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PUBLIC GUARANTEES AND CREDIT ADDITIONALITY DURING THE COVID-19 PANDEMIC

by Giuseppe Cascarino[*], Raffaele Gallo[*], Francesco Palazzo[*] and Enrico Sette[*]

Abstract

We study the public loan guarantee programs implemented in Italy in the aftermath of the Covid-19 pandemic. Guided by a theoretical model and relying on a unique loan-level dataset covering the period between December 2019 and March 2021, including both guaranteed and non-guaranteed loans, we quantify to what extent public guarantees created additional credit across programs with different coverage ratios and over time. Credit additionality was highest, at around 84 cents per euro of guarantees, for the fully guaranteed loans originated in the first quarter of the program (Q2-2020). In the following quarters, the additionality of the different programs decreased, hovering around 50-60 cents per euro of guarantees. We also document that bank capitalization affected additionality for loans with lower coverage, in which banks have more skin in the game. In contrast, the additionality of the public guarantees varied very little across firms with different levels of risk, liquidity, and size.

JEL Classification: G21, G24.
Keywords: public loan guarantees, credit additionality, bank capital, pandemic.
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Contents

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1 Introduction[1]

In many advanced economies public loan guarantee schemes have been a cornerstone of the government strategies to help the corporate sector weather the abrupt economic effects brought about by the Covid-19 pandemic. Public funds allocated to these programs were exceptionally large. For example, the Paycheck Protection Program (PPP) in the US had a $669 billion budget; in Europe national governments adopted even larger programs relative to the size of their economies: the German, Italian and French programs had a maximal budget of €757, €400 and €330 billion, about 20, 25 and 15 per cent of GDP, respectively.

Credit guarantee schemes may have significant implications for both economic activity and systemic risk, depending on take up and allocation choices. Rather than sustaining the provision of new credit to firms facing temporary liquidity shortages, they could, for example, induce banks to substitute existing credit for loans backed by public guarantees, thus shifting credit risk onto the Government.[2] Such incentive could be greater for low capital banks and in the case of loans to ex ante weaker firms, which would affect the extent of the risk-shifting. Importantly, the scheme effectiveness may significantly vary with the design of the program, in particular its coverage ratio (i.e. the share of the loan covered by the public guarantee). Intuitively, an higher coverage ratio reduces banks' skin in the game and could heighten their risk-shifting incentives.

In this paper we explore these key issues using a unique dataset of loans, both guaranteed and non-guaranteed, that provides granular information on the varying coverage ratio characterizing each guaranteed loan. Specifically, the Italian guarantee scheme –

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[2]Even if the design of most public loan guarantee schemes explicitly excludes that the guarantees can cover existing loans, these provisions can be bypassed with different strategies, such as debt repayment or the reduction of existing credit lines limits.

like other programs, most notably the German one – includes different sub-programs that provide different coverage ratios, depending on the size of the loan (or of the firm):[3] i) 100 per cent coverage and up to €30,000 (*guarantee program 100*); ii) 90 per cent coverage and guaranteed amount up to €5 million (*guarantee program 90*); iii) loans granted for debt renegotiation or consolidation, with a 80 per cent coverage (*renegotiations*). These features allow to gain a thorough understanding of: i) which firms and banks were more likely to take advantage of a specific guarantee program; ii) to what extent guaranteed loans with different coverage ratios were able to generate additional credit *vis-à-vis* substituting existing loans. In the spirit of the fiscal multiplier literature (see Acconcia et al., 2014), we test how much of each euro of public guarantees translates into additional credit to the firm by estimating a credit multiplier.[4] The larger the size of this multiplier the more the guaranteed amount, i.e. the amount of public subsidy, was used to generate new credit. We interact this ratio with dummies for each program to identify the heterogeneous effects of different coverage ratios.

The hypotheses to be tested in the empirical analysis are informed by a model of bank-firm relationships to identify the key trade-offs that banks and firms face when loan guarantees are available. Banks benefit from substituting existing loans with guaranteed ones because this reduces bank capital absorption as loans guaranteed by the Government carry lower credit risk weights (e.g. zero in the case of the fully guaranteed loans). In turn, guaranteed loans are originated at lower rates than existing loans because the guarantee abates credit risk, whose effect is amplified because banks compete to take advantage of it.[5] For firms, this means that substituting existing loans for cheaper guaranteed credit saves on interest expenses, but lowers the accumulation of liquidity, thus increasing the risk of being illiquid if a shock occurs. The model centers on this trade-off and derives a set of testable predictions, namely: i) a higher coverage ratio implies, *ceteris paribus*,

[3]For these programs guaranteed loans cannot exceed 25 per cent of firm revenues in 2019.

[4]To do so we regress, for each bank-firm relationship, the ratio between the change in credit provided by the lender in the period over total credit available to the firm at the beginning of the period, on the ratio between the loan guaranteed amount provided by the lender in the period, if positive, and total credit granted at the beginning of the period (i.e. the same denominator of the dependent variable).

[5]In practice, interest rates on loans guaranteed at 100% are lower also because of provisions of law setting interest rate caps.

a higher credit multiplier as it lowers firms' credit costs on guaranteed loans, pushing credit demand to better accommodate liquidity needs; ii) the provision of a guaranteed loan from banks with lower costs of debt and/or equity (e.g. higher capital banks) is associated with higher credit multipliers, especially for programs with lower guarantee coverage; iii) higher firm leverage leads to lower credit multipliers, while higher liquidity needs have the opposite effect.

The empirical analysis, based on granular microdata from the Italian Credit Register and from the *Fondo Centrale di Garanzia*, the entity managing the guarantee scheme, yields the following results. First, we consider which characteristics of firms and banks correlate with the issuance of a guaranteed loan. In the early phase of the pandemic, at the peak of the crisis, better capitalized banks were significantly more inclined to grant loans with 90% coverage, while such difference across banks was not sizeable for 100% guaranteed loans. By contrast, we find limited differences of firm heterogeneity in the recourse to public guarantees for all programs.

We then turn to the main issue of how credit additionality of the public guarantees depends on the coverage ratio and on the period in which the loan was issued. In line with the predictions of our model, the credit multiplier is highest for fully guaranteed loans, especially in the first quarter of the program (Q2-2020), coinciding with the first phase of the pandemic. For this program, each euro of guarantees is associated with around 84 cents of new loans. The loans originated under the other programs (with 90% or 80% guarantee) featured a lower credit multiplier, around 50-60 cents per euro of guarantee. Importantly, the multiplier decreased over time, in particular for fully guaranteed loans, as GDP started recovering and firms' liquidity needs softened. From Q3-2020 onwards, the additionality of the loans in the 100% program hovered around 60 cents per euro of guarantees, very close to that of the loans in the 90% program. Importantly, loan substitution is almost exclusively a within-bank phenomenon, namely it involves borrowers' pre-existing credit exposures with the bank originating the guaranteed loan, while it is essentially non-existent for loans granted by other lenders. In terms of differential effects across banks and firms, we find that the credit multiplier does not vary much across firm (observable) characteristics, while it is strongest for high capital banks, in particular for loans under the 90% program and especially in Q2-2020.

Relatedly, we consider how the size of the credit multiplier depends on the interest savings that the guaranteed loan provides relative to the pre-existing outstanding credit. This test, under the assumption that credit risk is fully controlled by the additional variables we include, is helpful to make some steps in understanding to what extent the substitution of existing loans for guaranteed loans is driven by firms' or banks' incentives. Indeed, in principle firms will prefer to substitute more the larger the interest differential relative to pre-existing exposures; on the contrary banks, for a given benefit in terms of capital absorption (positively associated to firm's riskiness) provided by the loan guarantee, have opposite incentives as higher credit substitution reduces interest income. We find that higher interest rate differentials lower the multiplier by between 8 to 13 cents per euro of guarantee (i.e. lower credit additionality), suggesting that the extent of loan substitution is partly driven by firms' incentives to save on interest expenses.

A potential threat to the identification of differences in credit additionality *across* guarantee programs – notably those with 100 and 90 coverage ratio – may come from the possible self-selection of firms and banks with different characteristics. We address this issue in several ways in the main specifications[6] and in a series of robustness tests that attenuate the concern that differences in the credit additionality across programs derive from a systematic selection of banks and/or firms into them.[7] A further identification challenge is that there could be specific characteristics of the bank-firm lending

[6]We include fixed effects at different levels of granularity, to control for credit demand and/or supply dynamics common across lenders and/or borrowers. In the most saturated specification we include firm fixed effects, estimating the additionality of loan guarantee programs by comparing the behavior of different banks lending to the same firm, in the spirit of Amiti and Weinstein (2018).

[7]First, to control for the potential banks' self-selection across guarantee programs, we consider bank-specific multipliers for the guarantee program 90 and estimate the difference relative to the guarantee program 100. Second, to better control for the potential heterogeneity in credit additionality for firms of different size, we perform additional robustness checks on a sample of very closely comparable small firms (between €500k and €1m of revenues) that can reasonably take advantage of both the 100 or the 90 guarantee schemes. Third, we find no discontinuity at the threshold of the guarantee program 100 (€30,000) for other firm characteristics such as liquidity (liquid assets to total assets), return on assets, firm size (log assets) and z-score (a proxy of the probability of default).

relationship which may lead firms to demand guaranteed loans from specific banks.[8] To attenuate these concerns we include several key relationship level controls, most notably proxies for the main bank (i.e. the lender holding the largest exposure to the firm) and the growth rate of credit in the relationship just before the pandemic outbreak, which are both natural proxies of potential bank-specific demand for credit. In addition, we verify that the magnitudes of credit multipliers estimated on the set of single-bank firms are broadly similar to those estimated on the set of multiple bank firms. As the latter group can choose to strategically apply for credit to some of their lending banks, differently from firms with a single lender, this test suggests that bank-specific demand for guaranteed loans, if any, has a small impact on the estimates of the credit multipliers of public guarantees.

Our findings deliver three main messages for the design of emergency loan guarantee programs, highlighting the relevance of the coverage ratio and, crucially, of the timing of the public intervention. First, in the initial phase of the Covid-19 shock, when the economic environment was extremely uncertain with large downside risks and exceptionally high corporate demand for liquidity, high coverage ratios have been important to generate additional credit. For comparison, in later periods, when uncertainty on the evolution of the pandemic eased and economic activity picked up allowing firms a higher availability of internal finance, credit additionality of the guarantee programs decreased substantially.

Second, bank strength, as proxied by bank capital, played a fundamental role to support higher lending through guaranteed loans in the face of this exceptional liquidity shock. This effect was particularly remarkable in the initial and most severe phase of the crisis and for loans not fully guaranteed. This piece of evidence confirms the key importance that a well-capitalized banking sector has for the financing of non-financial companies in times of severe economic distress, even when unprecedented public support measures such as the Covid-19 loan guarantee schemes were in place.

Third, we find that guaranteed loans were not granted relatively more frequently to

[8]See Berg et al. (2020) and Paravisini et al. (2020), Paravisini et al. (2015).

ex ante riskier firms, and, more generally, that the credit multiplier of the guarantees does not substantially depend on firm characteristics; in particular, for loans to riskier firms we find only a slightly higher substitution of existing credit for guaranteed loans. In other words, the quite loose eligibility requirements to benefit from Covid-19 public loan guarantee schemes – essentially having no exposure in non-performing status – did not led to a riskier pool of guaranteed borrowers relative to the firms' population. Hence, the ex ante risk-shifting concerns associated to a more intense utilization of public guarantees by riskier firms did not significantly materialize.

Our work contributes to several strands of the literature. First, we relate to very recent papers on the effectiveness of Covid-19 public guarantee schemes. In particular, Core and De Marco (2020) focus on Italy and study the allocation of the publicly guaranteed loans across bank and firm characteristics, showing that bank size and technology adoption are key drivers of the disbursement of guaranteed loans. We substantially extend their findings by looking at the key issue of the additionality of the guaranteed loans. Our work is also especially close to Altavilla et al. (2021). They use loan-level data similar to ours and look at the additionality of the guarantee scheme across four countries (Germany, France, Italy and Spain). We extend their findings by looking at the different programs and showing that the coverage of the guarantee is a key determinant of additionality. Moreover, we shed some light on the extent to which credit additionality reflects banks' or firms' incentives by using unique data on the interest rate differential between non-guaranteed and guaranteed loans.

We also relate to work, mostly on US data, on lending during the pandemic. Granja et al. (2020) show that credit growth depends to a non-trivial extent on banks' willingness to participate in loan guarantee programs, but also on the liquidity shock experienced in March 2020 when firms drew down substantial amount of funds from pre-committed credit lines (Kapan & Minoiu, 2020). A set of papers focuses on what firms or bank characteristics affect credit supply during the pandemic. Li et al. (2020) stress the importance of pre-Covid relationships in sustaining the availability of credit lines to firms. Kwan et al. (2021) focus on banks' IT capabilities. Chodorow-Reich et al. (2021) document that firm size played a crucial role in the ability of borrowers to drawdown from existing credit lines: only larger firms in fact used available lines, while smaller ones left large unused amounts even in the most acute phase of the pandemic-induced recession. Finally, Li and Strahan (2020) show the relevance of the strength of bank-firm relationships for credit growth during the pandemic.

Minoiu et al. (2021) focus on the Main Street Lending Program (MSLP), a support package targeting SMEs, which is not based on the provision of government guarantees. The paper finds a general increase in lending to business, also for loans not issued under the program and to firms non-eligible. Huneeus et al. (2022) study the public guarantee program enacted in Chile during the pandemic. They rely on firm-level data and focus on the selection of firms into the program and its effects on the overall firm indebtedness and real outcomes.

We contribute to these works by measuring the additionality of the guarantee programs, thanks to the availability of granular data on individual loans, including existing outstanding ones. Our results on the heterogeneity of credit additionality of the programs across the coverage ratios, banks' and firms' characteristics also contribute to this literature. Our findings also relate more broadly to recent works studying the real effects of US public guarantee schemes, looking at employment and firm shutdowns (Autor et al., 2020; Granja et al., 2020; Hubbard & Strain, 2020; Zwick, 2020).

Finally, our work is also closely related to Bachas et al. (2021) that study the elasticity of bank lending volume to loan guarantees exploiting US microdata from SBA loans. We extend their results in a key way by looking at the total credit that firms obtain which allows us to explore to what extent public guarantees created additional credit or led to the substitution of existing loans.

The paper is organized as follows. Section 2 provides a stylized model to derive the main implications to be empirically tested. Section 3 describes the data and the main institutional details of the FCG programs. Section 4 provides a descriptive overview of the effect of public guarantees on credit allocation across banks and firms. Section 5 illustrates the methodology and the sample adopted in the analysis. The main results on the impact of guarantee schemes on credit are reported in Section 6. Section 7 concludes.

2 Theoretical Framework

In this section we sketch the characteristics of a stylized model of lending that allows us to describe the main trade-offs that banks and firms face when a public guarantee scheme is in place. The formal version of the model is presented in the Appendix.

We assume that one firm has pre-existing loan exposures with several banks and chooses the amount of additional loans to obtain during the Covid-19 period. For this purpose banks and firms can take advantage of the public guarantee schemes, which are characterized by different maximum guaranteed loan amounts and coverage ratios; in particular, the higher the coverage, the lower the maximum loan size that can be obtained within the program. This is a characteristic that the Italian program shares with programs implemented in other countries (e.g. Germany). Any quantity in excess of the guaranteed loan amount can be provided via non-guaranteed loans. Banks in the model compete in an auction and offer competitive terms on both their pre-existing loans, that can be partly substituted, and the additional loan amount demanded in response to the Covid-19 shock.

Banks fund loans with a mix of debt and equity. Guaranteed loans carry lower risk weights than other loans as the guaranteed part of the loan receives a zero risk weight (the same as the sovereign); therefore, for a given amount of the guaranteed loan, a higher coverage ratio implies a lower expected loss and lower prudential credit risk weights. In turn, this allows banks to fund loans with less equity, thus saving on the costs of funding loans. As a result, *ceteris paribus* banks may prefer to substitute pre-existing loans, that carry higher risk weights, with guaranteed loans that are cheaper to fund and abate the expected loss associated to the firm's default. The cost of loan substitution for banks comes from the fact that bank competition pushes guaranteed loans to have a lower interest rate: indeed, banks' savings due to lower credit risk associated to guaranteed loans cascade to better loan terms for borrowers.

Firms need liquidity to face the consequences of the Covid-19 shock. When they apply for a guaranteed loan they optimize on the loan size and the extent to which they will use it to substitute existing loans. Higher substitution allows the firm to save on interest expenses, but, for example, exposes the firm to higher default risk, as the additional credit may not be enough to face future liquidity needs. The firm may apply for a larger loan, but the guaranteed fraction would consequently decrease and therefore larger loans end up being more expensive for borrowers.

The model delivers the following results that are the basis for the hypotheses tested in the empirical analysis. First, in equilibrium, higher coverage ratios increase the additionality of new guaranteed loans, i.e. they are associated to higher credit multipliers. Indeed a higher coverage leads to lower rates and this induces firms to demand larger loans, which, for a given existing exposure, end up being more additional. Second, a higher initial firm's indebtedness reduces the amount of new lending. The reason is that these firms have stronger incentives to substitute existing loans with guaranteed ones, as the savings on existing loans are greater. Third, higher costs of bank funding reduce the amount of new additional lending. This follows as the incentives to substitute existing loans are stronger so as to reduce banks' funding costs. The magnitude of these latter effects increases if coverage is lower.

Summary of the hypotheses that we will test empirically. This stylized but sufficiently rich model allows us to derive the following set of key testable empirical predictions.

- *H1* *Guarantee program.* A higher coverage ratio implies, *ceteris paribus*, a higher credit multiplier (i.e. more additionality).
- *H2* *Banks.* The provision of a guaranteed loan from banks with lower costs of debt and/or equity is associated with higher credit multipliers, especially for programs with lower guarantee coverage. To the extent that better capitalized banks have a lower cost of debt and equity, we expect that better capitalized banks provide more additional credit, everything else equal (including the coverage of the program).

H3 *Firms.* Higher firm leverage leads to lower credit multipliers. Higher liquidity needs lead to higher credit multipliers.

3 Data and institutional setting

3.1 Data sources

Our analysis relies on several datasets. The first is the Italian Credit Register ("Centrale dei Rischi", CR) that includes borrower level data at monthly frequency. CR is maintained by the Bank of Italy and covers the population of individual borrowers' outstanding exposure above €30,000 with a single intermediary and it provides data for all intermediaries operating in Italy. For each exposure, the database provides detailed information on the lender and the borrower identity, and the respective amounts of credit outstanding and granted (i.e. the sum of outstanding and loan commitments), divided into three loan type classes: overdraft facilities (revolving credit lines), term loans and loans backed by receivables. We aggregate the data at the bank holding company level because lending policies are typically decided at this level; for the same reason, we consider individually the small cooperative banks belonging to the two groups ICCREA and Cassa Centrale Banca as lending strategies are still predominantly decided at the individual bank level.

The second dataset is the register of all loans guaranteed by the *Fondo Centrale di Garanzia* (FCG),[9] which includes detailed information on all the guarantees provided by the fund. For each guaranteed loan, the dataset indicates the tax identifiers of the borrower, the date of the guarantee request, the lender that grants the loan, the guarantee program, the amounts of the loan and of the guarantee, as well as other information about the borrower receiving the guaranteed loan (henceforth guaranteed borrowers), such as her geographic location and sector of activity.

The third dataset is the Firm Register (CERVED) which includes annual balance sheet information of Italian corporations. For each firm we retrieve the natural logarithm of firm

[9] We obtained the data directly from the FCG. These are also publicly available on the website of the FCG, but the public version of the data does not include the lender identifier.

revenues (*FirmSize*), the ratio of liquid assets to total short term liabilities (*LiquidAssets*), the ratio of financial debts to total liabilities (*FinLeverage*), the average sales growth in the last 3 years (*SalesGrowth*). We also identify firms that have been established since less than 3 years (*NewFirm*), for which fewer information is available (e.g., credit history is shorter).

Finally, we use data on banks' consolidated balance sheets from the harmonized supervisory reports (FINREP) available at the Bank of Italy. We select key bank balance sheet characteristics such as the natural logarithm of total assets (*BankSize*); the share of non-interest income to total operating income (*ShareFee*); the difference between NFCs and households loans over total loans, excluding central bank ones (*RatioNFC*); the return on equity (pre-tax income over total equity; *ROE*); the ratio of total equity on total assets (*CapitalRatio*) as in Jiménez et al. (2014) and Peydró et al. (2021), among others.

We merge these datasets using the unique firm tax identifier or the unique bank identifier and perform two simple sample selection steps. Our data include the universe of Italian non-financial incorporated firms (NFCs). We study the period running from December 2019 to March 2021. In some tests we will also look at different quarters separately, to identify potential differences over time, coming from the evolution of the pandemic.

