BANCA D'ITALIA
EUROSISTEMA

Temi di discussione

(Working Papers)

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Number 1265

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ISSN 1594-7939 (print)
ISSN 2281-3950 (online)

Printed by the Printing and Publishing Division of the Bank of Italy

PUBLIC CREDIT GUARANTEES AND FINANCIAL ADDITIONALITIES ACROSS SME RISK CLASSES

by Emanuele Ciani[*], Marco Gallo[**] and Zeno Rotondi[***]

Abstract

In this paper we study the functioning of the Italian public guarantee fund ("Fondo Centrale di Garanzia", FCG) for small and medium enterprises (SMEs). Using an instrumental variable strategy, based on FCG eligibility, we investigate whether the guarantee generated additional loans and/or lower interest rates for SMEs. Unlike previous literature, by focusing on the lending activity of a single large Italian lender, we control for the probability of default as assessed by the bank's internal rating model, and we examine whether the effects of the guarantee differ across firms belonging to different classes of risk. We find that guaranteed firms receive an additional amount of credit equal to 7-8 percent of their total banking exposure. We also estimate a reduction of about 50 basis points in interest rates applied to term loans granted to guaranteed firms. The effects on credit availability are concentrated in the intermediate class of solvent firms, i.e. those that are neither too safe nor too risky. Conversely, interest rate effects are present in all classes, except for the least risky firms. Finally, we observe a stronger impact of the guarantee for solvent firms with a longer relationship with the bank, questioning the ability of very young firms to reduce financial frictions.

JEL Classification: L25, O12, G28.
Keywords: credit guarantees, access to credit, banking.
DOI: 10.32057/0.TD.2020.1265

Contents

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1. Introduction*

Extensive literature shows that small and medium-sized enterprises (SMEs) face greater difficulties in accessing finance because of their informational opaqueness. Public guarantee schemes for SMEs are a widespread form of government intervention whose aim is to lessen this market imperfection.[1] The lender (usually a bank) receives a pledge to repay the loan amount (partially or totally) from the government in case of borrower default. By means of the guarantee, the lender reduces his expected credit loss, hence increasing the chances that the borrower receives a loan and/or improves the lending conditions.

Following the 2008–09 global financial crisis, several governments around the world expanded the use of these schemes in order to mitigate the contraction in credit supply, which was usually more pronounced for SMEs. This was also the case in Italy, where SMEs are particularly widespread and the volume of public and private guarantees granted to them is large compared to other developed countries (Chatzouz et al., 2017). The Italian public guarantee scheme, called *Fondo Centrale di Garanzia* (FCG), has significantly increased its activity since the beginning of the global financial crisis: new loans guaranteed from 2009 to 2016 amounted to around 90 billion euros, compared to 11 billion euros in the period 2000–08.

The aim of this paper is to evaluate the effectiveness of the Italian FCG in terms of financial additionalities. As discussed by Gozzi and Schmukler (2015), the key issue is to understand whether public guarantee schemes allow targeted firms to increase their credit and/or improve their borrowing terms. However, these financial additionalities should be evaluated with respect to a counterfactual scenario in which the firm has not received any guarantee.[2] In order to overcome this identification problem, empirical studies use counterfactual methods. The most recent and comprehensive reviews on the topic argue that the literature provides evidence that credit guarantees generate financial additionality by increasing the availability of credit and/or reducing its costs (see for instance OECD, 2017).

Differently from previous studies, we focus on the lending activity of one of the largest Italian intermediaries, UniCredit bank.[3] The choice of restricting the analysis to a single bank allows us

* *We are indebted to Alessio D'Ignazio, Stefania De Mitri, Paolo Finaldi Russo, and Guido de Blasio for sharing part of their code with us. We also thank Doretta Cocchi for assistance in extracting data from Cerved/Cebil and Luisa Mancinelli Degli Esposti, Raffaela Torricelli, Stefano Cocchieri, and Emanuele Giovannini for assistance on the data from UniCredit. We gratefully acknowledge the very useful comments provided by Nicola Branzoli, Paolo Sestito, Federico Signorini, and participants at the Bank of Italy's workshops. We also thank participants at the International Risk Management Conference (IRMC) 2018 in Paris and the Money, Banking and Finance (MBF) Conference 2018 in Rome for their interesting comments and suggestions. All errors are ours. The opinions expressed in this paper are those of the authors and do not involve any responsibility of the institutions to which they are affiliated.*

[1] See Beck et al. (2010) for an overview on the relevance of public credit guarantee schemes around the world, with some important design features of these schemes.

[2] A related question is whether the public guarantee schemes also have the "second-round" effect on economic outcomes, such as investment. In the present paper we examine only direct "first-round" effects (on loans and interest rates), while we leave indirect "second-round" effects for future research. It must be added that our identification strategy is not fully appropriate to evaluate these effects; see Section 5.

[3] Loans granted by UniCredit bank and guaranteed by FCG increased sharply from 80 million euros in 2012 to 569 million euros and 1.2 billion euros respectively in 2013 and 2014. In 2015, they amounted to 2.3 billion euros, reaching a market share of 15 percent of total guaranteed loans in the Italian banking system.

to use a unique dataset based on a large portfolio of loans granted to SMEs during the recession period 2013–14, with access to private information on the bank-firm relationship, which is otherwise not available.[4] More precisely, we exploit information about the probability of default (PD) assessed by the bank through its internal rating based (IRB) model. This variable allows us: (i) to implement an instrumental variable (IV) strategy based on the difference between the IRB assessment and the eligibility rule for the FCG, and (ii) to study whether the effects are heterogeneous across the PD distribution. However, using a single-bank dataset comes with a cost in terms of external validity. Our results are relative only to a single intermediary, albeit a big one among the largest players on the public guarantee market. The findings therefore cannot be directly extrapolated to the whole Italian banking system, because the behavior of other banks might differ, both in terms of financial additionality and in the way they use the public guarantee. Nevertheless, our estimated effects on credit availability confirm results of previous papers and therefore corroborate their conclusions. Furthermore, our heterogeneity analysis illustrates some issues that are crucial in understanding which firms in terms of (ex-ante) risk profile are more likely to benefit from the policy.

Our analysis is divided into three parts. First, as in previous studies we try to understand whether public guarantees generate additional loans for SMEs (credit availability effect) and/or allow them to borrow at lower rates (interest rate effect). Our identification strategy is similar to that of de Blasio et al. (2018), as it exploits the eligibility mechanism used by the FCG to assign the guarantees. However, differently from them, we do not employ a Regression Discontinuity Design (RDD) but an instrumental variable (IV) strategy that uses overall eligibility as an instrument for the actual presence of the guarantee. To justify this choice, we assert that the score used by FCG for the eligibility is an imperfect measure of creditworthiness, provided that the bank relies on its IRB model to decide loan conditions. Therefore, we argue that the FCG eligibility criterion respects the exclusion restriction conditional on the internal rating, which we use as an additional control in our IV estimates.

Second, we investigate whether financial additionalities differ by firms' riskiness, as measured by the PD assessed through the internal rating system. The occurrence of heterogeneous effects on interest rates is due to the fact that the Expected Loss (EL) depends on the product of the PD and the Loss Given Default (LGD).[5] All other factors being equal, the decrease in LGD associated with the public guarantee has a stronger impact on the EL for riskier borrowers. We therefore expect a

[4] During the period examined in the present analysis, the Italian economy suffered the effects of the double-dip recession which proved to be worse than those of the Great Depression. From 2007 to 2013 GDP fell by 9 percent, industrial production by almost a quarter, investment by 30 percent, and consumption by 8 percent.
[5] It is known that Expected Loss (EL) = Exposure At Default (EAD) x Probability of Default (PD) x Loss Given Default (LGD), where the EAD is equivalent to the outstanding loan.

stronger reduction in interest rates for them. Conversely, it is unclear how the credit availability effect should differ by ex-ante firm riskiness. On the one hand, the additionality gives rise to a larger capital requirement for riskier SMEs, and therefore the bank has an incentive to grant more credit to safer firms. On the other hand, the additionality might be associated with a renewal of an old credit line. In this case, being guaranteed the whole loan (both the old one and the additionality), the bank has an incentive to expand loans to riskier firms. Alternatively, the bank could concede credit additionality to riskier firms in order to actually reduce their likelihood to default, which would increase capital requirement to cover write-offs.

Finally, we examine whether the length of the bank-firm relationship influences the impact of the guarantee. This is an important empirical issue, given that the guarantee is also intended to improve the financing of younger firms. Taking advantage of the bank's internal information about the length of the relationship with its borrowers, we use it to investigate potential heterogeneity in granting financial additionalities, namely to assess whether the bank grants stronger additionalities to its better- or worse-known borrowers. The bank could exploit public guarantees to offset worse knowledge of the borrowers, therefore improving credit conditions applied to younger relationships. Alternatively, it could use the better knowledge of borrowers as a means to improve its screening process. Since the public guarantee does not cover the total amount of the loan, the bank has to bear a fraction, albeit small, of credit risk. Therefore, it could decide to concentrate financial additionalities on better-known borrowers.

To summarize our results, we find that the public guarantee has a positive impact on loans to firms. Guaranteed firms receive from the bank an additional amount of credit equaling 7–8 percent of their total banking exposure. In addition, we observe a negative impact on long-term interest rates, as we estimate a reduction of about 50 basis points for term loans granted to guaranteed firms. Regarding the creditworthiness of the SMEs that have increased their loans by means of a public guarantee, our findings show that the effect is concentrated on the class of solvent lenders, namely firms whose rating ranges from BBB to BB according to the largest international agencies' scale. On the contrary, the effects on the cost of credit are widespread across risk classes, although they are still absent for very safe firms. Finally, we find evidence that a longer relationship is relevant for credit availability and lower cost of credit associated to a public guarantee. The financial additionalities are concentrated in solvent SMEs with longer relationships with the bank, while the effects of the guarantee are small and not significant for other firms.

The paper is structured as follows. Section 2 reviews the extant literature. Section 3 introduces the main features of the FCG. Section 4 describes our dataset and the main figures. Section 5 explains the empirical strategy. Section 6 shows the main results and Section 7 describes some robustness checks. Section 8 concludes the paper.

2. Background literature

Public guarantee schemes (PGSs) can represent a useful mechanism for improving access to finance for financially constrained firms, typically SMEs. However, as their performance and cost-effectiveness depend crucially on proper design of the guarantee scheme, we need analyses of existing programs, especially during recession periods. Unfortunately, empirical evidence on the impact of these schemes is limited. As suggested by OECD (2017), the main constraint to the proliferation of rigorous studies on PGSs is the limited availability of appropriate data needed for assessment. Data are often not available at the necessary level of disaggregation (SME level versus industry or regional/national level), while richer data sources are in general not publicly available.[6]

Given that the objective of PGSs is to improve credit availability for certain groups of firms, their existence is difficult to justify if they do not lead to financial additionality. Measuring financial additionality implies examining incremental credit flows and/or improvements in borrowing terms (e.g., longer maturities, lower rates) obtained by beneficiary firms. Accurately measuring them requires comparing the performance of the PGS with what would have happened in the absence of the scheme. As this counterfactual scenario in not observable, most empirical studies compare beneficiary firms with similar non-beneficiary SMEs. However, the identification of an appropriate control group could be a difficult task, as SMEs eligible for the PGS that have not received guaranteed loans can be systematically different from beneficiary firms. Another difficulty is lenders switching from non-guaranteed loans to guaranteed loans for the same borrower, or borrowers switching across lenders from non-guaranteed to guaranteed loans, which implies that no incremental credit might actually occur to financially constrained SMEs due to the PGS.

Previous literature has found evidence of financial additionalities for different countries (see Gozzi and Schmukler, 2015; and OECD, 2017, and the references therein). For Italy, Zecchini and Ventura (2009) use data on the FCG from 2000 to 2005. They employ a difference-in-differences estimation and find a positive, though small, impact on the amount of bank debt and a negative impact on the cost of borrowing (based on firms' balance sheet interest expenses). More recently, D'Ignazio and Menon (2020) analyze an Italian regional PGS. They tackle selection issues by using an IV regression, which exploits an exogenous event that expanded eligibility to the program

[6] Italian studies are usually based on data on credit guarantees of beneficiary SMEs from the Italian PGS database. However, such a database is not publicly available, typically lacks information on non-beneficiary SMEs, and does not include comprehensive information on the beneficiary firms. The bank of Italy manages the Central Credit Register, a database which is not publicly available (an exception are banks, but they have access only to information on their customers), and collects detailed firm level information on loans granted to SMEs. Another source is Cerved, which provides a commercial database on balance sheet data and—differently from AIDA—includes its own information on firms' solvency and creditworthiness. However, in the above databases information on banks' assessment of firms' solvency and creditworthiness is not available.

to firms previously cut out of it. They find no effect of the scheme on total debt. Yet, they document a shift in debt composition towards long-term borrowing. Moreover, they find evidence of eased-up financing conditions, in terms of lower interest rates. De Blasio et al. (2018) evaluate the FCG by means of a RDD on the years 2005–2010. They find evidence of financial additionalities, but no decrease in the cost of credit. Andini et al. (2018) apply machine learning methods to predict which firms are more likely to be both creditworthy (in terms of probability of default) and credit-rationed (in terms of the likelihood of not seeing an actual expansion of credit after a loan request). They use it to compare the FCG eligibility rule with an alternative allocation rule based on the machine-learning predictions. Accetturo et al. (2018) study a more recent regional PGS implemented in Trentino. They find that the policy achieved its main goal, that is, increasing beneficiary firms' debt maturity, but did not have any impact on their performance.

