0.019	-0.004	-0.013
	(0.012)	(0.037)	(0.009)	(0.031)
Bank ROA$_t$	-0.020	-0.105	0.014	0.017
	(0.049)	(0.214)	(0.024)	(0.096)
Bank ROA$_t$ $\times$ Periphery	0.027	0.129	-0.022	-0.040
	(0.050)	(0.216)	(0.028)	(0.106)
Bank maturity mismatch$_t$	-0.044	-0.144	0.032	0.097
	(0.063)	(0.234)	(0.047)	(0.191)
Bank maturity mismatch$_t$ $\times$ Periphery	-0.307***	-0.887***	0.158*	0.667**
	(0.099)	(0.327)	(0.091)	(0.326)
Bank size	-0.001	-0.000	0.017***	0.062***
	(0.007)	(0.023)	(0.005)	(0.020)
Firm characteristics	Business outlook$_t$, Own capital$_t$, Credit history$_t$ Size$_t$, Turnover$_t$, Sector$_t$, Age$_t$			
Other controls	GDP growth forecast$_t$, Wave dummies			
Observations	2,969	2,969	4,505	4,505
R^2	0.23		0.24	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

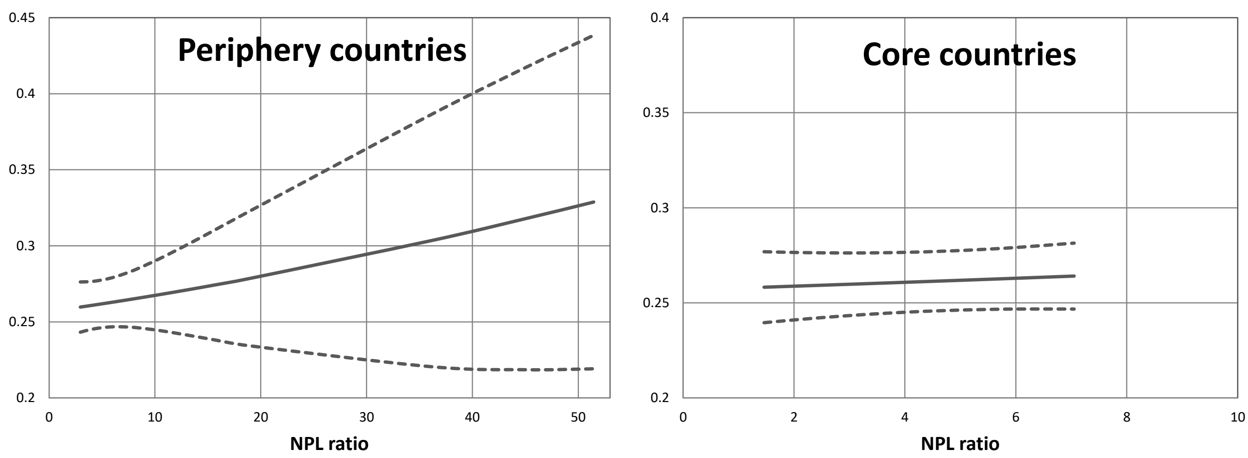
Notes: The bank variables in these regressions are defined as in Table 6. The dependent variable and the remaining independent variables are defined as in Table 2.

Figure 9: Adjusted predictions of NPL ratio – Crisis period



Notes: This figure shows the adjusted predictions at representative values and confidence bands (±2 standard deviations) of the bank NPL ratio in the crisis period, in terms of the probability that a firm linked with the bank having that NPL ratio will experience credit rejections (shown in decimals on the vertical axis). Adjusted predictions are derived from the probit model in Table 7. The left panel refers to periphery countries, while the right panel to core countries.

Figure 10: Adjusted predictions of NPL ratio – Post-crisis period



Notes: This figure shows the adjusted predictions at representative values and confidence bands (±2 standard deviations) of the bank NPL ratio in the post-crisis period, in terms of the probability that a firm linked with the bank having that NPL ratio will experience credit rejections (shown in decimals on the vertical axis). Adjusted predictions are derived from the probit model in Table 7. The left panel refers to periphery countries, while the right panel to core countries.