3.2 Institutional setting: the Italian public guarantees scheme for SMEs

The pandemic in Italy started at the end of February 2020. The first containment measures were applied only in limited geographic areas where local contagion clusters were detected, mostly in the Northern regions of Lombardy and Veneto. From March 8, 2020, a national lockdown was imposed. In the meanwhile the Government enacted a series of economic support measures to counteract the economic consequences of the pandemic and of the containment measures. In particular, on March 17, 2020 the Italian government approved a package of measures to limit the risk of a tightening in credit supply and to contrast the liquidity shortages induced by the economic crisis triggered by the pandemic. By far, the biggest support program was a loan government guarantee scheme that was fully operational at the end of March.

The scheme used a pre-existing institution, the FCG, that since 2000 was running smaller scale public guarantee schemes for SMEs (De Blasio et al., 2018).[10] The public guarantee scheme in place before the pandemic insured up to 80 per cent of the value of the loan, with a maximum amount of guarantees up to €2.5 million for each firm. In case of default, the lender can enforce the FCG to meet its obligation ("first demand guarantee"). To obtain a guarantee on a loan, the lender bank has to verify the eligibility of the borrower for the scheme and complete several application forms.

The new measures enacted after the Covid breakout and contained in Decree Law 18/2020 and Decree Law 23/2000: i) raised the maximum amount of guarantees that can be provided by the FCG to each firm from €2.5 million to €5 million; ii) introduced new public guarantee schemes for SMEs that could be requested until the end of 2020.[11]

The first new scheme ("Letter M" or guarantee program 100) allows automatic granting (i.e. without prior screening and authorization by the FCG) of loans of less than €30,000 with a 100 per cent coverage ratio. The law identifies the reference rate on these loans and puts a cap on the size of the spread[12] and a maturity up to 10 years. The second group of schemes ("Letter N and C" or guarantee program 90) has a 90 per cent coverage, with a maturity of up to 6 years and up to €5 million of guarantees, granted to SMEs and Midcap (i.e. firms with up to 500 workers) borrowers.[13] In addition, a specific program regards loans granted for debt renegotiation or consolidation ("Letter

[10]Firms with fewer than 250 employees and an annual turnover or annual balance sheet total not exceeding €50 million and €43 million, respectively; the definition of firms includes self-employed workers, family businesses, partnerships and associations or other entities regularly engaged in economic activities (Recommendation 2003/361/EC).

[11]Subsequently the 2021 Budget Law extended the deadline to 30th June 2021 for SMEs and to 28th February 2021 for Midcap firms.

[12]The interest rate is calculated as the rate of the State bond (*Rendistato*) with residual duration from 4 years and 7 months to 6 years and 6 months, plus the difference between the 5-year Bank CDS and the 5-year ITA CDS, plus 0.20 per cent.

[13]For simplicity, we disregard a small category of loans with an additional counter-guarantee by a mutual guarantee institution, so called *Confidi* (see Columba et al., 2010), that provides 100% coverage for loans of less than €800,000 granted to firms with less than 3.2 million revenues.

E" or renegotiations):[14] in this case the coverage ratio is equal to 80 per cent. For all schemes, the maximum guaranteed amount must not exceed 25 per cent of the borrower's revenues.[15]

An additional important provision regards the extension of the eligibility criteria: guarantees can be requested also for loans to firms with debts classified as non-performing after 31 January 2020 and those that in 2020 were admitted to a judicial composition with creditors as a going concern, signed restructuring agreements or submitted a recovery plan. However, firms holding bad loans are excluded from all public guarantee programs.

These schemes are very similar to those adopted in the same period by other major European countries (France, Germany, Spain) – they all comply with the European Commission Temporary Framework on State Aid measures – and also, though to a somewhat lesser extent, by the UK and the US.

Figure 1 shows the number of guaranteed loans (panel a) and their amount (panel b) for each program and for each quarter in our sample period. About half of guaranteed loans were granted in the second quarter of 2020, when the new schemes were launched. Guarantee program 100 was the most used scheme in all quarters. As these loans had a maximum size of €30.000, their overall amount is lower than that of loans guaranteed under the other schemes and declined over time. After the second quarter of 2020, the share of loans under guarantee program 90, which have a larger average amount, increased, as did the share of those granted under renegotiation schemes. The use of other programs, which include all pre-pandemic guarantee schemes with a coverage ratio up to 80%, remained about constant across quarters.

As far as concerns the amount of individual loans, these are shown in figure Figure 2. As usual (see e.g. Bachas et al., 2021) most loan amounts are round numbers. There is however some bunching at the 30,000 threshold which is the maximum amount that can receive the 100% guarantee, and at 25,000 as this was the the maximum threshold for

[14]Access to this program was conditional to an increase of least 25 per cent of the overall amount of credit provided by the lender.

[15]The maximum amount of loans under "Letter C" scheme can be alternatively calculated as the double of the staff expenses or the liquidity needs in the following 12-18 months.

the 100% guarantee until June 2020.

Overall, our sample is very comprehensive and representative. It includes 1,303,509 borrowers with revenues below €50 million (i.e. SMEs eligible for the examined guarantee schemes). For 459,545 of these we also observe balance sheet characteristics. We use data for the universe of banks (345)[16] for which we observe complete balance sheet data. These account for about 90% of total loans granted in the sample period to non-financial companies.[17]

Table A.1 shows the characteristics of borrowers across guarantee programs. As expected given the lower maximum amount, firms that received 100% guaranteed loans are on average smaller and younger than the borrowers that obtained other guaranteed loans, and they also have more liquid assets and lower leverage.

4 Non-parametric evidence

In this section we provide a descriptive analysis of the relation between the guarantee programs and credit growth as well as the distribution of the take-up across borrowers and banks.

As a first step, we compare firms that received a guaranteed loan from the FCG with other borrowers which were eligible but did not receive a guaranteed loan. Table 1 shows that firms that obtained a guaranteed loan experienced a substantial increase in credit (i.e. the average growth rate between March 2020 and March 2021 hovers around 18%), while credit to firms that did not receive a guaranteed loan was substantially unchanged (on average a 2% drop between March 2020 and March 2021). Importantly, the increase in credit for firms that obtained guaranteed loans is lower than the amount of guaranteed loans that have been taken-up by these firms, indicating that the new guaranteed credit was not fully additional.

[16] The sample includes bank holding companies for banking groups and individual banks for stand-alone intermediaries.

[17] When we compute total credit to firms we also add credit from non-banks entities, such as financial companies (e.g. intermediaries specialized in factoring or leasing, investment funds and SPVs). Therefore our measure of credit additionality considers all credit, including non-bank credit to firms.

To address the key question of measuring the degree of credit additionality of public guarantees, we start with a non-parametric analysis distinguishing for each quarter the different programs offered by the FCG during the pandemic. Figure 3 shows the growth rate in credit granted (inclusive of the guaranteed loans) for different levels of the ratio between the guaranteed amount taken in each quarter and the amount of granted credit at the beginning of the period (from 0 to 1 with a 0.05 interval). For example, a value of 0 indicates that the borrower has not received any guaranteed loan from a bank with whom it had a credit relationship at the beginning of the period; a value of 1 instead signals that the total amount of public guarantees with a bank during the quarter is equal to the overall amount of granted credit at the beginning of the period.[18] Conceptually, the closer the line is to the 45-degree line, the higher the credit multiplier of public guarantees, i.e. the higher additionality. For example, if the guaranteed amount is 50% of the initial credit and the growth rate of credit is 50%, then there is full additionality. This way of representing the results allows us to take into account potential differences in the relative size of guaranteed loans relative to existing credit and to check whether the strategy of estimating credit additionality through a multiplier – roughly speaking the slope of the line – is appropriate as it does not ignore substantial non-linearities.

Figure 3 documents two main patterns. The first is that additionality increases with the coverage of the public guarantee: we observe higher additionality for programs with a 100% or 90% guarantee than for the program with the 80% guarantee.[19] In particular, for the fully guaranteed loans (guarantee program 100), each euro of guaranteed credit generates around 80-90 cents of credit growth. Additionality is instead much lower for the other programs. Consistent with a risk-bearing capacity argument, high coverage ratios help banks to expand their lending supply to accommodate firm demand. The second is that the high additionality of the 100% guaranteed loans can be detected only in Q2-2020, i.e. during the first quarter of the pandemic crisis and at the very beginning of the program. In subsequent quarters, additionality drops and typically the 100% and

[18]The vertical axis shows the average growth rate of granted credit for each bucket.

[19]Additionality is, by construction, lower for the loans issued under renegotiation programs.

90% guarantee programs generate roughly the same amount of additional credit. This is important for the design of guarantee programs as it suggests that the firms that really needed the extra credit rushed to get it immediately. In subsequent quarters, the guaranteed loans seem to have helped also a restructuring or a rollover of existing loans. This may nevertheless be an intended consequence of the program as it reduces uncertainty on the availability of credit for firms and it reduces the incidence of NPLs on banks, thus averting a possible credit crunch in the coming quarters.

In what follows we explore whether these aggregate patterns conceal heterogeneity across bank characteristics.[20] Specifically, we focus on bank capital, as stronger and weaker banks may have different incentives to use the guarantee programs to substitute existing loans as opposed to provide new additional credit. Figure 4 shows the same non-parametric analysis depicted in Figure 3, distinguishing across banks with high and low capital (above/below the median capital ratio). The quarters after Q2-2020 are aggregated as there are limited differences across them. Figure 4 shows that for the 100 guarantee program additionality is very similar for banks with different capital. The drop in additionality in the quarters after Q2 is common to the two types of banks. An analogous pattern emerges for the renegotiation program. For the 90 guarantee program, instead, the additionality is higher for banks with more capital, but the difference disappears after Q2-2020.

In the regression analyses we adopt an empirical strategy to identify the credit multipliers activated by the guarantee programs, and test whether all these findings stand the inclusion of several controls and fixed effects.

[20]As we find limited heterogeneity across firm characteristics, we do not show these results, which are available on request.

5 Empirical Methodology

5.1 Empirical strategy

As a first step, we study the propensity of banks to grant a guaranteed loan and of a firm to receive it. This allows us to shed light on the type of selection, if any, of banks and firms into the guarantee programs. Importantly, guided by the descriptive evidence shown in Section 3 above, we distinguish across programs and periods. We start from the borrower level with the following OLS regressions:

$$D(GuaranteedLoan_i) = \beta_1 FirmCharacteristics_i + industry_i + province_i + \epsilon_i \tag{1}$$

$$\begin{split} D(GuaranteedLoanProgramY_i) = &\beta_1 FirmCharacteristics_i + industry_i + \\ &province_i + \epsilon_i \end{split} \tag{2}$$

Where $D(GuaranteedLoan_i)$ is a dummy equal to one if firm i obtained a guaranteed loan in the whole sample period, or in a specific quarter. $D(GuaranteedLoanProgramY_i)$ is a dummy equal to one if firm i obtained a guaranteed loan of a specific program (100%, 90%, 80%, renegotiation). We include the full set of firm characteristics, described in Section 3.1. In some specifications, we also add the growth rate of outstanding credit in Q1-2020 ($\Delta Credit2020Q1$), the quarter before the pandemic outbreak, to control for the credit dynamics immediately before the introduction of the public guarantee programs. Firms' controls aim at capturing their balance sheet strength, including default risk and the ability to withstand liquidity shocks, as well as proxies of the information available to lenders about the firm (for example, younger firms with a short credit history). We also include 1-digit Nace industry and province fixed effects. While these regressions are mostly descriptive, they are useful to understand which observable firm characteristics proxy for the selection of firms into different programs.

Next, we perform a similar test looking at bank characteristics. For this, we restrict the sample to firms that received at least one guaranteed loan in the period of interest. As a result, we analyze the determinants of the propensity of banks to provide a guaranteed loan to each firm, conditional on the firm receiving a guaranteed loan. This sample choice allows us to exclude all eligible borrowers that have not requested a guaranteed loan for idiosyncratic unobserved characteristics (e.g. reputational risks or aversion to leverage increase). We use the sample at the bank-firm lending relationship level and run the following regression:

$$\begin{aligned} D(GuaranteedLoan_{i,j}) =& \beta_1 BankCharacteristics_j \cdot ProgramY_{i,j} \\ &+ \beta_2 Relationship_{i,j} + Firm_i + \epsilon_{i,j} \end{aligned} \tag{3}$$

Where $D(GuaranteedLoan_{i,j})$ is a dummy equal to one if we observe a guaranteed loan in the relationship between bank j and firm i. $BankCharacteristics_j$ includes a set of proxies for the main determinants of credit supply (see Section 3.1 for a description of these variables). *ShareFee* and *RatioNFC* allow us to take into account the heterogeneity of business models across banks. The former captures the extent to which the bank may engage in cross-selling strategies, i.e. a commercial practice that aims at originating loans if they help to capture the client demand for other banking products. Lenders more engaged in cross-selling strategies may be interested in granting new guaranteed loans because, for these banks, they may represent low-risk products used to push the sales of other profitable services. *RatioNFC* is a proxy of the bank overall engagement in providing loans to firms as its core activity. In principle bank business models may have played a role in determining their willingness to originate guaranteed loans. The exceptional magnitude of the Covid-19 shock may interact with the lending exposure to NFCs in two opposite ways. On the one hand, banks with a NFCs' orientation may bear a higher burden in supporting firms' liquidity needs, hence expanding their loan supply; on the other hand, their pre-existing credit exposures towards NFCs and the likely effects on loan loss provisions due to the dramatic deterioration of the macroeconomic scenario may push these banks to a precautionary attitude slowing down the credit supply and/or engaging in loan substitution practices through the use of guaranteed loans. In addition, we include *ROE*, *CapitalRatio*, and *BankSize* that have been identified in the literature, both theoretical and empirical, as key determinants of credit supply. Each bank characteristic is interacted with a set of dummies to identify guarantee programs on loans between firm i and bank j (*ProgramY*). As a result, we can observe the impact of each characteristic differentiated across guarantee programs.

To take into account bank-firm relationship characteristics, we also include the vector *Relationship* that consists of two variables: *MainLender*, which is a dummy equal to 1 if bank j holds the largest share of credit granted to firm i in February 2020, and $\Delta Credit2020Q1$, which is the change between December 2019 and March 2020 in the ratio of outstanding credit provided to firm i by bank j to the overall credit extended to firm i. Generally, banks holding a large share of the overall credit granted to the firm have established a close relationship with the borrower. Indeed, the lender obtains better access to significant information about the firm (Elsas, 2005), reducing information asymmetries. As a result, a close relationship could allow the borrower to rely during a crisis on the credit offered by its main lender (Bolton et al., 2016). In addition, the $\Delta Credit2020Q1$ variable allows us to control for the short-term change in the outstanding credit observed in the emergency phase of the crisis that may capture unobservable bank-firm factors.

As we include a full set of firm fixed effects here ($Firm_i$), these tests are run on the sample of borrowers that obtain at least one guaranteed loan and that have at least two bank relationships. The fixed effect also controls for the number of banks each firm could potentially get a guaranteed loan from.

Once explored the characteristics of firms that correlate with the take-up of public guarantee loans, we move to estimate the credit multiplier of guaranteed loans, to measure the degree of additionality of the public guarantees. In this respect, the estimates are conditional on the sample of firms participating to the program. Nevertheless, what matters to policy makers is the overall extent to which loan guarantee programs translated into extra credit on top of existing credit for those firms requesting guarantee programs, as eligibility was almost universal as basically open to all SMEs without NPLs. For this purpose, we consider the following regression model:

$$\begin{aligned}\Delta Credit_{i,j} = {} & \beta GuarLoan_{i,j} \cdot ProgramY_{i,j} \cdot GuarAmount_{i,j} \\ & + \gamma GuarLoan_{i,j} \cdot ProgramY_{i,j} + FE_i + Bank_j + \epsilon_{i,j}\end{aligned} \tag{4}$$

where $\Delta Credit_{i,j}$ is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in $t-1$ for each period. Normalizing by the total credit to the firm, and not by the total credit in each relationship, allows us to measure how much the guaranteed loans contributed to increase firm i's overall access to credit.

We include interactions between dummies for each guarantee program ($ProgramY_{i,j}$), the ratio of the amount of the guaranteed loan provided by bank j to the total amount of granted credit to firm i in $t-1$ ($GuarAmount_{i,j}$), and a dummy variable equal to 1 if firm i received a guaranteed loan by bank j in t ($GuarLoan_{i,j}$). The coefficient of this interaction term represents the estimated credit multiplier of each program, and the intuition is analogous to that underlying the non-parametric results shown in Figure 3. By including *GuarLoan* in the interaction, we introduce different constant terms for guaranteed and not-guaranteed loans, while the dummy for each program allows the multiplier to vary across programs, which is a key question that our paper can address.

The model also includes all the other interaction terms, as well as a set of fixed effects for firm characteristics. In some specifications we include firm fixed effects, hence only focusing on firms borrowing from more than one bank. In other specifications, we include industry and province fixed effects, which allow us to estimate the model on the whole population of borrowers, including single-bank firms. This may be particularly important in our setting because the guarantee programs were targeted also to smaller firms which typically borrow from just one bank. The model also includes bank fixed effects $Bank_j$. We estimate the model both over the whole March 2020-March 2021 period and in each quarter separately in order to explore differences in the multipliers over time.

In a second step, for each guarantee program, we interact $GuarLoan_{i,j}$ as well as

$GuarAmount_{i,j}$ with firm and bank characteristics.[21] In this way, we are able to assess the impact of each characteristic on the credit multiplier of each program.

Finally, Table A.2 shows the main descriptive statistics for the variables employed in the following analyses.

5.2 Identification

Our main goal is identifying the multiplier effect of the guarantee programs. To this aim, there are some empirical issues that we address as follows.

First, on the side of borrowers, those that obtain guaranteed loans may have different characteristics – for example in terms of liquidity needs or default probability – that may affect their credit demand or banks' willingness to grant a guaranteed loan. Similarly, on the side of banks, those that extend more guaranteed loans could have specific characteristics that can affect their ability to provide credit or take additional risk. The same issue applies for the selection of different firms into programs. Firms that obtain loans with the 100% guarantee may be systematically different from those that obtain loans with the 90% or the 80% guarantee.

We address this potential concern in several ways. First, we include fixed effects at different levels of granularity in our tests. Specifically, in the most saturated specification, we include firm fixed effects which capture their observable and unobservable characteristics, most notably firms' demand for credit and credit adjustments due to changes in their riskiness after the pandemic outbreak. In other words, we estimate the additionality of guaranteed loan programs by controlling for the behavior of different banks lending to the same firm. This is in the same spirit of Amiti and Weinstein (2018) and Khwaja and Mian (2008). We also include bank fixed effects to control for all banks' observed and unobserved characteristics. Second, exploiting the threshold discontinuity in the loan amounts for firms that can receive the 100% guaranteed loans, we find no evidence of selection of borrowers into the 100% and 90% programs (the two main ones under the Italian Covid-19 scheme) as their characteristics are very similar across the threshold.

[21] In this case bank fixed effects are obviously not included.

Indeed, Figure A.1 shows that firm characteristics are continuous at the threshold of loan size of 30,000 euros (the maximum amount granted under guarantee program 100). In particular, there is no discontinuity in liquidity (liquid assets to total assets), return on assets, firm size (log assets), nor z-score, a proxy of the probability of default. This evidence attenuates substantially any concern that there has been a systematic selection of firms into different programs, at least based on observable firm characteristics.

A potential remaining issue is that there may be specific characteristics of the credit relationship that affect firm credit demand. For example, firms may strategically apply for a guaranteed loan at one of their lenders that they expect to be more likely to cut credit, hoping that in this way the bank will refrain from cutting it thanks to the guarantee. In this case, the degree of additionality of the guaranteed loans may be under-estimated. Alternatively, firms may prefer to apply to one of their lenders that they expect to be able to expand the overall exposure the most. In this case, the degree of additionality of the guaranteed loans may be over-estimated. We address this issue to some extent by including several controls at the relationship level, most notably proxies for the main lender (i.e. the bank that holds the largest exposure to the firm) and the growth rate of credit in the relationship before the pandemic outbreak, which are natural proxies of potential bank-specific demand for credit. In addition, the potential strategic behavior of firms in applying to different banks is relevant only in the case of multiple lenders; however the vast majority of guaranteed loans come from only one of the existing lenders (or goes to firms that get credit for the first time, for which no loan substitution is possible). To check the potential relevance of this issue we verify that the credit multipliers estimated on the set of single bank firms are broadly similar in magnitude to those estimated on the set of multiple bank firms, suggesting that bank-specific demand for guaranteed loans, if any, has a small impact on the estimated multipliers. More generally, if one is interested in the overall effect of guarantees on firms' access to credit, the possible influence of strategic applications to specific banks is part of what should be estimated.

6 Main results

6.1 Propensity to receive and to grant a guaranteed loan

We start looking at the firm characteristics that correlate with receiving a guaranteed loan. Table 2 shows the results of Eq. (1).[22] In column (1), which displays estimates for the whole March 2020-March 2021 period, firm size has a positive coefficient, showing that bigger firms are more likely to receive a guaranteed loan. While this may at first seem surprising, it depends on the fact that our sample includes only firms eligible to obtain a guarantee loans. This imposes a cap on firm size, as only SMEs were eligible to obtain a guaranteed loan. Thus, among eligible firms, which are smaller than the average firm in the whole population of Italian firms, size correlates positively with receiving a guaranteed loans. Firms with less liquidity, higher leverage, lower age, lower sales growth and higher credit growth before the pandemic are also more likely to receive a guaranteed loan. The results on liquidity and sales growth suggest that the firms that had the strongest liquidity needs were more likely to receive a guaranteed loan. Guaranteed credit was granted more often to riskier, proxied by high leverage, firms. This is consistent with the idea that guarantees allow banks to take higher risk. The positive sign on the dummy for new firms suggests that banks are more willing to grant credit to firms for which limited information is available if there is a third-party guarantee that allows to reduce the higher risk inherent in lending to these firms.