The international experience on PGSs suggests that banks do not automatically consider the guaranteed borrowers as creditworthy, but they re-assess their financial soundness, because they already have a credit appraisal infrastructure with greater experience in performing this activity compared to government agencies (Gozzi and Schmuckler, 2015). However, given that the guarantee leads to limited liability for the bank, letting the lender choose which loans should apply and receive the guarantee might increase adverse selection and moral hazard. This could imply that an excessive fraction of the risk is shifted to the PGS, causing high default rates of guaranteed loans. One solution for mitigating this problem is to reduce the coverage ratio, which is the share of the loan value covered by the guarantee (Gozzi and Schmuckler, 2015). By applying a coverage ratio lower than 100, a fraction of the credit risk is borne by the lender, and therefore the latter is incentivized to better screen the loans. In order to understand whether the chosen coverage ratio is appropriate to avoid excessive risk-shifting to the PGS we need to look at the firm's ex-ante likelihood of default as estimated by the bank, that is, the PD. As the PD is not publicly available, the literature usually focuses on ex-post default rates. Some studies on the outcomes of PGSs in terms of realized bad loans find evidence that loan guarantees are associated with increased default risk of beneficiary firms (see OECD, 2017). In particular, in case of Italy, de Blasio et al. (2018) show that loans guaranteed by the FCG have a higher probability of being classified by the bank as bad loans than unguaranteed loans to firms with similar characteristics. The presence of a PGS may induce banks to be quicker to report loans to borrowers for which a refund is readily available as bad debts (opportunistic behavior). However, de Blasio et al. (2018) were unable to verify whether there is an issue of moral hazard associated with this phenomenon, as they do not examine what happens within the bank-firm relationship. Moreover, in the case where firms borrow from multiple lenders, being classified as bad loans could also depend on the behavior of other banks (e.g., credit rationing) and not only on that of the bank that assists the firm vis-à-vis the FCG. In the present analysis we fill the gap in the empirical literature by estimating whether financial additionalities differ by firms' ex-ante riskiness, as measured by the PD assessed through the internal rating system by the bank when it grants the loan. In this way, we can observe the bank's behavior consistently with its assessment of borrowers' riskiness, regardless of events occurring after the granting of the loan that can affect the ex-post likelihood of default.

3. The functioning of the Italian Guarantee Fund

The Italian FCG is the main tool of public intervention in the credit market. Its aim is to facilitate the access to finance for SMEs, by granting a public guarantee that complements or substitutes the existence of a private guarantee. The FCG has an annual budget allocated by the government, that can be used to grant both direct and counter-guarantees[7]. The Fund acts as a guarantor, committing itself to repay the loan to the lender, typically a bank, if the borrower defaults. It is a standard triangular scheme that, in case of counter-guarantees, also involves a fourth agent, typically a Mutual Guarantee Institution (MGI, Italian Confidi). The counter-guarantee granted to MGIs commits the public fund to repay the loan if a) the borrower defaults, b) the direct guarantor does not fulfill his obligation and c) the guarantee is called on.

The public guarantee covers up to 80 percent of the loan value and cannot exceed the maximum of 2.5 million euros.[8] It is eligible for credit risk mitigation under the Capital Requirement Regulation, being direct, explicit, irrevocable, and unconditional. This is a key point for banks, because it relieves them of regulatory capital requirements. The government commitment of acting as a lender of last resort reduces the capital requirement for the guaranteed share of loan to zero. As a result, banks are able to grant loans at better conditions, increasing the amount of loan and/or reducing the cost.

Firms eligible for the guarantee are SMEs (as identified according to the European Commission's definition[9]) that have passed an assessment of financial soundness. The assessment relies on a scoring system set by the Ministry of Economic Development, which considers four

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[7] The FCG is also allowed to release co-guarantees, together with mutual guarantee institutions or other guarantee funds.

[8] The guaranteed share and the maximum amount to be financed are dependent on both the type of loan and the type of firm. For example, the guarantee on short-term debt consolidation covers only up to 30 percent and a maximum of 1.5 million euros.

[9] The European Commission defines SMEs as those enterprises employing fewer than 250 persons that have a turnover of less than 50 million euros and/or a balance sheet total of less than 43 million euros (see Commission Recommendation 2003/361/EC). According to the SME definition, the SME status of an enterprise which is part of an enterprise group may need to be determined on the basis of data on persons employed, turnover, and the balance sheet of the group, and not only on the basis of data on the enterprise itself.

basic balance sheet indicators of the previous two years.[10] Combining the partial scores obtained for each year, the firm is assigned to one of three categories—types A, B, and C. The first two are both eligible, while the third one is not eligible. Type-A firms automatically receive a positive assessment for the final decision taken from the Fund committee and therefore have a very high probability of obtaining the guarantee. We call these firms "eligible strong". Type-B firms are assessed on a case-by-case basis. They are, therefore, less likely to get the public guarantee. For this reason, we call these firms as "eligible standard". Type-C firms are not eligible.

The application for the public guarantee must be made through a bank or any other authorized financial intermediary. Before formally applying, the bank must assess the firm's eligibility by means of the FCG scoring system and then fill in the application. The application process for the guarantee may be initiated by the firm, asking the bank to apply for the FCG when requesting a loan. It may also be the bank itself that suggests it. The eligibility does not depend on the bank's assessment of the borrower, as it is solely based on balance sheet information. Nevertheless, it is very likely that the borrower's risk characteristics play a crucial role in driving the bank to propose the scheme to certain firms rather than to others. This is a key point because it makes the presence of the guarantee endogenous. We expect the guarantee to be used in cases where the bank is less willing to provide credit, because in these cases there are more incentives for both the bank and the client to go through the bureaucratic process of applying for the guarantee and to face the related costs. The endogeneity should therefore lead to negative selection.

After providing the public guarantee, the FCG applies a fee ranging from 0 to 3 percent of the guaranteed amount of loan. Although it might seem a low value, we must also account for the extra cost due to the significant amount of work needed to process the application.

The FCG started in 2000 but its activity ramped up in the aftermath of Lehman's collapse in 2008. The annual volume of loans granted to SMEs that benefited from the public guarantee has grown from 2.3 billion euros in 2008 to 16.7 billion euros in 2016. The progressive expansion of its range of operations implied a sharp increase in the Fund's capital endowment (Figure 1). Moreover, new potential beneficiaries were included and eligibility criteria were eased.

After our period of analysis, the FCG was deeply reformed in March 2019. First, the rating model has been further developed in order to improve the screening of firms, excluding those that are not creditworthy. The model, by means of a larger set of information with respect to previous

[10] Balance sheet indicators are dependent on both the economic sector and the accounting scheme of the firm. Moreover, specific rules concern start-ups, for which none of the indicators are available.

credit scoring models, allows to compute the firm's PD. Ratings range from 1 to 12 and are grouped in five classes of creditworthiness (safe, solvent, vulnerable, risky, not creditworthy). Firms falling in the fifth class (ratings 11 or 12) are not eligible for the guarantee. Second, in order to incentivize credit to riskier firms and longer-term loans, the new rules have lowered the coverage ratios for safer firms and short-term loans. The new rating model is not applied to start-ups: for these firms, an alternative evaluation process based on their business plan is followed and the coverage ratio is unique and equal to 80 percent.

4. Data

4.1 Data and sample selection

In order to investigate the functioning of the Italian FCG, we build a unique dataset from three different sources. The first one includes all small business credit applications to the bank during 2013 and 2014. For each request we know the applicant's tax identifier, the date, and the outcome of the application (approval or refusal).[11] From a different internal archive of the bank, we also know whether the firm has applied and has been awarded direct guarantee from FCG during the period.

The manner in which the two historical archives of applications (credit and FCG guarantee) have been maintained does not allow us to do a direct match between credit and FCG guarantee applications. We therefore match the two by using a temporal proximity criterion, assuming the date of sending the application to the FCG committee as the relevant time for the guarantee application, and the date of the bank's decision on granting the loan as the relevant time for the credit application. More precisely, the loan and the guarantee are matched when the temporal difference between the two dates is no longer than 90 days.[12] This distance can be positive or negative, since the timeline set by the FCG rules changed in March 2014. Before then, a bank's loan approval must precede the FCG's decision to grant the guarantee; the new rules state that loan approval by the bank must follow guarantee application to and approval by the FCG committee.[13]

[11] It is important to note that short-term loans are subjected to an annual reassessment by the bank in order to renew the credit. These renewals are treated as new requests. Therefore, many applications in the dataset are simply renewals and not new loans.

[12] We also checked that the main results are robust to reducing this distance to 60 days; Tables A5 and A6 in the Appendix show that results are actually slightly stronger and more significant using the 60-day rule.

[13] In line with the change in the timeline of the application, in 2013 the difference is on average negative (the bank decision is before the FCG application) and it becomes positive afterwards. The distance between the two dates that we used (the date of the bank's decision on the credit application and the date of submission to the FCG) is obviously also due to measurement error. Its distribution is nevertheless reasonable, with 51 percent between -30 and +30 days, and 85 percent between -60 and +60. This distance is neither correlated with the PD nor with the duration of the bank-firm relationship. We also tried, as a robustness check, to match the guarantee—only in the cases where the distance was between -60 and +60 days, and the results are similar (see Tables A5 and A6 in the Appendix).

For all applicants we also know the one-year probability of default as assessed by the bank according to its internal rating system (at the time of the application), and the length of the relationship between the bank and its borrowers. This dataset includes 538,018 applications from 290,896 firms.

The second source, provided by the Cerved group company, contains balance sheet data for the universe of Italian incorporated firms. From their database, we collect information about firm size, leverage, liquidity, and profitability. More importantly, these data allow us to simulate the company eligibility criteria used by FCG and build our instrumental variable for the guarantee (see next Section). However, matching bank and balance sheet dataset for the period 2010–13 significantly reduces our sample size to about 90,000 companies.[14] This is due to the fact that only limited liability companies are obliged to transmit their balance sheet information to the Italian business register.[15]

The third and last source used to build our dataset is the Italian Central credit register, an information system operated by the bank of Italy that collects information about all loans and guarantees—above a threshold of 30,000 euros—granted by banks and financial companies to their customers. Indeed, as a response variable of the treatment, we build two variables measuring the growth rate of credit following bank approval of loan applications. To do so, we need information about the borrowers' exposure to both the bank granting a new loan and the total outstanding credit exposure to financial intermediaries. We use this information on credit, neglecting the information on the required and approved amount that comes from the large bank registry of all credit applications, because it allows us to measure the total exposure of each firm to the banking system in a coherent way. This is useful because it allows us to test whether the guarantee with the bank also affects credit exposure with the rest of the banking system; a positive impact on the amount of credit with the bank might be associated with a reduction in loans contracted with other institutions, therefore reducing the gains for the firm.

By matching the three sources, we come up with the final sample of 150,673 loan applications made by 74,426 limited liability small companies to our bank during the two-year period 2013–14. As reported in Table 1, applications are mainly made from the Italian Center-North regions;

[14] Although credit applications concern only two years (2013–14), we need to increase the reference period in order to assess the company eligibility to receive the FCG guarantee. According to the FCG rules, each company receives a score calculated considering several aspects of the firm's performance based on the last two annual balance sheets. As balance sheet approval usually takes place at the end of April, applications made during the first four months of the year 2013 need balance sheet information concerning the year 2010.

[15] The Italian Business register is a public register that contains information (incorporation, amendments, cessation of trading) for all companies with any legal status and within any sector of economic activity, with headquarters or local branches within the country. It has been fully implemented since 1996. However, according to the Italian Civil code, only some company forms such as SRL (limited), SPA (PLC), and Cooperatives are due to report their balance sheet to the local Chamber of Commerce.

only 20 percent of the applications come from the Mezzogiorno (South regions and islands). Moreover, almost 50 percent of the total applications originate from industrial companies (manufacturing and construction sectors). Finally, we note that during the observed period, only 1 percent of SME applications (1,637) are characterized by the presence of the FCG guarantee; this percentage is slightly higher for industrial companies and for those located in the Italian Mezzogiorno.[16]

4.2 Descriptive statistics

As our dataset contains all the information from the last two budgets available at the time of credit application which are necessary to calculate the FCG score, we can replicate it and identify each firm's "type" ("eligible" or "not eligible").[17] Figure 2 shows the share of loan applications that have an approved guarantee, by the applicant's FCG eligibility status. According to the FCG management rules, eligible firms with better balance sheet indicators are classified as "strong", having to go through a less demanding assessment compared to "standard" ones. Our calculated type seems quite precise. The share of not eligible firms with guarantees is not equal to zero (as it should be), because of classification errors, but it is very small.[18] The strong eligibility criterion is associated with the highest likelihood to have a guarantee. The share is above 1.5 percent for applications made by eligible strong companies, while it goes only slightly beyond 0.5 percent for standard eligible ones.

