Public Guarantees for Small Businesses in Italy during Covid-19

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Abstract

This paper investigates whether the private sector can efficiently allocate public funds during a crisis. Using loan-level data, we exploit the unique features of the Italian public guarantee scheme during Covid-19 to study lenders' incentives to distribute government guaranteed credit. Our results indicate that two key bank characteristics facilitated loan disbursement: size and information technology. These factors are important because of the high volume of online applications and low interest margins on guaranteed lending. Pre-existing relationships matter for the allocation of guaranteed credit, as banks lend more in their core markets and where they have a larger share of branches.

Keywords: public guarantees; covid-19; liquidity constraints; information technology; lending relationships
JEL: G21, G28

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1 Introduction

What is the most effective way to deploy government funds to help the real economy during a crisis? Policymakers worldwide faced this question when Covid-19 forced a global business shutdown and caused a severe liquidity crunch, especially among small businesses (SMEs) that have no access to capital markets. Many countries relied on the private financial sector, and the banking system in particular, to act as a conduit of government-backed liquidity to SMEs.[1] Since these types of policy interventions are likely to continue in the aftermath of the pandemic, it is of crucial importance to understand whether the private sector can deliver the liquidity to the firms who need it or whether the existence of frictions distorts the allocation of public funds.

Governments can lend to non-financial firms either directly or through public guarantees on private credit.[2] Direct government lending has two main shortcomings: first, transaction costs and asymmetric information frictions may prevent governments from setting up lending facilities to small borrowers in a short window of time; second, lending by government-owned banks is typically characterized by inefficiencies emerging from political connections (Sapienza, 2004; Khwaja and Mian, 2005). For these reasons, governments often prefer to issue public guarantees on private bank loans rather than direct government loans. However, while providing credit through guarantees may promote productive efficiency, it may hinder allocative efficiency. In fact, if the banking sector is heterogeneous in its ability to disburse funds, especially in the presence of a high volume of online applications, or if pre-existing bank-firm relationships are sticky, funds may not reach the neediest firms.

We study this question exploiting the unique institutional features of the Covid-19 guarantee program in Italy. On April 8^{th}, 2020 the government expanded the existing public guarantee scheme for SMEs, increasing the guarantee coverage from 80% to 90% for loans up to

[1] For a summary of the stimulus measures approved in Europe and other countries see https://www.imf.org/en/Topics/imf-and-covid19/Policy-Responses-to-COVID-19.

[2] The government can also provide grants instead of loans. While the trade-off between grants and loans is a very important issue (Elenev et al., 2020), in this paper we focus on lending.

€5 million. Moreover, it introduced a 100% guarantee for €25,000 loans (increased to €30,000 in June) that requires no fee payment from the borrower and no formal credit assessment by the bank, in order to speed up the approval process. Since credit risk is fully absorbed by the government, the Italian guarantee program is thus ideal to study lenders' incentives to distribute public relief funds to small firms. Moreover, using loan-level information from the Italian Guarantee Fund (*Fondo di Garanzia*, FG), matched with both firm and bank balance sheet data allows us to distinguish credit supply from demand with a granular set of province×6-digit-industry fixed-effects, together with firm-level characteristics.[3] This is a key advantage of Italian FG data compared to the US Paycheck Protection Program (PPP).[4]

We first describe the program and its targeting. Between April and August 2020, Italian banks issued almost one million government guaranteed loans to around 900,000 small businesses for an aggregate amount of €79 billion. This is a significant amount of credit, representing about 10% of total lending to the private sector in 2019 and 2% of the average bank total assets. Most of the individual loans (86%) are fully guaranteed and hence are small (below €25,000) and they add up to a total of €18 billion. The overall take-up rate is 16% among all eligible firms in Italy and about 25% in our sample, that includes all companies with full financial accounts.[5] Given the different institutional setting and relative market size, we analyze fully guaranteed loans separately from partially guaranteed ones.

In general, we find that areas and sectors most affected by the pandemic and business shutdowns were more likely to obtain the 100% guaranteed loans, but the correlation is weaker for partially guaranteed loans. Moreover firms with less cash on hand, higher leverage

[3]In robustness tests we use a firm fixed-effect, exploiting the fact that firms could obtain multiple partially guaranteed loans from different banks. The results are quantitatively similar, indicating that 6-digit industry×province fixed-effects are already sufficient to capture most factors that affect credit demand.

[4]All limited liability companies in Europe, irrespective of their size, have to publicly disclose their financial accounts. This is not the case in the US. Thus, even though on December 1, 2020 the SBA released data that include the names of all 5.16 million PPP borrowers, these data cannot be matched to firm-level balance sheet data. Firm-level PPP evidence focuses on publicly listed firms (Balyuk et al., 2020; Duchin et al., 2020).

[5]While data on loan applications are not available, a May 2020 firm survey (ISTAT, 2020) suggests that 60% of eligible firms did not ask for a loan and that rejection rates on guaranteed loans were virtually zero (1.4%). The take-up rate on government guaranteed loans has been similarly low in Spain and France too (The Economist, 2020). Paaso et al. (2020) find that entrepreneurs' debt aversion may be one of the reasons for the low take-up of government guaranteed loans among Finnish firms.

and lower Altman Z-scores (i.e. riskier firms) have higher take-up rates in both types of guaranteed loans, with the only natural difference that fully guaranteed loans (up to €25,000) are obtained by smaller firms. However, these effects vary over time for 100% guaranteed loans: in the initial and most acute phase of the pandemic (April and May) financially fragile firms located in areas more severely affected were more likely to obtained guaranteed credit than other eligible firms. In the second phase (June-August), as the rate of infections slowed and the lockdown measures were lifted, the correlation reverses: all types of firms, including those in areas that were less affected by the pandemic, were likely to obtain the funds.

Second, and most importantly, we find significant supply-side heterogeneity in the allocation of credit, the loan interest rate and the disbursement time of guaranteed loans. For example, we find that large banks charge lower rates and disburse guaranteed loans faster than small local banks. This is true for fully guaranteed loans, but not for partially guaranteed ones. Large banks may have an advantage in issuing 100% guaranteed loans for two reasons. First, large banks have lower funding costs than small institutions, for example due to preferential access to ECB lending facilities. Second, since interest margins on government guaranteed credit are low, especially for small loans (1-2% in gross interest), only large banks that can process a large volume of loans in an automatized way can achieve profitability. Small and cooperative banks, that are traditionally thought to be able to better serve small businesses, especially in a crisis (Berger et al., 2017), cannot achieve efficient economies of scale on these loans and are much more reluctant to lend.

Another important supply side restriction pertains to the digital infrastructure which was needed to handle the surge in online loan applications. In this respect, we find that banks with better information technology (IT) systems, as proxied by the Google Playstore review rating on their mobile banking app, disburse guaranteed loans twice as fast as the average bank.[6] Thus banks with better IT systems were able to serve the surge in online loan

[6] Google's Android is the most commonly used smartphone operating system in Italy, capturing 80% of the market in 2019. Data on bank investment in IT is not available, hence mobile banking app reviews provide a customer-based measure of the quality of IT.

applications better than banks with a poor digital infrastructure. Importantly, this is true after controlling for standard bank characteristics, including bank size, which indicates that the quality of IT systems matters beyond the scale effect described above. These effects are not driven by credit demand, as we control for a full set of province×6-digit industry or even firm fixed-effects, when possible.[7]

Since most applications for guaranteed loans were filed online, one may question the relevance of the bank branch network over this period. Indeed, the number of bank branches has been steadily declining in Italy and other developed countries over the last ten years. Covid-19 has accelerated the adoption of digital technologies in all sectors of the economy, including banking (Fu and Mishra, 2020). However, since lending relationships are notoriously sticky (Petersen and Rajan, 1994; Degryse and Ongena, 2005), local lending markets and the bank branch network have remained important for the allocation of credit (Gilje et al., 2016). We find that this is case: banks lend more in their core markets, i.e. in provinces where they have a larger fraction of their branch network, and in markets where they have more market power, i.e. a larger share of local branches. Thus pre-existing lending relationships and local banking markets determine the allocation of guaranteed lending,

Lastly, we find that firms characteristics matter for explaining the pricing of guaranteed loans, even for those that are 100% guaranteed. Younger and smaller firms, with less cash on hand and higher leverage pay higher interest rates, but see lower disbursement times. However, the economic importance of these factors is limited and the variation in loan rates and disbursement times is mostly explained by bank heterogeneity.

Overall, our results indicate that, although the overall take-up rate was fairly low, funds did go to areas and firms most affected by the pandemic, at least initially. As the economic effects of the pandemic and the lockdown measures propagated across the rest of the country, financially healthier firms located in least affected areas started to receive the funds too. And

[7]Firm characteristics, as opposed to bank characteristics, instead explain the variation in loan size for partially guaranteed loans. Thus, whereas pricing and disbursement times are mostly affected by supply-side restrictions, loan size appears to be demand-driven.

although the banking sector has been relatively efficient in disbursing the fully guaranteed loans, handing them out one week before the approval of the guarantee, there is significant lender heterogeneity. Crucially, the quality of the bank IT infrastructure hampered the process of distributing guaranteed loans, in terms of pricing and processing times. Notably, local cooperative banks, which are thought to have a comparative advantage in lending to small businesses (Berger et al., 2017), are conspicuously inefficient in providing 100% government guaranteed loans that are meant to target the very small firms: they charge higher rates compared to other banks (145 vs 119 bps on average) and take almost a week longer to disburse them. Thus, these results indicate that relying on the private sector to distribute public funds may lead to heterogeneous outcomes, depending on the existing bank-firm match: if a firm was matched with an efficient bank it would receive guaranteed loans faster and at better conditions.

This paper contributes to the literature on public credit guarantees. Many papers have focused on the US loan guarantee program from the Small Business Administration (SBA) (Brown and Earle, 2017; Bachas et al., 2019). Others have studied the effect of loan guarantees on firm performance in the UK (Gonzalez-Uribe and Wang, 2020), the creation of new bank relationships in Chile (Mullins and Toro, 2017) or employment and earnings in France (Barrot et al., 2019). Few however have examined the effects of guarantees on loan outcomes such as interest rates or loan origination times with matched firm-bank data. We are also the first to uncover the importance of the bank IT infrastructure in allocating government-backed liquidity.

This paper also joins the burgeoning literature studying the impact of the Covid-19 pandemic on financial markets and corporate outcomes. Many papers have focused on stock market reactions to Covid-19 (Croce et al., 2020; Gerding et al., 2020; Ramelli and Wagner, 2020). Covid-19 led to the largest increase in demand for credit ever observed by commercial banks (Li et al., 2020), which improved the stock market performance of firms with access to such liquidity (Acharya and Steffen, 2020). Draw-downs on existing credit lines from large firms, that cannot be fully explained by differential demand for liquidity (Chodorow-Reich et al., 2020), may also have crowded out other forms of credit to smaller firms (Greenwald et al., 2020). Others have focused on the impact of Covid-19 on SMEs employment and default, both in the US (Bartik et al., 2020) and in Europe (Gourinchas et al., 2020). Italy is one of the country most severely affected by the rise in NPLs due to its high share of SMEs (Carletti et al., 2020). Balduzzi et al. (2020) show that Italian firms in more affected areas and sectors become more pessimistic about future sales.

Many contemporary studies have analyzed the impact of the US loan guarantee program (PPP) on employment and other outcomes (Autor et al., 2020; Chetty et al., 2020). Detailed balance-sheet information on PPP borrowers is typically restricted to publicly listed firms (Balyuk et al., 2020; Duchin et al., 2020). Our data instead allow us to trace the firm-level uptake for a large sample of private small firms. In terms of lender heterogeneity, Granja et al. (2020) analyze the allocation of PPP loans and find that funds did not flow to areas more adversely affected by the business shutdowns, partly because of significant heterogeneity across banks in terms of disbursing PPP funds. Erel and Liebersohn (2020) show that PPP loans from online banks and non-banks (FinTech) were used in ZIP codes typically under-served by banks. Finally, Li and Strahan (2020) show that PPP lending reflects traditional credit supply factors at bank level, such as bank size, lending commitments and the importance of core deposit markets.

The strong heterogeneity in lender participation is a prominent feature of our data too, suggesting that bank supply-side restrictions are relevant for the post-pandemic loan guarantee programs in different countries. A big picture insight of our results is that if low-cost government backed liquidity meant to support small businesses is channeled through the banking system, the existing lending technology and other local banking market characteristics will determine who gets credit first and at which condition.

2 The Role of Public Credit Guarantees

The goal of public credit guarantees is to improve access to credit for firms, especially SMEs or start-ups, that do not have adequate collateral to participate in private credit markets because of asymmetric information (Stiglitz and Weiss, 1981). Loan guarantees issued by government-backed entities, like the SBA in the US or the FG in Italy, have several supposed advantages over other types of public interventions in credit markets, such as direct lending by a public institution (Jimenez et al., 2019). First, by delegating screening and monitoring to private banks, issuing public guarantees mitigates the risk of politically connected lending (Khwaja and Mian, 2005). Since guarantees are typically partial, banks retain some skin-in-the-game, which limits moral hazard on their side. Second, guarantees are a cost-effective way for the government to support bank lending to SMEs, because they require low initial outlays compared to direct lending.

There are several potential downsides to the use of guarantees as well. If firms obtaining government guaranteed credit are those that would have obtained private funding anyways, there would be no impact on overall access to credit for firms. Worse, guarantees might lead to adverse selection, attracting marginally riskier borrowers and worsening the overall pool of firms receiving credit. Additionally, banks could have lower incentives in screening and monitoring of the borrowers in the presence of moral hazard. In this case, future defaults will eventually increase (de Blasio et al., 2018), leading to a high cost of the scheme for public finances ex-post. Thus, whether public credit guarantees are effective in supporting firms' access to credit is ultimately an empirical question, an answer to which remains elusive to date.