An interesting pattern emerges when we estimate the model period by period. Some firm characteristics, namely, liquidity, leverage, and prior credit growth have coefficients with the same sign across periods. By contrast, the coefficient of firm size, new firm and sales growth is different between Q2-2020, i.e. the first quarter of the pandemic crisis, and the subsequent quarters. Indeed, in Q2-2020 smaller firms were more likely to get a guaranteed loan: this reflects the prevalence of loans granted under the gurantee program 100, which are capped at €30.000 and therefore more palatable for smaller firms.

[22]In the following tables we focus on SMEs (i.e. firms with total assets below €50 million) that are eligible for the guarantee programs (see Section 3).

Interestingly, younger firms are less likely to obtain a guaranteed loan in this quarter, but are more likely to do so in the following ones. This may reflect the difficulty to gather information on new borrowers during the lockdown imposed in the first period of the pandemic. Finally, in Q2-2020 firms that had a lower growth of sales prior to the pandemic are more likely to obtain a guaranteed loan, contrary to what happens in the following quarters.

Overall, this evidence suggests that guaranteed loans went to firms with higher liquidity needs, and that this was especially the case for loans granted in the first quarter of the pandemic. The estimates run for Q3, Q4-2020 and Q1-2021 include a dummy for whether a firm had obtained a guaranteed loan in a previous quarter, interacted with its characteristics. Our results suggest that in subsequent quarters liquidity needs were less likely to be the main driver for the request of a guaranteed loan (as proxied by the observable characteristics included in our model). These findings are robust to estimating the model at the bank-firm level (Table A.3).

Next, we look at the propensity to receive a guaranteed loan by program. As the guarantee program 100 provides a maximum loan amount of €30,000, it is by construction aimed at very small firms; as a result, for this program we conduct the analysis only on the sample of firms with yearly revenues below €500,000. The results at the borrower level are shown in Table 3, while Table A.4 reports estimates at the bank-firm level.

Figure 5 reports the economic significance of the coefficients of Table 3 by multiplying them with the inter-quartile range of the corresponding variable. Larger firms have a higher chance to obtain a guaranteed loan (i.e. the likelihood is about 5 percentage points higher). Moreover, the chance to receive a guaranteed loan with 100% or 90% coverage is higher for younger firms. This is consistent with the idea that firms for which asymmetric information is a more compelling problem are more likely to receive loans with a higher coverage.

Similarly, the results also point out that firms with higher leverage are slightly less likely to receive a fully guaranteed loan, while the opposite result holds when public guarantees are only partial. The former result on 100% guaranteed loans can be rationalized by considering the different risk distribution across firms of different size. Indeed, the group of very small firms, to which the 100% guaranteed loans appeal, includes a higher proportion of particularly risky firms to which banks may have preferred not to disburse any additional loan. Indeed, despite the public guarantee, they faced nevertheless a legal risk (related to some provisions of the Italian penal code) when granting credit without an adequate control of the credit standing of the borrower.

The loan renegotiation programs was designed to partially substitute an existing loan for a government guaranteed one; as we would expect ex ante, it is more likely to be used by older firms.

We then explore the correlation between bank characteristics and the likelihood of observing a guaranteed loan. Table 4 shows the results of Eq. (3). In these models we include interactions of bank characteristics with dummies for each loan program. The base category is the 100% program. Figure 6 describes the magnitude of the coefficients for each of the bank characteristics: the likelihood difference is computed by using the corresponding coefficient of Table 4 and multiplying it by the inter-quartile range of the variable for our sample of banks.

Bigger banks and those with the largest exposure to the firm (i.e. the main lender) are more likely to grant a 100% guaranteed loan. Interestingly, for these types of loans there is little evidence that measures of bank strength matter: bank capital is not statistically significant, except in Q3-2020, and bank profitability has a positive coefficient in Q2-2020 and Q1-2021, but otherwise they have small and insignificant coefficients. Our proxy of bank specialization, the share of loans to NFCs out of total loans is negative and significant on average in all periods, consistent with the idea that banks less focused on loans to NFCs and less used to collect information on firms, especially SMEs, relied on the the guarantees relatively more, to compensate for the lower availability of information on borrowers.

As regards the other programs, bank heterogeneity is limited. The dummy main lender is associated with a higher likelihood of observing a loan issued under the renegotiation program, presumambly with the final goal to modify the terms of the loan, lengthening the maturity at a lower interest rate (thanks to the public guarantee).

But the most important result is that bank capital has a positive and very strong effect in the probability of granting a 90% guaranteed loan. The result is entirely driven by the loans issued in Q2-2020, the first period of the pandemic. This suggests that bank strength (as proxied by bank capital) matters for the propensity of issuing a loan in which the bank has some skin in the game.

To cross-check the robustness of our intuition, we look deeper at the role of bank capital, and test whether it matters for the issuance of a guaranteed loan when a bank is the most capitalized one among the lenders of the firm. We run this test by including firm and bank fixed effects. The results reported in Table 5 show that the most capitalized banks among the lenders are more likely to issue loans with the 90% guarantee, and less likely to do so for loans with 100% guarantee as well as for those in the renegotiation program. This suggests that, when ranking banks within the lenders of a given borrower, bank capital matters for the issuance of guaranteed loans. The loans that allow more risk shifting are issued relatively more frequently by the least capitalized banks. This result is important to understand the allocation of risk and of the guarantees across banks.

We also run tests interacting bank and firm characteristics, but we found very limited evidence of heterogeneous effects, for example of bank capital and firm proxies for risk. These results are not shown but are available on request.

Lastly, we explore whether credit growth displayed an heterogeneous response across banks and firms in the very initial phase of the pandemic crisis (December 2019 to March 2020)[23], also distinguishing between firms that subsequently took out a guaranteed loan and firms that did not. This is also relevant to understand to what extent credit growth to firms that subsequently received a guaranteed loan differ from that of other firms prior to the introduction of the guarantee programs.

Table 6 shows the results of a regression estimated by using $\Delta Credit$, which is the change between December 2019 and March 2020 in credit granted by bank j to firm

[23]The first local lockdowns were enacted in Italy as early as mid February 2020, the national lockdown was imposed since March 9, 2020.

i over the total amount of granted credit to firm i at the end of December 2019, as the dependent variable. It considers three different groups: all firms in the sample (*All firms*, columns 1 and 4), only firms that will subsequently obtain a guaranteed loan (*Guaranteed firms*, columns 2 and 5), only firms that did not obtain (possibly because they did not ask for them) a guaranteed loan until the end of the considered period (*Not-Guaranteed firms*, columns 3 and 6). The sample split allows to test whether banks with different characteristics responded differently to the two groups of firms even before the introduction of the Covid-19 public loan guarantee programs. For each sample we consider estimates obtained by including firm fixed effects (columns 1 to 3) or sector, province and bank fixed effects (columns 4 to 6).

The estimated coefficients for bank characteristics suggest that the heterogeneity across lenders before the introduction of the guarantee programs was limited. The estimates point out the positive effect on credit supply of non-interest income, higher levels of capital and lower bank size, but the magnitude is small. The coefficients of the lending relationship controls indicate that the credit growth from the main lender is slightly higher and also the availability of loan commitments not yet drawn correlates with credit growth. Moreover, the results in the last three columns suggest that credit growth in Q1-2020 was greater in all the sub-samples for borrowers with largher size and higher sales growth, lower liquid assets and leverage, as well as for younger firms.

Overall, these results indicate that there were not significant differences ex ante between guaranteed and not-guaranteed borrowers.

6.2 Additionality of guaranteed loans: the credit multiplier of the guarantees

We now turn to analyze the key questions of the paper, discussed in Section 7: to what extent is guaranteed credit additional? Are there differences across programs depending on the guarantee coverage? Are there heterogeneous effects across banks and firms?

The results of Eq. (4) are shown in Table 7. This is the parametric equivalent of

Figure 3, including also bank fixed effects and fixed effects at the firm-level (either sector and province when we include in the sample firms with a single bank credit relationship, or firm fixed effects when we restrict the sample to multiple-bank firms). Consistent with our main model implications (*H1*), the results show that the highest degree of additionality is for the 100% program (the base category in the table). On average, for the whole period from Q2-2020 to Q1-2021, €1 of guarantee generated 72 cents of additional credit. This is substantially lower for the other programs: about 60 cents for the 90% and for the renegotiation program, and about 50 cents for the other program (up to 80% coverage ratio). A further key result is that the additionality of the 100% guaranteed program drops over time. It is strongest in Q2-2020 when it reaches 82 cents per 1 euro of guarantee, but it drops to 60 and then to about 50 cents in the following quarters. The degree of additionality of the other programs does not change much across quarters. The results are very similar on the sample of multiple bank firms including firm fixed effects (Table 8). Quantitatively, the credit multipliers are slightly smaller: around 63 cents per euro on average for the 100% guarantee program (i.e. about 75 cents in Q2-2020, then around 60-50 cents).

As a robustness check on the effects of the coverage ratio on credit additionality, we consider a specification where we compute bank-specific credit multipliers for the program 90 and estimate the average difference with respect to the program 100. Table A.6 shows the results of this test. We find that in Q2-2020 the multiplier for the program 100 is about 25 cent higher for each euro of guarantee relative to the program 90. This difference instead reverses in the subsequent quarters.

In a second robustness check we focus on a sub-sample of borrowers of similar size (i.e. with revenues between €500,000 and €1,000,000) that received loans of a comparable amount (lower than €112,500, i.e. the median value for guarantee 90 loans) under guarantee program 100 and 90. This test allows us to focus on a sample of more comparable borrowers in terms of revenues that receive loans of similar amounts. The results in Table 9 show that the differences in credit additionality across guarantee program 100 and 90 remain significant and of similar magnitude also by adopting this sample restriction, suggesting that our findings are primarily due to differences in the coverage ratio and not in the characteristics of the borrower (which are nevertheless controlled for by firm fixed effects in the most saturated specification) or of the credit relationship.

A further interesting question is whether credit substitution occurred within credit relationships or across them. In this case some banks would increase their concentration of credit risk and guaranteed loans would mostly be used to repay existing loans issued by other banks. To run this test, we use the growth of credit granted by lenders that did not provide guaranteed loans as dependent variable in a regression on the amount of guarantees taken out by other lenders. Table A.7 shows the results. Our evidence supports the hypothesis that there was not a significant decrease in credit supply by lenders towards which no guaranteed loan was taken out during the period. Indeed, for example, the credit substitution across all periods for each euro of guarantees was around €0.02 for guarantee program 100 and renegotiations, while it was approximately zero for guarantee program 90. We replicate this exercise by focusing on drawn credit, to take into account also the actual substitution that a borrower may undertake among his lenders. The results reported in Table A.8 are unchanged.

Finally, we verify whether the differences in credit additionality are affected by the recourse of the borrower to other economic support measures introduced by the government since the beginning of the pandemic, such as the moratorium on loan repayment.[24] Therefore, we estimate a different credit multiplier across guarantee programs for borrowers that have also benefited from a moratorium on that credit relationship in the same quarter or in the previous one. The estimates, reported in Table A.9, show that the credit multiplier for guarantee programs 100 and 90 is slightly higher, by about €0.06 per euro of guarantee, for firms benefiting from a moratorium. Since the request of a moratorium is generally associated with a liquidity pressure on the firm's side, this result is consistent

[24] In addition to loan guarantee schemes, the Decree Law 18/2020 introduced also a debt moratorium for SMEs that had no non-performing loans when the measure was published. These firms were eligible for a deferment of loans maturing in the coming months, a suspension of mortgage loan instalments and lease payments, and a freezing of the existing available uncommitted credit facilities (current account overdrafts and loans granted against advances on receivables). These measures were initially active until 30 September 2020 and were successively renewed.

with our model implication *H3*, which indicates that higher liquidity needs lead to higher credit multipliers.

Overall, these results suggest that the fully guaranteed loans had a high additionality, especially right after the program was launched in Q2-2020, during a period of high uncertainty on the evolution of the pandemic and its economic impact. In later periods, additionality decreases substantially, although the characteristics of the firms that correlate with the take-up of the loans (either controlled by firm observables or by firm fixed effects) are basically unchanged across periods. Q2-2020 was also the period in which economic activity dropped the most in Italy also as a consequence of the national lockdown imposed to contain the spread of the pandemic. Then, this is also the period in which firms' liquidity needs to compensate the drop in external finance were highest. GDP quickly rebounded in Q3 and Q4 expanding the possibility to use internal finance. Hence additionality has been higher when firms' liquidity needs and uncertainty over the evolution of the pandemic were higher. In addition, our results show the relevance of the coverage amount of the guarantee. Even a relatively limited difference, of 10 percentage points, may lead to large differences in lending outcomes.

6.3 Differences across banks and firms

We now turn to study whether credit additionality of the guarantee programs differed across banks. First, we assess the heterogeneity of the guarantee multipliers across banks. To this end, we estimate Eq. (4) by interacting $GuarLoan \cdot GuarAmount$ with a fixed effect for each bank. As a result, we obtain a guarantee multiplier for each bank, differentiated by scheme and period. Figures 7, 8, and 9 show the distribution of these bank-specific guarantee multipliers for guarantee program 100, 90 and renegotiations, respectively. We separate the results observed at the height of the crisis (Q2-2020; panels a) and those obtained in the following quarters (Q3-2020 - Q1-2021; panels b). In line with the empirical evidence discussed in Section 6.2, we observe that the distribution of the multipliers for the guarantee program 100 is more concentrated at values above 0.5 than others, especially in Q2-2020 (i.e. the mean was equal to 0.69). In contrast, the distribution was more dispersed for the guarantee program 90 and the for the renegotiation program in the initial phase, while it became more concentrated at higher values in the following quarters.[25]

We then focus on the impact of bank characteristics on the credit additionality of guaranteed loans. For this purpose we estimate the model described in Eq. (4) by interacting $GuarLoan \cdot GuarAmount$ with bank characteristics for each guarantee program. Figure 10 displays how each bank characteristic affects banks' willingness to generate new credit through a guaranteed loan, examining the effect of each characteristic on the guarantee multiplier across programs. The magnitude of these differences across banks is computed by considering banks at the 25^{th} and 75^{th} percentile of the distribution for each variable.

Consistent with *H2*, we observe that bank capital plays a major role to explain cross-sectional differences in the magnitude of the guarantee multipliers, especially for the guarantee program 90 in Q2-2020. For this program the average difference across all periods in the guarantee multiplier between banks with higher and lower capital ratios is close to 0.2 points, while it raises to 0.25 in Q2-2020. Also for guarantee program 100 and renegotiations an inter-quartile range change in capital ratios leads to a difference of 0.15 and 0.10, respectively, in credit additionality. Other bank characteristics instead have lower (marginal) effects. The estimates of the regressions behind these figures are shown in Tables A.10, A.11, and A.12.

All in all, the size of the credit multiplier strongly depends on bank capital: well capitalized banks were much more effective at originating new credit. This is consistent with the idea that capital measures banks' risk-bearing capacity: a stronger capital position allows banks to better absorb the likely future deterioration in their loan portfolio. in turn, this allows banks to accommodate the liquidity demand by firms, mitigating at the same time the moral hazard problem related to the use of guarantees to transfer on the public sector credit risk originating from pre-existing loans. These results come

[25] For example, in the initial phase, the mean for guarantee program 90 was 0.46, with a standard deviation of 0.24; after Q2-2020, the mean rose to 0.64 and the standard deviation decreased to 0.18.

from specifications that include bank fixed effects, thus making more credible a causal interpretation of the effects of capital on the size of the credit multipliers.

Other bank level variables such as non-interest income diversification and size also have a statistically significant effect on guarantee multipliers, but the magnitude of their marginal effects is smaller (about 0.05).

An implicit assumption of our econometric framework is the perfect substitutability for the borrower of credit received from her lenders. However, when comparing guaranteed and non-guaranteed loans, the public guarantee significantly affects the terms at which these loans are offered and firm demand might have been very different between these two forms of credit. At the same time, guaranteed loans offered under the same program are a pretty homogeneous product as they are term loans with very similar characteristics. To get closer to the implicit assumption of perfect substitutability, we assess the effect of bank level characteristics on loan supply by exploiting the sample of borrowers with multiple guaranteed loans. Since some firms have received more than one loan with a 90 per cent coverage ratio from different banks in each period, we estimate our models on this sample of firms by including two fixed effects for each firm: one towards banks that provided a guaranteed loan and another with respect to all other lenders. This method also allows us to include bank fixed effects to control for unobserved bank heterogeneity. These additional estimates, reported in Table A.13, confirm our main findings, highlighting the key role played by bank capital to explain differences in credit supply across lenders.

As a further step, we focus on differences in credit additionality across firms. To this end, we estimate the model described in Eq. (4) by interacting $GuarLoan \cdot GuarAmount$ with firm characteristics for each guarantee program. Figure 11 shows the effect of each firm characteristic on credit additionality. Since there are no significant differences across quarters, we report the overall impact across all periods. Also the magnitude of the differences across firms is computed by considering firms at the 25^{th} and 75^{th} percentile of the distribution for each variable.

Interestingly, the credit multiplier of each guarantee program does not vary much across firms with different characteristics. The signs of the coefficients are consistent with the predictions of the model (prediction *H3*) as guarantee multipliers are lower for firms with high leverage, but the magnitude is rather small (below 0.05 for all programs). Only for the guarantee program 100 we observe that credit additionality is slightly lower (around 0.10) for larger firms and for younger borrowers. Overall, these results suggest that borrower characteristics were much less important determinants of credit additionality than bank characteristics.

Finally, we tested for cross bank-firm heterogeneity in additionality, but we found no evidence of differences in multipliers for certain banks (e.g. more or less capitalized) lending to certain firms (e.g. high risk). This attenuate concerns about the possibility that banks could have engaged in massive risk-shifting.

6.4 A driver of credit additionality: interest rate differential between existing loans and new guaranteed loans

In this section, we provide some evidence on the relative importance of one of the key drivers of the additionality of guaranteed credit: the interest rate differential between the latter and pre-existing non-guaranteed loans. The theoretical model described in Section 2 shows, indeed, that the interest rate differential between existing loans and guaranteed ones is taken into account in the firm maximization problem as it provides the opportunity to substitute existing more expensive non-guaranteed loans for cheaper guaranteed loans to save on interest expenses; this incentive is larger, the wider the interest rate differential. On the other hand, banks have an incentive – holding other things equal such as the amount of loan substitution and firms' credit risk – to substitute less when the interest rate differential is larger so as to avoid losing interest income.

To better understand the relevance of the interest rate differential for the additionality of the programs, we interact it with the credit multiplier. This allows us to obtain an estimate of the multiplier when the interest rate differential is zero and evaluate how the multiplier changes as the interest rate widens. This test is important for at least two reasons. First, guaranteed loans are cheaper than existing non-guaranteed loans. This occurs because of the presence of the guarantee which reduces credit risk for the bank and, for fully guaranteed loans, because of law provisions that impose caps on the interest rates applicable. Understanding how this feature of the programs affects credit additionality is critical for policy design. Second, it helps to shed light on the important question of the extent to which the degree of additionality reflects the prevalence (in equilibrium) of banks' or firms' incentives.[26] A limitation of this test to address this question is that the interest rate differential also reflects the ex ante riskiness of the firm. This creates an incentive for banks to substitute existing loans relatively more the higher the differential as this transfer credit risk onto the Government. While we include firm fixed effects, this may not be enough as different banks may assess the credit risk of the same firm differently. We therefore also control for interaction terms between the multiplier and firms' leverage, which would capture how the multiplier changes with proxies of firms' credit risk. Under the assumption that this specification fully controls for firms' credit risk, this test provides evidence on the extent to which the size of the credit multiplier depends on supply-side (bank) or demand-side (firm) incentives. In particular, a credit multiplier decreasing with the size of the differential is a sign that firms' incentives drive the substitution. The opposite would be true in case the multiplier was increasing with the differential.[27]

The results of this test are reported in Table 10. All regressions are fully saturated with firm and bank fixed effects. First, the credit multipliers not interacted with the interest rate differential are important because they measure the credit multiplier if the differential is zero. This shuts down a key incentive of firms to substitute existing loans for guaranteed loans. In this case, multipliers for both the 100 and the 90% programs

[26]Once a guaranteed loan is granted, banks may not have much leverage to avoid that firms repay existing loans or part of them using the newly issued guaranteed loans. This is implicitly taken into account, in equilibrium, by banks when deciding how much to grant and which program to choose.