Table 2 shows some descriptive statistics by eligibility. The first block focuses on companies "with guarantee", which also contains (very) few units of not eligible firms that are misclassified by our algorithms. The second block of the table reports statistics about companies that are eligible but did not apply for the guarantee. Finally, the third block refers to not eligible and not guaranteed firms. The eligibility criteria set by the FCG rules appears to be quite effective in selecting less

[16] The very low number of guarantees granted by FCG to firms located in the Centre is due to a ban on operating with firms located in the Lazio and Tuscany regions.
[17] We are indebted to Alessio D'Ignazio, Stefania De Mitri, Paolo Finaldi Russo, and Guido de Blasio for having provided us with the code to calculate the score.
[18] In theory, this misclassification error could also be due to firms manipulating their scores by misreporting their information to the committee. However, for the limited liability businesses that we consider, eligibility is based on publicly available budget sheet information, and therefore there is not much scope for manipulation.

risky companies. As also reported in Figure 3a, the IRB probability of default assigned by the bank to both guaranteed and eligible firms shows lower values (mean, median, first and third quartile) than those observed for not eligible firms. As an example, the PD within one year of the first two groups is around 3 percent, far lower than 7 percent of the not eligible group.

The lower riskiness of eligible firms finds further support from some balance sheet indicators reported in Table 2. Guaranteed and eligible companies are less indebted (leverage ratio), pay less borrowing costs (Net interest payments / EBITDA), and are more liquid (current ratio). Moreover, guaranteed firms are larger than both eligible without guarantee firms and not eligible firms in terms of total assets and outstanding loans.

On the contrary, there seems to be no relevant differences among the three groups in terms of other variables such as age, length of relationship with the bank, and share of total credit owed to the bank.

In order to inspect further differences inside the group of eligible firms, we have also reported one-year PD and balance sheet indicators separately for the two groups, compared to not eligible units. As shown in Figure 3b and Table 3, companies that are strongly eligible are the smallest ones and show the lowest probabilities of default assigned by the bank. The median (average) value of PD is equal to 0.56 (2.44) percent, far lower than 1.29 (4.58) percent observed for eligible standard companies, and 2.12 (6.76) percent observed for not eligible firms.

5. Empirical strategy

Our identification strategy builds on de Blasio et al. (2018). Let us define two potential outcomes y_{0i} and y_{1i}, where $i = 1, \dots, N$ represents the single credit request. The outcome of interest is the variation of credit between a month before and a month after the date on which the bank takes the final decision on the requested loan. For each application, let y_{1i} be the outcome in the case wherein the firm obtains the guarantee ($G_i = 1$), while y_{0i} is the outcome if it does not obtain the guarantee ($G_i = 0$). For each request we actually observe only one or the other state, and therefore the observed outcome y_i can be expressed as:

$$y_i = (y_{1i} - y_{0i})G_i + y_{0i} = \delta G_i + \varepsilon_i \qquad (1)$$

The main empirical issue is that having the guarantee is likely to be correlated to the outcome itself, for two main reasons:

1. Not all firms receive the guarantee.
2. Only some firms decide, together with the credit manager, to apply for the guarantee, so there is self-selection.

This implies that $E[\varepsilon_i|G_i]$ is not a constant, but depends on G_i, therefore OLS estimates of equation (1) are biased.

To account for the first problem, one possible solution is to control for all those characteristics X_i that are considered by the credit manager in evaluating the credit risk of the firm. Fortunately, we are in the position of accessing the relevant hard information available to the bank, because we not only have all the balance sheet information, but also the default probability estimated by the bank's model of risk assessment. The basic idea is that the unobservable component ($y_{0i} = \varepsilon_i$) depends on this set of characteristics, but there are no other observables that may influence both the guarantee and the outcome. The equation of interest becomes:

$$y_i = \beta_0 + \delta G_i + X_i\beta + \epsilon_i \qquad (2)$$

which identifies the effect of interest as long as the following holds:

$$E[\epsilon_i|X_i, G_i] = 0 \qquad \text{(A1)}$$

These variables are likely to account for all the observable hard information which conditions both the choice of the bank and of the firm to apply to the guarantee scheme and that are also likely to affect the outcome. Nevertheless, this choice is also likely to be affected by soft information, which is unobservable to the econometrician. In general, applying to the guarantee is a choice. In this case, assumption (A1) does not hold. To account for this problem, we exploit the fact that the process of allocating the guarantee scheme is based on a scoring system which is based only on hard information (from balance sheet data), but is far from the bank's model of risk assessment. We essentially exploit two features of the allocation process:

1. Eligibility, in particular strong eligibility (with no further assessment from the Fund) has a strong impact on the probability of receiving the guarantee.
2. From the point of view of the bank, the FCG score is a rough measure of the credit risk, which is dominated by the internal rating system. Therefore, if there were no public guarantee, then the FCG scoring would be completely irrelevant for the credit decision, after having considered the relevant balance sheet information and the bank's internal rating.[19]

[19] This could be violated if the bank believes that the scoring system used by the FCG is better and revises its internal scoring to make it more similar to the FCG's scoring system. This did not happen in practice. On the contrary, credit institutions asked for a reform of the FCG scoring to make it more similar to private banks' rating systems. The recent reform (see Section 3) has taken this direction.

More formally, E_i is defined as a dummy for those firms that are strongly eligible (which do not require further assessment). The outcome and the guarantee status are determined by a recursive system of two equations:

$$y_i = \beta_0 + \delta G_i + X_i\beta + \epsilon_i \quad (3)$$

$$G_i = \gamma_0 + \gamma_1 E_i + X_i\gamma_X + \omega_i \quad (4)$$

where X_i represents balance sheet information from the firm, its probability of default as estimated by the bank's internal rating system, as well as other relevant firm characteristics (such as age and economic sector), and variables pertaining to the bank-firm relationship (such as whether the bank is the main lender to the firm and the relationship duration). In order for the causal effect of the guarantee to be identified, we need the two features discussed above, that translate to the following assumptions:

$$\gamma_1 \neq 0 \qquad \text{(A2a)}$$

$$E[\epsilon_i | X_i, E_i] = 0 \quad \text{(A2b)}$$

If both conditions hold, the effect δ can be estimated by 2SLS, using E_i as an instrument for the guarantee G_i.

While condition (A2a) is testable, assumption (A2b) relies on the fact that the FCG scoring is dominated by the internal rating of the bank, which also has access to all the hard information from balance sheets that are used to build the FCG scoring. Essentially, we assume that the eligibility as determined by the FCG ranking is irrelevant in the credit decision process once we account for a set of observable characteristics X_i. One problem is that we do not know the correct functional form for the relation between the credit outcome and X_i. We start linearly adding a set of covariates that the literature suggests to be strong determinants of credit, together with the internal rating and a set of basic balance sheet indicators. We then use different polynomials of the continuous variables to allow more flexibility, up to a fifth-degree polynomial for all the continuous variables and up to a sixth for the internal rating. Apart from using polynomials, to account for the fact that the internal rating variable (the PD) is skewed, when we use it as a control, we rescale it as a variable going from 0 to 1000, where each value is the *n*-th of 1000 quantiles of the overall distribution of the PD. This rescaling follows the standard way in which the PD is used to create risk-class dummies.[20]

Our results hinge on the correct selection of the controls and on the correct functional form. In fact, if we run Oster's (2019) test assuming that the degree of selection on unobservables is proportional to the selection on observables, we obtain bounds for the coefficient of interests that

[20] We also tried adding risk class dummies in the main regression of Tables 4 and 6. As expected, our main results (where we include a third-degree polynomial of all controls and a fourth degree for the rescaled PD) are extremely similar, because risk class dummies are a (non-linear) function of the PD.

include zero.[21] We nevertheless believe that the logic of the FCG explained before supports our assumption that, by including the internal rating score and sufficiently flexible polynomials, we can control for all relevant unobserved heterogeneity, that is, we can account for differences in hard information between eligible and non-eligible firms that have a direct effect on the outcomes. To allow the reader to assess the soundness of our results, we provide the details of different specifications for all the main results, which progressively include up to the fourth-degree polynomial of the continuous variables (and the fifth for the rescaled PD). Furthermore, as a robustness check, we try starting from an even wider set of variables which, for the continuous variables, includes polynomials up to the sixth-degree and the first-order interactions among them. Instead of including all of them, we assume that only some have a non-zero coefficient (sparsity assumption) and we use a LASSO algorithm proposed by Belloni et al. (2014) to select a limited set of them. As they suggest, the selection should be conducted on the reduced forms for the outcome, for the guarantee dummy and for the instrument, and then the final set of variables must be the union of those selected in each reduced form.

Our empirical strategy is similar to that of de Blasio et al. (2018), as it exploits eligibility as an instrument. In their paper, they deal with the fact that eligibility is potentially correlated with the error term by means of a RDD. Given that eligibility depends on a score, they compare firms that are close to being eligible, but their score falls short, and other firms whose score is only slightly above the threshold. This allows them to compare firms that would have been very similar in the absence of the guarantee and to estimate the local effect around this threshold.

Differently, in this paper, we exploit the availability of the internal scoring system of the bank, which should capture all the relevant hard information. Firms that have a similar internal scoring (as well as other key balance sheet indices) are likely to be treated similarly by the bank in the absence of the FCG guarantee. This supports our assumption that the eligibility dummy is uncorrelated with ϵ_i and can, therefore, be used as an instrument. Similar to de Blasio et al. (2018), however, our estimates are "local". As in any IV setting with heterogeneous treatment effects, we can capture only the impact on compliers, which are those firms that apply to the guarantee because they are strongly eligible, but would not have applied otherwise. This is anyway a quite interesting population, given that 83 percent of the requests with a guarantee are from strongly eligible firms, and that E_i causes a significant increase in the likelihood of having the guarantee. In Section 7, we further discuss this choice.

[21] Oster's test can be performed on the reduced form regression, because if the coefficient on eligibility is not different from zero in the reduced form then also is not in the 2SLS. In the Appendix Table A7, we report the reduced form as well as the adjusted R2, which allow the interested reader to reproduce a basic version of the Oster (2019) test.

Finally, it is worth mentioning that our strategy is appropriate to evaluate only the first-round financial effects around the time of the bank's decision on the credit application (as our outcomes are variations in credit granted between one month before and one month after this date). In the longer run, eligible firms might apply for other FCG guarantees, both with the bank and with other financial institutions. These other guarantees would impact outcomes observed further away in time from the credit application (such as investments in the following year or the probability of default two years after), and therefore we cannot assume that, in the longer run, all the differences between eligible and non-eligible firms are due to the specific FCG guarantee that we associate with the i-th credit application. More in general, outcomes that are not specific to the credit application with the bank of our study are more likely to be influenced by other FCG guarantees obtained by eligible firms with other banks, which we do not observe. If we used our IV strategy to look at these different outcomes, we would strongly overstate the effects, because we would assign all the effects of the eligibility (the reduced form) to the specific guarantee obtained from UniCredit around the time of the credit application (as captured by the first stage), while in fact the effect of eligibility is also due to all the other FCG guarantees obtained later on and/or with other banks.

6. Results

In this Section we discuss our main results. We firstly show findings concerning the effect of the guarantee on credit availability and interest rates in the first two subsections. The third subsection is dedicated to an in-depth analysis of how the effect changes with credit risk. By using the one-year bank IRB probability of default, we investigate whether there are risk classes that benefit from better credit conditions as a result of the public guarantee. Finally, the fourth subsection provides insights on the role of bank-borrower length of relationship in explaining different effects of the public guarantee.

6.1 Credit availability

The first treatment effect we investigate concerns credit availability, captured by the rate of variation in the amount of credit granted to the treated borrowers. Since we are interested in the direct effectiveness of the guarantee scheme, we build an indicator that reflects the firm's position vis-à-vis the large bank that provided the guaranteed loan:

$$y_i = (credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$$

The numerator measures the change in the amount of credit loans granted by (only) the bank from t-1, at the end of the month before the bank's decision on granting the loan (month t), to t+1, at the end of the following month. The denominator of the ratio is the amount of outstanding credit granted by the banking system at t-1, rather than that granted only by the bank. We rescale by $credit_{t-1}^{total}$ in order to capture how the impact of the guarantee for loans with the bank affects global credit exposure. Moreover, rescaling by $credit_{t-1}^{total}$ is convenient as we do not need to drop the applicants whose granted credit is equal to zero (or very close to) at t-1. In Section 7, we use the rate of change in loans granted only by the bank of our study as an alternative dependent variable for robustness checks. The distribution of our dependent variable has quite long and thick tails. To avoid our results being driven by outliers, we truncated the sample by removing observations below the 5^{th} (-14.6 percent) and above the 95^{th} percentile (+26.1 percent) of the dependent variable. The results depend on this choice, but without this truncation, the estimates are less robust in the choice of different specifications and tend to display extreme values in some sample splits.