2.1 The Italian Public Guarantee Scheme

The recourse to credit guarantee schemes to alleviate funding constraints for small businesses is not new. These types of government interventions became increasingly popular after the

2007-08 financial crisis (Beck et al., 2010). In Italy, the public guarantees scheme, named *Fondo di Garanzia* (FG), started its operations in 2000 and has supported SME lending massively in the aftermath of both the financial crisis and the sovereign debt crisis (de Blasio et al., 2018). The loan guarantee program in Italy was already quite large compared to other countries even before Covid-19. For example, in 2017 a total of €17.5 billion in new loans to SMEs received a public credit guarantee, compared to €4 billion in France and $25 billion in the US. As required by EU State Aid rules, the borrower needs to pay a fee to benefit from the public guarantee. The fees vary between 25 and 200 bps, depending on the size of the firm and the residual maturity of the loan.

In response to the Covid-19 pandemic, on April 8^{th}, 2020 the Italian government approved a law decree, the so-called *DL Liquiditá*, that strengthened the FG capacity to issue guarantees by an additional €400 billion. Of these, €200 billion were dedicated to guarantees for small firms below 500 employees and represent the key novelty of the Italian guarantee fund. First of all, the guarantee coverage was increased from 80% to 90% and eligible loan size went from €1.5 to €5 million.[8] The amount of the loan is capped at one quarter of sales in 2019 or twice annual payroll. Second, for loan amounts up to €25,000 (increased to €30,000 in June), the guarantee is full and free, i.e. no extra-fees are charged to the borrower to obtain it. Moreover, interest rates on small loans are capped at around 2%, but can also be set below the ceiling.[9] The loans have a maturity of 6 years (increased to 10 years in June) and no principal payment, only interest, is due in the first two years of the loan. According to the law, guaranteed lending need to be new loans, not a replacement of existing credit facilities with the borrower.

Crucially, fully guaranteed loans require no application of the credit scoring model typically

[8] An additional 10% guarantee for loans below €800,000, bringing the total guarantee to 100%, can be granted by *Confidi*, a consortium of other guarantee funds. Firms whose loan exposures are classified as non-performing (unlikely to pay or bad debt) as of January 2020 are excluded.

[9] The interest rate cannot exceed the following: a weighted average of Italian sovereign bond yields (*tasso di rendistato*, standing at 1.46% in April 2020 and 0.6% in August 2020), plus the spread between Italian bank and sovereign 5-year CDS spreads, plus 0.2%. In early April, the interest rate cap was around 2% but it decreased to about 0.6% in August. For loans that are not 100% but only 90% government guaranteed, the interest rate is freely determined by the bank.

used by the FG to issue the guarantee. Normally, in fact, the public guarantee scheme involves three agents: a bank (i.e. the applicant), a firm (i.e. the beneficiary), and the FG. First, the firm needs to file a standard loan application with the bank of choice. Then, the bank has to verify the firm eligibility for the scheme through a scoring system software provided by the FG (see de Blasio et al. (2018) for further details) and file a separate application to the FG in order to request the public guarantee on the loan. As of April 2020, all these steps have been removed for loans below €25,000, so that SMEs can quickly obtain the needed liquidity. Firms have to complete a self-declaration form, that the bank will forward to the FG, in which they state that their business has been affected by Covid-19, and that they are eligible to receive 100% government guaranteed loans.

Other European countries, such as Germany, France, Spain and the UK have introduced similar measures. The US PPP is different, in that it offers government guaranteed loans that are forgiven, i.e. they become grants, if they are used to cover payroll costs or other fixed expenses such as mortgage interest, rent, and utility bills. Thus PPP is a substitute for short-time work programs which are instead common in European countries. Finally, loan guarantees are part of a larger menu of government interventions that include debt moratoria and other grants to support firms during the pandemic.

3 Data

Loan level data on the universe of guaranteed loans are publicly available in Italy.[10] These are loan origination data[11] that include basic information on the borrowing firm or the self-employed individual that accessed the guarantee (name, address, sector and, most importantly, the unique tax code), the amount of the loan and the guarantee, the approval date of the

[10]The act on data transparency made these data publicly available at https://www.fondidigaranzia.it/amministrazione-trasparente/

[11]Loan applications data on guaranteed credit do not exist (fully guaranteed loans are even below the €30,000 reporting threshold of the Italian Credit Register). However, anecdotal evidence from the Parliamentary Committee and a survey from ISTAT (2020) suggests that 100% guaranteed loans have rejection rates of almost zero. Banks, after an initial slow start in the approval process due to the large surge in applications and logistical bottlenecks, had disbursed at least two thirds of all applications by the end of May.

guarantee and the type of program (e.g. support for start-up, microcredit, SMEs in the South of Italy). We also obtained confidential loan-level data from the FG on loan interest rates and, for a subset of the loans, the date in which the loan was actually disbursed to the firm, matched with a bank identifier. We calculate the total number and value of guaranteed loans issued by each intermediary and we match this information with public records from Parliamentary Committee on the banking system, that contain the names of every intermediary in Italy who extended guaranteed loans. Doing so allows us to recover the names of about 120 lenders that extended 95% of total guaranteed credit. We then match the bank names to 2019 balance sheet characteristics from Bureau Van Dijk (BvD) Orbis BankFocus.

Next, we match the unique tax code of the borrowing firm in the FG dataset to BvD Orbis, a database with the financial accounts for the universe of Italian firms. From Orbis, we retrieve financial data for 2.9 million entities which filed in 2018. Most firms in Orbis (72%) are private partnerships and sole proprietorships, i.e. unlimited liability companies that are common legal structures for very small firms, for which we only have basic identifying information (name, tax code, address, sector and date of incorporation).[12] We have instead the full financial accounts of around 600,000 firms, mainly limited liability companies, which represent our estimation sample. Within this sample, about 120,000 firms obtained a 100% guaranteed loan, 40,000 obtained 80,000 loans with a partial guarantee, while the remaining did not obtain any guaranteed loan (the control group), despite being eligible.

We hand-collect data on bank IT systems by retrieving from the Google Playstore the rating of the mobile banking apps for the top 100 banks that represent more than 90% of total guaranteed loans. Google reviews range from 1 star (very bad) to 5 stars (excellent) and represent a customer-based measure of the quality of the bank digital infrastructure. Google's Android is the operating system for more than 80% of smartphones in Italy so its

[12] Overall, we thus obtain full financial accounts for 66% of the limited liability companies that appear on the FG data. We also match 43% of unlimited liability companies, but these do not enter our main estimation sample because they have missing balance sheet information. In Table A1 in the Online Appendix we show that our results on the local strength of the pandemic and the lockdown of non-essential sectors are robust when we include them too.

reviews capture the majority of bank customers. Although this is a coarse indicator of a bank investment in IT and its quality, a report from the Italian bank association (ABI, 2020) states that the development and maintenance of mobile banking apps is the main source of IT costs for banks. Furthermore Fu and Mishra (2020) show that both download and usage of finance mobile applications soared in countries more affected by the pandemic, underlying the importance of mobile apps as a measure of IT quality during this period.

We retrieve province-level information about infections from the Protezione Civile and fatalities from ISTAT, the national statistical office. We then construct two measures for the local strength of the Covid-19 pandemic at the province level: the share of population who tested positive (Share Covid-19 Positive) and the average percentage change in cumulated deaths between March and April 2020 and March and April 2019 (Excess Deaths 2020). We classify 6-digit NACE sectors as either essential (i.e., open) or non-essential (i.e. closed) depending on the list provided in the law decree of March 25^{th}, 2020. We also obtain the number of total hours approved for short-time work in 2020 by the social security administration (INPS) at the province level. Short-time work programs (*Cassa Integrazione*) allow firms experiencing economic difficulties to temporarily reduce hours worked, while maintaining employment contracts active, by having the state paying workers salaries.

Furthermore, we gather data from *Movimprese*, the statistical report about firms in Italy from the chambers of commerce (*Infocamere*). From Movimprese we extract the total number of registered firms of any legal form, i.e. both limited liability companies and unlimited partnerships, in Italy at the end of 2019. The data are disaggregated at the province and 2-digit NACE sector and we use it to measure take up of the guarantee program in the cross-section of provinces and sectors in Italy.

Panel A of Table 1 presents the summary statistics for the matched FG-Orbis sample. Summary statistics are presented separately for firms that obtained a 100% and a 90% guaranteed loan. About 25% of eligible SME firms in Italy that have full coverage of financial accounts in Orbis obtained a guaranteed loan, suggesting an overall low level of participation in the program. Partially guaranteed loans are much larger than fully guaranteed loans (€456,000 vs €23,000). According to the rules of the new guarantee program, firms cannot borrow more than one-quarter of their 2019 sales and indeed 90% of those with a loan strictly smaller than €25,000 have sales lower than €100,000. The average loan amount is about 11-13% of sales for both types of guaranteed loans which suggests that many firms did not borrow to the full extent allowed by the law. Moreover, 7.5% of the firms in the sample participated in a loan guarantee program at least once between 2018 and 2019, confirming that the existing public guarantee scheme was fairly large. 38% of firms are active in 6-digit sectors that were shut down on March 25, 2020. Most firms are rather small, with a median asset and sales below half a million euros and with less than 5 employees. Firms in the sample hold 16% of total assets as cash or other liquid assets, finance around 70% of the balance sheet with non-equity-like instruments such as bank debt or trade credit. We will discuss the summary statistics on interest rates and disbursement times in the empirical analysis later in the paper.

4 Results: Geographic and Firm Heterogeneity

4.1 Guarantee 2020: Aggregate stylized facts

Before turning to a more formal regression analysis of the firm-level uptake of the new guarantee program, we describe some general patterns in the data.

First of all, the guarantee program for SMEs in Italy was large even before Covid: from 2013 to 2019, €17 billion of loans per year have received a partial (64%) public guarantee, steadily increasing every year (Figure 1 - Panel A). However, in the first eight months of 2020 alone, the volume of guaranteed lending reached a total of €79 billion, representing 10% of the stock of bank credit to non-financial firms in 2019 and 2% of bank total assets. Figure 1 - Panel B further reveals an increase in the number, and not just the volume, of guaranteed loans which resulted in a reduction in the average size of the loans: after April 2020 the vast majority (86%) of loans are below €25,000.[13] These were extended to 829,053 borrowers, two thirds of which are private partnerships, sole proprietorships and self-employed individuals. While numerous, fully guaranteed loans represent only 0.2% of bank total assets.

Firms that accessed the new guarantee program after April 2020 represent about 16% of the universe of registered firms in Italy (*Movimprese*), including private partnerships and sole proprietorship, and 25% of our estimation sample. There are however large differences in the take-up rate both across geographic areas and sectors. For example, while virtually no firm in agriculture has accessed the guarantee, 25% of firms in the food and accommodation industry and almost 60% in the healthcare and social assistance sector have. While in some provinces the take-up rate is as low as 7%, in other areas it increases to 26%.

Figure 2 correlates the participation in the guarantee program in each province to the number of excess deaths or the share of non-essential (i.e. closed) firms. The take-up rate is generally higher in the north of the country, where the pandemic hit the hardest (correlation coefficient equal to 0.27). This is not the case in normal times, as the take-up rate is generally higher in the south of Italy (see Figure A2 in the Appendix). Moreover, the take-up rate in 2020 is higher in provinces with a higher share of closed businesses (correlation coefficient equal to 0.40) which, given the industry structure at the local level, also happen to be more prevalent in the north of Italy. Regarding the sector heterogeneity, in Panel A of Figure 3 we compute the take up rate of guaranteed loans in each sector, expressed as the number of firms that obtained a guaranteed loan over the number of registered firms, to measure the intensity of the uptake across different sectors. The sectors that have the highest usage of the guarantee are in services, of which especially healthcare and social assistance (e.g., nursing homes, dental care and other medical facilities), professional services (e.g., engineering and architecture) and food and accommodation. A similar ranking by sector is found in the US for

[13] There is also evidence of bunching in the loan size distribution after April 2020 (Figure A1 in the Online Appendix). In particular, among government guaranteed loans below €50,000 issued in April 2020, two thirds are exactly at the €25,000 threshold compared to 21% before then. As the loan threshold was increased to €30,000 in late June, a small excess mass appears at that cutoff too. Interestingly however the mode of the distribution remains at €25,000 even in July, suggesting that the old threshold is more salient to borrowers.

PPP loans (WSJ, 2020). Interestingly, the intensity of the take-up is not necessarily correlated with the share of closed businesses in the sector: while both agriculture and healthcare were considered essential and hence were not closed, they have respectively the bottom and top take-up rate (Figure 3 - Panel B). This suggests that the share of closed sectors is only part of picture, since the Covid-19 shock affected demand even in some of the essential sectors.

4.2 Guarantee: Firm-level evidence

We now test more formally which firm, province or sector characteristics matter to explain the uptake of the new 2020 guarantee program for SME by estimating the following linear probability model:

$$\text{Guarantee2020}_{f,p,s} = \beta_1 \text{Covid}_p + \beta_2 \text{Essential Sector}_s + \gamma' X_f + \epsilon_{f,p,s} \tag{1}$$

where $\text{Guarantee2020}_{f,p,s}$ is a dummy equal to one if firm f located in province p and active in the 6-digit sector s took a guaranteed loan after April 2020 (we analyze full and partial guaranteed loans separately). The control group in this estimation consists of firms who were eligible (i.e. all SME firms with less than 500 employees), but did not obtain any guaranteed loan.[14] Covid_p is a measure of the impact of the pandemic at the local level. We measure it in two ways: either excess deaths in the province, i.e. the percentage change in the number of recorded deaths between March-April 2020 and March-April 2019, or the share of people who tested positive in a province as of May. $\text{Essential Sector}_s$ is a dummy equal to one for the 6-digit sectors that remained open between March 25^{th} and May 15^{th}, 2020. Finally, X_f is a vector of firm controls (log of total assets and age; cash and liquid assets over total assets; leverage, i.e. total liabilities over assets; EBITDA over assets; the Altman Z-score (Altman et al., 2012)). Finally, we use clustered standard errors at the province level.

