# Public Guarantees for Small Businesses in Italy during Covid-19

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#### Abstract

This paper studies the allocation of credit through a public guarantee scheme for small businesses during the Covid-19 pandemic. In April 2020, the Italian government expanded existing guarantees and introduced a free 100% guarantee on loans below  $\pounds 25,000$  that required no credit assessment by banks. Using unique loan-level data from the Italian Guarantee Fund, we first show that funds initially flowed to ex-ante financially fragile firms located in areas more affected by the pandemic, but were later received by all types of firms nationwide. Second, we show that there is significant lender heterogeneity in disbursing guaranteed funds: larger banks and those with better information technology (IT) systems charge lower rates and disburse loans faster compared to other banks. Bank size and the digital infrastructure are important because of the small profitability margins on guaranteed lending and the large volume of online loan applications received during the pandemic. Finally, we show that the bank branch network still matters, because banks lend more in their core markets and where they have a larger market share of local branches. Our results shed light on the importance of understanding the role of information technology and the structure of local banking markets for the allocation of public relief funds during a crisis.

**Keywords:** public guarantees; covid-19; liquidity constraints; information technology; bank heterogeneity; interest rates **JEL:** G32, G38, H25, H32, E62

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## 1 Introduction

The Covid-19 pandemic forced a global business shutdown and caused a severe liquidity crunch, especially among small businesses that have no access to capital markets. Policymakers rushed to introduce credit guarantee schemes in order to support bank lending to liquidity constrained firms. These public guarantees are massive, especially in countries hit more severely by the pandemic: in Italy, the scheme amounts to  $\notin$ 400 billion in additional guarantees (equivalent to about 22% of GDP), similar in size to the \$660 billion the US Congress approved under the Paycheck Protection Program (PPP). Given that these policy interventions require the banking system to act as a conduit of government-backed liquidity, it is crucial to assess whether banks' incentives to participate in the program could distort the allocation of guaranteed credit, determining who gets it first and what conditions. In particular, local brick-and-mortar banks may have a hard time processing a large volume of online loan applications, at a time when there are restrictions that limit borrowers' access to local bank branches.

On April 8<sup>th</sup>, 2020 the Italian government expanded the existing public guarantee scheme for small businesses, increasing the guarantee coverage from 80% to 90% for loans up to  $\in 5$  million. Moreover, it introduced 100% guarantees for loans up to  $\in 25,000$  (increased to  $\in 30,000$  in June) that require no fee payment from the borrower and no formal credit assessment by the bank, in order to speed up the approval process. The interest rate on the fully guaranteed loans was capped with a time-varying formula that depends on government bond yields and bank-sovereign CDS spreads, which yielded in a maximum interest rate cap of about 2%. These unique features of the Italian guarantee program make it an ideal policy intervention to study lenders' incentives to distribute public relief funds to small firms, since credit risk is fully absorbed by the government.

Using loan-level data from the Italian Guarantee Fund (*Fondo di Garanzia*, FG) for Small and Medium Enterprises (SME) we first describe whether the program successfully targeted small business that were more affected by Covid-19. One advantage of Italian FG data compared to US PPP data is that they contain the unique firm tax code of the universe of firms which obtained a guaranteed loan.<sup>1</sup> This allows to match loan guarantees to firm balance sheet data for a large sample of SME firms from Bureau Van Dijk (BvD) Orbis. We also obtain the names of the lenders by matching the bank codes provided by the FG to public records from the Italian Parliamentary Committee on the guarantee program and end up with a full bank-firm matched dataset of guaranteed loans. This is important to establish that supply side restrictions matter for the allocation of government guaranteed funds, fully absorbing credit demand factors with a granular set of province×6-digit industry fixed-effects, together with firm-level characteristics.<sup>2</sup>

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  $\notin$ 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 (86%) were  $\notin$ 25,000 loans for a total of  $\notin$ 18 billion of which more than one third were obtained by firms in financial distress.<sup>3</sup> The overall take-up rate remained fairly low, since only 16% of eligible firms obtained a guaranteed loan.<sup>4</sup> Given the different institutional setting and the difference in relative market size, we analyze fully guaranteed loans separately from partially guaranteed ones.

We find that both the local strength of the pandemic, as measured by infections and fatalities, and the presence in a non-essential sector that was shut down in March increase the take-up rate in the 100% guarantee program, but not for the partially guaranteed loans. Moreover firms with less cash on hand, higher leverage and lower Altman Z-scores (i.e. riskier

<sup>&</sup>lt;sup>1</sup>On December 1, 2020 the SBA released data that include the names, but not the tax identifier, of all 5.16 million PPP borrowers. Thus, even with these data, it is very difficult to obtain firm-level characteristics for the small, private PPP borrowers, especially because private firms' balance sheet data do not exist in the US. Firm-level PPP evidence focuses on publicly listed firms (Balyuk et al., 2020; Duchin et al., 2020).