Table 4 reports econometric results, including OLS, first stage regression, and 2SLS estimates. Columns (1)–(6) refer to the order of the polynomial for the continuous variables used in the regressions. The OLS results show that the guarantee is always positively correlated with credit availability. The first-stage regressions confirm that the guarantee is strongly related with eligibility, no matter which specification is chosen; the first-stage F-tests are all well above the standard rule-of-thumbs used to detect weak-instrument problems. The 2SLS estimates are larger than OLS ones, which suggests that the latter suffer from a negative bias. This seems reasonable in this context, where the guarantee is likely to be necessary for firms that would not obtain the same amount of credit without it (negative selection; see also Section 3). The 2SLS results with the simplest specifications seem to provide an overestimate, as the effect decreases when we start adding higher order terms of the covariates, which are likely to better capture the non-linear relation between balance sheet information and the guarantee. Results appear to stabilize from the third order of the polynomial and they clearly show a positive effect ranging from 7 to 8 percent of the loans totally granted to guaranteed borrowers.[22]

Another empirical issue we address in this subsection concerns the relation between the guarantee and the duration of the loan. The FCG public guarantee was originally conceived as an economic policy instrument to foster private investments by increasing the collateral offered by safe firms to their lenders. As a result, FCG rules state that guarantees are to be granted mainly on

[22] The full list of included covariates is reported in the note of the Table. We do not discuss here the coefficients on the other covariates used as controls, because they are not of direct interest for our research question and also because our favorite specifications (the ones from column (3)) contain several non-linearities that are more difficult to interpret. Nevertheless, in the Appendix Table A1 we report the average marginal effects for all the covariates.

long-term loans.[23] However, the lack of short-term financing during the recent crisis has increased the possibility for SMEs to obtain the public guarantee even on short-term loans.[24] More importantly, the impact of the FCG guarantee is not necessarily limited to the single loan that is formally covered by it. The bank may use the guarantee to cover a long-term loan that would have been granted anyway, and may, at the same time, expand short-term exposure to the same firm. In this case, the guarantee has a positive effect on the total amount of credit to the firm, because the bank, having shifted part of its risk on long-term credit to the FCG, is now willing to expand short-term credit. In order to investigate whether this is the case, we replicate the 2SLS estimates by splitting the sample between short-term (up to 12 months) and long-term (more than 12 months) loans. It is important to note that the definition of long-term loan we use (longer than 1 year) does not coincide with that of the FCG (longer than 3 years). With this caveat in mind, the results reported in Table 5 show that the guarantee has a larger effect (between 4 and 5 percent) for short-term loans compared to long-term ones (1.5–3 percent considering the last three more stable specifications). This evidence appears consistent with the declining investment expenditure by Italian firms during the two-year period considered in our dataset (2013–14) and, at the same time, with a quite restrictive credit policy adopted by the banking system. Therefore, Italian firms' financing requirements mainly involved working capital rather than fixed assets.

6.2 Cost of credit

The second outcome of interest concerns the cost of credit. We use as dependent variable the variation in the level of interest rate charged by the bank to the treated borrowers:

$$rate\ of\ interest_{t+1}^{Bank} - rate\ of\ interest_{t-1}^{Bank}$$

Similar to the preceding subsection, the $rate\ of\ interest_{t+1}^{Bank}$ is the average rate, in terms of percentage points, applied by the bank during the quarter following its decision on granting the loan; that rate is compared to the cost of credit applied during the preceding quarter ($rate\ of\ interest_{t-1}^{Bank}$). In line with the previous subsection, we truncate the sample by removing observations below the 5th percentile and above the 95th percentile of the dependent variable, to avoid the results being driven by outliers.

The interest rates are those reported quarterly by the bank (included in a large sample of banks operating in Italy) to the CCR. Since each bank is due to report only borrowers whose granted

[23] According to the current rules, loans are required to have a maturity of at least 36 months.

[24] For example, the guarantee can be released in case of loans granted to pay suppliers and employees, debt consolidation, and advances for Public Administration receivables.

loans exceed 75,000 euros, we can estimate the treatment effect only for a limited subset of observations in our sample.

More importantly, we compare interest rates applied to homogenous categories of loans. Banks report to the Central Credit Register information about interest rates applied to three different loan asset classes: revolving credit lines, loans backed by accounts receivable, and term loans. The first two are short-term transactions, while the last one includes mainly long-term loans. Credit lines are the most expensive loans because no collateral is provided by the borrower. At the opposite end, term loans are the cheapest loans because most of them generally have real estate as collateral. Changes in interest rate applied to a single borrower could therefore reflect a shift from safer to riskier loans, or vice versa. However, comparing interest rates belonging to the same loan asset class allows the avoidance of confounding effects.

The results are reported separately for each type of loan in Table 6. Interest rates on short-term transactions are not statistically affected by the presence of a guarantee, although the coefficient for loans backed by accounts receivable appears to be economically relevant. Conversely, we find a negative treatment effect on interest rates applied to term loans. The estimated parameter, which is relatively stable across different orders of the polynomial used for both the PD and the other explanatory variables, shows a reduction of around 50 basis points in the price of term loans.

Jointly considering evidence on both quantity (previous subsection) and price (current subsection), a likely explanation of our findings is a change in equilibrium resulting from a downward shift of the supply curve. In the presence of the guarantee, the bank is able to offer the same credit amount at a lower rate, or to put it another way, a larger quantity at the same price. As a result, the new equilibrium will be marked by a higher quantity and a lower price, but the difference with respect to the old equilibrium depends also on the demand elasticity. In this context, it is worth noticing that while the price effect regards term loans, the quantity effect concerns short-term credit. The rationale for these results might be attributed to different elasticities of the demand curve. During our observation period, firms' requirement for new term loans was quite rigid and inelastic to interest rate. Therefore, the downward shift of the supply curve might have affected only equilibrium price rate without changing the amount of credit granted. Conversely, the sharp credit squeeze resulting from the Europeans sovereign debt crisis spurred firms to increase their credit lines as a buffer against further shocks. As a result, the short-term demand curve was remarkably elastic to interest rate. In this case, the shift of the supply curve might have impacted only the equilibrium outstanding loans, without significantly affecting the interest rate.

6.3 Firms' riskiness

The impact of the FCG guarantee may depend on the firms' riskiness. As discussed in the Introduction, assessing this heterogeneity is extremely important in order to properly target the scheme. We use the bank's internal classification of borrowers' riskiness (at the time of the loan application) in order to split our sample and run separate regressions over the two variables of interest, credit availability and cost of credit. According to this classification, borrowers are classified into four groups: safe, solvent, vulnerable, and risky.

Figure 4 reports the frequency distributions for four different risk classes, for both guaranteed and non-guaranteed relations. It can be observed that the distributions are quite similar. It means that there is no risk class for which the use of the public guarantee is privileged by the lender. The highest percentage of guaranteed relations (about 40 percent) involves solvent firms, but it is only slightly higher than that for non-guaranteed relations. The same small positive difference holds for vulnerable relations, while for safe and risky groups the frequency of guaranteed relations is lower. Another major evidence is that more than 40 percent of guaranteed relations include borrowers assessed as vulnerable or risky by the bank, in spite of the eligibility criteria stated by the FCG aiming at screening safer firms. Therefore, figures highlight a clear misalignment in the assessment criteria between banks and FCG.

Results in Table 7 show that the effects of the public guarantee are quite different across different risk classes.[25] In terms of credit availability, the impact of the guarantee is significant only for the class of solvent borrowers. We estimate that solvent guaranteed companies observe an increase in the amount of granted loans by about 19 percent. The effects are negligible for extreme categories (safe and risky), while for vulnerable companies the impact is small (5 percent) and not statistically significant. In contrast, the impact on the cost of credit is more widespread. Solvent and risky classes benefit from the guarantee, with a reduction of 0.8 and 1.2 percentage points in the cost of credit; for vulnerable firms the reduction is lower (oddly not statistically significant). Even in this case, no effect is detected for safe companies. At first glance, this result might appear counterintuitive, as it is not clear why safe companies should pay a fee (albeit small) without receiving more credit or benefiting from lower interest rates. However, we should not ignore the fact that there is still a gain involved for the bank in having the loan guaranteed by the FCG, and therefore it might push for the firm to obtain the public guarantee. As the firm does not

[25] Results are qualitatively similar if, instead of using risk classes as in Table 7, we split the sample in terms of quartile of PD (see Table A2 in the Appendix).

fully know the counterfactual scenario—what would happen without the guarantee—it is likely to accept to apply for it and incur the small fee.

In summary, solvent borrowers appear to be the class that has benefited the most from the public guarantee, receiving both quantity and (albeit low) cost additionalities. Looking at the bank IRB metrics, solvent firms are assessed as low-medium risk SMEs. Their probability of default, as can be seen from Figure 4 and Table 7, ranges from 0.2 to 1.2 percent. This assessment is also confirmed when we consider the External Credit Assessment Institutions (ECAI) standardized scale, as approved by European Central Bank. Under the ECAI scale, solvent firms lay between investment (BBB) and non-investment (BB) grade companies. However, they never reach the speculative grade.

Conversely, safe firms can be considered as the class that is least affected from getting a public guarantee. Not only are both estimated impacts not statistically significant, but they also appear economically negligible (i.e. very close to zero). This finding points out that granting a public guarantee to firms with a very low probability of default does not seem to be useful in generating financial additionalities.

6.4 Public guarantee and length of relationship

The last issue we address concerns the role of the length of the relationship between the bank and its borrowers. As discussed in Section 2, public guarantee schemes might allow financial intermediaries to mitigate their information asymmetry problem, improving credit conditions for borrowers with shorter relationships. Alternatively, banks could grant financial additionalities to borrowers with longer relationships in order to mitigate risk assumption. Longer and repetitive interaction with the borrower improves the ability of the bank to distinguish between good and bad investment projects.

We therefore divide borrowers into two groups: those having a relationship length above the sample median value, and those having shorter relationships.[26] In order to avoid having two unbalanced sub-samples, we chose the median relationship length (8 years) as the cut-off to split them.[27] We then separately estimate the two effects. Results in Table 8 show that treatment effects

[26] The duration of the relationship is the distance between the date the application was assessed and the date on which the bank first granted credit to the firm. The latter date is as recorded in the bank's archives, and therefore the relationship duration is not left censored.

[27] We also tried using a smaller cut-off (3 years) and the heterogeneity is nevertheless confirmed.

are significant only for long-term borrowers, namely customers that have been known by the bank for at least 8 years. For these firms, the provision of a public guarantee raises the amount of loans granted by the bank by 14 percent and reduces the cost of long-term credit by 90 basis points. These results suggest a preference of the bank to delimit to less informationally opaque SMEs (due to repeated interaction) the higher credit risk exposure resulting from granting additionalities.

The last issue we address is the interaction between the length of the relationship and the internal credit standing assessed by the bank. To do so, we split the sample by both the four classes of risk defined in the previous subsection and the two classes of relationship (length above and below the median) defined in this subsection. Table 9 reports the results concerning the loan amount granted to guaranteed SMEs, separately for each subgroup.[28] It can be seen that the effects are concentrated in the cell of solvent and well-known firms; for these companies we find an additionality equal to 37 percent of their total outstanding credit. No effects are detected for all the other guaranteed classes of borrowers.

On the whole, we interpret such results as evidence of cautious risk-taking behavior. On one hand, the bank delimits risk assumption choosing as a target for its additionalities the class of solvent (not too risky) borrowers; higher-risk classes do not receive more credit. On the other hand, within the class of solvent borrowers, the bank trusts only those with a longer relationship, that are better known and most likely more reliable and/or with a better outlook. However, a longer relationship, by itself, is not sufficient to improve the impact of the public guarantee.

7. Robustness checks

In our exercise we focused only on direct guarantees provided by the FCG. Nevertheless, firms could also apply for an indirect FCG guarantee through a Mutual Guarantee Institution (the *Confidi*). Given that this indirect guarantee follows the same process of the direct one, our estimates may be distorted. If we expect this indirect guarantee to have no effect, then there is no bias. Focusing on our main outcome (credit quantity), if both guarantees have a positive effect, then the bias is different for the OLS and IV estimators. When we use OLS, we assign to the

[28] Table 9 includes running regressions for eight subsamples; we do not replicate this exercise for interest rates because of the limited size of the sample in which we observe them.

control group (those with $G_i = 0$) those firms that have an indirect guarantee. The estimates are therefore biased downward. On the contrary, the IV estimator has an upward bias. The reason is a bit more convoluted, but it is informative to work it out. When we estimate the *reduced form*, which is the impact of the eligibility on the outcome:

$$y_i = \varphi_0 + \varphi_1 E_i + X_i \varphi_X + \varepsilon_i \qquad (5)$$

We are nevertheless able to identify the intention-to-treat effect of *all* the guarantees (direct and indirect) on the outcome (as long as assumption A2b holds). However, given that G_i is equal to 1 only for those with a direct guarantee, the coefficient γ_1 on E_i in the first stage (eq. 4) will measure only the increase in the fraction of direct guarantees associated with being strongly eligible. The increase in the fraction of direct and indirect guarantees should be larger. Given that the 2SLS estimator is the ratio of the reduced form and the first stage, we are therefore overestimating the total effect, as we are attributing the total impact of being (strongly) eligible only to direct guarantees.