[14]We restrict the estimation sample to all eligible Italian SME firms (i.e., < 500 employees or < €50 million in sales or < €43 million in total assets) that have a full financial account in Orbis. Furthermore, we exclude firms that obtained a 90% (100%) guarantee loan when studying take-up of 100% (90%) guaranteed loans.

The results for fully guaranteed loans uptake are presented in Table 2. The estimates in column (1) indicate that a firm located in a province more severely hit by the pandemic has a lower, not higher, probability of accessing the guarantee, at least in this specification. We shall see later that the sign of the coefficient on excess deaths depends on the month in which the guarantee was accessed. Being present in an essential sector, i.e. one that was not shut down between March 25 and May 15, decreases the probability of accessing the guarantee compared to a non-essential sector, by 3.5 percentage points, i.e. 16% lower probability compared to the mean take-up rate of 22%. In column (2) and (3) we further include province or 6-digit sector fixed-effects, which absorb the coefficient on either the excess deaths or the non-essential sector dummy, but not both at the same time. The coefficient on the essential sector dummy remains significant and, conditional on the 6-digit sector, the coefficient on excess deaths becomes insignificant.

Turning to firm characteristics, we find that if a firm previously accessed a guarantee program in 2018 and 2019 it is 50% more likely to obtain a 100% guaranteed loan in 2020 in the specification with province×industry fixed-effects. This is a large effect. This finding has two possible explanations: first, since the firm is already familiar with the process of applying for a government guaranteed loan it finds it easier to apply for a new one in 2020; second, the firm is likely to be a financially constrained firm, which is why it already applied and obtained a guaranteed loan in the past. We also find that smaller and younger firms, those with less cash on hand and more debt have a larger uptake rates. Since all firm-level variables have been normalized to have a mean of 0 and a standard deviation of 1, the coefficients can be directly compared and interpreted as the effect of a one standard deviation increase. As expected, firm size is one of the most important drivers (a 1 standard deviation decrease in total assets increases the take-up rate by 22% compared to the mean), but liquidity holdings are equally important in the most saturated specification. Moreover, riskier firms saddled with more debt, i.e. those with higher leverage and a lower z-score, are more likely to participate. All such firm characteristics matter over and above province and sector presence, since the coefficients remain stable when we include both province and 6-digit sector dummies in column (4), or the product between the two in column (5).

We also perform a similar analysis for loans larger than €25,000 that obtained a partial guarantee up to 90% of the value of the loan. The results are presented in Table 3. Neither the strength of the pandemic, nor the presence in a non-essential sector matter to explain the take-up of the non-fully guaranteed loans. We again find that firms with less cash on hand and riskier firms, with higher leverage and lower z-score, are more likely to take-up a partially guaranteed loan. Naturally, larger firms seek partially guaranteed loans more than smaller ones, since these loans can be as large €5 million. Overall, the results suggest that the small, fully guaranteed loans were obtained by financially weaker firms in more affected areas and sectors, while larger loans with a partial guarantee were obtained by larger, yet still risky firms.

4.3 Guarantee: Dynamic effects

Although the guarantee program was launched at the beginning of April, guaranteed loans only started to be granted in late April, reaching a peak in May and then decreased over the summer. As the rate of infections slowed and the lockdown measures were lifted in mid-May, it is natural to ask whether the firms obtaining the funds in second phase (June-August) are different from those in the first and most acute phase of the pandemic (April-May). Figure 4 suggests that the firms obtaining the 100% guarantee in June-August have somewhat stronger fundamentals from those receiving the guarantee in April and May. For example, they are 25% less likely to have obtained a guaranteed loan in the past, they have more liquid holdings, lower leverage, higher profits and less bank loans as a share of short-term funding. They are instead broadly similar in terms of size and overall Z-score. We now test more formally whether the firms receiving the guaranteed funds changed over time by estimating equation (1) separately for the period April-May and June-August.

The results are presented in Table 4. Strikingly, the coefficient on excess deaths reverses its sign in June compared to April-May: firms located in areas most affected by the pandemic are *more* likely to obtain a guaranteed loan in the first phase, but equally *less* likely to obtain it in the second phase. That is, funds initially flowed to areas most affected by the local strength of the pandemic, but were later channeled to least affected areas.[15] The coefficient is small, but not negligible: for example, a firm located in Bergamo, the province with the highest increase in excess deaths (+340%), has a 3% (0.7 percentage points) higher probability to participate in the guarantee program in April and May compared to a firm located in Napoli, which experienced no increase in excess deaths. However, in June-July the opposite is true. Figure A3 in the Appendix provides visual evidence that the intensity of the take-up was higher in the north of Italy, where the pandemic struck the hardest, in April and May, but moved toward the center and south after June.

The correlation between the guarantee uptake and firm characteristics declines over time, which means that firms receiving funds in June and August are financially stronger than firms receiving funds in April and May. Riskier firms, i.e. those with less cash on hand, more debt and who previously accessed guaranteed funds in 2018-19, are half as likely to receive the guarantee in June compared to April and May. In July and August, firm level characteristics are precisely estimated but very small, implying that even safer firms obtained the 100% guaranteed loans.[16]

The result suggests that weaker firms located in areas that experienced the pandemic effects early on had larger negative effects on the demand for their products and were the first to need a liquidity injection. Only later, as the economic consequences induced by the pandemic and the lockdown measures were felt in the rest of the country, financially stronger firms located in other areas obtained the guaranteed funds. In this respect, Balduzzi et al.

[15] In Table A2 in the Online Appendix we use the share of infections instead of excess deaths to measure the local effect of the pandemic. This measure is more likely to suffer from measurement error than statistics on reported deaths, because test policies varied widely from one region to another. In fact, while the coefficient on local infections follows the same pattern as excess deaths, it is only weakly statistically significant.

[16] We also perform a similar analysis for 90% guaranteed loans and find that the correlation of the take-up rate with local or other firm characteristics is instead much more stable over-time (Table A3 in the Online Appendix).

(2020) survey Italian firms in early April and find those located in areas with more reported Covid-19 deaths are more pessimistic about their future sales. These pessimistic entrepreneurs may have been more likely to apply for a loan earlier on.

4.4 Guarantee 2020: Interest Rates and Disbursement Times

Finally, we analyze the firm-level cross-sectional heterogeneity in the confidential data about loans' interest rates and disbursement times we obtained from the FG. While the interest rate on the 100% guaranteed loans is capped at around 2%, it can also be lower than that: the average and median rate reported in Panel A of Table 1 is 1.2% with a standard deviation of 35 basis points, suggesting significant cross-sectional variation. Partially guaranteed loans do not have an interest rate cap, but still, given the 84% average guarantee and the low long-term interest rate in this period, have an interest rate of only 2.8%.

We then calculate disbursement time as the number of days between the approval date of the guarantee by the FG and the date on which banks effectively pay out the loan to the borrower.[17] Notably, disbursement times may be negative as banks can disburse the loan before the FG approves the guarantee. In general, we find that the banking sector has been relatively efficient in disbursing the fully guaranteed loans, which require no formal credit approval, handing them out 1 week before the approval of the guarantee. However, partially guaranteed loans, which are larger and require the application of the rating algorithms from the FG, take almost three weeks longer. In both cases there is a notable cross-sectional variation: the standard deviation of disbursement times for 100% guaranteed loans is twice as large as the mean.

In this section we study whether firm characteristics matter for the pricing and disbursement times. Since the loans have a full or almost full government guarantee it is not clear ex-ante how banks would price firm-level risk. Table 5 shows that firm risk is priced: younger, smaller, more levered and with less cash on hand, pay higher interest rates on their guaranteed loans.

[17]We have data on disbursement times only for about half of the loan in the matched FG-Orbis dataset because banks have up to six months to report the data to the FG.

While the difference turns out to be only a few basis points (bps) for 100% guaranteed loans, since interest rate on these loans is capped by law, the magnitudes are larger for partially guaranteed loans. In particular a one standard deviation increase in firm assets decreases the interest rate by 500 bps, 18% lower than the mean. Notably, including a bank fixed-effect (column 3) further reduces the effect of firm-level controls, but improves the overall fit of the regression (the R^2 increases from 0.18 to 0.62), suggesting that bank heterogeneity, which we will analyze in the next section is key to explain differences in interest rates.

Finally, we notice that the disbursement times of 100% guaranteed loans differ depending on firm characteristics: smaller, younger firms with less cash on hand receive fully guaranteed loans somewhat faster than others, although the difference is less than a day, so not economically meaningful. There is instead limited impact of firm heterogeneity on the disbursement time of partially guaranteed loans. Much like with interest rates, bank heterogeneity seems to be a key driver of overall disbursement times (the R^2 increases from 0.11 to 0.58 when we include bank fixed-effects).

5 Bank Heterogeneity

The evidence presented so far is consistent with a demand channel, where more affected firms, i.e. small, more levered and riskier firms, were more likely to obtain a government guaranteed loan. But it is also possible that the supply side of guaranteed lending depends on bank characteristics and on bank local presence through the branch network. In this section, we show that supply side restrictions matter, after controlling for credit demand by comparing guaranteed loans issued by different banks in the same area and 6-digit sector.

Ample evidence shows that the local bank branch network affects the allocation of credit (Gilje et al., 2016). Banks protect their existing customers during crisis times (Bolton et al., 2016) and mitigate the impact of shocks by cutting lending less in their core markets, i.e. in areas where they own at least one branch (Cortés and Strahan, 2017). The local nature of banking markets and lending relationships could be relevant for the supply of guaranteed loans as well, especially in the presence of supply constraints, such as in the first round of PPP funding (Li and Strahan, 2020) and for large corporate clients (Balyuk et al., 2020). Granja et al. (2020) find significant lender heterogeneity in the allocation of PPP loans, with some banks "underperforming" their normal share of small business lending in the PPP program. Since small business lending is local, firms near underperforming banks will be cut out of PPP lending.

However the importance of the bank branch network may be diminished over this period, since shelter-in-place orders made it difficult for borrowers to physically reach the local branch and loan applications were made online. The bank digital infrastructure may then be more important than the branch network in that it allows banks with better IT systems to process a large volume of loan applications. Moreover, since 100% guaranteed loans pay at most €500 in interest per year, to ensure profitability banks need to decrease average costs by issuing a large volume of loans and by automatizing the approval process, since otherwise the fixed cost per loan (e.g. a loan officer's hourly wage) would exceed interest payment. Thus, large banks that can naturally exploit economies of scale are in a better position to issue these loans.

In this section, we show that the structure of the local banking market matters for obtaining a guaranteed loan and, conditional on obtaining the guaranteed loan, we find that lender-specific heterogeneity, and the quality of IT systems in particular, affects interest rates and disbursement time.

5.1 Individual Bank Characteristics and IT systems

We now test whether the pricing and disbursement times of guaranteed loans depend on a number of individual bank characteristics. This allows to control for credit demand conditions by saturating the regression with province×6-digit sector fixed-effects, i.e. comparing loans made by different banks to borrowers in the same area and sector.

First of all, we notice that there is significant heterogeneity in both interest rates and disbursement times of guaranteed loans across lenders. Panel A of Figure 6 shows that the average interest rate charged by each bank for 100% guaranteed loans is negatively associated with bank size, as measured by the volume of guaranteed loans issued by each bank. Furthermore, Panel B shows that the average disbursement time is similarly negatively correlated with bank size. Larger banks take on average a week less than small banks, disbursing the loans 5 days before approval by FG.

Size is not the only driver of differences in disbursement times across banks. During the pandemic, most loan applications were made online, through bank websites. Presumably, banks with better IT systems were able to cater to the surge in online loan applications better than banks with a poor digital infrastructure. In fact, we find that banks with a good or excellent Google rating (4-5 stars) on their mobile banking app are very fast at disbursing guaranteed loans, taking on average two weeks less than those with 3 stars or less. In Panel A of Figure 6 we show that the entire distribution of disbursement times for banks with high-rated apps is shifted to the left compared to the low-rated apps. The difference in app rating is correlated with size, since large banks tend to have better rated apps, but it's not only explained by that: in Panel B of Figure 6 we show that indeed larger banks have a distribution of disbursement times shifted to the left, but the distributions are much more aligned than for rating on the mobile banking app.

We provide a more formal test of the effects of the bank digital infrastructure and other bank characteristics by running the following specification:

$$\mathrm{Y}_{i,f,b} = \beta_1 AppRating_b + \lambda' X_f + \gamma' X_b + industry \times provinceFE + \epsilon_{f,p,s} \tag{2}$$

where $Y_{i,f,b}$ is either the interest rate or the disbursement time of loan i made by bank b to firm f. As before, we run regression separately for fully and partially guaranteed loans. $AppRating_b$ is a dummy equal to one if bank b has a 4-5 star rating on its mobile banking app from the Google Playstore. X_f is a vector of firm characteristics and X_b of bank characteristics such as size, capitalization, the quality of the loan portfolio (NPL), profitability and interbank funding. We fully absorb credit demand with an exhaustive set of 6-digit industry×province fixed-effects for each borrowing firm.[18] We also include a dummy for the month in which the guaranteed loan was obtained. The calendar date when the loan was issued is relevant because the interest rate cap varies over time with government bond yields and CDS spreads, so that loans issued in April have a higher interest rate cap than those issued over the summer, when market interest rates fell after the ECB expanded its asset purchase programs. Processing loans also took longer in the initial phase of the pandemic, as many banks were not ready to accommodate a large surge in government guaranteed loan applications. Finally, standard errors are two-way clustered at the bank and province level. Results are presented in Table 6.