[27]In principle, also the interest rates on the newly issued guaranteed loans could reflect firms' credit risk and its expected evolution during the pandemic. This is not a major concern in our setting, though, because the rates on guaranteed loans have very limited correlation with firm (observable) risk. The loans issued under the 100% guarantee program have a capped rate which varies very little across firms. In an unreported robustness check, we have verified that the loans issued under the 90% program display very little correlation with firm risk, and, as expected, much less than non-guaranteed loans.

hover around 0.7-0.75 per euro of guarantee with limited variability over time, the only exception being the 100% program in Q4-2020, when the multiplier is 0.58.

Next, the interaction terms show that credit additionality is significantly lower for loans with a wider differential between the interest rate on the existing and guaranteed loans.[28] For the 100% program, at the average rate differential (300 basis points), the multiplier drops from 0.68 to 0.63. For the 90% program, at the average differential (250 basis points), it drops from 0.76 to 0.58.

Overall, these results suggest that setting very low interest rates on guaranteed loans, for example by imposing caps, may incentivize credit substitution, potentially weakening the effectiveness of the program. Low rates may have other benefits, such as, for example, increasing firm survival as their profits get a boost by the drop in interest expenses. In addition, under the assumption that our specification fully controls for firms' credit risk, these results suggest that absent an interest rate differential between existing loans and guaranteed loans, credit additionality would be around 70 cents per euro of guarantee. This deviation from full additionality reflects banks' incentives to save on risk-weights. The presence of an interest rate differential induces further substitution (i.e. less additionality), lowering the multipliers by between 8 to 13 cents per euro of guarantee. This, in equilibrium, reflects firms' incentives to save on interest expenses over banks' incentives to preserve interest income.

6.5 Credit multiplier: aggregate effects at the firm-level

Lastly, we verify the degree of credit additionality at the firm-level. This test is complementary to the previous analysis. The identification of the effects is somewhat weaker than in the specification at the bank-firm relationship level as we cannot control for firm and bank fixed effects. Yet, this test is informative to gauge the overall impact of the guarantees on firm's access to credit. As we found negligible cross-bank substitutition (Section 6.2), we expect that the size of the credit multiplier for total credit at the firm-level is similar to that estimated at the relationship level, shown in our baseline Tables

[28] When more than one loan is present we take the credit weighted average across all loans.

7 and 8. Results, shown in Table 11, indicate a large size of the credit multipliers across programs, even slightly larger than that estimated in the baseline. This confirms that there has not been cross-banks substitution, i.e. that firms did not use guaranteed loans obtained by bank j to repay loans to bank k. The slightly larger size of the multiplier at the firm-level, compared to that estimated at the relationship level, may be due to spillover effects, which could have led other lenders to increase their loans to the firm, as this got a guaranteed loans.

Overall, this result is important because it confirms that public guarantees had a positive effect of the overall credit at the firm-level. For the 100% program, the average across all periods is 86 cents of additional credit per euro of guarantee. For the 90% program the multiplier is 78 cents.

7 Conclusions

This paper analyzes the public loan guarantee schemes introduced in Italy after the Covid-19 pandemic outbreak. It studies the take-up of the guaranteed loan programs according to bank and firm characteristics. Next, it studies the additionality of each program, again also distinguishing across banks' and firms' characteristics. Crucially, we distinguish across different quarters after the burst of the pandemic, finding significant differences in credit additionality and in the relevance of banks' characteristics over time.

As far as concerns the granting of guaranteed loans: in the early phase of the pandemic, better capitalized banks were significantly more inclined to grant loans with 90% coverage, while such difference across banks was not relevant for fully guaranteed loans. Over the whole period banks with lower exposures to non-financial companies displayed a somewhat higher propensity to grant guaranteed loans, suggesting that banks less specialized in lending to corporations exploited relatively more the benefits provided by the public guarantee. By contrast, we find limited differences of firm heterogeneity in the recourse to public guarantees for all programs.

Turning to the key question of this paper, credit additionality of the guarantee programs, we document that it depends on the guarantee coverage and on the period in which the loan was issued. It was highest for fully guaranteed loans issued in the first quarter of the program, Q2-2020, coinciding with the first phase of the pandemic. Credit additionality decreased over time, in particular for fully guaranteed loans, it was strongest for high capital banks, mainly for the 90% program in Q2-2020, and it did not vary much across firm (observable) characteristics. Finally, we document that credit additionality reduces when the interest rate differential between existing loans and guaranteed loans is wider, suggesting that the extent to which existing loans are substituted for guaranteed loans is also influenced by firms' decisions.

Our findings provide three main messages. First, in the initial phase of the Covid-19 shock, when the economic environment was extremely uncertain, downside risks large and liquidity demand by firms highest, very high coverage ratios have been important to generate additional credit. Second, bank capital plays a fundamental role to support higher lending through guaranteed loans in the face of this exceptional liquidity shock. This effect was particularly strong in the initial and most severe phase of the crisis and for loans not fully guaranteed. Third, we find that guaranteed loans were not granted relatively more frequently to riskier firms and the credit additionality of the guarantees does not substantially depend on firm characteristics. In particular, the substitution of existing credit with guaranteed loans is only slightly higher for loans to riskier firms. These findings suggest that, despite high coverage ratios, the adoption of these guarantee schemes was not associated with an increase in risk-shifting by banks, at least during the first 12 months after the pandemic shock. Our results may help policy makers to design emergency loan guarantee programs. In particular, the generosity of the program should be highest when liquidity needs and uncertainty are highest.

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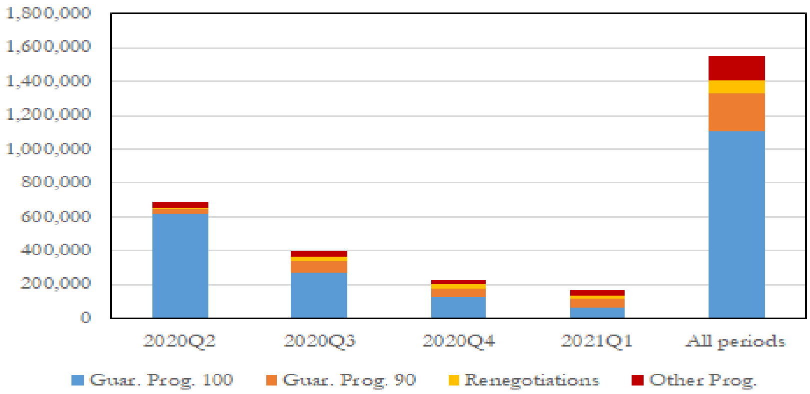
Figures and Tables

Figure 1: **FCG guaranteed loans**

a) Number of guaranteed loans



b) Amount of guaranteed loans (*billion EUR*)

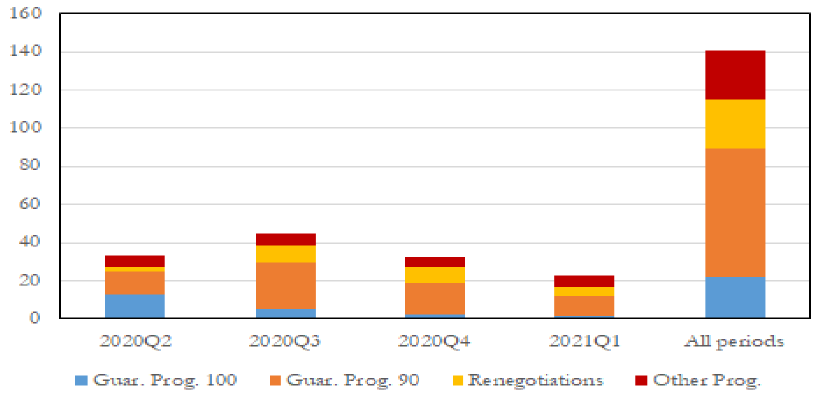


Figure 2: **Frequency of loan amounts**

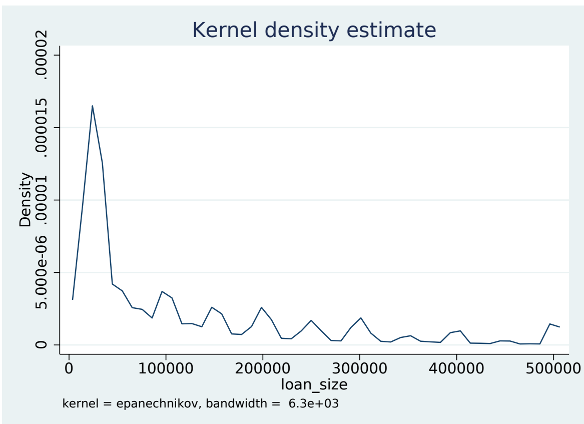
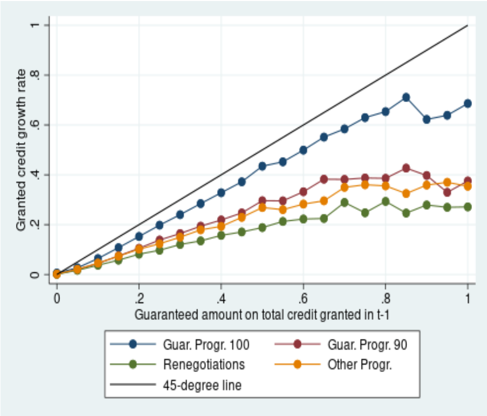
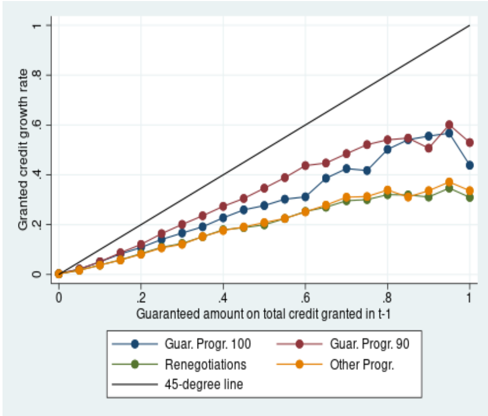


Figure 3: **Guaranteed loan usage across programs**

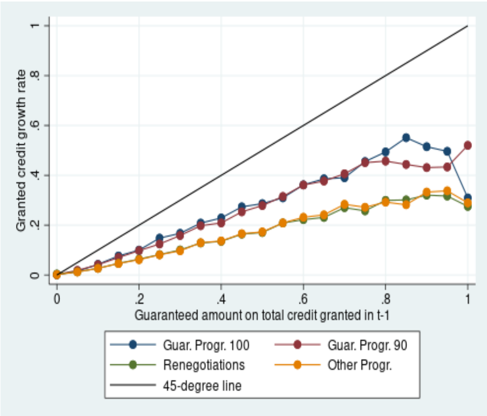
a) Multiplier 2020Q2



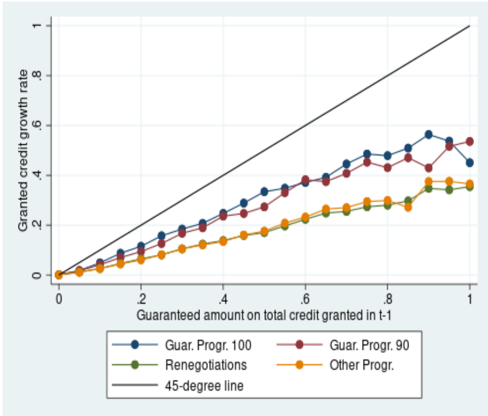
b) Multiplier 2020Q3



c) Multiplier 2020Q4



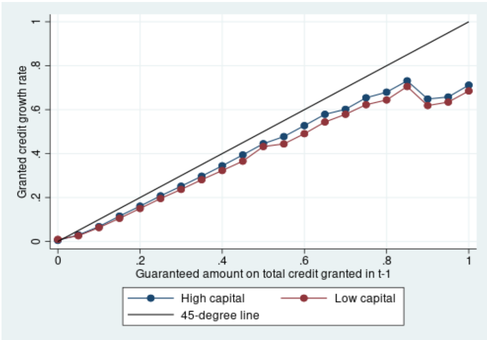
d) Multiplier 2021Q1



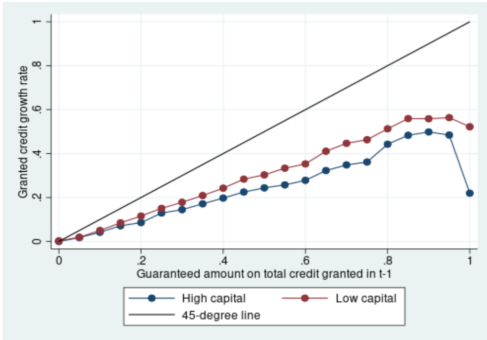
Note. The sample includes all borrowers that have received a guaranteed loan of the reported scheme for which we have information from the Credit Registry. In each period we preliminary assign each bank-firm relationship to 20 buckets based on the ratio between the guaranteed amount taken in each quarter and the amount of granted credit at the beginning of the period (from 0 to 1 with a 0.05 interval). For example, a value of 0 indicates that the borrower has not received any guaranteed loan from a bank with whom it had a credit relationship at the beginning of the period; a value of 1 instead signals that the total amount of public guarantees with a bank during the quarter is equal to the overall amount of granted credit at the beginning of the period. For each bucket we compute the average of the growth of granted credit.

Figure 4: **Guaranteed loan usage across programs and bank capital**

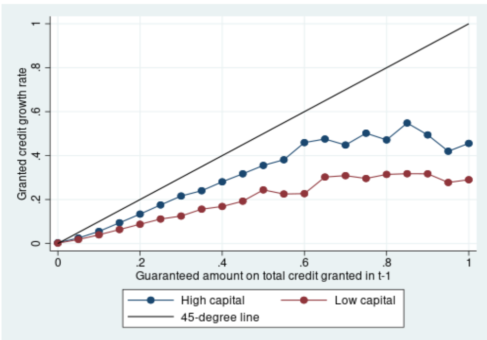
a) Multiplier guarantee program 100: 2020Q2



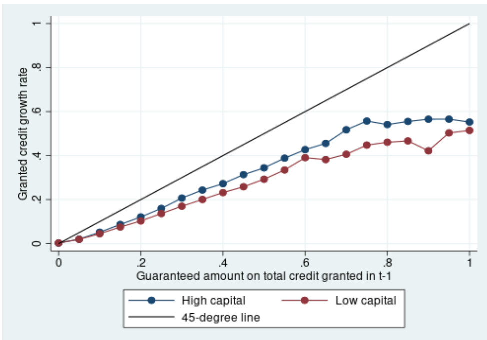
b) Multiplier guarantee program 100: 2020Q3-2021Q1



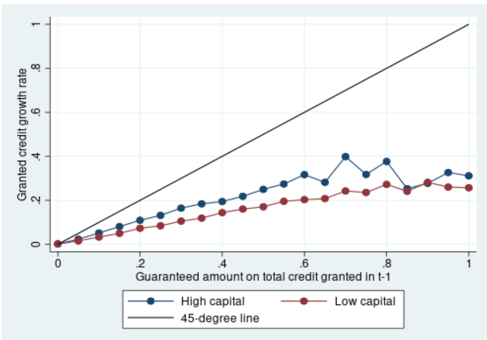
c) Multiplier guarantee program 90: 2020Q2



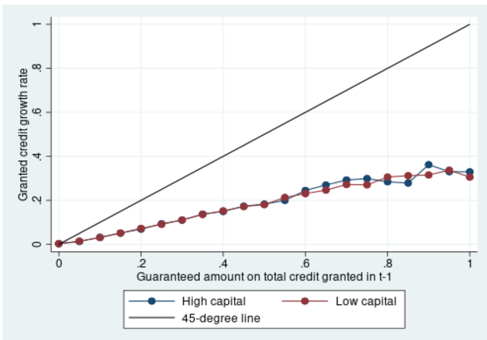
d) Multiplier guarantee program 90: 2020Q3-2021Q1



e) Multiplier renegotiations: 2020Q2

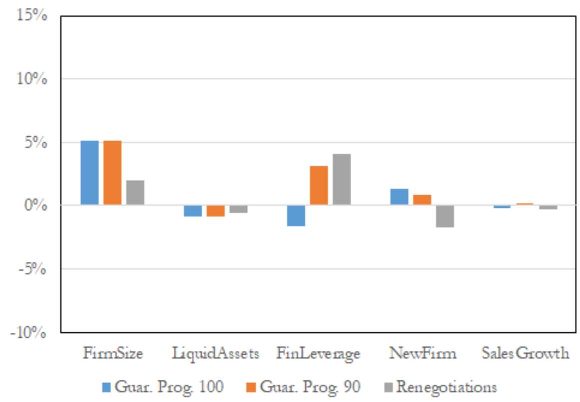


f) Multiplier renegotiations: 2020Q3-2021Q1



Note. See note to Figure 3 for a descriptions of the sample and the definition of the outcome variable. The figure reports different lines for banks with capital ratios above (high capital) or below (low capital) the median level for each program (guarantee program 100, guarantee program 90, and renegotiations).

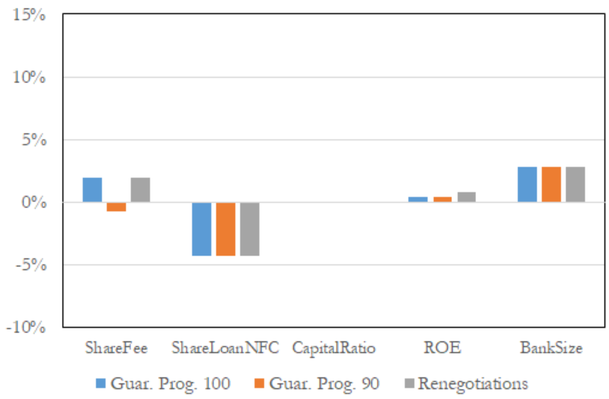
Figure 5: **Likelihood differences across firms (2020Q2-2021Q1)**



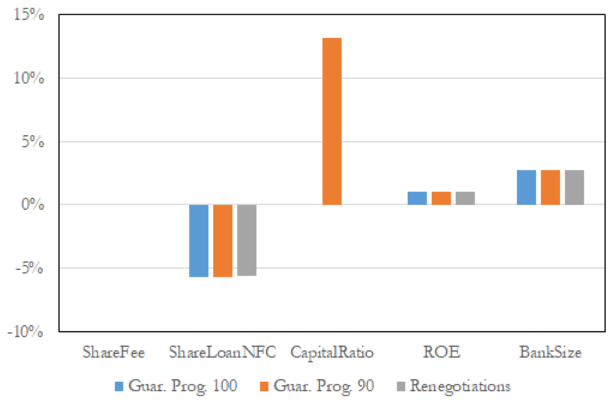
Note. For each variable of the vector *FirmCharacteristics*, the likelihood difference is computed using the corresponding coefficient in Table 3 and multiplying it by the inter-quartile range (IQR) of that variable.

Figure 6: **Likelihood differences across banks to grant a guaranteed loan**

a) All periods



b) 2020Q2



Note. For each variable of the vector *BankCharacteristics* the likelihood difference is computed using the corresponding coefficient in Table 4 (column 1 in panel a and column 2 in panel b) and multiplying it by the inter-quartile range (IQR) of the variable for the sample of banks. The figures show only the statistically significant marginal effects.