To gauge the impact of this issue on our estimates, and to evaluate our identification strategy, we exploit the fact that during 2013 and 2014 the direct guarantee, on which we focus, was not available in only one Italian Region, Tuscany. As a strong system of Mutual Guarantee Institutions was available, the legislator decided that firms located in the region could only apply through the *Confidi.* In this scenario we expect that, as long as assumption (A2b) holds and the indirect guarantees have no effect, there should be no effect of being eligible ($\varphi_1 = 0$) in the reduced form (5) restricted to Tuscany. In panel A of Table 10, we show results for this check. Reassuringly, the coefficient of E_i in the reduced form for our main outcome (credit quantity) is never significant in Tuscany. Furthermore, while the estimate is still sizable in the simplest specification, when we move to our favorite specification (the third column), the coefficient becomes basically zero in Tuscany. Differently, these robustness checks raise some issues regarding the estimates for interest rates. The relation between strong eligibility and the interest rate on term loans is also negative in Tuscany, where it should capture the effect of the indirect guarantees. Assuming that both direct and indirect guarantees lead to a reduction in interest rates, it is implied that our estimates overestimate (in absolute size) the true effect of the direct guarantee.

One issue is that eligible firms, being more financially stable, might also be able to provide more personal and real guarantees. Given that the FCG eligibility depends on balance sheet data of the two years before the application, our concern is the pre-existing availability of other guarantees. We therefore replicated the main regressions of Tables 4 and 6 including among the controls a variable, measured the month before the date of the application's assessment, calculated as the sum of personal and real warranties divided by the total credit granted by the banking system. We also include a similar variable but with only warranties with the bank object of our study as the numerator.[29] The results basically remain unchanged (see Tables A3 and A4 in the Appendix). It seems, therefore, that the controls included in our main specification are already sufficient to address this issue.

Another concern is related to the problem of using a single-bank dataset, as already mentioned in the Introduction. Although this dataset allows us to access important information on the PD as assessed by the bank's IRB, the focus on a single bank poses an issue of external validity: our results cannot be directly extended to all other banks, because we cannot be certain that a different intermediary would have behaved in the same way. Nevertheless, our results are in line with findings from previous studies which focus on the entire banking sector (Zecchini and Ventura, 2009; de Blasio et al., 2018).

A related problem is that the positive results on granted credit could actually capture a substitution effect with credit from other banks. We can check for this by looking, as an outcome, at the variation in interest rate and granted credit in the rest of the banking system. In this way, we monitor the evolution of the amount of loans granted and interest rates applied by all the other banks during the same period. The results reported in panels A and B of Table 11 corroborate our previous findings, because no effects are detected for the rest of the banking system as a whole, in terms of both credit availability and interest rates. However, we cannot exclude that some substitution will occur over a longer period of time.

Yet another issue is that our main dependent variable was defined using the total exposure with the banking system as the denominator. Panel C of Table 11 instead reports the estimates for the impact of the guarantee on the variation in credit with the large bank scaled with the previous total credit with the same large bank. These outcomes are consistent with those reported in Table 4. As expected, the magnitude of the impact is greater in case of Table 11 as it refers only to the total loans of the bank that has provided the guaranteed loans and not to the total loans received by the firm by the banking system.

[29] Both these additional controls have been censored as 1 (which implies that the entire amount of credit was covered).

The final issue regards to our choice of using only strong eligibility as an instrument. As shown in Figure 2, this is motivated by the fact that the strongest jump in the proportion of loan applications with an FG guarantee is between the weak and strong eligibilities. Nevertheless, our estimates are local in the sense that they capture only the effect of compliers. Therefore, using 1[eligible strong] as an instrument, we identify the effect for firms that received the guarantee because they were strongly eligible, but would not have otherwise received the guarantee, either because the Fund would have rejected them, or because the bank would have found it too risky to proceed with the application and discovered later that the firm could not receive it. Following Angrist and Pischke (2009), we can calculate the proportion of treated borrowers that are compliers, by using the first stage coefficient together with the proportions of eligible and treated. It turns out that, in our exercise, 55 percent of the treated loan applications belong to this group of compliers. Hence, even if our estimates capture only the local average treatment effect, they cover a significant fraction of the treated. An alternative strategy would be to use, as an additional instrument, a dummy for 1[weakly eligible]. If we do this, the first stage is still strong, although the contribution of the additional instrument (1[weakly eligible]) is very small, as the increase in the proportion of guarantees associated with weak eligibility is only 0.2 percent. The 2SLS estimates of the effect of the guarantee turns out to be very similar to the main results (0.084, s.e. 0.035), hence supporting our conclusions.

The interpretation of the 2SLS estimate is also relevant when comparing our results with those of de Blasio et al. (2018). The authors use a RDD design around the lower cut-off, which distinguishes non-eligible firms from those that are weakly eligible. Their estimates, which suggest a larger effect on granted credit and a non-significant impact on interest rates, are relative to firms that receive the guarantee because they are eligible and are around the lower cut-off for eligibility. Conversely, our estimates as discussed above, identify the effect for a different group of compliant firms, that is, those that received the guarantee because they were strongly eligible. In fact, if we exclude strongly eligible firms from the sample and run the same IV regression but using weak eligibility as instrument (i.e. we implicitly compare weak eligible firms with non-eligible ones), we find an effect on granted credit which is more similar to that found by de Blasio et al. (2018), that is $\delta = 0.498$ (s.e. 0.257). This should identify the effect on weakly eligible firms. However, there are two important reasons for focusing on the other results. First, in this case the estimate is much less precise, because the first stage is weaker (F=22): a 95 percent c.i. would actually include zero. In fact, when we use both kinds of eligibility as instruments, the 2SLS regression is closer to our main results. Second, as argued above, almost 55 percent of the treated belong to the group of compliers, whose effect is identified by our main regression. Furthermore, 82 percent of the actual treated are strongly eligible.

8. Conclusions

In this paper, we investigate the functioning of the Italian public guarantee fund for SMEs. Using a unique dataset from a large Italian bank, we exploit the access to private information on the bank's credit-risk assessment of a firm and the lender-borrower relationship. Adopting an IV estimation strategy based on the eligibility for the guarantee, we inspect whether the impact of the guarantee differs according to this private information. Our IV strategy hinges on the assumption that, conditional on the hard information used by the bank to assess credit applications (in particular the internal rating as expressed by the PD that we observe), the eligibility for the FCG is irrelevant for the bank's decision.

We find that, overall, the public guarantee has a positive impact on loans to SMEs. Guaranteed firms receive an additional amount of credit equaling to 7–8 percent of their total banking exposure from the bank. In addition, we observe a negative impact on long-term interest rates, which is smaller by about 50 basis points for term loans granted to guaranteed firms. The average effects mask substantial heterogeneity with respect to this private information. We show that the effect on the quantity of credit is concentrated on the class of solvent firms. The effects on the cost of credit are more widespread, but they are still null for firms with very low probability of default. Finally, we find evidence that the impact of the public guarantee on credit availability and cost are stronger for firms with a longer relationship with the bank.

A firms' PD is a measure of credit risk which is updated with some inertia as it is based on information from firm's balance sheet. Thus, the empirical evidence that financial additionality is concentrated mainly in the class of solvent firms instead of riskier firms may be due to a cautious evaluation by the bank of the stability/reliability of current ratings. In fact, the period examined in the paper is characterized by a deep and prolonged recession, and the sharp rise in business failures, not concentrated in any specific sector of the economy, increased the rate of migration of firms' ratings to the worse classes of ratings.

Using a single-bank dataset allows us to take advantage of private information that is not otherwise available, but suffers from limitations in terms of external validity. However, our findings are consistent with the empirical evidence for the entire Italian banking system (Zecchini and Ventura, 2009; De Blasio et al., 2018), especially in terms of the credit availability effect. Furthermore, our heterogeneity analysis highlights important issues in the functioning of the guarantee, particularly regarding which firms are more likely to benefit from it.

In terms of policy implications, our findings suggest that the Italian public guarantee scheme did not generate financial additionalities for firms with a very low probability of default, and which are therefore likely to be financially unconstrained. The recent reform of the FCG has strengthened this selection process, as it has introduced a disincentive to assigning guaranteed loans to safe firms, by providing a lower coverage ratio for them. Furthermore, our findings suggest that the FCG was not sufficient to counteract financial frictions for firms with a short duration of relationship with the bank.

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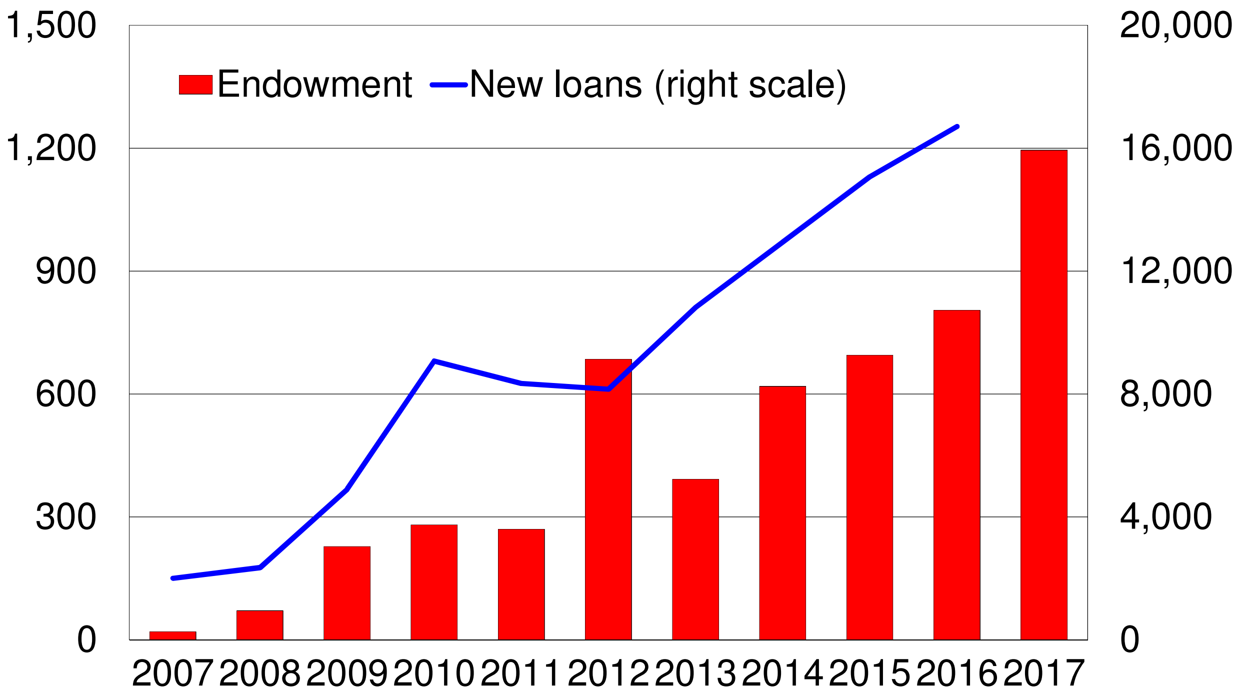
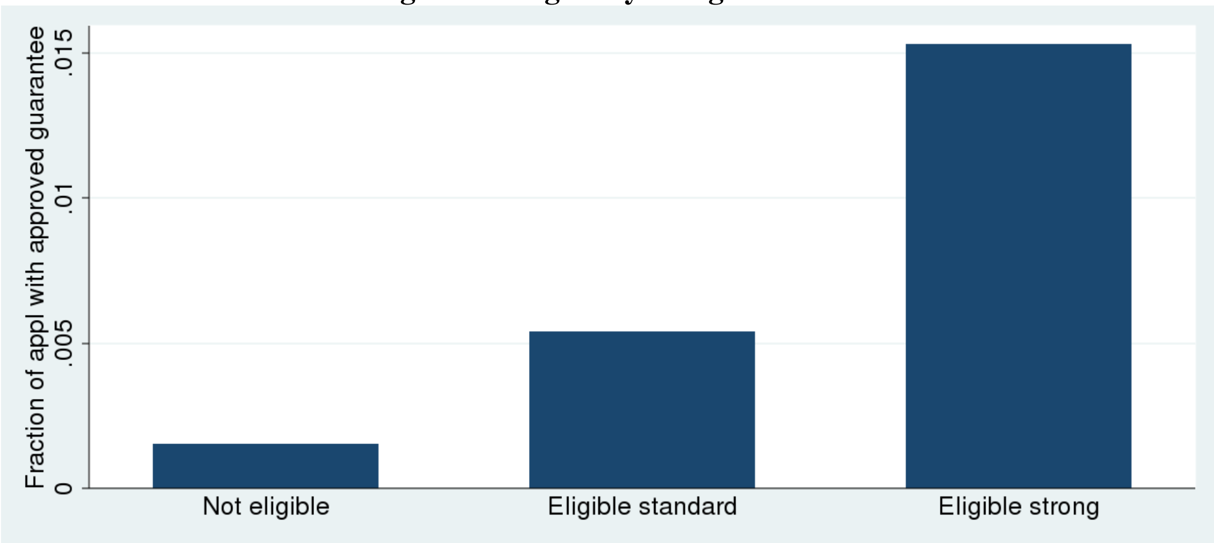
Figures and Tables

Figure 1: FCG endowment and loans backed by public guarantee
(millions of euros)



Source: Fondo Centrale di Garanzia and Ministry of Economic Development.