We find that banks with highly rated app (4-5 stars) disburse both partial and fully guaranteed loans 5-7 days earlier compared to other banks. This is a sizable effect, since the average fully guaranteed loan is processed a week before the approval of the guarantee and the partially guaranteed loans take almost three weeks longer. While the coefficient of $AppRating_b$ on loan interest rates for fully guaranteed loans is not significant, the point estimate is negative, suggesting that banks with better digital infrastructure charge lower rates. Crucially, the coefficient on disbursement times remains significant even when we control for bank size and other characteristics, which means that the quality of the IT system is not simply explained by traditional balance sheet factors. Disbursement times are a key loan outcome because one of the objectives of the government was that the funds should be timely allocated to the firms most in need of the funds.

Another key bank characteristic that is significantly correlated with both loan rates and disbursement times for fully guaranteed loans is bank size. Banks with a one standard deviation increase in total assets offer 100% guaranteed loans at 15 bps lower than other banks, an effect of about 12% compared to the mean, and disburse loans taking 2 and half

[18] In robustness tests we also exploit the fact that some firms obtained multiple partially guaranteed loans from different banks and include a firm fixed-effect, to fully absorb firm-specific credit demand. In fact, firms are allowed to have multiple partially guaranteed loans above €25,000 as long as the total loan amount is less than a quarter of 2019 sales. Results are quantitatively unchanged (Table A4 in the Online Appendix), suggesting that province×6-digit sector fixed-effects are already fully controlling for demand.

days less than other banks. Other bank characteristics tend not to be significant. In particular, bank capitalization, which could potentially play a role because guaranteed loans do not count for RWA, is not significant. Banks with a higher fraction of interbank funding are able to offer larger discount to partially guaranteed loans, possibly because these banks have lower funding costs over this period.

Overall, the evidence presented in Table 6 is consistent with a story in which large banks with better IT system are better able to process guaranteed loans, disbursing them faster and at lower interest rates. The quality of the bank digital infrastructure may be an especially relevant margin during a pandemic, when most loan applications happen online. It is also worth noting that, given that the maximum interest rate on €25,000 loans is about €500 per year, only processing a large number of loans through an automated procedure allows banks to maintain a positive profit margin. If a loan officer had to approve the loans one by one, the fixed cost per loan would probably exceed the interest income.

5.2 Loan Size

In Table 5 and in the previous section we established that bank heterogeneity, as opposed to firm heterogeneity, is key to understand the variation in loan rates and disbursement times of guaranteed loans. Is the same true for loan size? This is important to know for policy design: if supply side restrictions determine the size of the loan, along with the pricing and the efficiency of loan disbursements, policy makers should set minimum size threshold to target specific groups of firms. We test whether firm or bank characteristics explain loan size, which for 90% guaranteed loans is allowed to vary up to €5 million, by estimating equation (2) changing the dependent variable to be the logarithm of the loan amount. The results are reported in Table 7.

We find that larger guaranteed loans are obtained by financially stronger financial firms: they are less likely to have obtained a guaranteed loan in the past, they are larger, older, with more cash at hand, lower leverage and higher profitability. Differently from interest rates and disbursement times, firm characteristics explain a lot more of the variation in loan amounts (R^2=0.48) than bank characteristics ($R^2 = 0.05$). Moreover, when we include firm characteristics or province×sector fixed-effects (or firm fixed-effect in Table A4 in the Online Appendix), no bank characteristics is significantly correlated with the size of the loan. However, firm characteristics remain highly statistically significant, even when we include bank fixed-effects (column 5 of Table 7). Overall we conclude that the size of the loan is not constrained by supply and it is mostly demand driven.

5.3 Local Banking Markets

Since most applications for guaranteed loans were filed online, one may wonder whether the bank branch network matters at all for the allocation of government guaranteed credit. Since they can easily reach any small business nationwide with online offers, banks are not restricted to lend in areas where they have a branch or to their own clients. Put it differently, guaranteed loans during Covid-19 provide the perfect setting to test whether lending relationships are sticky (Petersen and Rajan, 1994): if small businesses reach out for new funding only to the banks they normally do business with and banks keep serving only their existing customers, it means that indeed lending relationships are sticky and determine the allocation of guaranteed credit.

We test this hypothesis by using the full map of bank branches available from Bank of Italy and measure local bank presence with the share of branches. Formally, we estimate the following:

$$\log(Lending)_{b,p} = \beta_1 LocalMarketShare_{b,p} + \beta_2 CoreMarketShare_{b,p} + \lambda_p + \lambda_b + \epsilon_{b,p} \quad (3)$$

where the dependent variable is the log of the total amount of guaranteed credit by bank b in province p, including both fully and partially guaranteed loans.[19] $LocalMarketShare_{b,p}$ is

[19] We ran the specification separately for each type of guaranteed credit and obtained very similar results.

the share of local bank branches of bank b in province p relative to all bank branches in province p. This measure captures the local presence of the bank in the province. $CoreMarketShare_{b,p}$ is the share of local bank branches of bank b in province p relative to all bank branches of bank b, i.e. it captures the importance of the province for the overall branch network of the bank. We include both province and bank fixed-effects, thus using only within bank and within province variation in the share of local branches.

The results are presented in Table 8. First of all, we find that banks with higher local presence supply more guaranteed credit in the province: a one standard deviation increase in the local market share increases lending by about 7.7% relative to the mean. We emphasize that this measure is not simply capturing a size effect, i.e. the fact that larger banks both have a larger share of branches and supply more loans, since we either control for bank size (column 1) or include a bank fixed-effect (column 2), exploiting within bank variation only. The coefficient on $LocalMarketShare_{b,p}$ is remarkably stable and it suggests that the structure of local banking market is relevant, even if the applications are filed online. Second, we find that when the local market is important for the bank, i.e. when the province has a large share of the overall branch network, the bank is willing to supply more credit: a one standard deviation increases in $CoreMarketShare_{b,p}$ increases local guaranteed credit by 12%. Once again, the effect is not just driven by large provinces, which are likely to be more important across all banks, or by large banks, which have larger market shares in larger markets, since the specification includes a province and a bank fixed-effect. Third, when we include both market shares together, we find that, while the effect of each diminishes by about 25-30%, they are both positive and significant, indicating that they have an independent effect on the supply of guaranteed credit.

Finally, we also confirm that bank size is one of the most important driver of guaranteed credit, since it matters as much as the local market shares to determine the overall amount of credit. Thus, differently from the US, where small local banks were able to supply more PPP loans (Balyuk et al., 2020; Li and Strahan, 2020), large banks in Italy were instrumental in delivering government guaranteed credit. These results highlight the importance of understanding both the local banking market and bank-level characteristics for the transmission and allocation of a policy stimulus to firms through the use of public guarantees.

6 Conclusion

Since several countries worldwide introduced credit guarantees to support small businesses affected by the Covid-19 pandemic, it is crucial to assess whether allocating public funds using the banking system is efficient. Studying the Italian experience has several advantages. Italy was one of the first western countries to be hit by the pandemic and its guarantee program has some unique institutional features: it covers 100% of the loan up to €25,000 and requires no credit check by the bank granting the loan. This makes it ideal to study lenders' incentives to allocate public funds. Moreover, Italian loan-level data on public guarantees allow a full bank-firm match of balance sheet characteristics even for very small firms.

Our results indicate that although there was a low take-up of the new public guarantee program, funds went to areas, sectors and firms most affected by the pandemic and the lockdown, at least initially. Importantly, bank heterogeneity, in terms of both lender size and the quality of the digital infrastructure, matters and it suggests that the banking sector plays an important role in directing such policy stimulus. The structure of local banking markets and bank branch presence is also relevant, as banks' pre-existing geographical footprints and lending relationships are an important determinant of the overall volume of guaranteed credit. Policy makers should keep this in mind when designing policies that are meant to address firm liquidity shortages during a crisis.

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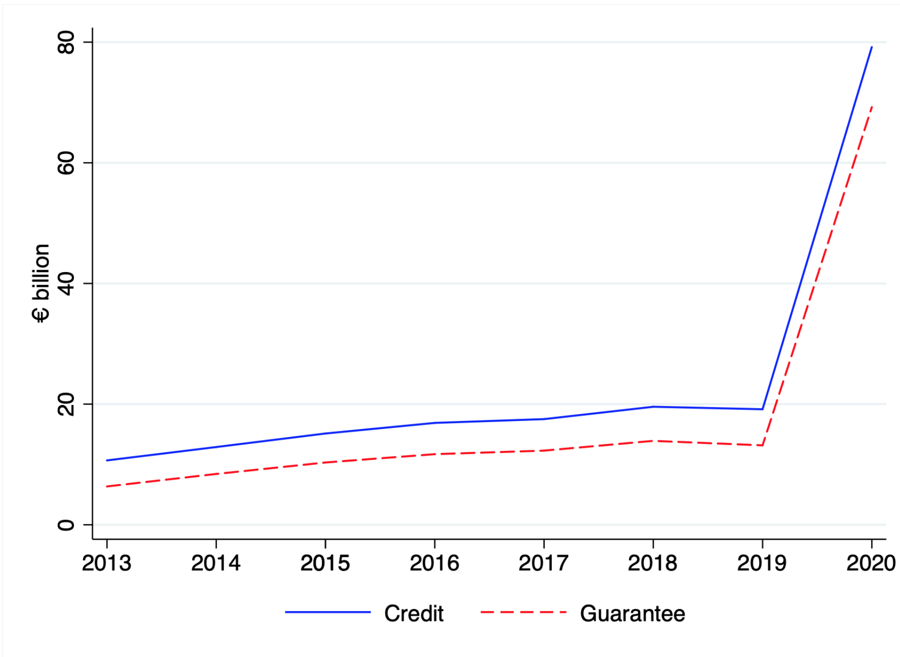
Figure 1: Loan Amounts and Number of Loans with Public Guarantees in Italy

This figure plots the time series of loans with public guarantees from the Italian guarantee fund. Panel A reports total loan volumes and guarantees at a yearly frequency from 2013 to 2020 (up to August 2020). Panel B reports the monthly number of government guaranteed loans from March 2019 to August 2020 (solid line) and the share of loans <€25,000 (dashed line, RHS axis).

(a) Panel A. Credit Amounts with Guarantees



(b) Panel B. Number of Loans with Public Guarantee in 2019-2020

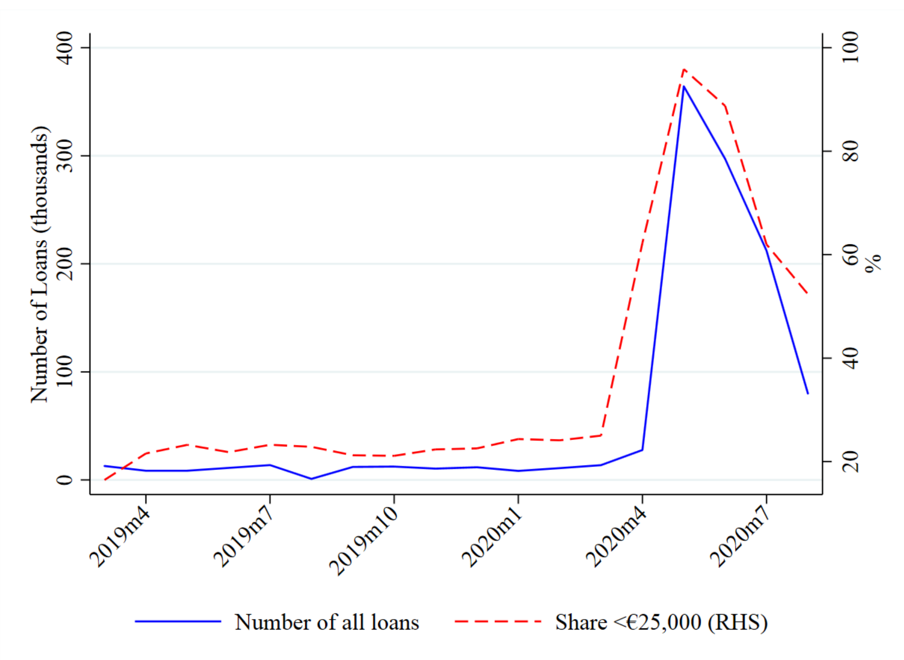


Figure 2: Guarantee, Excess deaths and Closed firms by Province

This figure plots the share of firms that obtained a loan under the 100% public guarantee scheme from April 2020 over the total number of firms in the province, the percentage of excess deaths and the share of closed firms in a province. The total number of firms in a province is obtained from the universe of registered Italian firms (Movimprese). The correlation coefficients between the take-up rate and excess deaths or share of closed firms are: 0.27 and 0.39.