Appendix: Additional tables

Table 8: Credit rejection and firm leverage, including panellist firms the first time only

	Full sample		Crisis period		Post-crisis period	
Dependent variable:	(1)	(2)	(3)	(4)	(5)	(6)
Credit rejection$_t$	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.10***	0.34***	0.17***	0.52***	0.10***	0.34***
	(0.01)	(0.04)	(0.01)	(0.03)	(0.01)	(0.04)
			AME:	0.17***	AME:	0.10***
Periphery $\times$ Crisis$_t$	0.07***	0.19***				
	(0.02)	(0.08)				
Firm leverage$_{t-s}$	0.26***	0.83***	0.28***	0.86***	0.26***	0.82***
	(0.02)	(0.06)	(0.02)	(0.05)	(0.02)	(0.07)
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	0.01	0.02				
	(0.02)	(0.08)				
Business outlook deteriorated$_t$	0.08***	0.23***	0.07***	0.19***	0.10***	0.32***
	(0.01)	(0.03)	(0.01)	(0.03)	(0.02)	(0.05)
Own capital deteriorated$_t$	0.14***	0.40***	0.13***	0.39***	0.15***	0.46***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.06)
Credit history deteriorated$_t$	0.14***	0.40***	0.13***	0.38***	0.15***	0.43***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.02)	(0.06)
Other firm characteristics						
Size$_t$ – 1 to 9 employees	0.08***	0.24***	0.05*	0.13	0.13***	0.40***
	(0.02)	(0.06)	(0.03)	(0.08)	(0.03)	(0.10)
Size$_t$ – 10 to 49 employees	0.01	0.04	-0.00	-0.02	0.04*	0.16*
	(0.02)	(0.06)	(0.02)	(0.07)	(0.02)	(0.09)
Size$_t$ – 50 to 249 employees	-0.01	-0.02	-0.01	-0.04	0.00	-0.00
	(0.01)	(0.05)	(0.02)	(0.06)	(0.02)	(0.08)
Turnover$_t$ – up to €2mn	0.13***	0.47***	0.15***	0.47***	0.11***	0.47***
	(0.02)	(0.06)	(0.02)	(0.08)	(0.02)	(0.10)
Turnover$_t$ – €2mn to €10mn	0.08***	0.31***	0.09***	0.31***	0.06***	0.32***
	(0.01)	(0.06)	(0.02)	(0.07)	(0.02)	(0.09)
Turnover$_t$ – €10mn to €50mn	0.04***	0.18***	0.04**	0.15**	0.04**	0.24***
	(0.01)	(0.05)	(0.02)	(0.07)	(0.02)	(0.09)
Sector$_t$ – Industry	0.02*	0.05*	0.02	0.05	0.02	0.07
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.05)
Sector$_t$ – Construction	0.05***	0.15***	0.06***	0.17***	0.03*	0.11*
	(0.01)	(0.04)	(0.02)	(0.05)	(0.02)	(0.06)
Sector$_t$ – Trade	-0.01	-0.04	0.01	0.02	-0.04**	-0.14***
	(0.01)	(0.03)	(0.01)	(0.04)	(0.01)	(0.05)
Age$_t$ – Young	0.06***	0.19***	0.04*	0.12*	0.11***	0.35***
	(0.02)	(0.05)	(0.02)	(0.06)	(0.03)	(0.09)
Other control variables						
2y-ahead GDP growth forecast$_t$	0.07***	0.21***	0.06***	0.16***	0.08***	0.25***
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.03)
Wave dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,324	15,324	9,091	9,091	6,233	6,233
R^2	0.18		0.17		0.18	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: This table repeats the exercise done in Table 2, with dependent and independent variables being defined likewise, but including panellist firms only the first time they appear in the sample.