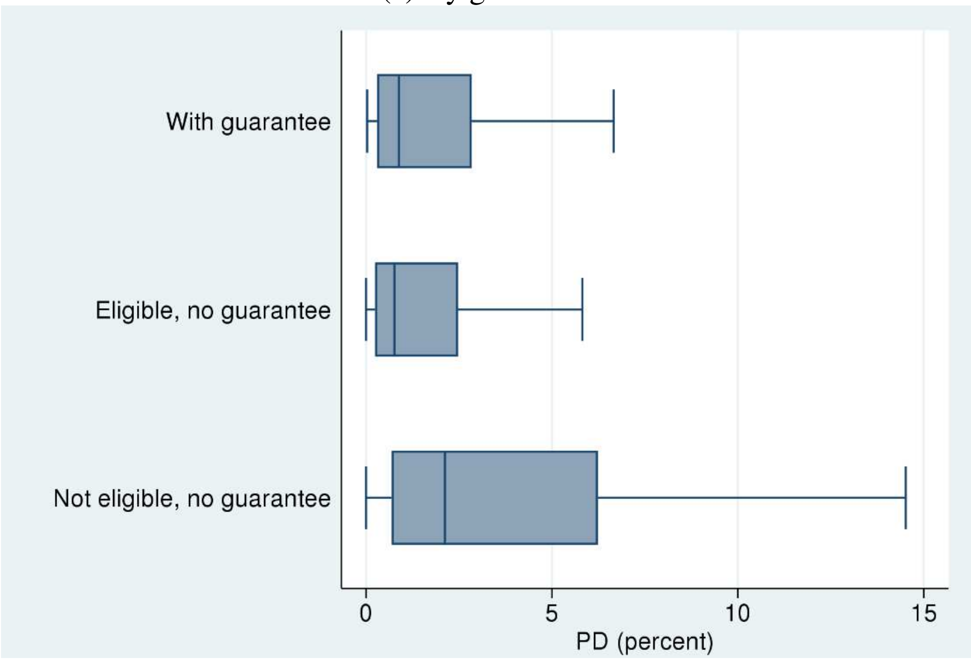
Figure 2: Eligibility and guarantee



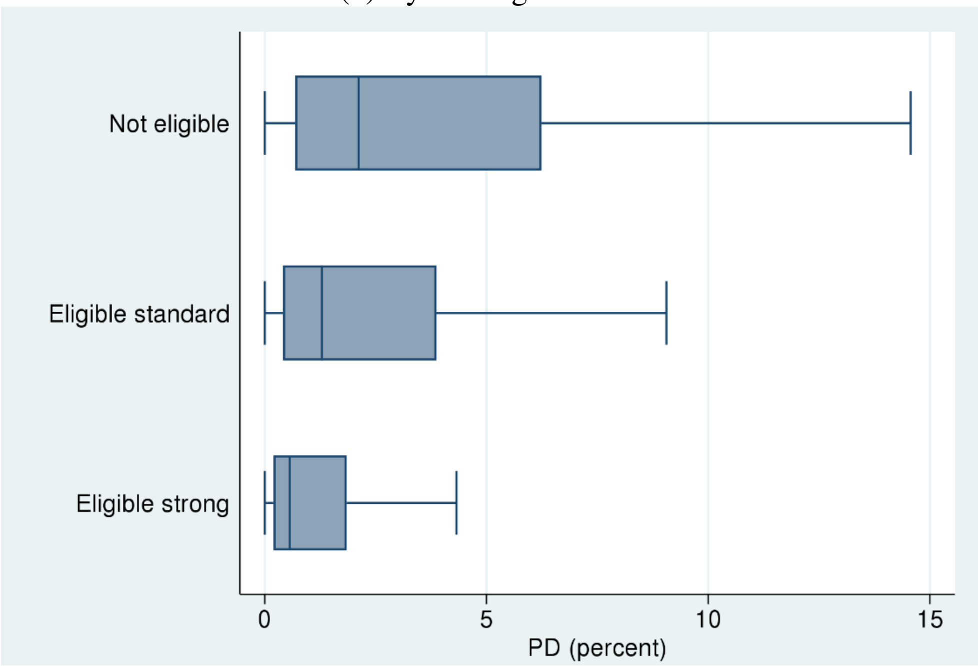
Note: main sample (see Tables 1-3).

Figure 3: Distribution of the probability of default

(a) By guarantee

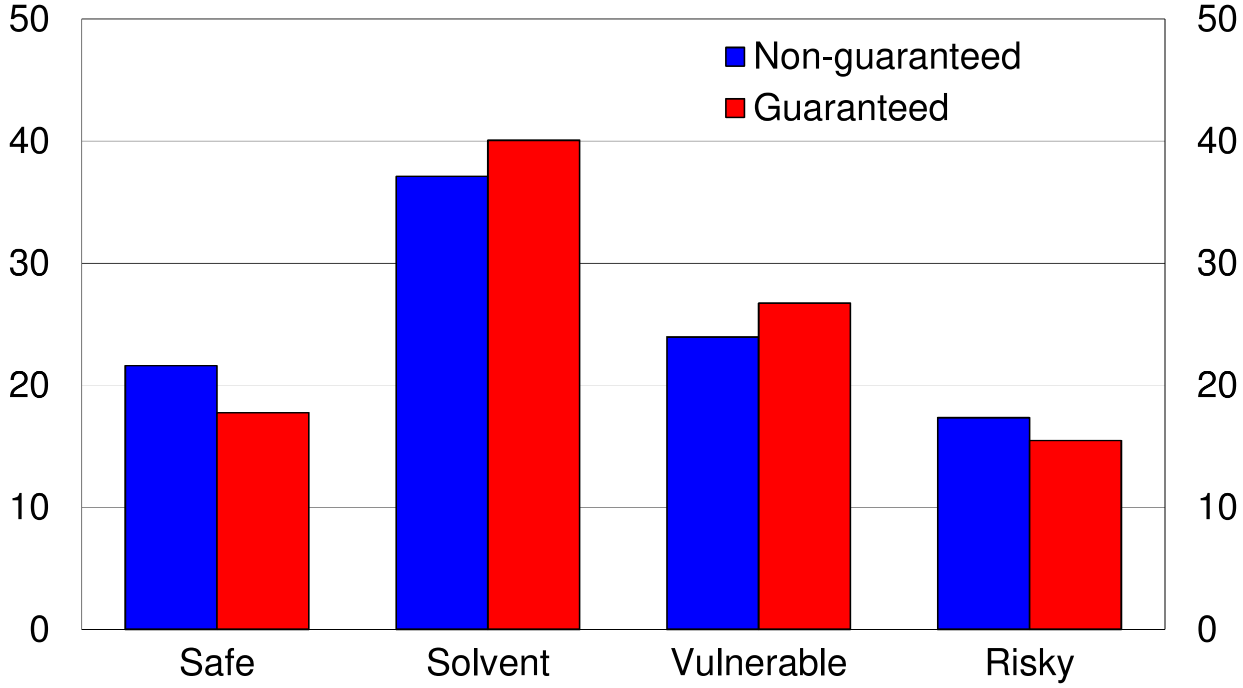


(b) By ranking for FCG



Note: main sample (see Tables 1-3). The rectangular box shows where the 25th-75th range of the distribution lies, with the middle vertical line corresponding to the median. The horizontal line is delimited by the lower and upper adjacent values, where the lower adjacent value is the smallest value ≥ (lower quartile - 1.5 × interquartile range) and the opper adjacent value is the largest value ≤ (upper quartile - 1.5 × interquartile range).

Figure 4: Share of relations by borrowers' class of risk
(percent)



Note: Risk classes are created according to the value of one-year borrowers' PD assessed by the bank. The brackets of PD (in percentage points) for each group are: Safe [0.000-0.206), Solvent [0.206-1.234), Vulnerable [1.234-4.608), Risky [4.608-9.99).

Table 1. Observations

area	Manufactu-ring and agricolture	Construction	Trade	Transporta-tion	Other services	Total
			Total observations			
North West	14,913	4,502	11,054	1,420	8,415	40,304
North East	17,056	5,420	12,507	1,853	8,229	45,065
Centre	9,245	4,852	11,028	1,305	6,415	32,845
South and Islands	7,895	5,063	12,431	1,328	4,092	30,809
Area missing	747	113	506	40	244	1,650
Total	49,856	19,950	47,526	5,946	27,395	150,673
			With FCG guarantee			
North West	240	78	131	13	94	556
North East	2232	62	127	27	62	510
Centre	41	23	43	8	19	134
South and Islands	143	69	158	17	36	423
Area missing	5	1	6	0	1	13
Total	661	233	465	65	212	1,636

Table 2. Sample statistics by presence of the guarantee

	Average	Standard deviation	p25	p50	p75	obs
		With guarantee				
Bank's outstanding loans (000s €)	1226	1210	385	895	1657	1,636
Probability of default (PD, %)	2.91	5.87	0.30	0.88	2.84	1,636
Total Assets (000s €)	2028	1486	831	1589	2898	1,636
Firm Age (years)	16.9	11.9	8.0	14.0	23.0	1,636
EBITDA / Assets (%)	9.7	6.4	5.6	8.5	12.6	1,636
Leverage (%)	67.5	20.6	56.3	72.4	83.5	1,636
Net interest payments/ EBITDA (%)	28.7	26.8	13.2	25.0	41.6	1,636
Current ratio (%)	120.3	40.0	98.0	112.7	134.1	1,636
Duration of bank relationship (years)	9.0	5.8	4.6	8.2	13.1	1,636
Bank Share of total credit (%)	36.6	29.7	13.0	29.4	53.5	1,636
First 3 lenders share of total credit (%)	89.2	14.1	81.1	97.1	100.0	1,636
		Eligible, no guarantee				
Bank's outstanding loans (000s €)	874	1100	187	497	1150	135,552
Probability of default (PD, %)	3.21	7.85	0.24	0.76	2.47	135,552
Total Assets (000s €)	1577	1403	502	1086	2212	135,552
Firm Age (years)	16.8	11.7	8.0	14.0	23.0	135,552
EBITDA / Assets (%)	8.3	7.8	3.8	7.5	12.5	135,552
Leverage (%)	63.3	26.6	44.8	69.6	85.5	135,552
Net interest payments/ EBITDA (%)	24.5	35.1	6.5	20.4	40.0	135,552
Current ratio (%)	124.3	50.5	94.6	113.6	143.3	135,552
Duration of bank relationship (years)	8.8	6.1	4.0	7.9	12.8	135,552
Bank Share of total credit (%)	39.1	35.3	8.6	28.6	64.5	135,552
First 3 lenders share of total credit (%)	93.7	11.2	90.5	100.0	100.0	135,552
		Not eligible, no guarantee				
Bank's outstanding loans (000s €)	892	1321	188	484	1107	13,485
Probability of default (PD, %)	6.74	12.21	0.69	2.12	6.24	13,485
Total Assets (000s €)	1697	1484	560	1172	2423	13,485
Firm Age (years)	17.0	12.3	7.0	14.0	24.0	13,485
EBITDA / Assets (%)	0.6	6.0	-3.8	0.8	4.3	13,485
Leverage (%)	75.2	27.4	61.8	87.9	96.2	13,485
Net interest payments/ EBITDA (%)	20.5	61.4	-31.6	17.4	70.0	13,485
Current ratio (%)	106.6	55.6	71.2	92.2	121.9	13,485
Duration of bank relationship (years)	9.0	6.1	4.2	7.9	13.2	13,485
Bank Share of total credit (%)	40.1	35.4	9.7	29.2	66.7	13,485
First 3 lenders share of total credit (%)	94.0	10.7	91.2	100.0	100.0	13,485

Note: outstanding refers to granted loans. Balance sheet variables refer to the most recent financial statement available in the month in which the bank makes the credit assessment and decides whether to grant the loan; credit exposure variables refer to the month before the credit assessment. Continuous variables are winsorized at 5th and 95th percentile (apart from age, duration of bank relationship, bank share of total credit and first 3 lenders share of total credit). The Probability of default is the likelihood of failure over 1 year, assessed by the bank. Leverage is calculated as a ratio between financial debt and the sum of financial debt and equity. EBITDA = Earnings Before Interest, Taxes, Depreciation and Amortization. Current ratio = Current Assets / Current Liabilities. Bank share of total credit refers to the fraction attributable to our large bank.