Figure 7: **Distribution of guarantee multipliers across banks – Guar. Prog. 100**

a) 2020Q2 b) 2020Q3-2021Q1

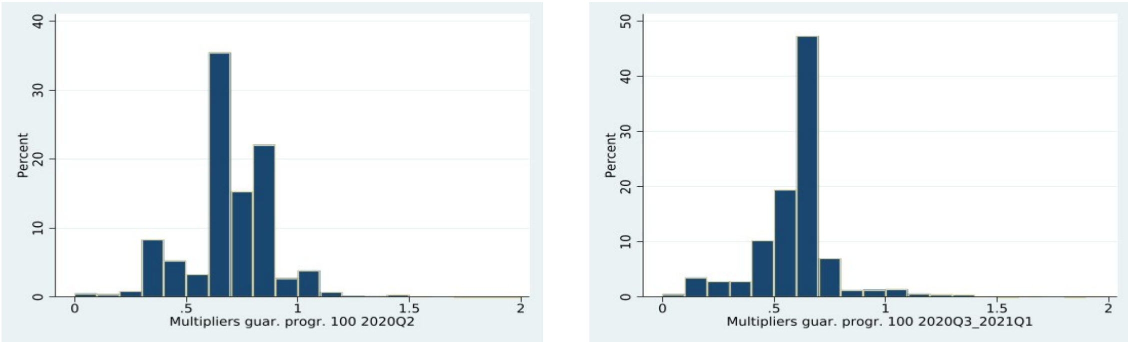


Figure 8: **Distribution of guarantee multipliers across banks – Guar. Prog. 90**

a) 2020Q2 b) 2020Q3-2021Q1

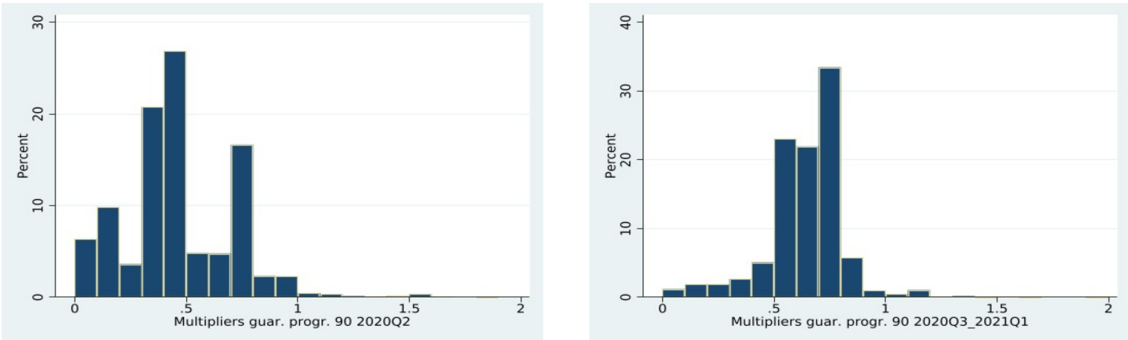
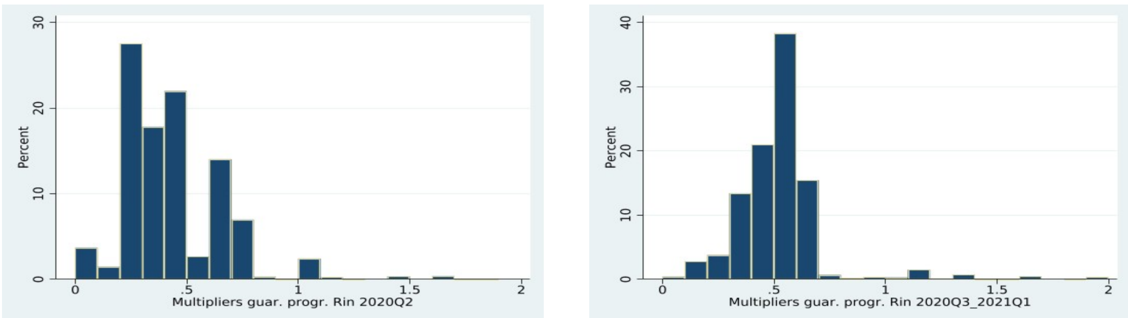


Figure 9: **Distribution of guarantee multipliers across banks – Renegotiations**

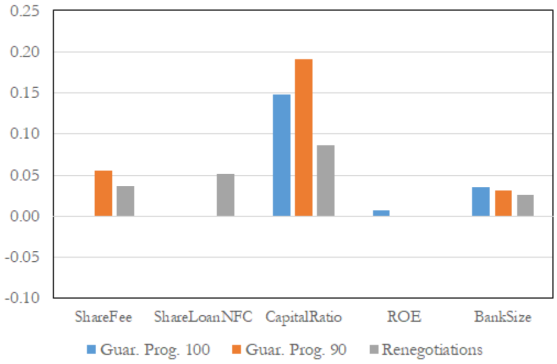
a) 2020Q2 b) 2020Q3-2021Q1



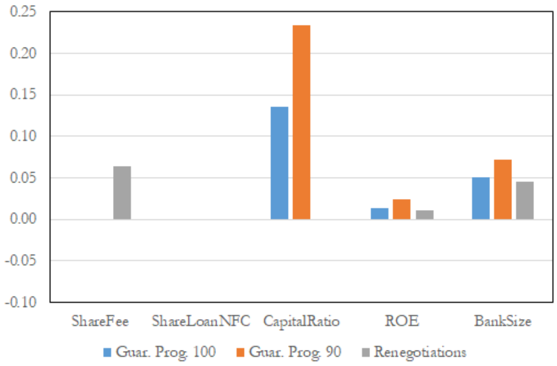
Note. The figures present the distribution of guarantee multipliers across banks, expressed in percentage. For each program and period, the guarantee multipliers of each bank are obtained estimating Eq. (4) by interacting $GuarLoan \cdot GuarAmount$ with a dummy variable for each lender. The value of the guarantee multiplier is weighted with the number of guaranteed loans granted by each bank to the total number of guaranteed loans observed in the same period.

Figure 10: **Difference in marginal effects on guarantee multipliers across banks**

a) All periods

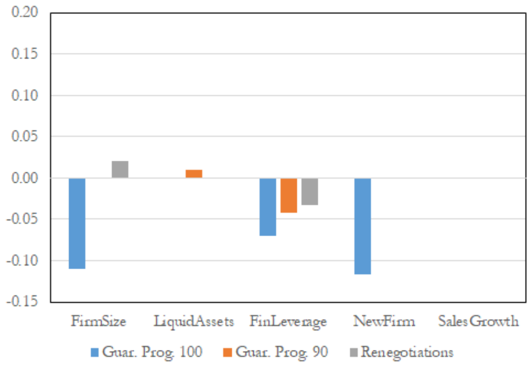


b) 2020Q2



Note. For each variable of the vector *BankCharacteristics* the difference in guarantee multipliers across banks is computed using the coefficient of *GuarLoan*× *GuarAmount*× *BankCharacteristics* in Table A.10, Table A.11, and Table A.12 (column 1 in panel a and column 2 in panel b) for guarantee program 100, guarantee program 90, and renegotiations, respectively, and multiplying it by the inter-quartile range (IQR) of the variable for the sample of banks. The figures show only the statistically significant marginal effects.

Figure 11: **Difference in marginal effects on guarantee multipliers across firms (2020Q2-2021Q1)**



Note. The difference in guarantee multipliers is computed using the corresponding coefficient in Table A.14 and multiplying it by the inter-quartile range (IQR) of that variable. The figure shows only the statistically significant marginal effects.

Table 1: **FCG guaranteed loans for borrowers in the Italian Credit Registry**

For each quarter, the table reports the number of firms, the amounts of credit granted (i.e. the sum of outstanding and loan commitments), the growth rate, and the median growth rate for borrowers with records in the Italian Credit Registry with no non-performing exposure. Borrowers are divided into two groups: those that had received at least one loan covered by the FCG guarantee in that quarter (*Guar. Borrowers*) and other borrowers (excluding firms with revenues above €50 million). The last column reports the amount of guaranteed loans to the former group. Credit amounts are indicated in billion EUR.

Borrower type	Quarter	Num. of firms	Credit at the start	Credit at the end	Gr.rate of credit (%)	Median gr.rate (%)	Guar. loans
Guar. Borrowers	2020Q2	276,307	188	207	9.95	17.39	32.2
	2020Q3	151,260	182	203	11.63	11.85	35.2
	2020Q4	113,341	160	174	8.58	8.59	30.1
	2021Q1	78,106	101	110	8.09	9.02	18.4
Other borrowers	2020Q2	709,464	483	485	0.44	-0.42	
	2020Q3	606,887	383	380	-0.60	-0.42	
	2020Q4	549,672	318	317	-0.31	-0.85	
	2021Q1	521,863	297	292	-1.77	-0.96	

Table 2: **Propensity to receive a guaranteed loan at the borrower level – firm characteristics**

The table shows the results of Eq. (1) estimated at the borrower level. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 if the borrower has received a guaranteed loan in 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) fixed effects are interacted with quarter dummies. The data include the universe of Italian non-financial firms that are recorded in the Central Credit Register. Firm balance sheet data are as of december 2019. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
FirmSize	0.0176***	-0.0075***	0.0304***	0.0321***	0.0221***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LiquidAssets	-0.0552***	-0.0962***	-0.0528***	-0.0396***	-0.0241***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FinLeverage	0.0674***	0.0394***	0.1012***	0.0895***	0.0500***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NewFirm	0.0224***	-0.0401***	0.0597***	0.0597***	0.0366***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
SalesGrowth	-0.0041***	-0.0286***	0.0052***	0.0107***	0.0083***
	(0.0000)	(0.0000)	(0.0011)	(0.0000)	(0.0000)
ΔCredit2020Q1	0.2726***	0.4125***	0.3320***	0.2305***	0.1331***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters)			-0.3281***	-0.1226***	-0.0899***
			(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x FirmSize			0.0369***	0.0149***	0.0142***
			(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x LiquidAssets			0.0307***	0.0120***	0.0047***
			(0.0000)	(0.0000)	(0.0001)
D(GuarLoan in prev. quarters) x FinLeverage			0.0095	0.0114*	0.0143***
			(0.1430)	(0.0578)	(0.0033)
D(GuarLoan in prev. quarters) x NewFirm			-0.0527***	-0.0391***	-0.0229***
			(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x SalesGrowth			-0.0073**	-0.0011	0.0027
			(0.0479)	(0.7248)	(0.2876)
D(GuarLoan in prev. quarters) x ΔCredit2020Q1			-0.3607***	-0.2663***	-0.1690***
			(0.0000)	(0.0000)	(0.0000)
Constant	0.1138***	0.4156***	0.0168***	-0.0400***	-0.0344***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.1043	0.0944	0.1033	0.0705	0.0435
Observations	1286100	397784	411041	418818	421632

Table 3: **Propensity to receive a guaranteed loan at the borrower level by program – firm characteristics**

The table shows the results of Eq. (2) estimated at the borrower level. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 if, between 2020Q2 and 2021Q1, the borrower has received a guaranteed loan under guarantee program 100 (column 1), guarantee program 90 (column 2), renegotiation program (column 3), or other programs (column 4), respectively. The model in column (1) is estimated by including in the control group only firms with revenues below €500 thousands in order to compare more similar borrowers. In all columns fixed effects are interacted with quarter dummies. The data include the universe of Italian non-financial firms that are recorded in the Central Credit Register. Firm balance sheet data are as of december 2019. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) Guar.Prog.100	(2) Guar.Prog.90	(3) Ren.	(4) Other Prog.
FirmSize	0.0395***	0.0398***	0.0157***	0.0205***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LiquidAssets	-0.0286***	-0.0279***	-0.0205***	-0.0298***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FinLeverage	-0.0528***	0.0888***	0.1168***	0.1389***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NewFirm	0.0132***	0.0081***	-0.0170***	-0.0179***
	(0.0000)	(0.0006)	(0.0000)	(0.0000)
SalesGrowth	-0.0101***	0.0100***	-0.0163***	-0.0100***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔCredit2020Q1	0.2864***	0.0921***	-0.0020***	0.0059***
	(0.0000)	(0.0000)	(0.0067)	(0.0000)
D(GuarLoan in prev. quarters)	0.0968***	-0.0330***	-0.0583***	-0.0520***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x FirmSize	-0.0325***	0.0051***	0.0093***	0.0092***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x LiquidAssets	0.0256***	0.0077***	-0.0015*	0.0009
	(0.0000)	(0.0000)	(0.0868)	(0.4196)
D(GuarLoan in prev. quarters) x FinLeverage	0.0550***	-0.0404***	-0.0102***	-0.0205***
	(0.0000)	(0.0000)	(0.0075)	(0.0000)
D(GuarLoan in prev. quarters) x NewFirm	-0.0057**	0.0108**	0.0054**	0.0140***
	(0.0223)	(0.0110)	(0.0420)	(0.0001)
D(GuarLoan in prev. quarters) x SalesGrowth	0.0128***	0.0184***	-0.0019	0.0022
	(0.0000)	(0.0000)	(0.3221)	(0.3386)
D(GuarLoan in prev. quarters) x ΔCredit2020Q1	-0.2857***	-0.0982***	-0.0262***	-0.0480***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0444***	-0.2146***	-0.0752***	-0.0836***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.2478	0.0441	0.0359	0.0340
Observations	704300	944975	944975	944975

Table 4: **Propensity to provide a guaranteed loan – bank characteristics**

The table shows the results of Eq. (3) estimated for the sample of guaranteed borrowers. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 for guaranteed loans granted in 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm fixed effects are interacted with quarter dummies. The sample includes bank-firm relationships from the Central Credit Register. The sample of firms includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Bank balance sheet data refer to the initial quarter of each period. Standard errors are clustered at the bank level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
ShareFee	0.1982*	0.2012	0.2721**	0.1291	0.2011**
	(0.0876)	(0.1732)	(0.0190)	(0.4117)	(0.0472)
ShareLoanNFC	-0.1546**	-0.2050**	-0.1320**	-0.0260	-0.0821
	(0.0168)	(0.0147)	(0.0422)	(0.7469)	(0.1105)
CapitalRatio	-0.2341	-0.8428	0.8828*	-0.0378	-0.0837
	(0.5820)	(0.1144)	(0.0960)	(0.9464)	(0.8425)
ROE	0.0852*	0.1959***	-0.0754	0.0504	0.1147***
	(0.0995)	(0.0000)	(0.5422)	(0.4427)	(0.0008)
BankSize	0.0163***	0.0160***	0.0140***	0.0131***	0.0215***
	(0.0000)	(0.0001)	(0.0003)	(0.0033)	(0.0000)
MainLender	0.0889***	0.0940***	0.0959***	0.0825***	0.0675***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔCredit2020Q1	0.1364***	0.1086*	0.1516**	0.2176***	0.0504
	(0.0006)	(0.0761)	(0.0126)	(0.0000)	(0.4245)
GuarFirm90 x ShareFee	-0.2674**	-0.2126	-0.2366*	-0.3056**	-0.4470***
	(0.0477)	(0.3704)	(0.0570)	(0.0399)	(0.0005)
GuarFirm90 x ShareLoanNFC	-0.0280	-0.1230	-0.0082	-0.0908	-0.0188
	(0.7749)	(0.4857)	(0.9150)	(0.2631)	(0.8119)
GuarFirm90 x CapitalRatio	1.2367	3.2853**	0.3283	0.4419	-0.2854
	(0.1651)	(0.0456)	(0.6374)	(0.5357)	(0.5996)
GuarFirm90 x ROE	-0.0092	-0.1414	0.1529***	0.0165	-0.0543*
	(0.8123)	(0.1416)	(0.0088)	(0.6037)	(0.0537)
GuarFirm90 x BankSize	0.0073	0.0198	0.0033	0.0061	0.0038
	(0.4370)	(0.2439)	(0.6597)	(0.3257)	(0.4376)
GuarFirm90 x MainLender	0.0060	0.0461***	0.0002	-0.0196*	-0.0112
	(0.4717)	(0.0048)	(0.9745)	(0.0595)	(0.3311)
GuarFirm90 x ΔCredit2020Q1	-0.2296***	0.0596	-0.3047***	-0.4027***	-0.1131*
	(0.0000)	(0.5913)	(0.0000)	(0.0000)	(0.0663)
GuarFirmRen x ShareFee	0.3688	0.2154	0.3669	0.6089**	0.6337
	(0.1219)	(0.2601)	(0.2841)	(0.0419)	(0.1202)
GuarFirmRen x ShareLoanNFC	0.2237	0.3822**	0.3199*	0.0496	0.0592
	(0.1063)	(0.0112)	(0.0932)	(0.7367)	(0.7479)
GuarFirmRen x CapitalRatio	-0.3956	-0.8842	-0.3331	-0.5099	0.4198
	(0.5114)	(0.2456)	(0.6493)	(0.5956)	(0.6686)
GuarFirmRen x ROE	-0.3528***	-0.1972	-0.2714	-0.3761***	-0.3447***
	(0.0092)	(0.2196)	(0.1074)	(0.0007)	(0.0006)
GuarFirmRen x BankSize	0.0023	-0.0092	0.0017	-0.0009	0.0049
	(0.7166)	(0.1981)	(0.8474)	(0.9166)	(0.6734)
GuarFirmRen x MainLender	0.0551***	0.0796***	0.0718***	0.0533***	0.0076
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.6581)
GuarFirmRen x ΔCredit2020Q1	-0.1787	0.3822	0.1401	-0.3426***	-0.2566
	(0.1231)	(0.1469)	(0.2523)	(0.0002)	(0.1101)
GuarFirm80 x ShareFee	-0.3566	-0.1026	-0.3980	-0.6372**	-0.6146
	(0.1268)	(0.4771)	(0.2809)	(0.0237)	(0.1329)
GuarFirm80 x ShareLoanNFC	-0.0098	0.0017	-0.0295	-0.0756	0.0262
	(0.9180)	(0.9851)	(0.8299)	(0.5050)	(0.8576)
GuarFirm80 x CapitalRatio	-0.5499	-0.3151	-1.1895	-0.9221	-0.6133
	(0.3772)	(0.6607)	(0.1870)	(0.2129)	(0.6015)
GuarFirm80 x ROE	0.0786*	0.0679	0.0662	0.0638	0.0426
	(0.0926)	(0.1718)	(0.4670)	(0.2213)	(0.5343)
GuarFirm80 x BankSize	0.0017	-0.0091	0.0012	0.0175**	0.0052
	(0.7657)	(0.1057)	(0.9151)	(0.0301)	(0.6341)
GuarFirm80 x MainLender	0.0313***	0.0144	0.0477***	0.0279**	0.0461***
	(0.0000)	(0.1519)	(0.0035)	(0.0421)	(0.0008)
GuarFirm80 x ΔCredit2020Q1	-0.1439***	-0.0265	-0.1935**	-0.2790***	-0.0516
	(0.0027)	(0.7733)	(0.0212)	(0.0001)	(0.4772)
Constant	-0.2612*	-0.2135	-0.2211	-0.2835***	-0.3904***
	(0.0543)	(0.3662)	(0.1256)	(0.0003)	(0.0001)
Firm FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.1918	0.1834	0.1956	0.2024	0.2004
Observations	600259	197774	166212	142381	93892

Table 5: **Propensity to provide a guaranteed loan – high capital lenders**

The table shows the results of Eq. (3) estimated for the sample of guaranteed borrowers by replacing the vector *Bank* with *HighCapBank*, which is a dummy variable equal to 1 if bank j has the highest capital ratio among the lenders with credit relationships with borrower i. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 for guaranteed loans granted in 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
HighCapBank	-0.0175***	-0.0368***	0.0088	0.0205***	0.0238**
	(0.0000)	(0.0000)	(0.1895)	(0.0089)	(0.0402)
GuarFirm90 x HighCapBank	0.0754***	0.1487***	0.0437***	0.0392***	-0.0122
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2521)
GuarFirmRen x HighCapBank	-0.0282***	-0.0468***	-0.0320***	-0.0390***	0.0173
	(0.0000)	(0.0000)	(0.0017)	(0.0000)	(0.1141)
GuarFirm80 x HighCapBank	0.0075*	0.0322***	-0.0187*	-0.0278***	-0.0352***
	(0.0990)	(0.0000)	(0.0653)	(0.0043)	(0.0061)
Constant	0.2615***	0.2864***	0.2539***	0.2523***	0.2349***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2222	0.2211	0.2235	0.2224	0.2205
Observations	600209	197759	166198	142373	93879

Table 6: **Credit growth 2020Q1 – firm and bank characteristics**

The table shows the results of a regression model estimated by considering all firms (columns 1 and 4), only borrowers that will request a guaranteed loan in the following quarters (columns 2 and 5), and only firms that will not request a guaranteed loan until 2021Q1 (columns 3 and 6), respectively. The dependent variable is $\Delta Credit_{i,j}$, which is the change between December 2019 and March 2020 in credit granted by bank j to firm i over the total amount of granted credit to firm i in 2019Q4. The sample includes bank-firm relationships from the Central Credit Register. The sample of firms includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Bank balance sheet data refer to the initial quarter of each period. Standard errors are clustered at the bank level in columns 1-3 and at the firm level in columns 4-6. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All firms	(2) Guar. firms	(3) Non-guar. firms	(4) All firms	(5) Guar. firms	(6) Non-guar. firms
ShareFee	0.0138**	0.0159**	0.0091**			
	(0.0265)	(0.0257)	(0.0446)			
ShareLoanNFC	-0.0009	-0.0009	-0.0014			
	(0.7613)	(0.8054)	(0.6012)			
CapitalRatio	0.0277*	0.0364*	0.0109			
	(0.0944)	(0.0711)	(0.3880)			
ROE	-0.0026	-0.0028	-0.0023			
	(0.1907)	(0.1561)	(0.2712)			
BankSize	-0.0003*	-0.0004**	-0.0002*			
	(0.0518)	(0.0375)	(0.0728)			
MainLender	0.0032***	0.0037***	0.0023***	0.0013***	0.0029***	-0.0013***
	(0.0001)	(0.0002)	(0.0004)	(0.0000)	(0.0000)	(0.0021)
ShareLoanCommittment	0.0163***	0.0174***	0.0146***	0.0116***	0.0155***	0.0073***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FirmSize				0.0027***	0.0028***	0.0025***
				(0.0000)	(0.0000)	(0.0000)
LiquidAssets				-0.0028***	-0.0031***	-0.0011***
				(0.0000)	(0.0000)	(0.0000)
FinLeverage				-0.0057***	-0.0066***	-0.0056***
				(0.0000)	(0.0000)	(0.0000)
NewFirm				0.0128***	0.0138***	0.0093***
				(0.0000)	(0.0000)	(0.0000)
SalesGrowth				0.0070***	0.0085***	0.0048***
				(0.0000)	(0.0000)	(0.0000)
Constant	-0.0061*	-0.0052	-0.0077***	-0.0250***	-0.0255***	-0.0239***
	(0.0706)	(0.1657)	(0.0055)	(0.0000)	(0.0000)	(0.0000)
Firm FE	Yes	Yes	Yes	No	No	No
Sector FE	No	No	No	Yes	Yes	Yes
Province FE	No	No	No	Yes	Yes	Yes
Bank FE	No	No	No	Yes	Yes	Yes
Adj. R-squared	0.1394	0.1533	0.1015	0.0080	0.0099	0.0066
Observations	742192	512003	230189	746973	515210	231732