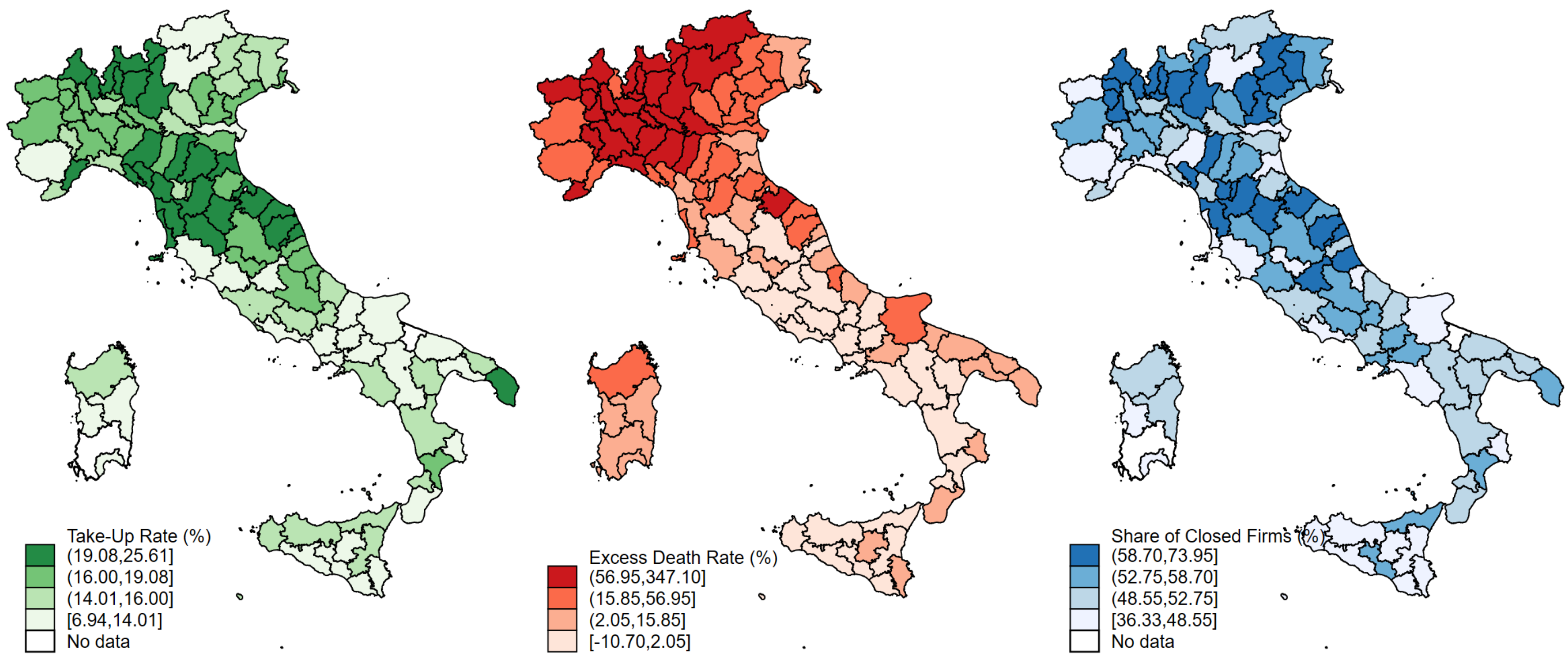
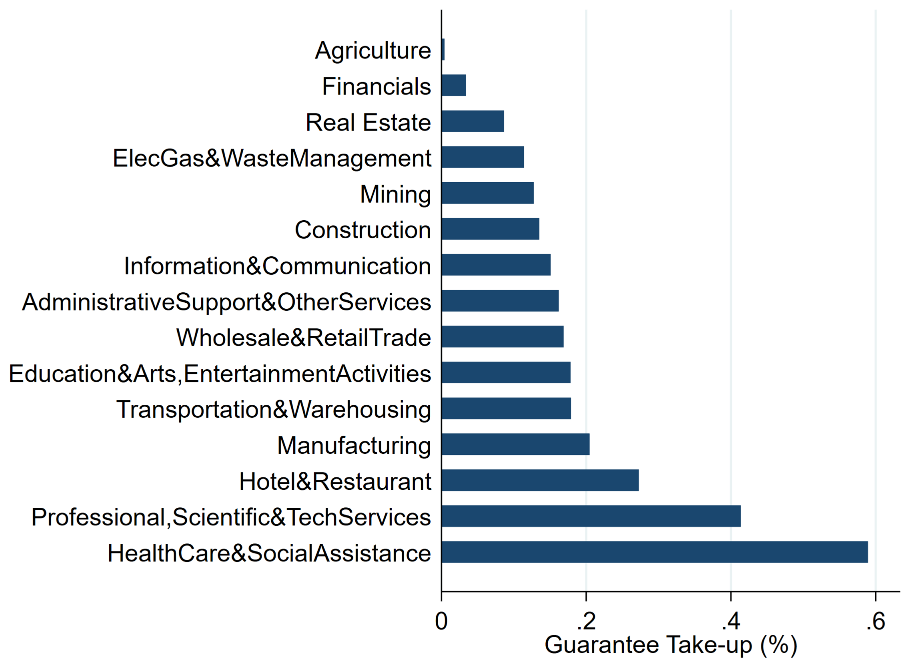


Figure 3: Guarantee by Sector

This figure plots the take-up rate of guaranteed loans, expressed as number of firms that obtained a guaranteed loan over the number of firms registered in each 1-digit sector in Panel A and the take-up rate of guarantees against the value-added weighted share of closed businesses in the sector in Panel B.

(a) Panel A. Take-up rate by sector



(b) Panel B. Take-up rate and share of closed businesses

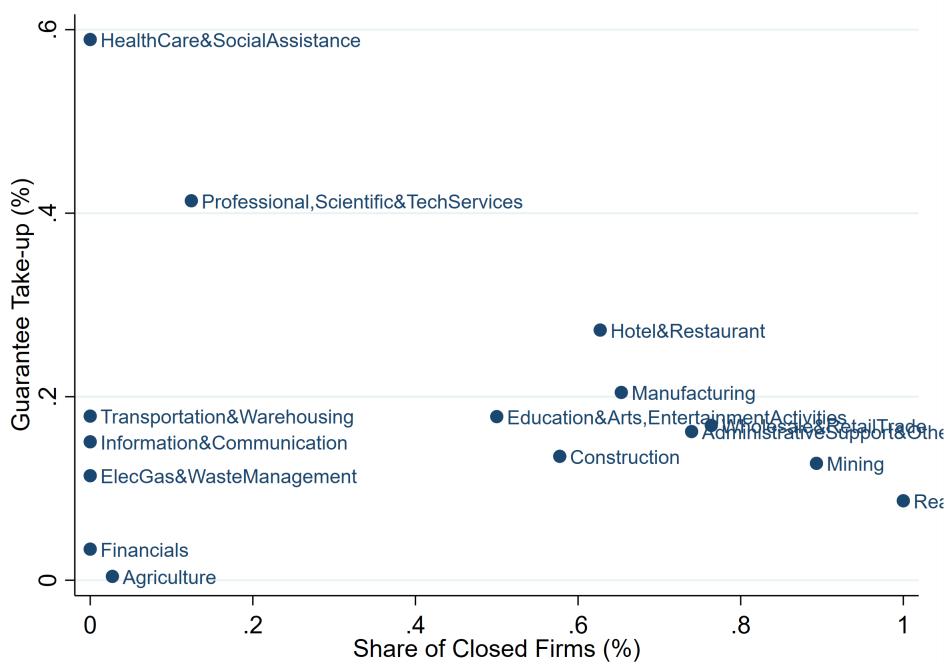


Figure 4: Firm characteristics in Apr-May vs Jun/Jul/Aug

This figure plots the average characteristics of firms that obtained guaranteed loan in Apr-May vs Jun-Jul-August 2020.

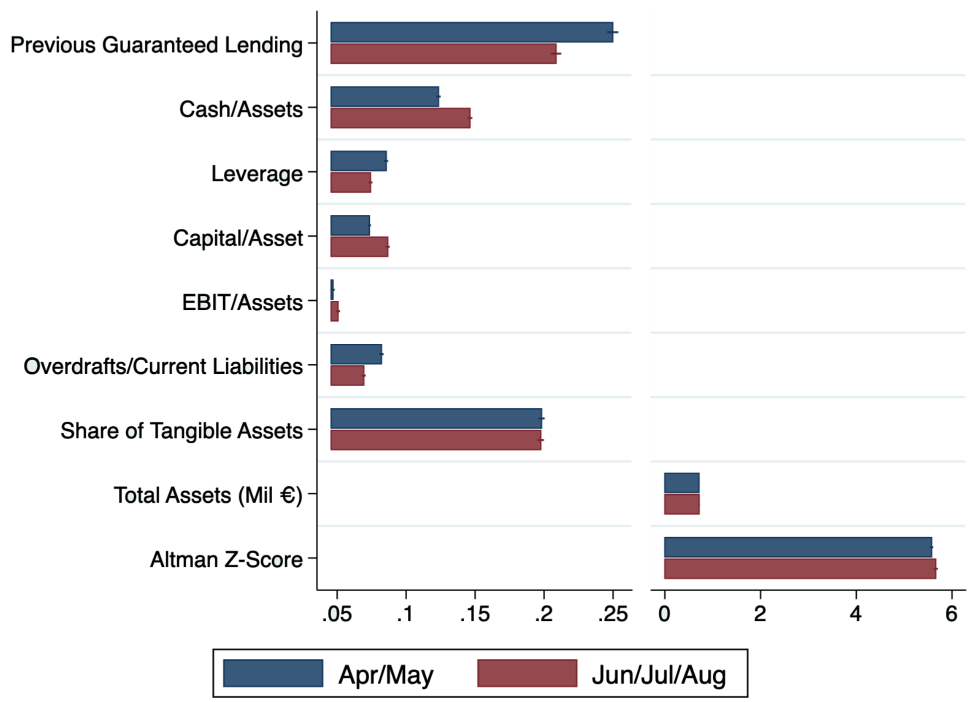
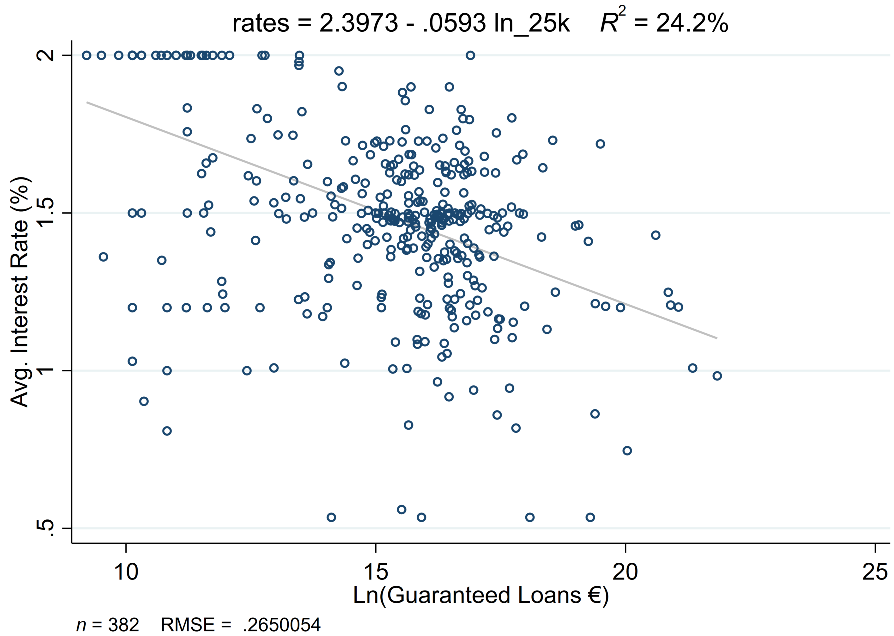


Figure 5: Loan Rates and Disbursement Times by Lender Size (number of loans)

The scatter plots shows the relationship between the bank average interest rate (Panel A) and average disbursement times (Panel B) on government guaranteed loans against the logarithm of the number of guaranteed loans approved by each bank. Disbursement times are calculated as number of days between the date of approval of the loan by the FG and the day of disbursement of the loan to the firm by the bank.

(a) Panel A. Average interest rate



(b) Panel B. Average disbursement time

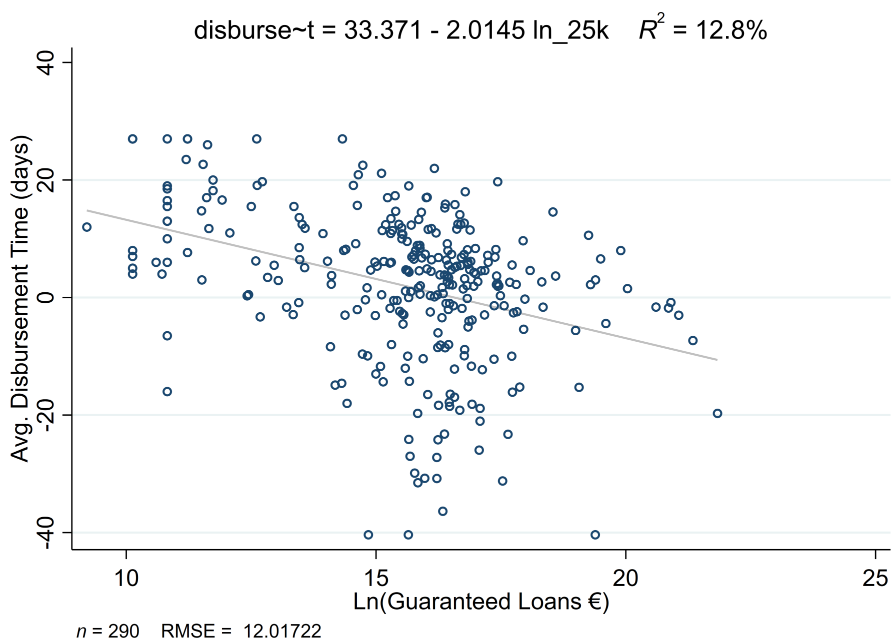
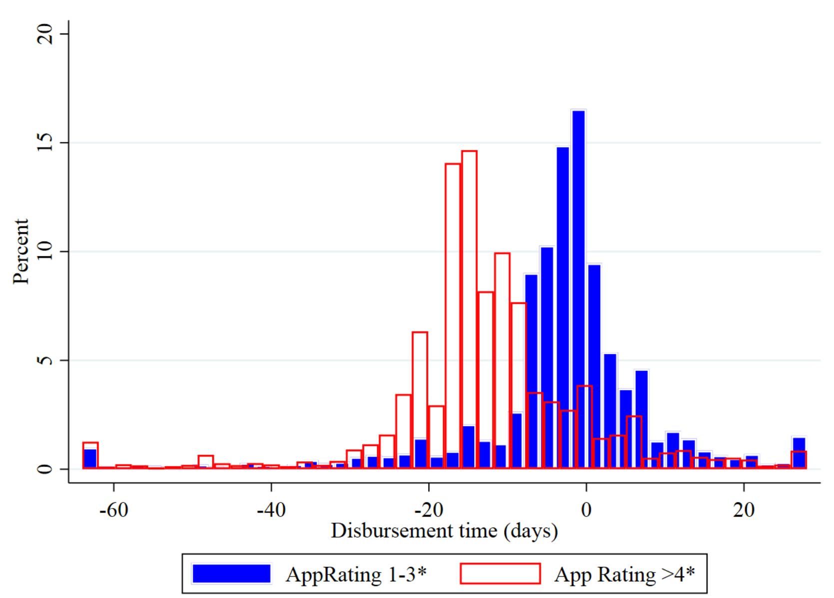


Figure 6: Bank Heterogeneity in Disbursement Times

We report the histogram of disbursement times on government guaranteed loans for two groups of banks: those with high (4+ stars) and low mobile banking app ratings in Panel A; large (>€21 billion in total assets, according to the Bank of Italy definition, found here) and small banks in Panel B. Disbursement times are calculated as number of days between the date of approval of the loan by the FG and the day of disbursement of the loan to the firm by the bank.