Table 3. Sample statistics by FCG rank

	Average	Standard deviation	p25	p50	p75	obs
		Not eligible				
Bank's outstanding loans (000s €)	891	1320	188	484	1106	13,506
Probability of default (PD, %)	6.73	12.21	0.69	2.12	6.24	13,506
Total Assets (000s €)	1696	1483	560	1172	2423	13,506
Firm Age (years)	17.0	12.3	7.0	14.0	24.0	13,506
EBITDA / Assets (%)	0.6	6.0	-3.8	0.8	4.3	13,506
Leverage (%)	75.2	27.3	61.8	87.8	96.2	13,506
Net interest payments/ EBITDA (%)	20.6	61.4	-31.5	17.4	70.0	13,506
Current ratio (%)	106.7	55.6	71.3	92.2	121.9	13,506
Duration of bank relationship (years)	9.0	6.1	4.2	7.9	13.2	13,506
Bank Share of total credit (%)	40.1	35.4	9.7	29.3	66.7	13,506
First 3 lenders share of total credit (%)	94.0	10.7	91.2	100.0	100.0	13,506
		Eligible standard				
Bank's outstanding loans (000s €)	894	1120	200	522	1186	48,907
Probability of default (PD, %)	4.58	9.63	0.41	1.29	3.87	48,907
Total Assets (000s €)	1653	1411	559	1176	2332	48,907
Firm Age (years)	16.6	11.7	8.0	14.0	23.0	48,907
EBITDA / Assets (%)	4.3	6.2	1.3	4.5	7.4	48,907
Leverage (%)	71.6	25.0	58.1	80.1	91.1	48,907
Net interest payments/ EBITDA (%)	30.6	45.5	7.1	31.1	56.0	48,907
Current ratio (%)	112.9	47.9	84.0	105.4	128.4	48,907
Duration of bank relationship (years)	8.8	6.1	4.1	7.9	12.8	48,907
Bank Share of total credit (%)	39.3	34.0	11.1	29.7	62.0	48,907
First 3 lenders share of total credit (%)	93.0	11.6	88.6	100.0	100.0	48,907
		Eligible strong				
Bank's outstanding loans (000s €)	870	1093	181	489	1140	88,260
Probability of default (PD, %)	2.44	6.50	0.20	0.56	1.85	88,260
Total Assets (000s €)	1544	1400	477	1047	2158	88,260
Firm Age (years)	16.8	11.7	8.0	14.0	23.0	88,260
EBITDA / Assets (%)	10.6	7.6	5.8	9.7	15.2	88,260
Leverage (%)	58.7	26.2	39.3	63.7	80.6	88,260
Net interest payments/ EBITDA (%)	21.2	27.0	6.5	16.8	32.0	88,260
Current ratio (%)	130.6	50.6	99.8	118.8	150.9	88,260
Duration of bank relationship (years)	8.7	6.1	4.0	7.9	12.8	88,260
Bank Share of total credit (%)	38.9	35.9	7.2	27.9	65.8	88,260
First 3 lenders share of total credit (%)	94.0	11.0	91.5	100.0	100.0	88,260

Note: outstanding refers to the granted loan. Balance sheet variables refer to the most recent financial statement available in the month in which the bank makes the credit assessment and decides whether to grant the loan; credit exposure variables refer to the month before the credit assessment. Continuous variables are winsorized at 5° e 95° percentile (all but age, duration of bank relationship, bank share of total credit and first 3 lenders share of total credit). The Probability of default is the likelihood of failure over 1 year, assessed by the bank. Leverage is calculated as a ratio between financial debt and the sum of financial debt and equity. EBITDA = Earnings Before Interest, Taxes, Depreciation and Amortization. Current ratio = Current Assets / Current Liabilities. Bank share of total credit refers to the fraction attributable to our large bank.

Table 4. The impact of the guarantee on the amount of credit

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS: Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.004***	0.004***	0.003**	0.003**	0.004**	0.004**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
	First stage: Dependent variable *1[Guarantee]*					
1[Eligible strong]	0.013***	0.012***	0.011***	0.010***	0.010***	0.011***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
First stage F	364.5	304.9	248.2	244.8	233.5	257.3
	2SLS: Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.165***	0.121***	0.079**	0.072**	0.076**	0.066*
	(0.029)	(0.032)	(0.035)	(0.035)	(0.036)	(0.034)
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X
N	135,607	135,607	135,607	135,607	135,607	135,607

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The unit of observation is the single credit request. Time *t* refers to the month in which the bank makes the credit assessment and decides whether to grant the loan. The main outcome is the variation in credit with the Bank between a month before and a month after *t*, divided by the total credit with the banking system in the month before. The instrument in 2SLS regressions is *1[Eligible strong]*. The sample excludes firms without credit with the banking sector one month before *t*. We further truncated the sample by removing observations below the 5th and above the 95th percentile of the dependent variable. Because of its skewness, the PD (included as covariate) is rescaled as 1000-quantiles of its distribution. The other continuous variables included as controls are (i) balance sheets indices (log total Assets, Leverage, EBITDA / Assets, Net interest payments/ EBITDA, Current ratio) in the year before *t* (or two years before if *t* is before May, when balance sheet are usually approved and made public); (ii) credit variables (Used loans / Granted loans, Bank Share of total credit, First 3 lenders share of total credit) at *t-1*; (iii) Firm age and Duration of bank relationship (in years) at *t*. Finally, the regressions include dummies for: sector of economic activity (reference group: Manufacturing and agriculture), geographical area (reference: North), year of application, a dummy (Main Bank) that is equal to 1 if the Bank is the main bank and a dummy (New Customer) that is equal to 1 if the borrower did not have loans with the Bank at *t-1*. All the shares and indices are on the original scale (i.e., they are not expressed as percent). In column 6, we include all the dummies, while for the continuous variables we select only a set of them following the procedure suggested by Belloni et al (2014) and using the ado program written by them. The selection of the continuous covariates is run starting from a set that also includes all the interactions between them and their powers up to the sixth (PD included). All these variables have been standardized before running the selection. The algorithm converges in few iterations.

Table 5. The impact of the guarantee on the amount of credit, by kind of credit, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Short-term loans					
	Dep. Var: $(credit_{t+1}^{Bank,} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.068***	0.056**	0.045*	0.040	0.048*	0.043*
	(0.020)	(0.022)	(0.025)	(0.025)	(0.026)	(0.024)
N	135,607	135,607	135,607	135,607	135,607	135,607
First stage F	349.2	288.4	234.5	230.8	219.1	244.5
	Panel B: Long-term loans					
	Dep. Var: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.068***	0.042**	0.021	0.015	0.019	0.029
	(0.017)	(0.018)	(0.021)	(0.021)	(0.022)	(0.020)
N	135,607	135,607	135,607	135,607	135,607	135,607
First stage F	346.1	285.5	231.2	227.9	214.8	243.7
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The sample and the control variables are the same as in Table 4; see notes to Tables 4 for other info. Both dependent variables are calculated by using total credit (of any form) as denominator, so that they can be interpreted as contributions to the variation of $credit^{Bank}$ from Table 4. Short-term loans include revolving credid lines and loans backed by accounts receivable. Long-term loans include loans whose duration exceeds 1 year.

Table 6. The impact of the guarantee on the cost of credit, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Loans backed by accounts receivable					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	0.404	0.488	0.762	0.815	0.738	0.800
	(0.424)	(0.475)	(0.536)	(0.540)	(0.546)	(0.530)
N	64,931	64,931	64,931	64,931	64,931	64,931
First stage F	207.1	172.6	139.6	138.4	133.1	141.9
	Panel B: Revolving credit lines					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	-0.759	-0.622	-0.0753	-0.183	-0.130	-0.237
	(0.607)	(0.686)	(0.775)	(0.785)	(0.799)	(0.764)
N	74,776	74,776	74,776	74,776	74,776	74,776
First stage F	220.8	179.8	144.1	141.2	135.7	147.3
	Panel C: Term loans					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	-0.428**	-0.436**	-0.562**	-0.557**	-0.515**	-0.529**
	(0.192)	(0.221)	(0.245)	(0.247)	(0.250)	(0.246)
N	42,528	42,528	42,528	42,528	42,528	42,528
First stage F	139.7	114.4	95.9	94.9	91.6	94.8
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The regressions also include all the control dummies as in Table 4; see notes to Table 4 for other info. The variables relative to interest rates are expressed in percentage points. In each panel, we further truncated the sample by removing observations below the 5th and above the 95th percentile of the dependent variable.

Table 7. The impact of the guarantee on the amount and cost of credit, by risk classes, 2SLS

	(1)	(2)	(3)	(4)
Group:	Safe	Solvent	Vulnerable	Risky
PD range:	[0.000-0.206)	[0.206-1.234)	[1.234-4.608)	[4.608-9.999]
	Panel A: Amount of total loans			
	Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$			
1[Guarantee]	-0.0170	0.187***	0.0496	-0.0513
	(0.115)	(0.069)	(0.055)	(0.054)
N	27,358	51,601	33,835	22,813
First stage F	38.7	77.8	94.9	48.4
	Panel B: Interest rate on term loans			
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)			
1[Guarantee]	0.0750	-0.839*	-0.195	-1.165**
	(0.543)	(0.444)	(0.391)	(0.535)
N	10,802	17,909	8,416	5,401
First stage F	28.4	30.3	29.3	16.3
Group fraction of total:				
$credit_{t+1}^{Bank}$	0.260	0.408	0.214	0.118
$credit_{t-1}^{Bank}$	0.258	0.403	0.215	0.123
$credit_{t-1}^{total}$	0.217	0.381	0.242	0.160
Included covariates:				
Polynomial of PD	3	3	3	3
Polynomial of other continuous covariates	3	3	3	3
Dummies	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. In Panels A and B the overall sample corresponds to the regressions in Tables 4 and 6 (Panel C), respectively. The polynomial of PD has been limited to the 3rd because, due to the split, the 4th term is highly collinear with the others. The regressions also include all the control dummies as in Table 4; see notes to Table 4 for other info.

Table 8. The impact of the guarantee on the amount and cost of credit, by relationship duration with the bank, 2SLS

	(1)	(2)
	Below the median [0-8 years]	Above the median [>8 years]
	Panel A: Amount of total loans	
	Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$	
1[Guarantee]	0.004	0.144***
	(0.049)	(0.052)
N	68,531	67,076
First stage F	131.2	111.7
	Panel B: Interest rate on term loans	
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)	
1[Guarantee]	-0.298	-0.896**
	(0.323)	(0.385)
N	18,893	23,635
First stage F	48.07	44.25
Included covariates:		
Polynomial of PD	4	4
Polynomial of other continuous covariates	3	3
Dummies	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The median is calculated on the selected sample for the regressions on credit quantity. The regressions also include all the control dummies as in Table 4; see notes to Table 4 for other info. In Panels A and B the overall sample corresponds to the regressions in Tables 4 and 6 (Panel C), respectively.

Table 9. The impact of the guarantee on the amount of credit, by risk classes and relationship duration with the bank, 2SLS

Bank Risk classes		(1)	(2)
		Relationship duration	
		Below the median [0-8 years]	Above the median [>8 years]
Safe [0.000-0.206)	1[Guarantee]	-0.226	0.016
		(0.330)	(0.120)
	N	8,795	18,563
	First stage F	4.8	36.9
Solvent [0.206-1.234)	1[Guarantee]	-0.008	0.370***
		(0.106)	(0.106)
	N	25,369	26,232
	First stage F	34.7	37.9
Vulnerable [1.234-4.608)	1[Guarantee]	0.041	0.018
		(0.075)	(0.079)
	N	19,924	13,911
	First stage F	54.3	39.7
Risky [4.608-9.999]	1[Guarantee]	-0.005	-0.193
		(0.060)	(0.121)
	N	14,443	8,370
	First stage F	41.7	10.1

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The regressions also include all the control dummies as in Table 7; see notes to Tables 4 and 7 for other info. The overall sample corresponds to the regressions in Table 4.

Table 10. The impact of eligibility for the guarantee in Tuscany vs other regions

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Reduced form (OLS), Dependent variable: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$						
Tuscany						
1[Eligible strong]	0.00110	0.00033	-0.00017	-0.00009	-0.00003	-0.00015
	(0.00129)	(0.0013)	(0.00135)	(0.00135)	(0.00137)	(0.00135)
N	8,660	8,660	8,660	8,660	8,660	8,660
Rest of Italy						
1[Eligible strong]	0.00215***	0.00146***	0.00090**	0.00081**	0.00083**	0.00076**
	(0.00036)	(0.00037)	(0.00038)	(0.00038)	(0.00038)	(0.00037)
N	126,947	126,947	126,947	126,947	126,947	126,947
Panel B: Red form (OLS), Dep var $term\ loans$: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
Tuscany						
1[Eligible strong]	-0.02500*	-0.02451*	-0.02480*	-0.02743**	-0.03116**	-0.02211
	(0.01313)	(0.01352)	(0.01348)	(0.01355)	(0.01377)	(0.01370)
N	2,259	2,259	2,259	2,259	2,259	2,259
Rest of Italy						
1[Eligible strong]	-0.00602*	-0.00538	-0.00688**	-0.00671**	-0.00588*	-0.00648*
	(0.00322)	(0.00332)	(0.00340)	(0.00341)	(0.00345)	(0.00341)
N	40,269	40,269	40,269	40,269	40,269	40,269
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The regressions also include all the control dummies as in Table 4; see notes to Table 4. The covariates selected in column (6) are those selected on the whole sample (Table 4). In Panels A and B the overall sample corresponds to the regressions in Tables 4 and 6 (Panel C), respectively.