Table 7: **Public guarantees and credit growth**

The table shows the results of Eq. (4). The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) sector, province, and bank fixed effects are interacted with quarter dummies. Specific dummies for each guarantee program are not reported. The sample includes bank-firm relationships from the Central Credit Register. The sample of firms includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	0.7263***	0.8370***	0.6025***	0.4845***	0.5674***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirm90 x GuarAmount	-0.0996***	-0.2550***	0.0714***	0.0733***	0.0086
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.5626)
GuarLoan x GuarFirmRen x GuarAmount	-0.1072***	-0.1908***	-0.0535***	-0.0731***	-0.0701***
	(0.0000)	(0.0000)	(0.0023)	(0.0000)	(0.0002)
GuarLoan x GuarFirm80 x GuarAmount	-0.2334***	-0.2708***	-0.1538***	-0.0739***	-0.1226***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0015***	0.0013***	0.0036***	0.0011***	-0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3044)
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2958	0.5117	0.2752	0.1629	0.1393
Observations	3507628	851018	877850	888597	890163

Table 8: **Public guarantees and credit growth - firm FE**

The table shows the results of Eq. (4) estimated for the sample of borrowers with multiple lending relationships. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. The sample includes bank-firm relationships from the Central Credit Register. The sample of firms includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	0.6312***	0.7437***	0.6364***	0.4644***	0.5995***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirm90 x GuarAmount	0.0027	-0.1604***	0.0697***	0.1083***	0.0086
	(0.6635)	(0.0000)	(0.0000)	(0.0000)	(0.6465)
GuarLoan x GuarFirmRen x GuarAmount	-0.1101***	-0.2194***	-0.0471***	-0.0879***	-0.1017***
	(0.0000)	(0.0000)	(0.0094)	(0.0000)	(0.0000)
GuarLoan x GuarFirm80 x GuarAmount	-0.1258***	-0.1581***	-0.1558***	-0.0209	-0.1089***
	(0.0000)	(0.0000)	(0.0000)	(0.2631)	(0.0000)
Constant	0.0014***	0.0012***	0.0030***	0.0015***	0.0001
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.2303)
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.3592	0.4317	0.4133	0.3035	0.2802
Observations	2681064	660041	673801	674770	672452

Table 9: **Public guarantees and credit growth - comparable borrowers receiving *Guarantee100* and *Guarantee90* loans**

The table shows the results of Eq. (4) estimated for the sample of borrowers that have received *Guarantee100* or *Guarantee90* loans with an amount lower than the €112,500 (the median value for guarantee 90 loans) and with revenues between €500,000 and €1,000,000. Firms are selected from the universe of Italian non-financial corporations that are recorded in the central Credit Register. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan	-0.0012	0.0034	-0.0117**	0.0028	-0.0095
	(0.5851)	(0.1164)	(0.0271)	(0.7042)	(0.2895)
GuarLoanxGuarFirm90	0.0212***	0.0315***	0.0182**	0.0227**	0.0186*
	(0.0000)	(0.0001)	(0.0144)	(0.0156)	(0.0950)
GuarLoanxGuarAmount	0.8380***	0.8357***	0.8580***	0.6713***	0.8347***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoanxGuarFirm90xGuarAmount	-0.2529***	-0.4484***	-0.1202***	-0.1764***	-0.2083***
	(0.0000)	(0.0000)	(0.0005)	(0.0003)	(0.0001)
Constant	0.0037***	0.0034***	0.0049***	0.0046***	0.0013
	(0.0000)	(0.0000)	(0.0000)	(0.0016)	(0.4675)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.6287	0.7055	0.5870	0.4426	0.5206
Observations	69058	41417	14302	8453	4886

Table 10: **Public guarantees and credit growth – interest rates differential between existing loans and guaranteed loans**

The table shows the results of Eq. (4) estimated for the sample of borrowers with multiple lending relationships and by interacting, for each program, *GuarAmount* with $\Delta InterestRate$, which is the difference between the average interest rate on credit granted by bank j to firm i in *t-1* and the interest rate on the guaranteed loan (for not-guaranteed loans, this term is 0). For each program, we also include an interaction between *GuarAmount* and *FinLeverage* (unreported). The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. The sample includes bank-firm relationships from the Central Credit Register. The sample of firms includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	0.7129***	0.7922***	0.7155***	0.5841***	0.7266***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirm90 x GuarAmount	0.0688***	-0.0514***	0.1152***	0.1517***	0.0493
	(0.0000)	(0.0032)	(0.0000)	(0.0000)	(0.1027)
GuarLoan x GuarFirmRen x GuarAmount	-0.1129***	-0.1850***	-0.0501**	-0.0326	-0.1961***
	(0.0000)	(0.0000)	(0.0471)	(0.2381)	(0.0000)
GuarLoan x GuarFirm80 x GuarAmount	-0.1075***	-0.1299***	-0.1554***	-0.0896***	-0.0335
	(0.0000)	(0.0000)	(0.0000)	(0.0037)	(0.4064)
GuarLoan x GuarAmount x ΔInterestRate	-2.5643***	-0.8955**	-4.6054***	-4.6391***	-2.8734***
	(0.0000)	(0.0321)	(0.0000)	(0.0000)	(0.0001)
GuarLoan x GuarFirm90 x GuarAmount x ΔInterestRate	-5.2907***	-8.7663***	-4.6153***	-2.6777***	-2.7844***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirmRen x GuarAmount x ΔInterestRate	0.2670	-0.1967	-1.0873	-1.1062*	1.3179*
	(0.4424)	(0.8284)	(0.1694)	(0.0622)	(0.0820)
GuarLoan x GuarFirm80 x GuarAmount x ΔInterestRate	-1.8125***	-4.3270***	1.0087	1.4176**	-1.8203**
	(0.0000)	(0.0000)	(0.2706)	(0.0378)	(0.0458)
Constant	0.0062***	0.0048***	0.0097***	0.0055***	0.0042***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Interactions with FinLeverage	Yes	Yes	Yes	Yes	Yes
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.3945	0.4600	0.4480	0.3412	0.3123
Observations	1915762	476436	483003	482885	473438

Table 11: **Public guarantees and credit growth – firm level**

The table shows the results of Eq. (4) estimated at the firm level. The dependent variable is $\Delta Credit_i$, which is the change in credit granted by bank j over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) fixed effects are interacted with quarter dummies. The sample includes the universe of Italian non-financial firms that are recorded in the Central Credit Register. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarAmount	0.8579***	0.9641***	0.7422***	0.6841***	0.7083***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarFirm90 x GuarAmount	-0.0767***	-0.2530***	0.0774***	0.0622***	0.0351***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0085)
GuarFirmRen x GuarAmount	-0.2375***	-0.2921***	-0.1458***	-0.1969***	-0.2464***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarFirm80 x GuarAmount	-0.2131***	-0.1954***	-0.1898***	-0.1418***	-0.1085***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	0.0137***	0.0098***	0.0188***	0.0152***	0.0104***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.1810	0.3481	0.1729	0.0995	0.0812
Observations	1612565	382159	398076	411459	420871

Appendix

A. Model

This section contains a stylized model to summarize the main economic forces underlying the equilibrium degree of credit additionality generated by public guarantees and on how this depends on the size of the guarantee coverage and on borrowers' and lenders' characteristics. This is important to gain intuition on the effects of the public guarantee on banks and firms' choices, and, in particular, to inform the empirical analysis.

A.1 Setup

Consider a firm i with $N \geq 2$ credit relations with a set $B(i) = \{b_i^1, ..., b_i^N\}$ of risk-neutral banks and two periods $t = 0, 1$. The first period, $t = 0$, can be interpreted as the pre-pandemic period. In the second period, $t = 1$, the pandemic shock hits the economy and each bank $b \in B(i)$ funds each unit of loan it grants through debt D_i^b and equity E_i^b with respective costs r_D^b and r_E^b, with $r_E^b > r_D^b$. We assume borrower i is infinitesimal so that r_D^b and r_E^b do not depend on whether the bank grants a loan to i (i.e. they do not depend on the riskiness of the individual borrower). Each bank b faces a constraint (internal and/or regulatory) to finance at least a share e_i^b of the credit risk exposure to firm i with equity and the remaining part with debt. We assume the total indebtedness of firm i, L_i, to be common knowledge for all banks, for example because of a credit register, while the cost of debt and equity may be private information for each bank, although their prior distribution is common knowledge.

At $t = 1$ the government introduces a set of guarantee programs $X = \{X_1, ..., X_T\}$ where $X_j = (\bar{L}_i(x_j), x_j)$, with $\bar{L}_i(x_j)$ being the maximum loan amount that firm i can request under program j and $x_j \in [0, 1]$ the share of the loan that is backed by the public guarantee. Without loss of generality, we assume $X_N = (+\infty, 0)$, i.e. there is a program

X_N with zero guarantee.[29] Moreover, it is natural to assume that the maximum loan amount that can be granted under each public guarantee program is strictly decreasing in the coverage rate, i.e. $\bar{L}_i(x)$ is strictly decreasing in x. This feature characterizes several Covid-19 public guarantee schemes, including the Italian one.

We model the interaction between borrower i and banks in $B(i)$ at $t = 1$, in particular the granting of additional credit and the choice of a guarantee program, and for each bank-firm relationship we take as given the legacy amount of credit originated at $t = 0$ and still outstanding at $t = 1$.

The timing of the model is as follows: i) borrower i demands an amount $L_{1,i}$ of new credit, i.e. the flow of new credit at time 1 net of any reimbursement of existing loans; ii) given $L_{1,i}$, banks in $B(i)$ formulate best response offers according to an auction mechanism taking into account the guarantee programs X available and their pre-existing credit exposures with respect to i; iii) borrower i picks the offer(s) that maximize his utility. We adopt a standard notion of Bayesian Nash equilibrium: i) borrower i optimally chooses $L_{1,i}$ given her consistent belief on its expected cost, arising from the competitive game among her lenders; ii) banks best respond given their prior belief on other banks' expected cost of granting credit and the overall indebtedness L_i that will result in $t = 1$, a quantity including $L_{0,i}$ and the additional credit $L_{1,i}$ demanded at $t = 1$.

In Section A.2 we discuss how the guarantee programs affect the cost of providing credit (i.e. the cost of funding a loan and its capital absorption), and banks' optimal choice of the guarantee program for borrower i. Given the bank cost function, we solve the model by backward induction. In Section A.3 we derive, for an arbitrary amount of additional credit $L_{1,i}$, the optimal choice of i among her banks' offers and, in turn, how banks optimally set their offers and what is the equilibrium expected payoff for borrower i. Second, in Section A.4 we derive borrower i's optimal choice of additional credit $L_{1,i}$, trading-off the marginal benefit from additional credit against its marginal

[29] This allows for the possibility that banks grant loans that are not part of the public guarantee program.

cost, as determined by the expected payoff (which depends on banks' offers). From this optimal choice we derive comparative statics results, notably on the derived guarantee multiplier, that represent the empirical testable predictions that we bring to the data.

A.2 Banks cost function

As common in practice, we assume that banks are not obliged to hold any equity to finance the guaranteed amount of a loan under program X_j as it is equivalent to a government credit risk exposure. In other words, the guaranteed amounts carry a zero risk weight for the computation of banks' capital ratios. Hence, if a program offers a guarantee of 90% of the loan amount, the bank needs to hold equity only for a fraction e_i^b of the remaining 10% of the loan amount, the part that is not backed by the public guarantee. Other than the funding costs in terms of debt and equity, each bank b considers all information available at $t = 1$ to compute the expected loss per-unit of not guaranteed loan for bank b, $\mathbb{EL}_i^b(L_i)$, that is weakly increasing and convex in the overall amount of debt L_i held by borrower i, including any newly originated loan, with respect to all his lenders. Specifically, let $L_{t,i}^b$ be the amount of loans, net of any reimbursement, originated to firm i by bank b and define $L_i = \sum_{t=0,1} \sum_{i \in B(i)} L_{t,i}^b$. For future reference, we refer with L_i^{-b} to the the amount of loans granted by banks other than b, i.e. $L_i^{-b} = L_i - L_{0,i}^b - L_{1,i}^b$.

Therefore, for given L_i the per-unit cost for a bank of originating a loan under guarantee program X_j is:

$$c_i^b(x_j, L_i) = r_D^b + (1 - x_j) \left[\mathbb{EL}_i^b(L_i) + e_i^b(r_E^b - r_D^b) \right] \tag{5}$$

Notice that $c_i^b(x_j, L_i)$ is strictly decreasing in the coverage rate x and weakly increasing in L_i. Therefore, for all $x < 1$ it is always optimal for the bank to use the guaranteed loan up to the maximum possible, i.e. the lower between $\bar{L}(x)$ and $L_{0,b} + L_{1,b}$. Therefore, from bank b perspective, the minimum expected cost of rolling over a pre-existing debt

$L^b_{0,i}$ and issuing a new loan $L^b_{1,i}$, given L_i^{-b}, with guarantee program X_j is:

$$\begin{aligned}\mathcal{C}_i^b(L_i^{-b}, L^b_{0,i}, L^b_{1,i}, x_j) &= \min\left\{L^b_{1,i}, \bar{L}_i(x_j)\right\} c_i^b(x_j, L_i) + \left[L^b_{1,i} - \min\left\{L^b_{1,i}, \bar{L}_i(x_j)\right\}\right] c_i^b(0, L_i) \\ &+ \min\left\{\max\left\{L^b_{1,i}, \bar{L}_i(x_j)\right\} - L^b_{1,i}, L^b_{0,i}\right\} c_i^b(x_j, L_i) \\ &+ \left[L^b_{0,i} - \min\left\{\max\left\{L^b_{1,i}, \bar{L}_i(x_j)\right\} - L^b_{1,i}, L^b_{0,i}\right\}\right] c_i^b(0, L_i) \\ &= (L^b_{0,i} + L^b_{1,i}) c_i^b(0, L_i) - \min\left\{L^b_{1,i}, \bar{L}_i(x_j)\right\}\left(c_i^b(0, L_i) - c_i^b(x_j, L_i)\right) \\ &- \min\left\{\max\left\{0, \bar{L}_i(x_j) - L^b_{1,i}\right\}, L^b_{0,i}\right\}\left(c_i^b(0, L_i) - c_i^b(x_j, L_i)\right)\end{aligned} \tag{6}$$

To simplify exposition let's focus on two programs X_h and X_l with $x_h > x_l$ so that $\bar{L}_i(x_h) < \bar{L}_i(x_l)$ and assume that no program allows for complete loan substitution of pre-existing loans, i.e. $\bar{L}_i(x_l) < L^b_{0,i}$. Then, for guarantee program X_j, $j = h, l$, Eq. (6) simplifies to:

$$\mathcal{C}_i^b(L_i^{-b}, L^b_{0,i}, L^b_{1,i}, x_j) = (L^b_{0,i} + L^b_{1,b}) c_i^b(0, L_i) - \bar{L}_i(x_j)\left[c_i^b(0, L_i) - c_i^b(x_j, L_i)\right] \tag{7}$$

Then the program with lower guarantee coverage X_l is (weakly) preferred to X_h when

$$\mathcal{C}_i^b(L_i^{-b}, L^b_{0,i}, L^b_{1,i}, x_l) \leq \mathcal{C}_i^b(L_i^{-b}, L^b_{0,i}, L^b_{1,i}, x_h) \Leftrightarrow \frac{\bar{L}_i(x_l)}{\bar{L}_i(x_h)} \geq \frac{c_i^b(0, L_i) - c_i^b(x_h, L_i)}{c_i^b(0, L_i) - c_i^b(x_l, L_i)} = \frac{x_h}{x_l} \tag{8}$$

as $c_i^b(0, L_i) - c_i^b(x_j, L_i) = x_j\left[\mathbb{E}\mathbb{L}_i^b(L_i) + e_i^b(r_E^b - r_D^b)\right]$.

Remark 1. The relative preference of banks across guarantee programs, given an overall amount of loans L_i, only depends on the maximum amount of public guarantees obtained, i.e. the program with higher $x\bar{L}_i(x)$ for borrower i. As all banks access the same guarantee programs then all banks have the same relative preferences irrespective of their idiosyncratic costs of debt and equity funding, the capital absorption and/or the assessment of the borrower expected loss.

Remark 2. If $\bar{L}_i(x_j) = \min\left\{M_{x_j}, \alpha * FirmSales_i\right\}$, where $M_{x_j}$is a constant and $\alpha < 1$ a share of firm revenues, then for firms with higher sales eventually banks will prefer to choose guarantee programs with lower coverage ratios but higher loan amounts.

This condition is relevant in our setting because some of the guarantee programs in the Italian Covid-19 scheme contemplate loan amount limits that depend on a share of firms' pre-Covid revenues.

A.3 Borrower's cost minimization problem

Given a liquidity need $L_{i,1}$ at $t = 1$ and pre-existing exposures, firm i minimizes its total cost that includes both the pre-existing debt $L^b_{0,i}$ with an average cost of $p^b_{i,0}$ and the newly granted loan $L^b_{1,i}$ at cost $p^b_{1,i}$. Firm i and bank b can renegotiate the terms on pre-existing debt if both parties are willing to do so. However, as the pandemic shock has likely tightened credit supply conditions for all banks when originating not-guaranteed credit we assume that $\min_{b\in B(i)} \left\{c^b_i(0, L_i)\right\} \geq \max_{b\in B(i)} \left\{p^b_{0,i}\right\}$. Therefore, it is not convenient for firm i to renegotiate at $t = 1$ any existing loan outstanding with another non-guaranteed loan from the same or another bank. However, such renegotiation between i and b on the amount and conditions of pre-existing debt $L^b_{0,i}$ can take place if they agree on a new publicly guaranteed loan as this provides a public subsidy. As the public guarantee lowers both the expected loss and capital absorption it also represents the main incentive for the bank to grant a guaranteed loan to the borrower. From the previous section the optimal program for i is generally unique, say X^*_i.

Without loss of generality assume that firm i takes a guaranteed loan only from a single bank.[30] Let $\mathcal{P}^b_i(L^b_{0,i}, L_{1,i})$ be the remuneration offered by bank b to firm i for the total amount of loans $L^b_{0,i} + L_{1,i}$; if b's offer is accepted, the firm will pay $\mathcal{P}^b_i(L^b_{0,i}, L_{1,i})$ substituting the previous expenditure $p^b_{0,i}L^b_{0,i}$. Hence the cost-minimization problem for firm i boils down to:

$$\min_{b\in B(i)} \left\{\mathcal{P}^b_i(L^b_{0,i}, L_{1,i}) - p^b_{0,i}L^b_{0,i}\right\} \tag{9}$$

[30]In equilibrium banks have a linear cost in providing any amount $L^b_{1,i} \in [0, L_{i,1}]$: irrespective of the combination of banks, providing guaranteed loans the final amount of debt for firm i will be $L_i = L_{0,i} + L_{1,i}$, so the parameters on $\mathbb{E}^b_i(L_i)$ determining its per unit cost are constant in this interval irrespective of the precise amount of credit provided by bank b. But competition among banks with linear cost functions will push the most cost-efficient lender to provide all credit (in case of more than one bank we can always randomize). Moreover, by assumption the maximum amount of guaranteed loan cannot cover liquidity needs at $t = 1$ and completely substitute pre-existing exposures $L^b_{0,i}$.

Bank b would be willing to offer $\mathcal{P}_i^b(L_{0,i}^b, L_{1,i})$ if and only if the following holds:

$$\mathcal{P}_i^b(L_{0,i}^b, L_{1,i}) - \mathcal{C}_i^b(L_i^{-b}, L_{0,i}^b, L_{1,i}, x_i^*) \geq \left[p_{0,i}^b - c_i^b(0, L_i)\right] L_{0,i}^b \tag{10}$$

Notice that both banks and firms take into account the interest rate on the existing exposure when making and accepting offers, respectively. As the interest rate on existing exposures is typically higher than that on guaranteed loans, the more the existing exposure is substituted, the more the bank loses on interest income but gains in terms of the expected costs of originating the loan (funding cost and capital absorption). Analogously, firms' acceptance decision takes into account the cost of the existing exposure. Rearranging Eq. (10):

$$\mathcal{P}_i^b(L_{0,i}^b, L_{1,i}) - p_{0,i}^b L_{0,i}^b \geq \mathcal{C}_i^b(L_i^{-b}, L_{0,i}^b, L_{1,i}, x_i^*) - c_i^b(0, L_i) L_{0,i}^b \tag{11}$$

where the LHS is equal to the firm i objective function while the RHS can be simplified as:

$$\begin{aligned}
\mathcal{C}_i^b(L_i^{-b}, L_{0,i}^b, L_{1,i}, x_i^*) - c_i^b(0, L_i) L_{0,i}^b &= c_i^b(0, L_i) L_{1,i} - \bar{L}_i(x_i^*)[c_i^b(0, L_i) - c_i^b(x_i^*, L_i)] \\
&= L_{1,i} \left\{ r_D^b + \left[\mathbb{E}_i^b(L_i) + e_i^b(r_E^b - r_D^b)\right] \right\} \left(1 - \frac{x_i^* \bar{L}_i(x_i^*)}{L_{1,i}}\right) \\
&= c_i^b(0, L_i) \left[L_{1,i} - x_i^* \bar{L}_i(x_i^*)\right]
\end{aligned} \tag{12}$$

Notice that the $c_i^b(0, L_i)$ are independent private values across banks: indeed, the capital absorption e_i^b, the cost of debt r_D^b and equity r_E^b of each bank do not depend on whether bank b actually lends to borrower i, and the per-unit expected loss $\mathbb{EL}_i^b(L_i)$ only depends on the information about the aggregate indebtedness of firm i, i.e. L_i, that is common knowledge also in reality thanks to the information available to banks from the credit registry.