(a) Panel A. Mobile Banking App Rating



(b) Panel B. Total Assets

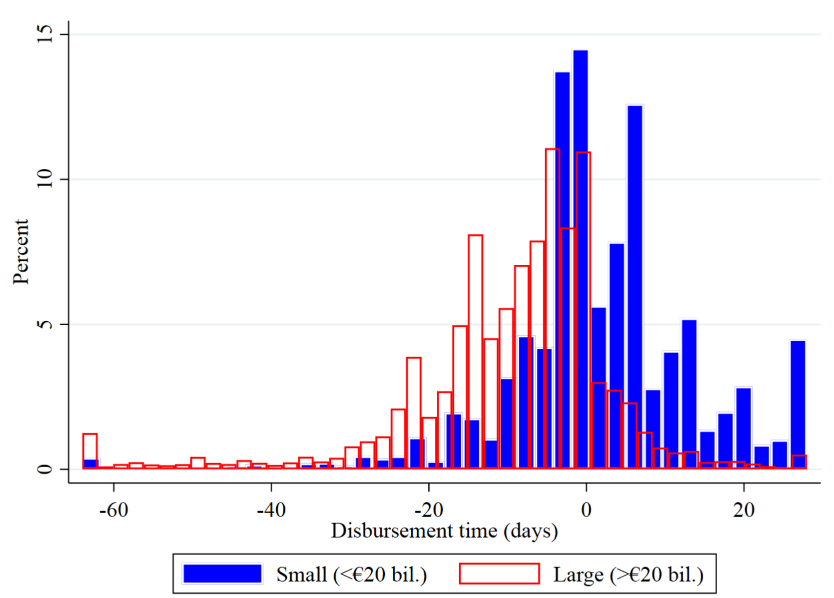


Table 1: Summary statistics

This table contains the summary statistics for the variables used in the empirical analysis. In Panel A, we report summary statistics on all government guaranteed loans to all eligible SME firms for which we have full financial accounts. Guarantee2020 is a dummy equal to one for firms that obtained the public guarantee after April 2020 in the *DL Liquditá*, either at 100% or below. Panel B reports all firm characteristics from BvD Orbis in December 2018. Essential Sector is a dummy equal to one for the 6-digit sectors that were considered essential and hence were not shutdown as of the government decree on March 25^{th}, 2020. Leverage is total liabilities (total assets minus total shareholders' funds) over total assets. Panel C reports province level characteristics. Ln(V.A. per Capita) is log of value-added per capita in 2017. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (data from ISTAT). Panel D reports bank-level characteristics on the banks that extended government guaranteed loans.

	N	Mean	Std.Dev.	5^{th} pct.	Median	95^{th} pct.
Panel A: Loan level						
100% Guarantee 2020	586599	0.223	0.416	0	0	1
100% Guaranteed Loan (000s €)	120869	23.656	4.850	11.300	25	30
100% Guarantee Loan/Sales	120869	0.130	0.196	0.013	0.080	0.247
100% Guarantee Interest Rate (%)	120869	1.199	0.356	0.550	1.200	1.750
100% Guarantee Disbursement time (days)	48416	-7.488	14.020	-29	-5	12
90% Guarantee 2020	550273	0.162	0.369	0	0	1
90% Guaranteed Loan (000s €)	79914	456.29	638.89	39.71	250	1500
90% Guarantee Loan/Sales	79914	0.117	0.232	0.008	0.058	0.328
90% Guarantee Interest Rate (%)	79914	2.803	2.031	0.75	2	7.3
90% Guarantee Disbursement time (days)	29439	12.774	15.155	-5	10	43
Panel B: Firm level						
Essential Sector	593907	0.388	0.487	0	0	1
Previous Guaranteed Lending (2018-19)	593907	0.075	0.263	0	0	1
Total Assets (million €)	593907	1.583	3.197	0.019	0.449	7.408
Sales (million €)	593907	1.174	3.181	0.000	0.241	5.132
Firm Age (years)	593907	14.948	12.284	2	11	41
Cash/Assets	593907	0.168	0.213	0.001	0.079	0.654
EBIT/Assets	593907	0.043	0.169	-0.207	0.023	0.339
Leverage	593907	0.699	0.325	0.106	0.754	1.000
Altman Z-Score	593907	7.447	11.377	1.076	5.464	14.619
Number of employees	353993	10.008	21.345	1	4	35
Panel C: Province level						
Excess Deaths	105	0.389	0.613	-0.056	0.164	1.586
Ln(Population) (2019)	105	12.941	0.721	11.973	12.868	14.041
Ln(V.A. per Capita) (2017)	105	10.035	0.279	9.566	10.075	10.422
SME's % of Total Sales	105	0.476	0.189	0.192	0.463	0.805
Short-time work hours per firm	103	260.01	171.07	58.79	227.65	567.56
Panel D: Bank-level						
Total Assets (billion €)	114	31.310	141.364	0.544	2.226	106.459
Tier1 Ratio	114	16.376	5.918	11.094	14.894	24.229
NPL/Loans	114	10.361	6.603	3.625	8.997	20.067
ROA	114	0.113	0.594	-0.928	0.247	0.642
Interbank/Asset	114	14.479	8.160	0.231	14.351	31.997
AppRating $\geq$ 4*	114	0.360	0.482	0.000	0.000	1.000
Number of Reviews (thousand)	114	16.370	24.577	0.011	4.632	37.244
Average App Rating	114	3.388	1.321	-0.090	3.600	4.400

Table 2: **100% Guarantee 2020 and Covid-19 (Excess Deaths)**

The sample is restricted to eligible SME firms. The dependent variable is a dummy equal to one if the firm obtained a loan under the 100% public guarantee program after April 2020, 0 otherwise. Essential Sector is a dummy equal to one for the 6-digit sectors that were considered essential and hence were not shutdown as of 25th March 2020; 0 otherwise. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Previous Guaranteed Lending is a dummy equal to one if the firm previously accessed any FG program in 2018 or 2019, 0 otherwise. Leverage is bank overdrafts and long-term debt over total assets. All firm characteristics are dated December 2018 and have been normalized to have a mean of 0 and a standard deviation of 1. Clustered standard errors at the province-level presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	100% Guarantee 2020 = 1				
	(1)	(2)	(3)	(4)	(5)
Excess Deaths	-0.003*		-0.001		
	(0.002)		(0.001)		
Essential Sector	-0.035***	-0.034***			
	(0.004)	(0.004)			
Previous Guaranteed Lending	0.156***	0.157***	0.117***	0.118***	0.118***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Log(Assets)	-0.071***	-0.069***	-0.053***	-0.052***	-0.051***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(Age)	-0.011***	-0.011***	-0.009***	-0.010***	-0.010***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cash/Assets	-0.046***	-0.046***	-0.054***	-0.054***	-0.053***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Leverage	0.048***	0.048***	0.035***	0.035***	0.034***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
EBIT/Assets	0.041***	0.040***	0.033***	0.033***	0.033***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Altman Z-Score	-0.014***	-0.014***	-0.006***	-0.006***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Ln(Population) (2019)	-0.000		-0.003		
	(0.002)		(0.002)		
Ln(V.A. per Capita) (2017)	-0.019*		-0.014		
	(0.011)		(0.011)		
SME's % of Total Sales	-0.004		-0.002		
	(0.005)		(0.005)		
Short-time work hours per firm	0.000		0.000		
	(0.000)		(0.000)		
South Dummy	-0.014		-0.012		
	(0.010)		(0.010)		
Fixed effects					
Province	No	Yes	No	Yes	-
6-digit Industry	No	No	Yes	Yes	-
Province×6-digit Industry	No	No	No	No	Yes
Observations	586599	586599	586599	586599	586599
R^2	0.065	0.068	0.115	0.118	0.187

Table 3: **90% Guarantee 2020 and Covid-19 (Excess Deaths)**

The sample is restricted to eligible SME firms. The dependent variable is a dummy equal to one if the firm obtained a loan under the 90% public guarantee program after April 2020, 0 otherwise. Essential Sector is a dummy equal to one for the 6-digit sectors that were considered essential and hence were not shutdown as of 25th March 2020; 0 otherwise. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Previous Guaranteed Lending is a dummy equal to one if the firm previously accessed any FG program in 2018 or 2019, 0 otherwise. Leverage is bank overdrafts and long-term debt over total assets. All firm characteristics are dated December 2018 and have been normalized to have a mean of 0 and a standard deviation of 1. Clustered standard errors at the province-level presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Guarantee 2020 = 1				
	(1)	(2)	(3)	(4)	(5)
Excess Deaths	-0.002		-0.001		
	(0.001)		(0.001)		
Essential Sector	-0.003	-0.002			
	(0.002)	(0.002)			
Previous Guaranteed Lending	0.514***	0.512***	0.460***	0.459***	0.436***
	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)
Log(Assets)	0.079***	0.079***	0.074***	0.074***	0.066***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)
Log(Age)	0.001	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Cash/Assets	0.000	0.000	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Leverage	0.026***	0.026***	0.020***	0.020***	0.017***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
EBIT/Assets	0.006***	0.005***	0.001	0.001	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Altman Z-Score	-0.003***	-0.003***	0.004***	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Fixed effects					
Province	No	Yes	No	Yes	-
6-digit Industry	No	No	Yes	Yes	-
Province×6-digit Industry	No	No	No	No	Yes
Province Controls	Yes	-	Yes	-	-
Observations	550273	550273	550273	550273	550273
R^2	0.347	0.350	0.384	0.386	0.477

Table 4: **100% Guarantee 2020: Month of access**

The sample is restricted to eligible SME firms. The dependent variable is a dummy equal to one if the firm obtained a loan under the 100% public guarantee program after April 2020, 0 otherwise. In each column, the sample is restricted to firms that either obtained the guarantee in a given month or did not obtain the guarantee at all. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Previous Guaranteed Lending is a dummy equal to one if the firm previously accessed any FG program in 2018 or 2019, 0 otherwise. Leverage is bank overdrafts and long-term debt over total assets. All firm characteristics are dated December 2018 and have been normalized to have a mean of 0 and a standard deviation of 1. Clustered standard errors at the province-level presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Apr-May		June		July		August	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess Deaths	0.002*		-0.004***		-0.003***		-0.001***	
	(0.001)		(0.001)		(0.001)		(0.000)	
Essential Sector	-0.024***		-0.018***		-0.006***		-0.001**	
	(0.002)		(0.002)		(0.001)		(0.000)	
Previous Guaranteed Lending	0.121***	0.095***	0.061***	0.045***	0.035***	0.028***	0.015***	0.012***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)
Log(Assets)	-0.046***	-0.033***	-0.027***	-0.019***	-0.014***	-0.011***	-0.005***	-0.004***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
Log(Age)	-0.003**	-0.003**	-0.007***	-0.006***	-0.005***	-0.005***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Cash/Assets	-0.033***	-0.037***	-0.017***	-0.020***	-0.008***	-0.010***	-0.003***	-0.004***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.033***	0.024***	0.017***	0.012***	0.008***	0.006***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
EBIT/Assets	0.026***	0.021***	0.017***	0.015***	0.008***	0.007***	0.003***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Altman Z-Score	-0.006***	-0.001**	-0.005***	-0.002***	-0.003***	-0.001***	-0.001***	-0.000***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects								
Province controls	Yes	-	Yes	-	Yes	-	Yes	-
Province×6-digit Industry	No	Yes	No	Yes	No	Yes	No	Yes
Observations	516961	516961	490260	490260	470051	470051	457655	457655
R^2	0.044	0.167	0.027	0.134	0.015	0.114	0.005	0.097