Table 11. Robustness

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: Amount of loans			
	Dep. var.: $(credit_{t+1}^{rest\ of\ the\ banking\ system} - credit_{t-1}^{rest\ of\ the\ banking\ system})/credit_{t-1}^{rest\ of\ the\ banking\ system}$					
1[Guarantee]	0.011	0.006	0.002	0.000	0.002	0.010
	(0.008)	(0.009)	(0.01)	(0.010)	(0.011)	(0.010)
N	135,607	135,607	135,607	135,607	135,607	135,607
First stage F	304.7	246.9	198.5	194.8	186.6	208.4
			Panel B: Interest rate on term loans			
	Dep. var.: $interest\ rate_{t+1}^{rest\ of\ the\ banking\ system} - interest\ rate_{t-1}^{rest\ of\ the\ banking\ system}$					
1[Guarantee]	0.209	0.242	0.227	0.267	0.325	0.249
	(0.199)	(0.221)	(0.246)	(0.249)	(0.254)	(0.245)
N	55,932	55,932	55,932	55,932	55,932	55,932
First stage F	188.3	160.4	133.3	132.2	126.6	133.7
			Panel C: Amount of loans			
	Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{Bank}$					
1[Guarantee]	0.376***	0.326***	0.257***	0.223**	0.217**	0.295***
	(0.074)	(0.081)	(0.090)	(0.091)	(0.093)	(0.089)
N	121,562	121,562	121,562	121,562	121,562	121,562
First stage F	334.0	278.4	226.3	223.5	211.3	234.1
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The regressions also include all the control dummies as in Table 4; see notes to Table 4 for other info. The variables relative to interest rates are expressed in percentage points. In each panel, we further truncated the sample by removing observations below the 5th and above the 95th percentile of the dependent variable. Because of the denominator used for the dependent variable, the last panel excludes firms that did not have credit with the bank at *t-1*.

Appendix - Additional Tables

Table A1. The impact of the guarantee on the amount of credit, 2SLS, marginal effects of the covariates

	(1)	(2)	(3)	(4)
	Dependent variable: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$			
Polynomial of PD	2	3	4	5
Polynomial of other cont. cov.	1	2	3	4
1[Guarantee]	0.165***	0.121***	0.079**	0.072**
	(0.029)	(0.032)	(0.035)	(0.035)
	Firm characteristics			
Log total Assets	-0.00284***	-0.00301***	-0.00392***	-0.00418***
	(0.000210)	(0.000212)	(0.000341)	(0.000353)
Age (years)	0.00000585	-0.0000298	-0.0000529*	-0.000133***
	(0.0000183)	(0.0000295)	(0.0000299)	(0.0000405)
Quantile of PD [1000 quantiles]	-0.0000303***	-0.0000232***	-0.0000233***	-0.0000193***
	(0.000000659)	(0.00000136)	(0.00000134)	(0.00000233)
Leverage	-0.00284***	-0.00628***	-0.00535***	-0.00617***
	(0.000722)	(0.00109)	(0.00116)	(0.00199)
Net interest payments/ EBITDA	-0.0000927	-0.000226	-0.000166	-0.000664*
	(0.000166)	(0.000166)	(0.000347)	(0.000366)
Current ratio	-0.00103***	0.000784**	0.00153***	0.000913**
	(0.000195)	(0.000367)	(0.000386)	(0.000462)
EBITDA / Assets	0.00938***	0.00813***	0.0167***	0.0153***
	(0.00187)	(0.00185)	(0.00330)	(0.00332)
	Bank-firm relationship characteristics			
Bank Share of total credit	-0.00125	0.00424***	0.0109***	0.0214***
	(0.000944)	(0.00130)	(0.00180)	(0.00293)
Duration of bank relationship (years)	-0.000463***	-0.000787***	-0.000612***	-0.000285***
	(0.0000354)	(0.0000467)	(0.0000495)	(0.0000806)
Used loans / Granted loans	0.0204***	0.0287***	0.0289***	0.0274***
	(0.000799)	(0.00103)	(0.00114)	(0.00180)
New Customer	0.0158***	0.0138***	0.0106***	0.00827***
	(0.000891)	(0.000914)	(0.000957)	(0.00102)
Main Bank	0.00160***	0.00110*	-0.000692	-0.00148**
	(0.000620)	(0.000597)	(0.000681)	(0.000699)
First 3 lenders share of total credit	0.0116***	0.0139***	0.0109	0.0271*
	(0.00169)	(0.00415)	(0.00888)	(0.0162)
	Other controls			
Sector fixed effect	Yes	Yes	Yes	Yes
Geographic area fixed effect	Yes	Yes	Yes	Yes
N	135,607	135,607	135,607	135,607

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. See Table 4 for other info.

Table A2. The impact of the guarantee on the amount and cost of credit, by quartile of default probability, 2SLS

	(1) I quartile PD [0.00, 0.26]	(2) II quartile PD [0.26, 0.84]	(3) III quartile PD [0.84, 2.78]	(4) IV quartile PD [2.78, 9.99]
	Panel A: Amount of loans			
	Dependent variable: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$			
1[Guarantee]	0.067	0.129	0.143**	-0.025
	(0.093)	(0.086)	(0.066)	(0.046)
N	33,904	33,902	33,903	33,898
First stage F	57.5	45.8	78.7	76.0
	Panel B: Interest rate on term loans			
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)			
1[Guarantee]	-0.148	-0.502	-0.526	-0.926**
	(0.484)	(0.526)	(0.415)	(0.446)
N	13,412	12,111	9,041	7,964
First stage F	36.8	17.2	28.7	22.3
Included covariates:				
Polynomial of PD	3	3	3	3
Polynomial of other continuous covariates	3	3	3	3
Dummies	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The quartiles are calculated on the selected sample for the regressions for the main variable ($(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$). The polynomial of PD has been limited to the 3rd because, due to the split, the 4th term is highly collinear with the others. See notes to Table 4 for other info.

Table A3. The impact of the guarantee on the amount of credit, including controls for the previous presence of other guarantees, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.159***	0.115***	0.071**	0.064*	0.066*	0.083**
	(0.029)	(0.032)	(0.035)	(0.035)	(0.036)	(0.034)
N	135,279	135,279	135,279	135,279	135,279	135,279
First stage F	363.7	304.7	248.7	245.1	233.9	258.4
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. We include among the controls all personal and real guarantees divided by the total credit granted by the banking system, measured at *t*-1. We also include a similar variable but with only guarantees with the bank as numerator. Both these additional controls have been top-censored at 1 (which implies that the entire amount of credit was covered). The regressions also include all the control variables and dummies as in Table 4. With respect to Table 4, we lose some observations because we do not observe the variables on additional guarantees. See notes to Table 4 for other info.

Table A4. The impact of the guarantee on the cost of credit, including controls for the previous presence of other guarantees, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A: Loans backed by accounts receivable					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	0.393	0.462	0.730	0.780	0.695	0.806
	(0.424)	(0.473)	(0.533)	(0.537)	(0.543)	(0.519)
N	64,931	64,931	64,931	64,931	64,931	64,931
First stage F	207.7	173.7	140.6	139.5	134.3	147.7
	Panel B: Revolving credit lines					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	-0.765	-0.613	-0.0694	-0.177	-0.123	-0.131
	(0.607)	(0.684)	(0.773)	(0.782)	(0.797)	(0.768)
N	74,776	74,776	74,776	74,776	74,776	74,776
First stage F	221.1	180.7	145.0	142.0	136.3	145.9
	Panel C: Term loans					
	Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)					
1[Guarantee]	-0.422**	-0.420*	-0.540**	-0.535**	-0.496**	-0.490**
	(0.192)	(0.220)	(0.243)	(0.245)	(0.249)	(0.244)
N	42,528	42,528	42,528	42,528	42,528	42,528
First stage F	140.0	114.8	96.3	95.3	91.7	96.6
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. We include among the controls all personal and real warranties divided by the total credit granted by the banking system, measured one month before the credit application assessment. We also include a similar variable but with only warranties with the Bank as numerator. Both these additional controls have been top-censored at 1 (which implies that the entire amount of credit was covered). The regressions also include all the control dummies as in Table 4. With respect to Table 6, we lose some observations because we do not observe the variable on guarantees. See notes to Tables 4-6 for other info. The variables relative to interest rates are expressed in percentage points.

Table A5. The impact of the guarantee on the amount of credit, restricting the time distance criterion for matching guarantees with credit applications, 2SLS

	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS: Dependent variable $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$					
1[Guarantee]	0.193***	0.142***	0.092**	0.084**	0.089**	0.107***
	(0.034)	(0.037)	(0.041)	(0.041)	(0.043)	(0.040)
N	135,607	135,607	135,607	135,607	135,607	135,607
First stage F	314.2	263.1	212.6	209.1	198.5	220.8
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The regressions also include all the control variables and dummies as in Table 4. We match guarantees with credit applications only if the distance between the date of the Bank decision about the credit application and the date of submission to the FCG is at most 60 days. See Table 4 for other info.

Table A6. The impact of the guarantee on the cost of credit, restricting the time distance criterion for matching guarantees with credit applications

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Loans backed by accounts receivable						
Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Guarantee]	0.453	0.562	0.877	0.935	0.847	0.928
	(0.489)	(0.548)	(0.617)	(0.620)	(0.627)	(0.598)
N	64,931	64,931	64,931	64,931	64,931	64,931
First stage F	179.9	149.6	121.2	120.9	116.3	128.1
Panel B: Revolving credit lines						
Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Guarantee]	-0.899	-0.732	-0.0882	-0.214	-0.152	-0.135
	(0.714)	(0.806)	(0.908)	(0.918)	(0.933)	(0.886)
N	74,776	74,776	74,776	74,776	74,776	74,776
First stage F	188.5	152.4	122.5	120.5	116.0	127.6
Panel C: Term loans						
Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Guarantee]	-0.474**	-0.490**	-0.627**	-0.622**	-0.574**	-0.561**
	(0.216)	(0.248)	(0.273)	(0.276)	(0.279)	(0.274)
N	42,528	42,528	42,528	42,528	42,528	42,528
First stage F	127.6	103.8	88.0	86.8	84.2	88.3
Included covariates:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The regressions also include all the control dummies as in Table 4; see notes to Tables 4 and 6 for other info. The variables relative to interest rates are expressed in percentage points. We match guarantees with credit applications only if the distance between the date of the bank decision about the credit application and the date of submission to the FCG is at most 60 days.

Table A7. The impact of the guarantee on the quantity and cost of credit, reduced forms (OLS)

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Credit amount Dependent variable: $(credit_{t+1}^{Bank} - credit_{t-1}^{Bank})/credit_{t-1}^{total}$						
1[Eligible strong]	0.00208***	0.00139***	0.000830**	0.000750**	0.000776**	0.000708*
	(0.000347)	(0.000355)	(0.000365)	(0.000365)	(0.000370)	(0.000366)
N	135,607	135,607	135,607	135,607	135,607	135,607
Adjusted R2	0.040	0.045	0.046	0.047	0.047	0.047
Panel B: Loans backed by accounts receivable (reference: Table 6) Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Eligible strong]	0.00666	0.00743	0.0105	0.0112	0.0101	0.0112
	(0.00698)	(0.00721)	(0.00735)	(0.00736)	(0.00740)	(0.00733)
N	64,931	64,931	64,931	64,931	64,931	64,931
Adjusted R2	0.012	0.012	0.013	0.013	0.014	0.012
Panel C: Revolving credit lines (reference: Table 6) Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Eligible strong]	-0.01080	-0.00806	-0.000884	-0.00213	-0.00149	-0.00283
	(0.00865)	(0.00886)	(0.00911)	(0.00912)	(0.00920)	(0.00910)
N	74,776	74,776	74776	74,776	74,776	74,776
Adjusted R2	0.009	0.010	0.010	0.011	0.011	0.010
Panel D: Term loans (reference: Table 6) Dependent variable: $interest\ rate_{t+1}^{Bank} - interest\ rate_{t-1}^{Bank}$ (percentage points)						
1[Eligible strong]	-0.00708**	-0.00648**	-0.00782**	-0.00769**	-0.00708**	-0.00732**
	(0.00312)	(0.00322)	(0.00330)	(0.00331)	(0.00335)	(0.00330)
N	42,528	42,528	42,528	42,528	42,528	42,528
Adjusted R2	0.015	0.015	0.015	0.016	0.016	0.015
Included variables:						
Polynomial of PD	2	3	4	5	6	Selected by double selection
Polynomial of other continuous covariates	1	2	3	4	5	
Dummies	X	X	X	X	X	X

Note: * p<.10 ** p<.05 *** p<.01. S.e. clustered by firm in brackets. The instrument in 2SLS regressions is *1[Eligible strong]*. The regressions also include all the control dummies as in Table 4; see notes to Tables 4 6 for other info. The variables relative to interest rates are expressed in percentage points. The regressions also include all the control variables and dummies as in Table 4. We match guarantees with credit applications only if the distance between the date of the bank decision about the credit application and the date of submission to the FCG is at most 60 days.

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