As a result, the conditions for Myerson Revenue Equivalence Theorem apply,[31] i.e. the expected payoff for the borrower is equal to the expectation of the second lowest offer, equal to $\mathcal{C}_i^b(L_i^{-b}, L_{0,i}^b, L_{1,i}, x_i^*) - c_i^b(0, L_i)L_{0,i}^b$, from the N banks in the set $B(i)$. Notice that if $L_{1,i} > x_i^* \bar{L}_i(x_i^*)$ then the bank with the lowest $c_i^b(0, L_i)$ will grant the guaranteed loan and its proposal will provide to firm i in expectation a payoff of $\mathbb{E}(c_i^b(0, L_i)^{(2)})$ $\left[L_{1,i} - x_i^* \bar{L}_i(x_i^*)\right]$ where $c_i^b(0, L_i)^{(2)}$ is the second order statistics, i.e. the second lowest per-unit loan cost on non-guaranteed credit from the set of banks in $B(i)$. If instead $L_{1,i} < x_i^* \bar{L}_i(x_i^*)$ then the guaranteed loan will be partly used to substitute existing loans and the accepted offer will be the one from the bank b with the highest $c_i^b(0, L_i)$ that provides the most convenient terms to firm i. In this case, the expected payoff for the firm is $\mathbb{E}(c_i^b(0, L_i)^{(N-1)}) \left[L_{1,i} - x_i^* \bar{L}_i(x_i^*)\right]$, i.e. it depends on the expectation of the $N-1$ order statistics of $c_i^b(0, L_i)$.

To summarize, the cost-minimizing choice for firm i to obtain an additional amount $L_{1,i}$ of credit at $t = 1$ can be expressed as follows:

$$\mathcal{C}_i(L_{0,i}, L_{1,i}) = \begin{cases} \mathbb{E}\left[c_i^b(0, L_{0,i} + L_{1,i})^{(2)}\right]\left[L_{1,i} - x_i^* \bar{L}_i(x_i^*)\right] & \text{if } L_{1,i} \geq x_i^* \bar{L}_i(x_i^*) \\ \mathbb{E}\left[c_i^b(0, L_{0,i} + L_{1,i})^{(N-1)}\right]\left[L_{1,i} - x_i^* \bar{L}_i(x_i^*)\right] & \text{if } L_{1,i} < x_i^* \bar{L}_i(x_i^*) \end{cases} \tag{13}$$

This function points out that the probability that a bank originates a new guaranteed loan depends both on its cost of non-guaranteed credit $c_i^b(0, L_{0,i})$ and on the extent to which the overall amount of new credit compares to the amount fully guaranteed by the government.

A.4 Firm optimal borrowing

We move to consider the optimal choice of $L_{1,i}$ for firm i. For this purpose let's introduce a differentiable utility function $\rho_i(L_{1,i})$ for the loan amount that we assume strictly

[31] Clearly, if private values are publicly known, the equilibrium offer will be exactly equal to the second lowest one as in a Bertrand competition setup; if instead private values $c_i^b(0, L_i)$ are private information for each bank then the expected payoff for firm i is computed as an expectation over the relevant order statistics.

increasing and concave in $L_{1,i}$.[32] Then the utility maximization problem for firm i is simply:

$$\max_{L_{1,i}} \mathcal{U}_i(L_{1,i}) = \rho_i(L_{1,i}) - \mathcal{C}_i(L_{0,i}, L_{1,i}) \tag{14}$$

The overall maximization problem captures the idea that the firm takes additional liquidity, for example to pay suppliers, because not doing so would be very costly, but then the benefit of having extra liquidity decreases as the firm becomes more indebted, and this raises the risk of future default notwithstanding the presence of a public guarantee.

As $\mathcal{C}_i(L_{0,i}, L_{1,i})$ is quasi-convex a sufficient condition for deriving the optimal $L^*_{1,i}$ is the first order condition:

$$\text{FOC:}\ \frac{\mathrm{d}\,\mathcal{U}}{\mathrm{d}\,L_{1,i}} = \frac{\mathrm{d}\,\rho_i(L^*_{1,i})}{\mathrm{d}\,L_{1,i}} - \mathbb{E}\left[c^b_i(0, L_{0,i} + L^*_{1,i})^{(win)}\right] - \frac{\mathrm{d}\,\mathbb{E}\left[c^b_i(0, L_{0,i} + L^*_{1,i})^{(win)}\right]}{\mathrm{d}\,L_{1,i}}\left[L^*_{1,i} - x^*_i \bar{L}_i(x^*_i)\right] = 0 \tag{15}$$

where $win = 2$ if $L^*_{1,i} \geq x^*_i \bar{L}_i(x^*_i)$ and $N - 1$ otherwise.

Higher liquidity needs as expressed by higher $\dfrac{\mathrm{d}\,\rho_i(L^*_{1,i})}{\mathrm{d}\,L_{1,i}}$ leads to higher $L^*_{1,i}$. To obtain other simple additional comparative statics results from this FOC we restrict attention to the case in which $c^b_i(0, L_{0,i} + L^*_{1,i})$ is linearly increasing (or constant) in the overall indebtedness L_i, i.e. we consider $\mathbb{EL}^b_i(L_i) = \mathbb{EL}^b_i \cdot L_i$ for some positive constant $\mathbb{EL}^b_i$.

To measure the extent to which the public subsidy induced by the public guarantee translates into additional credit we consider a credit multiplier. This is conceptually analogous to a fiscal multiplier (see Acconcia et al., 2014 among others) and allow us to measure how much additional credit is generated by each euro of public guarantee received.[33] More formally, a credit multiplier can be expressed as the ratio between the increase in credit and the amount of guaranteed credit. In the context of this stylized

[32]For example, strict concavity can be micro-founded assuming that the expected return on one unit of additional credit is constant when the firm survives, but firm survival is decreasing in the overall firm indebtedness.

[33]This provides a more transparent measure of the effect of the guarantees on credit supply than a multiplier based on the amount of the loan guaranteed, as this also includes a fraction which is not guaranteed. This is especially relevant in our context because there are several different guarantee programs characterized by different coverage ratios, and a multiplier based on the amount of the guarantee allows for a more transparent comparison across programs.

model the guarantee credit multiplier is equal to $\dfrac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}$. It varies with respect to a primitive variable y of the model according to:

$$\frac{\partial \frac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial y} = \frac{\partial \frac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial L^*_{1,i}} \cdot \frac{\partial L^*_{1,i}}{\partial y} = \frac{1}{x^*_i \bar{L}_i(x^*_i)} \cdot \frac{\partial L^*_{1,i}}{\partial y} \tag{16}$$

Hence the sign is affected by the partial derivative of $L^*_{1,i}$ with respect to the variable of interest y. This derivative can be computed using the implicit function theorem and exploiting the concavity of $\rho_i(L_{1,i})$ and the linearity of $c^b_i(0, L_{0,i} + L^*_{1,i})$. It is straightforward to obtain:

$$\frac{\partial \dfrac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial x_i} = -\frac{1}{x^*_i \bar{L}_i(x^*_i)} \frac{\mathbb{E}\left[\mathbb{EL}^{(win)}_i(L_{0,i} + L^*_{1,i})\right] \bar{L}_i(x^*_i) + \mathbb{E}\left[c^b_i(0, L_{0,i} + L^*_{1,i})^{(win)} - r^{(win)}_D\right]}{\Psi(x^*_i, L_{0,i}, L^*_{i,1})} > 0$$

$$\frac{\partial \dfrac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial L_{0,i}} = \frac{1}{x^*_i \bar{L}_i(x^*_i)} \frac{\mathbb{E}\left[\mathbb{EL}^{(win)}_i(L_{0,i} + L^*_{1,i})\right]}{\Psi(x^*_i, L_{0,i}, L^*_{i,1})} < 0$$

$$\frac{\partial \dfrac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial r^b_D} = \frac{1}{x^*_i \bar{L}_i(x^*_i)} \frac{1 - \mathbb{E}\left[e^{(win)}_i\right]}{\Psi(x^*_i, L_{0,i}, L^*_{i,1})} < 0$$

$$\frac{\partial \dfrac{L^*_{1,i}}{x^*_i \bar{L}_i(x^*_i)}}{\partial r^b_E} = \frac{1}{x^*_i \bar{L}_i(x^*_i)} \frac{\mathbb{E}\left[e^{(win)}_i\right]}{\Psi(x^*_i, L_{0,i}, L^*_{i,1})} < 0$$

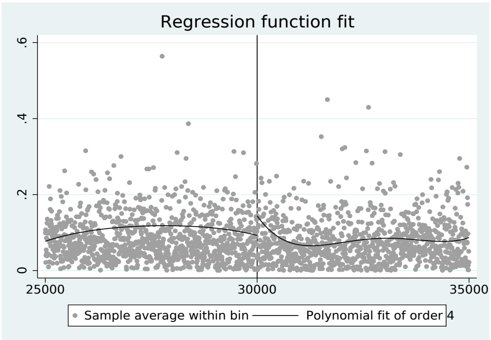
where $\Psi(x^*_i, L_{0,i}, L^*_{i,1}) = \frac{\mathrm{d}^2 \ \rho_i(L^*_{1,i})}{\mathrm{d}^2 \ L_{1,i}} - 2\mathbb{E}\left[\mathbb{EL}^{(win)}_i(L_{0,i} + L^*_{1,i})\right] < 0$.

Remark 3. A higher guarantee coverage x increases the guarantee multiplier. Moreover, a higher initial indebtedness $L_{0,i}$ reduces the amount of new lending $L_{1,i}$. Similarly, higher costs of bank funding r^b_E and r^b_D reduce the amount of new lending. The magnitude of these latter effects increases if coverage x_i is lower.

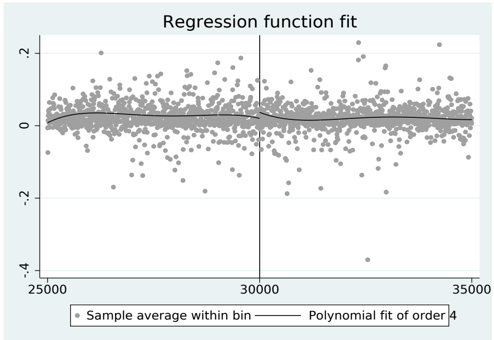
B. Additional Figures and Tables

Figure A.1: **FCG guaranteed loans**

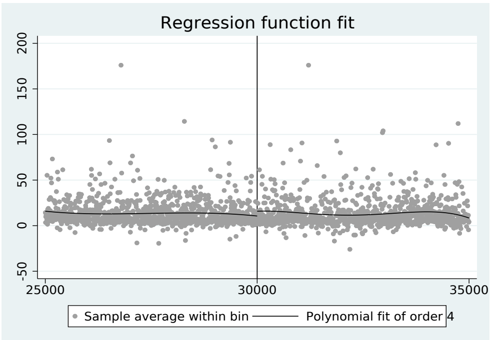
a) Liquidity



b) ROA



c) Interest Coverage Ratio



d) Dummy Bad Z-Score=1

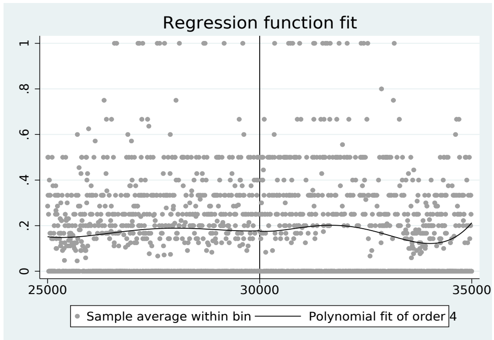


Table A.1: **Firm characteristics across guarantee programs**

		GuarFirm100	GuarFirm90	GuarFirmRen	GuarFirm80
FirmSize	mean	6.410	8.382	8.223	8.119
	sd	1.183	1.268	1.348	1.340
LiquidAssets	mean	0.230	0.186	0.129	0.146
	sd	0.482	0.364	0.271	0.316
FinLeverage	mean	0.171	0.260	0.305	0.284
	sd	0.213	0.200	0.208	0.209
NewFirm	mean	0.046	0.017	0.011	0.014
	sd	0.210	0.128	0.103	0.118
SalesGrowth	mean	0.075	0.120	0.074	0.091
	sd	0.327	0.272	0.255	0.266

Table A.2: **Summary statistics**

A. Dependent variables

	mean	median	p25	p75	sd	N
D(GuaranteedLoan)	0.097	0.000	0.000	0.000	0.296	3,721,682
ΔCredit	0.016	0.000	-0.004	0.000	0.114	3,526,516

B. Guaranteed loan variables

	mean	median	p25	p75	sd	N
GuarAmount	0.018	0.000	0.000	0.000	0.087	3,702,995
GuarFirm100	0.091	0.000	0.000	0.000	0.287	3,721,682
GuarFirm90	0.117	0.000	0.000	0.000	0.321	3,721,682
GuarFirm80	0.108	0.000	0.000	0.000	0.311	3,721,682
GuarFirmRen	0.074	0.000	0.000	0.000	0.261	3,721,682
D(GuarLoan in prev. quarters)	0.181	0.000	0.000	0.000	0.385	3,721,682

C. Bank-level controls

	mean	median	p25	p75	sd	N
ShareFee	0.333	0.372	0.259	0.379	0.079	3,057,009
ShareLoanNFC	0.090	0.095	0.032	0.202	0.137	3,057,009
CapitalRatio	0.073	0.071	0.066	0.079	0.019	3,057,009
ROE	0.046	0.075	0.039	0.087	0.120	3,057,009
BankSize	24.505	25.093	22.001	27.198	2.442	3,057,009
HighCapBank	0.182	0.000	0.000	0.000	0.386	664,673

D. Firm-level controls

	mean	median	p25	p75	sd	N
FirmSize	7.255	7.283	6.155	8.430	1.673	3,659,587
LiquidAssets	0.331	0.096	0.021	0.324	0.678	3,719,385
FinLeverage	0.198	0.131	0.000	0.350	0.219	3,715,862
NewFirm	0.034	0.000	0.000	0.000	0.181	3,721,682
SalesGrowth	0.079	0.038	-0.044	0.162	0.346	3,687,254

E. Relationship controls

	mean	median	p25	p75	sd	N
MainLender	0.455	0.000	0.000	1.000	0.498	3,217,193
ΔCredit2020Q1	-0.004	0.000	-0.020	0.007	0.107	3,207,147

Table A.3: **Propensity to receive a guaranteed loan at the bank-firm level – firm characteristics**

The table shows the results of Eq. (1) estimated at the bank-firm level. *Firm Controls* include either sector and geographical location controls. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 for guaranteed loans granted in 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) sector, province, and bank fixed effects are interacted with quarter dummies. Standard errors are clustered at the firm level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
FirmSize	-0.0006***	-0.0110***	0.0045***	0.0047***	0.0015***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LiquidAssets	-0.0267***	-0.0474***	-0.0238***	-0.0164***	-0.0096***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FinLeverage	0.0185***	0.0086***	0.0280***	0.0300***	0.0145***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NewFirm	0.0134***	-0.0099***	0.0362***	0.0244***	0.0118***
	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)
SalesGrowth	0.0040***	-0.0055***	0.0102***	0.0103***	0.0058***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
ΔCredit2020Q1	0.0424***	0.1862***	0.0140***	-0.0121***	-0.0198***
	(0.0000)	(0.0000)	(0.0020)	(0.0008)	(0.0000)
D(GuarLoan in prev. quarters)			-0.1005***	0.0519***	0.0186***
			(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x FirmSize			0.0061***	-0.0078***	-0.0014***
			(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x LiquidAssets			0.0090***	-0.0008	-0.0006
			(0.0000)	(0.5994)	(0.5610)
D(GuarLoan in prev. quarters) x FinLeverage			0.0012	-0.0192***	-0.0126***
			(0.7697)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x NewFirm			-0.0335***	-0.0052	0.0061
			(0.0000)	(0.3349)	(0.1494)
D(GuarLoan in prev. quarters) x SalesGrowth			0.0026	0.0046*	0.0067***
			(0.3501)	(0.0638)	(0.0004)
D(GuarLoan in prev. quarters) x ΔCredit2020Q1			-0.0514***	-0.0568***	-0.0201***
			(0.0000)	(0.0000)	(0.0000)
Constant	0.0980***	0.2267***	0.0599***	0.0376***	0.0332***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Num. Banks	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.0589	0.0734	0.0394	0.0296	0.0205
Observations	2640783	818261	798318	772612	737748

Table A.4: **Likelihood to receive a guaranteed loan at the bank-firm level by program – firm characteristics**

The table shows the results of Eq. (2) estimated at the bank-firm level. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 if, between 2020Q2 and 2021Q1, the borrower is included in *GuarFirm100* (column 1), *GuarFirm90* (column 2), *GuarFirmRen* (column 3), and *GuarFirm80* (column 4), respectively. The model in column (1) is estimated by including in the control group only firms with revenues below €500 thousands in order to compare more similar borrowers. In all columns fixed effects are interacted with quarter time variables. Standard errors are clustered at the firm level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) Guar.Prog.100	(2) Guar.Prog.90	(3) Ren.	(4) Other Prog.
FirmSize	0.0212***	0.0054***	-0.0008***	-0.0018***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
LiquidAssets	-0.0160***	-0.0085***	-0.0076***	-0.0103***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
FinLeverage	-0.0222***	0.0093***	0.0275***	0.0295***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
NewFirm	0.0103***	0.0121***	0.0011	0.0021*
	(0.0000)	(0.0000)	(0.2413)	(0.0836)
SalesGrowth	-0.0044***	0.0088***	-0.0021***	0.0019***
	(0.0000)	(0.0000)	(0.0000)	(0.0002)
ΔCredit2020Q1	0.0840***	-0.0018	-0.0007	-0.0026*
	(0.0000)	(0.2645)	(0.5745)	(0.0919)
D(GuarLoan in prev. quarters)	0.0237***	0.0469***	0.0421***	0.0520***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x FirmSize	-0.0132***	-0.0069***	-0.0057***	-0.0063***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x LiquidAssets	0.0102***	0.0059***	0.0003	-0.0007
	(0.0000)	(0.0000)	(0.6931)	(0.3815)
D(GuarLoan in prev. quarters) x FinLeverage	0.0344***	-0.0154***	-0.0121***	-0.0160***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
D(GuarLoan in prev. quarters) x NewFirm	-0.0097***	-0.0003	-0.0006	0.0036
	(0.0001)	(0.9292)	(0.8161)	(0.2456)
D(GuarLoan in prev. quarters) x SalesGrowth	0.0027**	0.0038***	-0.0010	0.0018
	(0.0122)	(0.0041)	(0.3973)	(0.2021)
D(GuarLoan in prev. quarters) x ΔCredit2020Q1	-0.0754***	-0.0257***	-0.0300***	-0.0375***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Constant	-0.0215***	-0.0109***	0.0263***	0.0443***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes
Num. Banks	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.1361	0.0249	0.0247	0.0252
Observations	719038	2407762	2407762	2407762

Table A.5: **Propensity to provide a guaranteed loan – bank characteristics with bank-program FE**