Table 5: **Firm Heterogeneity: Interest Rates and Disbursement Times**

The sample is restricted to firms that took out a 100% guaranteed loan in Panel A and a 90% guaranteed loan in Panel B. The dependent variable is the interest rate (in percentage), columns 1-3, and disbursement times (in days), columns 4-6, of the loans taken under the 100% public guarantee program after April 2020. Previous Guaranteed Lending is a dummy equal to one if the firm previously accessed any FG program in 2018 or 2019, 0 otherwise. All firm characteristics are dated December 2018 and have been normalized to have a mean of 0 and a standard deviation of 1. Province controls are province characteristics included in Table 2. Standard errors clustered at the province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)			Disbursement Time (Days)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. 100% Guaranteed Loans						
Previous Guaranteed Lending	0.015***	0.019***	0.007***	-0.420*	-0.504**	-0.879***
	(0.004)	(0.005)	(0.002)	(0.217)	(0.218)	(0.145)
Log(Assets)	-0.010***	-0.010***	-0.007***	0.746***	0.595***	0.759***
	(0.002)	(0.002)	(0.002)	(0.132)	(0.154)	(0.125)
Log(Age)	-0.013***	-0.012***	-0.002*	-0.987***	-0.880***	-0.534***
	(0.002)	(0.002)	(0.001)	(0.084)	(0.089)	(0.060)
Cash/Assets	-0.008***	-0.006***	-0.003***	0.263***	0.301***	0.316***
	(0.002)	(0.002)	(0.001)	(0.076)	(0.078)	(0.060)
Leverage	0.013***	0.014***	0.006***	-0.216*	-0.099	-0.088
	(0.002)	(0.002)	(0.001)	(0.127)	(0.112)	(0.087)
EBIT/Assets	0.000	0.002	0.001	-0.247**	-0.250***	-0.261***
	(0.001)	(0.001)	(0.001)	(0.094)	(0.084)	(0.074)
Altman Z-Score	-0.001	0.001	-0.003	-0.006	0.047	-0.090
	(0.002)	(0.002)	(0.002)	(0.188)	(0.202)	(0.200)
Observations	120869	120869	120869	53287	53287	53287
R^2	0.027	0.184	0.623	0.116	0.303	0.582
Panel B. 90% Guaranteed Loans						
Previous Guaranteed Lending	0.374***	0.349***	0.230***	0.814**	0.760**	0.279
	(0.041)	(0.038)	(0.019)	(0.362)	(0.378)	(0.334)
Log(Assets)	-0.512***	-0.428***	-0.335***	-0.552**	-0.187	0.469*
	(0.042)	(0.037)	(0.027)	(0.257)	(0.296)	(0.272)
Log(Age)	-0.115***	-0.101***	-0.033**	-0.794***	-0.458**	-0.146
	(0.023)	(0.021)	(0.013)	(0.200)	(0.208)	(0.200)
Cash/Assets	-0.316***	-0.276***	-0.192***	-0.448	-0.161	0.317
	(0.027)	(0.025)	(0.025)	(0.316)	(0.264)	(0.302)
Leverage	0.216***	0.181***	0.169***	-0.271	0.110	-0.207
	(0.032)	(0.029)	(0.020)	(0.417)	(0.414)	(0.372)
EBIT/Assets	-0.099***	-0.098***	-0.062***	-0.930**	-0.799*	-0.459
	(0.029)	(0.025)	(0.024)	(0.451)	(0.441)	(0.374)
Altman Z-Score	0.088**	0.020	-0.009	0.668	0.932	-0.046
	(0.040)	(0.043)	(0.069)	(0.662)	(0.631)	(0.408)
Fixed effects						
Province controls	Yes	-	Yes	-	Yes	-
Month	Yes	Yes	Yes	Yes	Yes	Yes
Province×6-digit Industry	No	Yes	Yes	No	Yes	Yes
Bank	No	No	Yes	No	No	Yes
Observations	79914	79914	79914	29439	29439	29439
R^2	0.148	0.429	0.712	0.073	0.423	0.523

Table 6: **Bank Heterogeneity: Interest Rate and Disbursement Time**

The sample is restricted to firms that obtained a 100% guarantee loan in Panel A and 90% guaranteed loan in Panel B. The dependent variable is the interest rate, in percentage, (columns 1-3) and the disbursement time, in days, (columns 4-6). AppRating $\geq 4^*$ is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4 and have been standardized to have a mean of 0 and a standard deviation equal to 1. Firm controls are firm characteristics included in Table 2 and dated December 2019. Month fixed-effects refer to the month when the guarantee was approved (April to August). Standard errors two-way clustered at the province and bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)			Disbursement Time (Days)		
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. 100% Guaranteed Loans						
AppRating $\geq 4^*$	-0.059	-0.042	-0.094	-7.808***	-5.839***	-5.490***
	(0.084)	(0.087)	(0.067)	(2.283)	(1.670)	(1.435)
Log(Number Reviews)		-0.034	0.128**		-3.134***	-2.710**
		(0.059)	(0.050)		(1.138)	(1.318)
Bank - Ln(Assets)			-0.153***			-2.508***
			(0.021)			(0.682)
Bank - T1 Ratio			0.104			3.901
			(0.083)			(2.597)
Bank - NPL share			0.098			-7.387***
			(0.060)			(2.232)
Bank - ROA			0.025			0.465
			(0.024)			(1.281)
Bank - Interbank/Asset			-0.032			0.493
			(0.027)			(1.722)
Observations	108005	108005	108005	48416	48416	48416
R^2	0.191	0.197	0.369	0.359	0.385	0.454
Panel B. < 100% Guaranteed Loans						
AppRating $\geq 4^*$	-0.380	-0.262	-0.566***	-6.274***	-4.425***	-4.349***
	(0.307)	(0.313)	(0.163)	(0.557)	(0.673)	(0.787)
Log(Number Reviews)		-0.222*	0.177		-2.730***	-1.950***
		(0.124)	(0.142)		(0.454)	(0.690)
Bank - Ln(Assets)			-0.194			-0.695
			(0.162)			(0.464)
Bank - T1 Ratio			0.072			-3.559**
			(0.398)			(1.561)
Bank - NPL share			-0.038			0.532
			(0.182)			(0.682)
Bank - ROA			-0.407*			0.327
			(0.237)			(0.547)
Bank - Interbank/Asset			-0.594**			-0.025
			(0.296)			(0.892)
Fixed effects						
Province×6-digit Industry	Yes	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59882	59882	59882	22420	22420	22420
R^2	0.426	0.433	0.473	0.438	0.453	0.455

Table 7: **Heterogeneity: Log(Loan Amount)**

The sample is restricted to firms that took out a 90% guarantee loan. The dependent variable is the logarithm of the loan amount (in Euros) of the loans taken under the 90% public guarantee program after April 2020. AppRating $\geq$ 4* is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4 and have been standardized to have a mean of 0 and a standard deviation equal to 1. Firm controls are firm characteristics included in Table 2 and dated December 2019. Month fixed-effects refer to the month when the guarantee was approved (April to August). Standard errors two-way clustered at the province and bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Log(Loan Amount)				
	(1)	(2)	(3)	(4)	(5)
Previous Guaranteed Lending	-0.256***		-0.251***	-0.202***	-0.183***
	(0.029)		(0.026)	(0.021)	(0.020)
Log(Assets)	1.141***		1.133***	1.113***	1.112***
	(0.030)		(0.029)	(0.021)	(0.021)
Log(Age)	-0.091***		-0.094***	-0.083***	-0.075***
	(0.009)		(0.008)	(0.008)	(0.007)
Cash/Assets	0.261***		0.255***	0.211***	0.213***
	(0.018)		(0.017)	(0.020)	(0.020)
Leverage	-0.083***		-0.083***	-0.079***	-0.084***
	(0.014)		(0.015)	(0.012)	(0.013)
EBIT/Assets	0.140***		0.136***	0.126***	0.125***
	(0.014)		(0.015)	(0.009)	(0.009)
Altman Z-Score	-0.043		-0.041	-0.009	-0.010
	(0.055)		(0.054)	(0.040)	(0.036)
AppRating $\geq$ 4*		0.117	0.056	0.041	
		(0.123)	(0.098)	(0.071)	
Bank - Ln(Assets)		0.082**	0.033	0.036	
		(0.036)	(0.029)	(0.022)	
Bank - T1 Ratio		-0.225	-0.113	-0.034	
		(0.169)	(0.136)	(0.085)	
Bank - NPL share		0.062	0.040	0.033	
		(0.066)	(0.052)	(0.036)	
Bank - ROA		0.035	0.064	0.045	
		(0.074)	(0.057)	(0.042)	
Bank - Interbank/Asset		0.054	0.017	0.018	
		(0.050)	(0.042)	(0.033)	
Fixed effects					
Province Controls	Yes	Yes	Yes	No	No
Province×6-digit Industry	No	No	No	Yes	Yes
Month	Yes	Yes	Yes	Yes	Yes
Bank	No	No	No	No	Yes
Observations	59624	59624	59624	59624	59624
R^2	0.483	0.052	0.489	0.629	0.645

Table 8: **Guaranteed Lending and Local Banking Markets**

The dependent variable is the log of total guaranteed lending by bank b in province p. LocalMarketShare$_{b,p}$ is the share of branches of bank b in province p relative to the total number of bank branches in province p. CoreMarketShare$_{b,p}$ is the share of branches of bank b in province p relative to the total number of branches of bank b. All bank characteristics are dated December 2019 and have been normalized to have a mean of 0 and a standard deviation of 1. Standard errors clustered at the province and bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

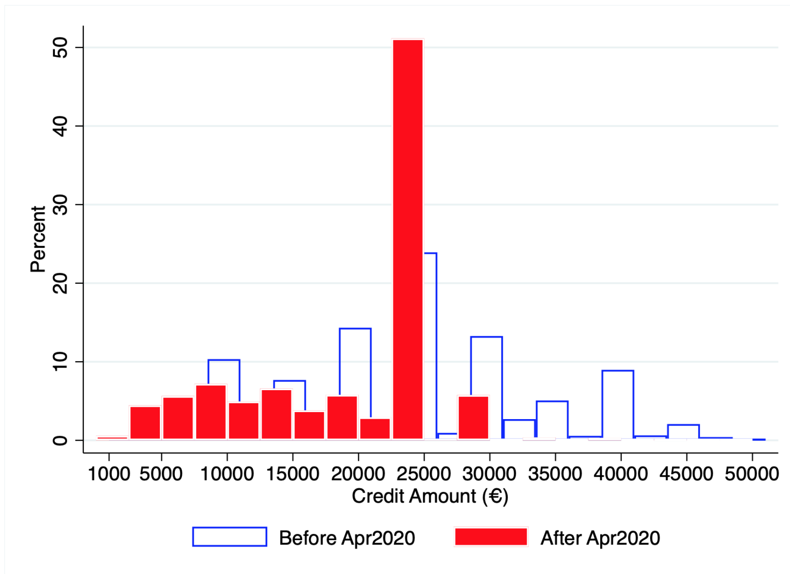
	Log(GuaranteedCredit)				
	(1)	(2)	(3)	(4)	(5)
LocalMarketShare$_{b,p}$	1.045***	1.006***			0.682***
	(0.137)	(0.132)			(0.086)
CoreMarketShare$_{b,p}$			1.666***	1.623***	1.235***
			(0.102)	(0.092)	(0.079)
AppRating $\geq$ 4*	0.083		0.001		
	(0.150)		(0.158)		
Log(Number Reviews)	-0.279**		-0.203		
	(0.133)		(0.136)		
Bank - Ln(Assets)	1.158***		1.691***		
	(0.101)		(0.102)		
Bank - T1 ratio	-0.185		-0.083		
	(0.272)		(0.205)		
Bank - NPL share	0.205		0.209		
	(0.143)		(0.161)		
Bank - ROA	0.086		0.026		
	(0.115)		(0.118)		
Bank - Interbank/Asset	0.116		0.042		
	(0.172)		(0.189)		
Fixed effects					
Province	Yes	Yes	Yes	Yes	Yes
Bank	No	Yes	No	Yes	Yes
Observations	3861	3861	3861	3861	3861
R^2	0.534	0.633	0.540	0.654	0.696

Online Appendix

Figure A1: Bunching at €25,000 and €30,000 threshold

This figure shows the distribution of loan amounts for government guaranteed in Italy. Panel A shows the distribution of loan amounts below €50,000 before and after April 2020, while Panel B shows the same distribution between April and August 2020.

(a) Panel A. Credit Amounts below €50,000 (Jan2018-Aug2020)



(b) Panel B. Credit Amounts below €50,000 (Apr-August 2020)

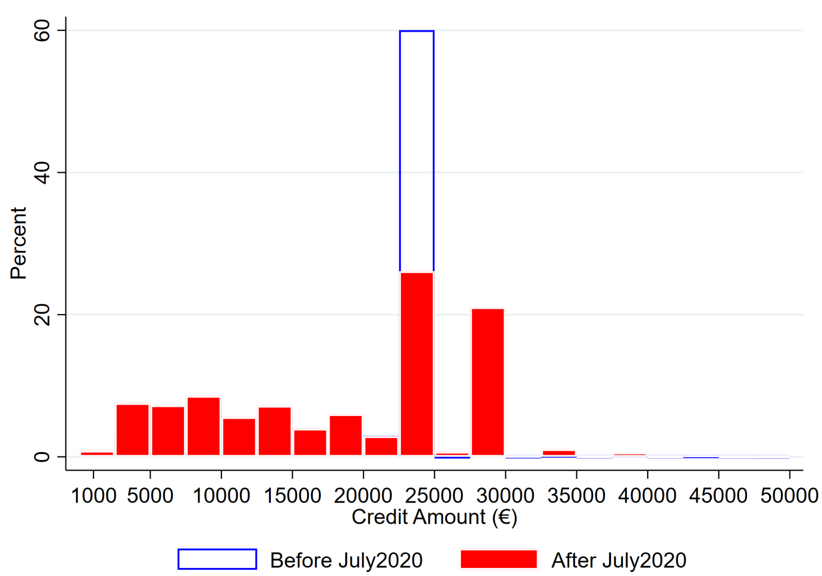


Figure A2: Guarantee Uptake in 2018-19

This figure plots the share of firms that obtained a guaranteed loan in 2018 and 2019. The total number of firms in a province is obtained from the universe of registered Italian firms (Movimprese).