Table 9: Credit rejection and firm leverage, wave by wave

	Linear probability model																
Cr. rejection$_t$	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	W15	W16	W17	W18	W19
Periphery	0.06	0.13***	0.14***	0.23***	0.24***	0.21***	0.17***	0.16***	0.11***	0.09***	0.08***	0.07***	0.10***	0.08***	0.09***	0.12***	0.03
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Leverage$_{t-s}$	0.38***	0.25***	0.25***	0.20***	0.35***	0.27***	0.26***	0.29***	0.31***	0.28***	0.33***	0.30***	0.25***	0.27***	0.26***	0.28***	0.27***
	(0.05)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.04)	(0.04)
B. outlook$_t$	0.03	0.09***	0.12***	0.04	0.07**	0.03	0.09***	0.06**	0.03	0.07**	0.08***	0.11***	0.11***	0.10***	0.09***	0.07**	0.09***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Own capital$_t$	0.19***	0.07**	0.08**	0.17***	0.11***	0.19***	0.14***	0.13***	0.15***	0.15***	0.16***	0.17***	0.08**	0.22***	0.15***	0.19***	0.04
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Cr. history$_t$	0.13***	0.15***	0.10***	0.07**	0.14***	0.12***	0.12***	0.15***	0.18***	0.14***	0.20***	0.19***	0.17***	0.09**	0.15***	0.14***	0.26***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)	(0.05)
Other firm characteristics			Size$_t$, Turnover$_t$, Sector$_t$, and Age$_t$														
GDP forecast$_t$	0.03	0.10*	0.08***	-0.02	0.07**	0.02	0.12***	0.11***	0.08***	0.09***	0.08***	0.09***	0.08***	0.07***	0.07***	0.07***	0.07***
	(0.06)	(0.05)	(0.03)	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)
W. dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,005	1,380	1,375	1,420	1,331	1,409	1,573	1,481	1,766	1,828	1,619	1,811	1,580	1,773	1,468	1,592	1,208
R^2	0.16	0.13	0.17	0.19	0.19	0.19	0.19	0.18	0.21	0.20	0.21	0.21	0.17	0.20	0.17	0.19	0.17

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: This table includes results from regression separately run for each wave of SAFE in the sample (with W3 corresponding to the first semester of 2010, W4 to the second semester of 2010, and so forth until W19, corresponding to the first semester of 2018). Dependent and independent variables are defined as in Table 2.