The table shows the results of Eq. (3) estimated for the sample of guaranteed borrowers. The model includes an interaction between *BankFE2020Q1*, a bank-specific fixed effect, and the vector *ProgramY*. The dependent variable is $D(GuaranteedLoan)$, which is a dummy variable equal to 1 for guaranteed loans granted in 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm fixed effects are interacted with quarter dummies. Standard errors are clustered at the bank level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
BankFE2020Q1	1.0096	0.6423	2.1439***	0.6089	0.7120
	(0.1099)	(0.4517)	(0.0001)	(0.3564)	(0.1543)
ShareFee	0.1440	0.1680	0.1540	0.0997	0.1576
	(0.1573)	(0.2047)	(0.1426)	(0.5032)	(0.1082)
ShareLoanNFC	-0.1567**	-0.2080**	-0.1334**	-0.0243	-0.0829
	(0.0176)	(0.0138)	(0.0281)	(0.7713)	(0.1009)
CapitalRatio	-0.3147	-0.8911*	0.6644	-0.0652	-0.1512
	(0.4226)	(0.0854)	(0.1333)	(0.9066)	(0.7098)
ROE	0.0932*	0.2005***	-0.0506	0.0532	0.1239***
	(0.0509)	(0.0000)	(0.6388)	(0.4067)	(0.0007)
BankSize	0.0168***	0.0163***	0.0153***	0.0132***	0.0218***
	(0.0000)	(0.0001)	(0.0000)	(0.0035)	(0.0000)
GuarFirm90 x BankFE2020Q1	1.4241**	2.5678*	0.7013	1.1491**	1.0192*
	(0.0267)	(0.0702)	(0.3168)	(0.0308)	(0.0528)
GuarFirm90 x ShareFee	-0.3267***	-0.3280	-0.2504**	-0.3588**	-0.4867***
	(0.0073)	(0.1333)	(0.0406)	(0.0148)	(0.0001)
GuarFirm90 x ShareLoanNFC	-0.0275	-0.1225	-0.0119	-0.0921	-0.0156
	(0.7748)	(0.4853)	(0.8766)	(0.2403)	(0.8425)
GuarFirm90 x CapitalRatio	1.1536	3.1181**	0.3587	0.3406	-0.3315
	(0.1550)	(0.0377)	(0.5760)	(0.6066)	(0.5174)
GuarFirm90 x ROE	0.0135	-0.0996	0.1625**	0.0359	-0.0452
	(0.6985)	(0.1596)	(0.0159)	(0.2564)	(0.1334)
GuarFirm90 x BankSize	0.0080	0.0208	0.0033	0.0070	0.0047
	(0.3665)	(0.1952)	(0.6372)	(0.2309)	(0.2995)
GuarFirmRen x BankFE2020Q1	1.9076*	0.3829	2.9982*	2.5176**	3.6985**
	(0.0971)	(0.7866)	(0.0510)	(0.0246)	(0.0206)
GuarFirmRen x ShareFee	0.2832	0.2235	0.2156	0.4851*	0.4549
	(0.1727)	(0.3039)	(0.4628)	(0.0738)	(0.1823)
GuarFirmRen x ShareLoanNFC	0.2322**	0.3978***	0.3253**	0.0539	0.0554
	(0.0493)	(0.0058)	(0.0411)	(0.6751)	(0.7009)
GuarFirmRen x CapitalRatio	-0.6088	-0.9611	-0.6382	-0.7533	0.0587
	(0.3061)	(0.1897)	(0.3746)	(0.4299)	(0.9489)
GuarFirmRen x ROE	-0.3158***	-0.1819	-0.2200	-0.3366***	-0.2841***
	(0.0062)	(0.2278)	(0.1100)	(0.0002)	(0.0001)
GuarFirmRen x BankSize	0.0022	-0.0106	0.0026	0.0001	0.0061
	(0.7177)	(0.1679)	(0.7527)	(0.9931)	(0.5585)
GuarFirm80 x BankFE2020Q1	-0.4056	1.0472	-1.9946	-1.3932	-1.2146
	(0.7271)	(0.2940)	(0.1600)	(0.2815)	(0.4725)
GuarFirm80 x ShareFee	-0.3353	-0.1551	-0.2875	-0.5673*	-0.5486
	(0.1855)	(0.3678)	(0.4380)	(0.0557)	(0.1757)
GuarFirm80 x ShareLoanNFC	-0.0150	-0.0055	-0.0332	-0.0778	0.0273
	(0.8692)	(0.9531)	(0.7858)	(0.4509)	(0.8384)
GuarFirm80 x CapitalRatio	-0.4885	-0.3282	-0.9837	-0.8237	-0.5035
	(0.4385)	(0.6370)	(0.2603)	(0.2630)	(0.6633)
GuarFirm80 x ROE	0.0754*	0.0790	0.0470	0.0502	0.0256
	(0.0859)	(0.1204)	(0.5517)	(0.3259)	(0.7225)
GuarFirm80 x BankSize	0.0020	-0.0073	0.0001	0.0167**	0.0045
	(0.7322)	(0.1886)	(0.9902)	(0.0338)	(0.6665)
Constant	-0.2427**	-0.2022	-0.1935*	-0.2661***	-0.3676***
	(0.0268)	(0.3327)	(0.0855)	(0.0003)	(0.0000)
Firm FE	Yes	Yes	Yes	Yes	Yes
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.1957	0.1876	0.2015	0.2049	0.2048
Observations	600259	197774	166212	142381	93892

Table A.6: **Public guarantees and credit growth - test with bank-specific multipliers on *Guarantee90* loans**

The table shows the results of Eq. (4) estimated for the sample of borrowers that have received *Guarantee100* or *Guarantee90* loans. The model includes an interaction between bank-specific fixed effects, *GuarLoan* and *GuarAmount*. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan	-0.0061***	-0.0071*	-0.0030	-0.0095**	-0.0068
	(0.0096)	(0.0658)	(0.4784)	(0.0266)	(0.3702)
GuarLoan x GuarFirm100	0.0129***	0.0038**	0.0115***	0.0134***	0.0168***
	(0.0000)	(0.0131)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirm100 x GuarAmount	0.0592***	0.2542***	-0.0940***	-0.0696***	-0.0911***
	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.0073)
Constant	0.0021***	0.0024***	0.0026***	0.0014***	0.0012***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)
Firm FE	Yes	Yes	Yes	Yes	Yes
Rel. Controls	Yes	Yes	Yes	Yes	Yes
BankFE x GuarLoan x GuarAmount	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.5871	0.6054	0.6461	0.5512	0.5608
Observations	494972	192571	141655	98662	62084

Table A.7: **Non-guaranteed granted credit growth for guaranteed borrowers**

The table shows the results of a model estimated by adopting as the dependent variable $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. We consider only credit granted by banks that did not provide guaranteed loans to each guaranteed borrower. In column (1) sector, province, and bank fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarAmount	-0.0192***	-0.0257***	-0.0094***	-0.0201***	-0.0202***
	(0.0000)	(0.0000)	(0.0089)	(0.0000)	(0.0000)
GuarFirm90xGuarAmount	0.0122***	0.0200***	0.0037	0.0096***	0.0146***
	(0.0000)	(0.0000)	(0.2598)	(0.0000)	(0.0000)
GuarFirmRenxGuarAmount	-0.0046***	0.0008	-0.0035	-0.0068***	-0.0091***
	(0.0003)	(0.7957)	(0.1402)	(0.0019)	(0.0011)
GuarFirm80xGuarAmount	0.0107***	0.0150***	0.0038	0.0109***	0.0128***
	(0.0000)	(0.0000)	(0.2795)	(0.0000)	(0.0012)
GuarFirm90	-0.0027***	-0.0040***	-0.0034***	-0.0003	-0.0012*
	(0.0000)	(0.0000)	(0.0000)	(0.4727)	(0.0592)
GuarFirmRen	-0.0014***	-0.0013**	-0.0006	-0.0012**	-0.0015**
	(0.0000)	(0.0241)	(0.3060)	(0.0155)	(0.0131)
GuarFirm80	-0.0019***	-0.0021***	-0.0039***	-0.0003	0.0004
	(0.0000)	(0.0001)	(0.0000)	(0.5372)	(0.5962)
Constant	0.0070***	0.0068***	0.0103***	0.0047***	0.0035***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	621942	196585	171781	146444	107132

Table A.8: **Non-guaranteed outstanding credit growth for guaranteed borrowers**

The table shows the results of a model estimated by adopting as the dependent variable $\Delta OutstandingCredit_{i,j}$, which is the change in outstanding credit by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. We consider only credit granted by banks that did not provide guaranteed loans to each guaranteed borrower. In column (1) sector, province, and bank fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarAmount	-0.0392***	-0.0790***	-0.0081	-0.0330***	-0.0467***
	(0.0000)	(0.0000)	(0.3389)	(0.0002)	(0.0000)
GuarFirm90xGuarAmount	0.0289***	0.0667***	0.0017	0.0188**	0.0392***
	(0.0000)	(0.0000)	(0.8310)	(0.0117)	(0.0001)
GuarFirmRenxGuarAmount	-0.0121***	-0.0067	-0.0111	-0.0098*	-0.0203**
	(0.0002)	(0.4695)	(0.1166)	(0.0729)	(0.0165)
GuarFirm80xGuarAmount	0.0262***	0.0491***	0.0077	0.0186**	0.0411***
	(0.0000)	(0.0000)	(0.4017)	(0.0236)	(0.0006)
GuarFirm90	-0.0027***	0.0012	-0.0084***	-0.0041***	-0.0070***
	(0.0000)	(0.2844)	(0.0000)	(0.0021)	(0.0000)
GuarFirmRen	-0.0050***	-0.0003	-0.0054***	-0.0059***	-0.0049***
	(0.0000)	(0.8262)	(0.0005)	(0.0000)	(0.0005)
GuarFirm80	0.0008	0.0029*	-0.0053***	-0.0001	-0.0029
	(0.2819)	(0.0511)	(0.0021)	(0.9681)	(0.1335)
Constant	0.0050***	-0.0076***	0.0168***	0.0105***	0.0135***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Observations	619127	195485	171077	145799	106766

Table A.9: **Public guarantees and credit growth – loan moratorium**

The table shows the results of Eq. (4) estimated by interacting, for each program, $GuarAmount$ with $Moratorium$, which is a dummy equal to 1 if the borrower benefited from a moratorium on that credit relationship in t and/or t-1. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in t-1 for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	0.7110***	0.8244***	0.5852***	0.4720***	0.5604***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarFirm90 x GuarAmount	-0.0992***	-0.2638***	0.0798***	0.0779***	0.0168
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.3201)
GuarLoan x GuarFirmRen x GuarAmount	-0.0983***	-0.1357***	-0.0671***	-0.0798***	-0.0659***
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0016)
GuarLoan x GuarFirm80 x GuarAmount	-0.2247***	-0.2718***	-0.1442***	-0.0647***	-0.1072***
	(0.0000)	(0.0000)	(0.0000)	(0.0005)	(0.0000)
GuarLoan x Moratorium x GuarAmount	0.0646***	0.0519***	0.0785***	0.0536***	0.0326
	(0.0000)	(0.0000)	(0.0000)	(0.0010)	(0.1336)
GuarLoan x GuarFirm90 x Moratorium x GuarAmount	-0.0040	0.0169	-0.0378***	-0.0168	-0.0320
	(0.5692)	(0.2436)	(0.0032)	(0.3082)	(0.1402)
GuarLoan x GuarFirmRen x Moratorium x GuarAmount	-0.0409***	-0.1818***	0.0012	0.0006	0.0217
	(0.0015)	(0.0000)	(0.9624)	(0.9835)	(0.4667)
GuarLoan x GuarFirm80 x Moratorium x GuarAmount	-0.0274**	0.0154	-0.0374	-0.0342	-0.0764**
	(0.0233)	(0.4054)	(0.1469)	(0.2273)	(0.0213)
Constant	0.0006***	-0.0002	0.0020***	0.0009***	-0.0006***
	(0.0000)	(0.1689)	(0.0000)	(0.0000)	(0.0000)
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
Sector FE	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.2965	0.5131	0.2765	0.1630	0.1394
Observations	3507628	851018	877850	888597	890163

Table A.10: **Guarantee program 100 and credit growth - bank characteristics**

The table shows the results of Eq. (4) estimated by interacting $GuarLoan \cdot GuarAmount$ with bank characteristics and by employing the sample of borrowers that have received a guaranteed loan under the guarantee program 100. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. Standard errors are clustered at the bank level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	-0.2022	-0.3837**	-0.0161	-0.1051	0.4181*
	(0.1499)	(0.0323)	(0.9463)	(0.6463)	(0.0941)
GuarLoan x GuarAmount x ShareFee	0.3514	0.3424	0.1626	0.2170	0.2238
	(0.2052)	(0.2844)	(0.6538)	(0.4641)	(0.6174)
GuarLoan x GuarAmount x ShareLoanNFC	-0.1225	-0.1885	0.1883	-0.2878*	-0.0314
	(0.3068)	(0.2200)	(0.3111)	(0.0902)	(0.9098)
GuarLoan x GuarAmount x CapitalRatio	2.7462***	2.4986**	3.5197***	4.0247**	-2.0942
	(0.0002)	(0.0139)	(0.0015)	(0.0115)	(0.2938)
GuarLoan x GuarAmount x ROE	0.1305**	0.2658***	0.0645	-0.2731**	0.0923
	(0.0463)	(0.0067)	(0.4954)	(0.0378)	(0.5678)
GuarLoan x GuarAmount x BankSize	0.0207***	0.0294***	0.0137	0.0132	0.0105
	(0.0008)	(0.0004)	(0.1192)	(0.1462)	(0.4620)
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
GuarLoan x BankVar	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.5120	0.5656	0.4586	0.4109	0.4511
Observations	144274	93988	27903	15918	6465

Table A.11: **Guarantee program 90 and credit growth - bank characteristics**

The table shows the results of Eq. (4) estimated by interacting $GuarLoan \cdot GuarAmount$ with bank characteristics and by employing the sample of borrowers that have received a guaranteed loan under the guarantee program 90. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. Standard errors are clustered at the bank level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	-0.2638	-0.9801***	0.1310	-0.1405	-0.1575
	(0.1831)	(0.0047)	(0.3884)	(0.4844)	(0.3704)
GuarLoan x GuarAmount x ShareFee	0.5534**	0.4107	0.3826	0.4121	1.2514***
	(0.0446)	(0.4025)	(0.1203)	(0.1144)	(0.0000)
GuarLoan x GuarAmount x ShareLoanNFC	-0.0815	-0.1652	0.0542	-0.1029	-0.0945
	(0.3953)	(0.4011)	(0.6066)	(0.2825)	(0.4254)
GuarLoan x GuarAmount x CapitalRatio	3.5376***	4.3214***	2.6161***	4.0476***	3.4090***
	(0.0000)	(0.0014)	(0.0026)	(0.0000)	(0.0003)
GuarLoan x GuarAmount x ROE	0.0659	0.4808**	0.1859***	-0.0398	-0.2873**
	(0.3928)	(0.0178)	(0.0044)	(0.7368)	(0.0158)
GuarLoan x GuarAmount x BankSize	0.0182***	0.0414***	0.0100**	0.0134**	0.0046
	(0.0008)	(0.0000)	(0.0243)	(0.0174)	(0.5045)
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
GuarLoan x BankVar	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.6014	0.5911	0.6582	0.5617	0.5528
Observations	284878	74451	95849	69111	45467

Table A.12: **Renegotiation program and credit growth - bank characteristics**

The table shows the results of Eq. (4) estimated by interacting $GuarLoan \cdot GuarAmount$ with bank characteristics and by employing the sample of borrowers that have received a renegotiated guaranteed loan. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. In column (1) firm and bank fixed effects are interacted with quarter dummies. Standard errors are clustered at the bank level. Robust p-values in parentheses.. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	-0.1343	-0.6045**	-0.0559	0.0132	0.2541*
	(0.3045)	(0.0286)	(0.7265)	(0.9254)	(0.0560)
GuarLoan x GuarAmount x ShareFee	0.3653*	0.6486*	0.3847	0.1264	0.3508*
	(0.0791)	(0.0845)	(0.1001)	(0.5209)	(0.0670)
GuarLoan x GuarAmount x ShareLoanNFC	0.1853*	-0.0908	0.2915***	0.2214*	0.3122**
	(0.0505)	(0.4939)	(0.0050)	(0.0640)	(0.0104)
GuarLoan x GuarAmount x CapitalRatio	1.5960***	1.9319	1.4179	1.9610***	1.0176
	(0.0070)	(0.1213)	(0.1164)	(0.0021)	(0.1790)
GuarLoan x GuarAmount x ROE	-0.0478	0.2179*	0.0767	-0.2416***	-0.1122
	(0.2930)	(0.0718)	(0.1816)	(0.0000)	(0.1080)
GuarLoan x GuarAmount x BankSize	0.0148***	0.0262**	0.0140***	0.0106**	0.0004
	(0.0023)	(0.0189)	(0.0074)	(0.0460)	(0.9436)
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
GuarLoan x BankVar	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.4927	0.4996	0.5428	0.4557	0.4691
Observations	195778	32398	60841	64490	38049

Table A.13: **Firms with multiple guarantee program 90 loans and credit growth - bank characteristics**

The table shows the results of Eq. (4) estimated by interacting $GuarLoan \cdot GuarAmount$ with bank characteristics and by employing the sample of borrowers that have received more than one guaranteed loan under the guarantee program 90. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in *t-1* for each period: 2020Q2-2021Q1 (column 1), 2020Q2 (column 2), 2020Q3 (column 3), 2020Q4 (column 4), 2021Q1 (column 5), respectively. The models are estimated by including firm fixed effects interacted with *GuarLoan*. In column (1) firm and bank fixed effects are interacted with quarter dummies. Standard errors are clustered at the bank level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) All periods	(2) 2020Q2	(3) 2020Q3	(4) 2020Q4	(5) 2021Q1
GuarLoan x GuarAmount	-0.5218**	-0.9040**	-0.2716	-0.0292	-0.9443
	(0.0480)	(0.0453)	(0.2916)	(0.9461)	(0.1654)
GuarLoan x GuarAmount x ShareFee	0.1920	0.3560	0.3706	-0.4577	0.4044
	(0.5832)	(0.5485)	(0.3661)	(0.3472)	(0.6455)
GuarLoan x GuarAmount x ShareLoanNFC	-0.0957	-0.0563	0.0701	-0.1809	-0.6121
	(0.5662)	(0.8498)	(0.7456)	(0.4679)	(0.2000)
GuarLoan x GuarAmount x CapitalRatio	5.9125***	4.0250*	5.4759***	7.2421***	10.3466***
	(0.0000)	(0.0856)	(0.0006)	(0.0059)	(0.0007)
GuarLoan x GuarAmount x ROE	0.0077	0.8667***	0.0719	-0.2762	-0.2246
	(0.9603)	(0.0069)	(0.7320)	(0.2566)	(0.5875)
GuarLoan x GuarAmount x BankSize	0.0224***	0.0361**	0.0121	0.0119	0.0199
	(0.0065)	(0.0134)	(0.2042)	(0.4632)	(0.5576)
Rel. Controls	Yes	Yes	Yes	Yes	Yes
Guar. program dummies	Yes	Yes	Yes	Yes	Yes
GuarLoan x BankVar	Yes	Yes	Yes	Yes	Yes
Firm FExGuar. program dummies	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.6202	0.6050	0.6497	0.5796	0.6195
Observations	41127	14679	15453	7671	3161

Table A.14: **Public guarantees and credit growth – firm characteristics**

The table shows the results of Eq. (4) estimated by interacting $GuarLoan \cdot GuarAmount$ with firm characteristics. The dependent variable is $\Delta Credit_{i,j}$, which is the change in credit granted by bank j to firm i over the total amount of granted credit to firm i in 2020Q1 for borrowers included in *GuarFirm100* (column 1), *GuarFirm90* (column 2), *GuarFirmRen* (column 3), and *GuarFirm80* (column 4), respectively. In all columns fixed effects are interacted with quarter time variables. Standard errors are clustered at the firm level. Robust p-values in parentheses. * $p < .1$, ** $p < .05$, *** $p < .01$.

	(1) Guar.Prog.100	(2) Guar.Prog.90	(3) Ren.	(4) Other Prog.
GuarLoan x GuarAmount	1.2108***	0.6438***	0.4383***	0.3799***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarAmount x FirmSize	-0.0851***	-0.0021	0.0119***	0.0159***
	(0.0000)	(0.6394)	(0.0013)	(0.0000)
GuarLoan x GuarAmount x LiquidAssets	0.0318	0.0339**	0.0212	-0.0015
	(0.1631)	(0.0109)	(0.1488)	(0.9240)
GuarLoan x GuarAmount x FinLeverage	-0.2000***	-0.1214***	-0.1136***	-0.0945***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
GuarLoan x GuarAmount x NewFirm	-0.1165**	-0.0725	0.0018	-0.0148
	(0.0262)	(0.1417)	(0.9624)	(0.7493)
GuarLoan x GuarAmount x SalesGrowth	0.0138	-0.0163	0.0359**	0.0183
	(0.6336)	(0.3934)	(0.0201)	(0.2732)
GuarLoan	0.0373***	0.0236***	-0.0145***	0.0056
	(0.0000)	(0.0000)	(0.0010)	(0.2474)
GuarLoan x FirmSize	-0.0032***	-0.0023***	0.0009*	-0.0013**
	(0.0000)	(0.0003)	(0.0642)	(0.0177)
GuarLoan x LiquidAssets	0.0016	0.0088***	0.0090***	0.0058*
	(0.5472)	(0.0023)	(0.0040)	(0.0871)
GuarLoan x FinLeverage	-0.0060*	-0.0087**	0.0043	0.0046
	(0.0543)	(0.0174)	(0.1397)	(0.1649)
GuarLoan x NewFirm	0.0182**	0.0323***	0.0072	0.0117
	(0.0116)	(0.0026)	(0.4564)	(0.3280)
GuarLoan x SalesGrowth	0.0037	0.0079**	0.0023	0.0028
	(0.2188)	(0.0131)	(0.3865)	(0.3293)
Constant	0.0035***	0.0025***	0.0020***	0.0015***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Firm FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Rel. Controls	Yes	Yes	Yes	Yes
Adj. R-squared	0.5403	0.5922	0.4894	0.4925
Observations	186229	350916	337058	236362

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