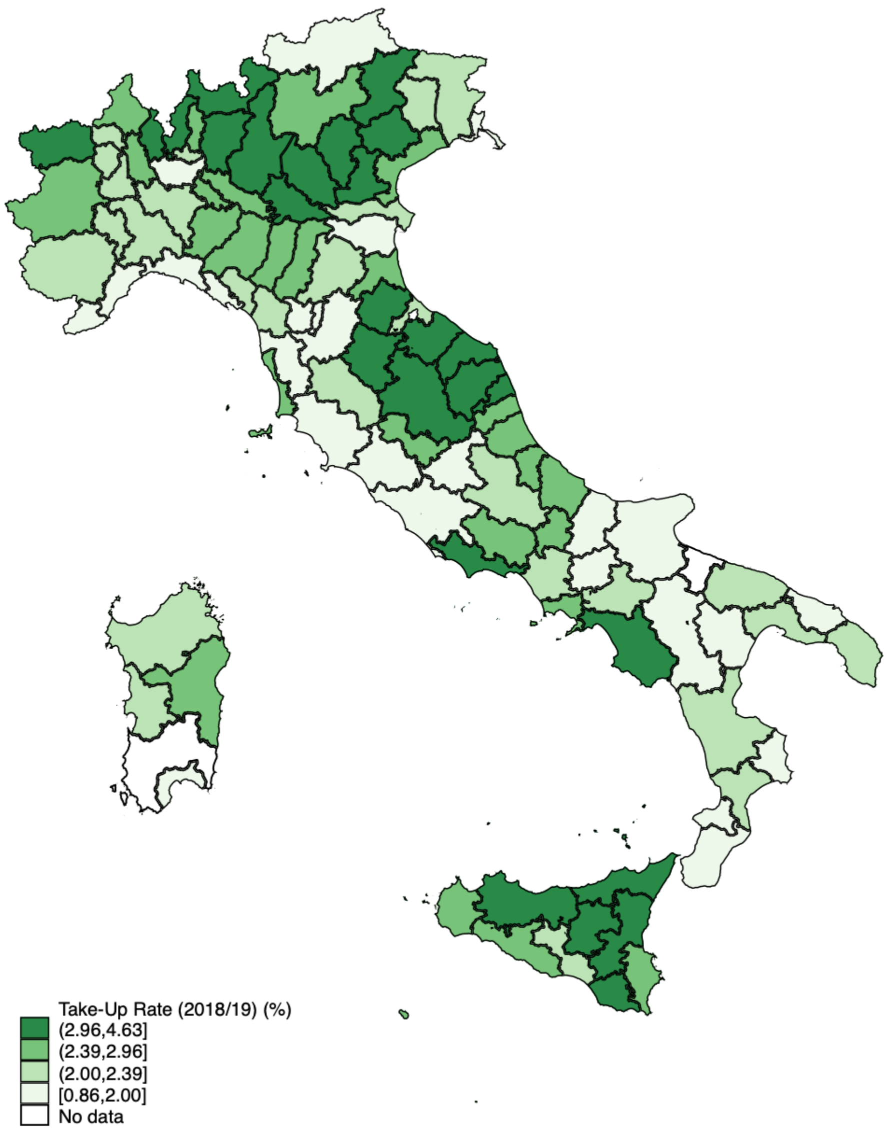


Figure A3: Guarantee Uptake in Apr-May vs. Jun-Jul-August 2020

This figure plots the share of firms that obtained a guaranteed loan in Apr-May vs Jun-Jul-August 2020.

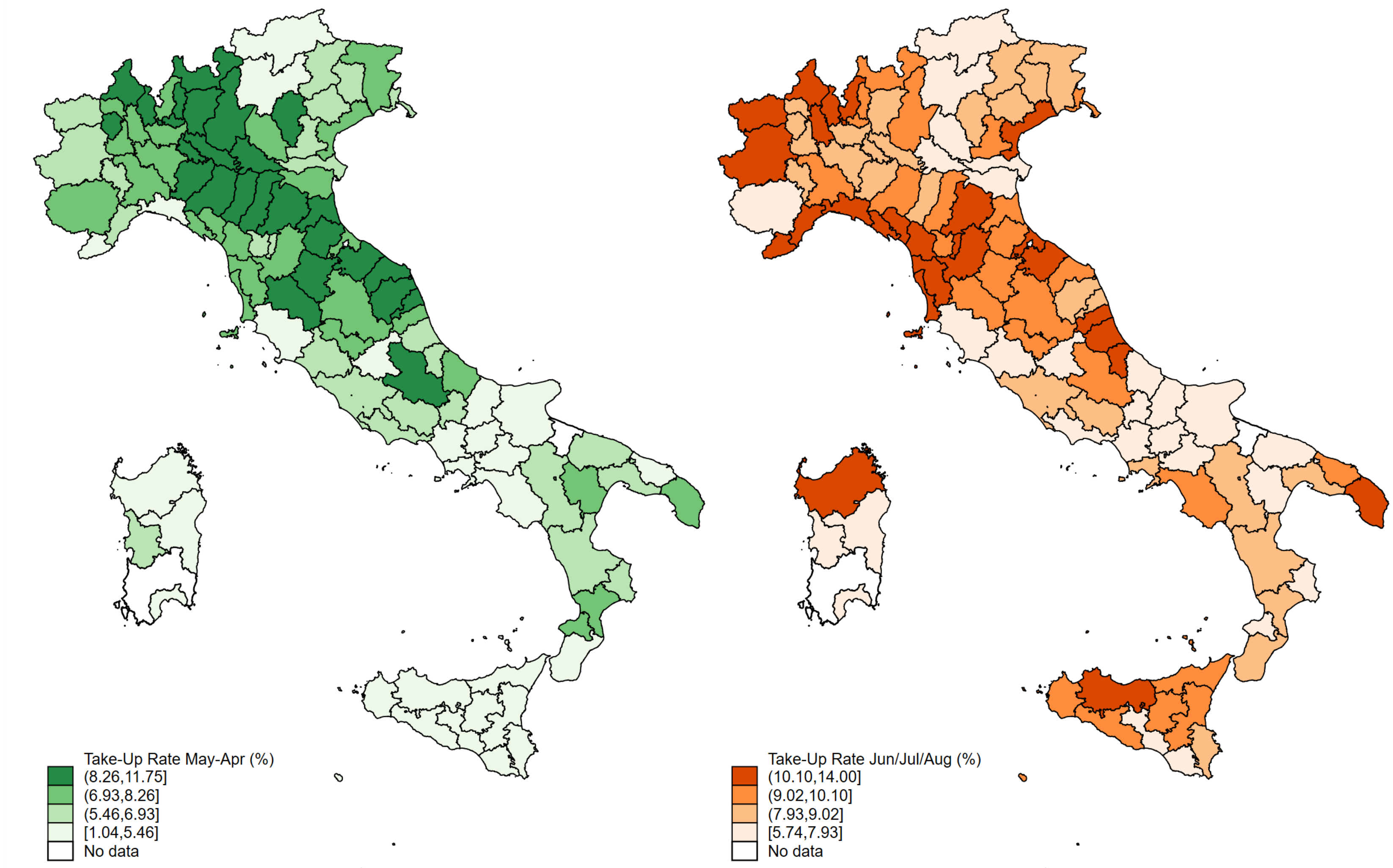


Table A1: **2020 Guarantee: All Firms, including unlimited liability companies**

The sample is restricted to eligible SME firms, including unlimited liability companies such as private partnerships and sole proprietorships. The dependent variable is a dummy equal to one if the firm obtained a loan under the 100% public guarantee program after April 2020, 0 otherwise. Essential Sector is a dummy equal to one for the 6-digit sectors that were considered essential and hence were not shutdown as of 25th March 2020; 0 otherwise. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Clustered standard errors at the province-level presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	All	Apr-May	June	July	August
	(1)	(2)	(3)	(4)	(5)
Excess Deaths	0.002	0.006***	-0.002**	-0.001***	-0.000***
	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Essential Sector	-0.046***	-0.025***	-0.021***	-0.009***	-0.002***
	(0.005)	(0.003)	(0.002)	(0.001)	(0.000)
Ln(Population) (2019)	-0.002	-0.003*	-0.001	0.001*	0.000
	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)
Ln(V.A. per Capita) (2017)	0.000	0.002	-0.001	-0.001	-0.000
	(0.005)	(0.004)	(0.002)	(0.001)	(0.000)
SME's % of Total Sales	-0.001	-0.001	-0.000	0.001	-0.000
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)
South Dummy	-0.007	-0.009	0.000	-0.001	-0.000
	(0.008)	(0.007)	(0.003)	(0.002)	(0.001)
HHI Bank Branches	0.001	0.004	-0.003*	-0.002*	0.001
	(0.004)	(0.003)	(0.002)	(0.001)	(0.000)
Observations	2,811,120	2,542,263	2,488,682	2,422,340	2,370,805
R^2	0.005	0.005	0.003	0.002	0.000

Table A2: **Guarantee 2020 and Covid-19 (Positive Tests)**

The sample is restricted to eligible SME firms. The dependent variable is a dummy equal to one if the firm obtained a loan under the 100% public guarantee program after April 2020, 0 otherwise. Essential Sector is a dummy equal to one for the 6-digit sectors that were considered essential and hence were not shutdown as of 25th March 2020; 0 otherwise. COVID19 Cases per Capita is the share of positive test in a province between March-June 2020 (from Protezione Civile). In columns 3 through 6, the sample is restricted to firms that either obtained the guarantee in a given month or did not obtain the guarantee at all. Firm controls are firm characteristics included in Table 2 and dated December 2018. Province controls are province characteristics included in Table 2. Clustered standard errors at the province-level presented in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	All Loans		Apr-May	June	July	August
	(1)	(2)	(3)	(4)	(5)	(6)
COVID19 Cases per Capita	-0.004*	-0.001	0.003	-0.002*	-0.002**	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Essential Sector	-0.035***					
	(0.004)					
Fixed effects						
6-digit Industry	No	Yes	Yes	Yes	Yes	Yes
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Province Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	584946	584941	517927	492268	472846	460809
R^2	0.065	0.115	0.086	0.050	0.027	0.010

Table A3: **90% 2020 Guarantee: Month of access**

The sample is restricted to eligible SME firms. The dependent variable is a dummy equal to one if the firm obtained a loan under the 90% public guarantee program after April 2020, 0 otherwise. In each column, the sample is restricted to firms that either obtained the guarantee in a given month or did not obtain the guarantee at all. Excess Deaths 2020 is the percentage increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Previous Guaranteed Lending is a dummy equal to one if the firm previously accessed any FG program in 2018 or 2019, 0 otherwise. Leverage is bank overdrafts and long-term debt over total assets. All firm characteristics are dated December 2018 and have been normalized to have a mean of 0 and a standard deviation of 1. Standard errors clustered ata the province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Apr-May		June		July		August	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Excess Deaths	-0.002**		0.000		-0.000		-0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
Essential Sector	0.000		-0.003**		-0.001		0.001	
	(0.001)		(0.001)		(0.001)		(0.001)	
Previous Guaranteed Lending	0.377***	0.322***	0.357***	0.301***	0.382***	0.327***	0.275***	0.238***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.006)	(0.007)	(0.007)	(0.007)
Log(Assets)	0.021***	0.017***	0.034***	0.028***	0.041***	0.035***	0.018***	0.015***
	(0.002)	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Log(Age)	0.000	0.000	0.001	0.001	0.001	0.001	0.000	0.000
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Cash/Assets	-0.000	-0.002***	0.001***	-0.002***	0.001*	-0.004***	-0.000	-0.002***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Leverage	0.006***	0.004***	0.010***	0.007***	0.014***	0.010***	0.006***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
EBIT/Assets	0.000	-0.000	0.001***	0.000	0.003***	0.001	0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Altman Z-Score	0.000	0.002***	-0.001***	0.002***	-0.001***	0.002***	0.000**	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fixed effects								
Province controls	Yes	-	Yes	-	Yes	-	Yes	-
Province×6-digit Industry	No	Yes	No	Yes	No	Yes	No	Yes
Observations	482173	481694	488310	488074	496626	496611	476373	475752
R^2	0.288	0.429	0.234	0.385	0.236	0.377	0.182	0.331

Table A4: **Within Firm Variation**

The sample is restricted to firms taking out more than one partially guarantee loan. The dependent variables are the interest rate (in percentage), disbursement times in days, and logarithm of the loan amount (in Euros) of 90% guaranteed loans. Bank characteristics are banks' balance sheet items, as resulting from the last available balance sheet and have been normalized to have a mean of 0 and a standard deviation of 1. Standard errors clustered at the province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)	Disbursement Time (Days)	Log(Loan Amount)
	(1)	(2)	(3)
AppRating $\geq$ 4*	-0.532***	-5.007***	-0.019
	(0.132)	(0.724)	(0.047)
Log(Number Reviews)	0.204	-1.681**	0.022
	(0.126)	(0.684)	(0.022)
Bank - Ln(Assets)	-0.182	-0.606	0.029
	(0.145)	(0.537)	(0.018)
Bank - T1 Ratio	0.165	-3.208*	-0.038
	(0.379)	(1.770)	(0.053)
Bank - NPL share	-0.037	0.808	0.014
	(0.151)	(0.586)	(0.021)
Bank - ROA	-0.432**	0.444	0.031
	(0.211)	(0.580)	(0.027)
Bank - Interbank/Asset	-0.571**	-0.871	-0.017
	(0.245)	(1.053)	(0.024)
Fixed effects			
Firm	Yes	Yes	Yes
Month	Yes	Yes	Yes
Observations	39388	13228	39388
R^2	0.702	0.758	0.754