Table 10: Alternative matching: Random bank

	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Crisis period		Post-crisis period	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Credit rejection$_t$	LPM	LPM	LPM	LPM	LPM	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.007	0.051***	0.052***	0.052***	0.056***	0.006	0.056	0.028	0.000	-0.083	-0.306
	(0.014)	(0.013)	(0.014)	(0.013)	(0.014)	(0.016)	(0.059)	(0.062)	(0.208)	(0.061)	(0.215)
Periphery $\times$ Crisis$_t$	0.118***	0.112***	0.118***	0.117***	0.118***	0.126***	0.371***				
	(0.023)	(0.019)	(0.021)	(0.019)	(0.019)	(0.025)	(0.089)				
Firm leverage$_{t-s}$	0.337***	0.321***	0.326***	0.324***	0.322***	0.335***	1.156***	0.261***	0.844***	0.334***	1.161***
	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)	(0.022)	(0.088)	(0.028)	(0.103)	(0.022)	(0.089)
Firm leverage$_{t-s}$ $\times$ Crisis$_t$	-0.076**	-0.075**	-0.080**	-0.078**	-0.076**	-0.076**	-0.320**				
	(0.035)	(0.033)	(0.033)	(0.033)	(0.033)	(0.035)	(0.135)				
Bank NPL ratio$_t$	0.007***					0.006***	0.018***	-0.012***	-0.051**	-0.003	-0.012
	(0.001)					(0.001)	(0.002)	(0.005)	(0.021)	(0.003)	(0.014)
Bank NPL ratio$_t$ $\times$ Crisis$_t$	-0.002*					-0.000	-0.001				
	(0.001)					(0.001)	(0.004)				
Bank NPL ratio$_t$ $\times$ Periphery								0.021***	0.076***	0.009**	0.030**
								(0.005)	(0.021)	(0.004)	(0.015)
Bank Capitalisation$_t$		0.007***				0.003	0.011	-0.008	-0.029	0.002	0.008
		(0.002)				(0.002)	(0.008)	(0.005)	(0.021)	(0.003)	(0.013)
Bank Capitalisation$_t$ $\times$ Crisis$_t$		-0.008***				-0.009**	-0.032**				
		(0.003)				(0.004)	(0.014)				
Bank Capitalisation$_t$ $\times$ Periphery								0.003	0.012	0.002	0.007
								(0.007)	(0.026)	(0.004)	(0.016)
Bank Z-score$_t$			-0.004***			-0.000	-0.002	0.000	0.001	-0.000	-0.002
			(0.001)			(0.002)	(0.006)	(0.002)	(0.009)	(0.002)	(0.007)
Bank Z-score$_t$ $\times$ Crisis$_t$			0.003			0.002	0.008				
			(0.002)			(0.002)	(0.010)				
Bank Z-score$_t$ $\times$ Periphery								0.011	0.033	0.002	0.012
								(0.009)	(0.028)	(0.008)	(0.027)
Bank ROA$_t$				-0.044***		-0.014*	-0.043	-0.013	-0.073	0.003	-0.023
				(0.007)		(0.008)	(0.026)	(0.048)	(0.212)	(0.025)	(0.098)
Bank ROA$_t$ $\times$ Crisis$_t$				0.037***		0.017	0.055*				
				(0.009)		(0.011)	(0.034)				
Bank ROA$_t$ $\times$ Periphery								0.012	0.074	-0.020	-0.030
								(0.049)	(0.214)	(0.027)	(0.104)
Bank maturity mismatch$_t$					0.051	0.008	0.015	-0.058	-0.204	-0.030	-0.133
					(0.034)	(0.038)	(0.141)	(0.059)	(0.222)	(0.047)	(0.185)
Bank maturity mismatch$_t$ $\times$ Crisis$_t$					-0.105***	-0.064	-0.208				
					(0.038)	(0.046)	(0.172)				
Bank maturity mismatch$_t$ $\times$ Periphery								-0.103	-0.246	0.076	0.336
								(0.090)	(0.299)	(0.081)	(0.291)
Bank size	0.012***	0.014***	0.009***	0.010***	0.012***	0.010***	0.036***	0.006	0.022	0.008*	0.030*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.014)	(0.006)	(0.021)	(0.005)	(0.018)
Control variables	Firms: Business outlook$_t$, Own capital$_t$, Credit history$_t$, Size$_t$, Turnover$_t$, Sector$_t$, and Age$_t$; 2y-ahead GDP growth forecast$_t$; Wave dummies.										
Observations	7,719	8,433	8,359	8,369	8,526	7,534	7,534	2,968	2,968	4,566	4,566
R^2	0.23	0.21	0.21	0.22	0.21	0.23		0.23		0.24	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: This table repeats the exercise done in Table 6 (in the first 7 columns) and Table 7 (in the last 4 columns), but each firm is matched with one of its listed banks randomly.

Table 11: Alternative matching: Healthiest bank

	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Full sample	Crisis period		Post-crisis period	
Dependent variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Credit rejection$_t$	LPM	LPM	LPM	LPM	LPM	LPM	Probit	LPM	Probit	LPM	Probit
Periphery	0.013	0.050***	0.039***	0.054***	0.049***	0.011	0.075	0.094	0.261	-0.074	-0.290
	(0.014)	(0.013)	(0.014)	(0.013)	(0.013)	(0.015)	(0.056)	(0.060)	(0.195)	(0.065)	(0.233)
Periphery × Crisis$_t$	0.111***	0.112***	0.121***	0.111***	0.116***	0.116***	0.338***				
	(0.022)	(0.019)	(0.021)	(0.019)	(0.019)	(0.024)	(0.084)				
Firm leverage$_{t-s}$	0.340***	0.337***	0.344***	0.341***	0.336***	0.341***	1.183***	0.247***	0.802***	0.340***	1.188***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.088)	(0.028)	(0.100)	(0.022)	(0.089)
Firm leverage$_{t-s}$ × Crisis$_t$	-0.090***	-0.083**	-0.097***	-0.091***	-0.083**	-0.093***	-0.387***				
	(0.035)	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.133)				
Bank NPL ratio$_t$	0.007***					0.006***	0.019***	-0.005	-0.015	-0.001	-0.005
	(0.001)					(0.001)	(0.002)	(0.005)	(0.019)	(0.003)	(0.014)
Bank NPL ratio$_t$ × Crisis$_t$	-0.002*					-0.000	-0.001				
	(0.001)					(0.001)	(0.004)				
Bank NPL ratio$_t$ × Periphery								0.013***	0.043**	0.007**	0.024
								(0.005)	(0.020)	(0.004)	(0.015)
Bank Capitalisation$_t$		0.001				0.000	-0.001	-0.009	-0.030	-0.000	-0.002
		(0.002)				(0.002)	(0.008)	(0.005)	(0.021)	(0.003)	(0.014)
Bank Capitalisation$_t$ × Crisis$_t$		-0.005*				-0.006	-0.016				
		(0.003)				(0.004)	(0.013)				
Bank Capitalisation$_t$ × Periphery								0.004	0.018	0.002	0.008
								(0.007)	(0.024)	(0.004)	(0.017)
Bank Z-score$_t$			-0.005***			-0.001	-0.005	0.000	0.001	-0.000	-0.001
			(0.001)			(0.002)	(0.006)	(0.002)	(0.009)	(0.002)	(0.007)
Bank Z-score$_t$ × Crisis$_t$			0.003			0.002	0.007				
			(0.002)			(0.002)	(0.010)				
Bank Z-score$_t$ × Periphery								-0.002	-0.006	-0.002	-0.001
								(0.010)	(0.028)	(0.008)	(0.027)
Bank ROA$_t$				-0.059***		-0.022**	-0.068**	0.020	0.082	-0.016	-0.101
				(0.007)		(0.009)	(0.030)	(0.043)	(0.190)	(0.025)	(0.104)
Bank ROA$_t$ × Crisis$_t$				0.048***		0.028**	0.091**				
				(0.010)		(0.012)	(0.039)				
Bank ROA$_t$ × Periphery								-0.009	-0.046	-0.004	0.040
								(0.044)	(0.193)	(0.028)	(0.111)
Bank maturity mismatch$_t$					0.062*	0.068*	0.234*	-0.058	-0.224	0.061	0.225
					(0.034)	(0.037)	(0.140)	(0.059)	(0.220)	(0.047)	(0.188)
Bank maturity mismatch$_t$ × Crisis$_t$					-0.111***	-0.097**	-0.373**				
					(0.037)	(0.045)	(0.169)				
Bank maturity mismatch$_t$ × Periphery								-0.126	-0.321	0.087	0.348
								(0.094)	(0.307)	(0.079)	(0.293)
Bank size	0.013***	0.012***	0.009***	0.011***	0.013***	0.013***	0.045***	0.005	0.017	0.017***	0.061***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.004)	(0.013)	(0.006)	(0.020)	(0.005)	(0.018)
Control variables	Firms: Business outlook$_t$, Own capital$_t$, Credit history$_t$, Size$_t$, Turnover$_t$, Sector$_t$, and Age$_t$; 2y-ahead GDP growth forecast$_t$; Wave dummies.										
Observations	7,883	8,214	8,183	8,212	8,296	7,740	7,740	3,066	3,066	4,674	4,674
R^2	0.23	0.22	0.22	0.23	0.22	0.24		0.23		0.24	

Robust standard errors in parenthesis – ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$

Notes: This table repeats the exercise done in Table 6 (in the first 7 columns) and Table 7 (in the last 4 columns), but each firm is matched with its listed bank that has the lowest NPL ratio.

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