 $<sup>^{2}</sup>$ In robustness tests we use within firm variation exploiting the fact that firms could obtain multiple partially guaranteed loans from different banks. The results are quantitatively similar when we include a firm fixed-effect, indicating that 6-digit industry×province fixed-effects are already sufficient to capture most factors that affect credit demand.

<sup>&</sup>lt;sup>3</sup>Firms in distress represent about 35% of the overall population of firms according to the measure developed by Altman et al. (2012) for Italian companies. Thus, the share of distressed firms that obtained government guaranteed loans is similar to the share of distressed firms in the overall firm population.

<sup>&</sup>lt;sup>4</sup>The take-up rate on government guaranteed loans has been similarly low in Spain and France too (Economist, n.d.). 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.

firms) have higher participation rates in both types of guaranteed loans, with the only natural difference that fully guaranteed loans (up to  $\notin 25,000$ ) are obtained by smaller firms. These firm characteristics matter over and above the strength of the shock at the local and industry level, since the estimated coefficients remain stable when we include both province and 6-digit industry dummies or their interaction. However, these effects vary over time: 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 use the new guarantee 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 guaranteed funds.

Second, and most importantly, we find significant supply side restrictions in the allocation of credit, the loan interest rate and the disbursement time of guaranteed loans. For example, we find that large banks issue more guaranteed loans, charge lower rates and disburse them faster than small, local banks. Large banks may have an advantage in issuing guaranteed loans because they have lower funding costs, for example due to preferential access to ECB lending facilities. Moreover, since interest margins on government guaranteed credit and especially on small loans below &25,000 are low, only large banks that can process a large volume of loans in an automatized way can achieve profitability. Small cooperative banks, that are traditionally thought to be able to better serve local small businesses, especially in a crisis (Berger et al., 2017), were not able to achieve efficient economies of scale on these loans and were 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. The quality of the bank IT systems is likely to matter because most loan applications were made online, and banks with better IT systems were able to cater to the surge in online loan 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 fixed-effects and firm controls.

Since most applications for guaranteed loans were filed online, one may question the importance 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, lending relationships remain important and since they are notoriously sticky (Petersen and Rajan, 1994; Degryse and Ongena, 2005), local lending markets and the bank branch network may remain 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 portion of their branch network, and in markets where they have more market power, i.e. a larger share of local branches. Overall, these results indicate that the both the digital and physical bank infrastructure matter for the allocation of credit.

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 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. Crucially, lender heterogeneity further suggests that supply side restrictions, in particular the quality of the bank IT infrastructure, hampered the process of distributing guaranteed loans, in terms of quantity, pricing and processing times. Notably, local cooperative banks, which are typically 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.

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) (de Andrade and Lucas, 2009; 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; Ding 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.

To our knowledge, this is the first paper examining the credit guarantee program in Italy or in Europe after Covid-19. This has several advantages. First of all, the loan-level data from the Italian guarantee fund contain the universe of guaranteed loans at the individual borrower level. This allows for a granular analysis of the firm-level drivers of the participation rate and loan interest rates or disbursement times. Second, not only Italy was one of the countries more severely hit by the global pandemic, but it also introduced one of the largest public credit guarantee scheme, equivalent to 22% of GDP. Finally, the distinctive features of the Italian guarantee compared to other guarantee programs (100% guarantee up to &25,000 with no credit check and an interest rate which is capepd but can vary across banks and firms) contribute to make it an unprecedented type of policy intervention which warrants further examination.

## 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; Holmström and Tirole, 1997). Loan guarantees issued by government-backed entities, such as 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 other types of support schemes, such as direct lending or interest rate subsidies.

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  $\in$ 17.5 billion in new loans to SMEs received a public credit guarantee, compared to  $\in$ 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<sup>th</sup>, 2020 the Italian government approved a law decree, the so-called *DL Liquiditá*, that strengthened the FG capacity to issue guarantees by an additional  $\notin$ 400 billion. Of these,  $\notin$ 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  $\notin$ 1.5 to  $\notin$ 5 million.<sup>5</sup> The amount of the loan is capped at one quarter of sales in 2019 or twice annual payroll. Second, for loan amounts up to  $\notin$ 25,000 (increased to  $\notin$ 30,000 in June), the guarantee is full and free, i.e. no extra-fees are charged to the borrower to obtain the state aid. Moreover, interest rates on small loans are capped at around 2%, but can also be set below the ceiling.<sup>6</sup> The loans have a maturity of 6 years (increased to 10 years in June) and

<sup>&</sup>lt;sup>5</sup>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.

<sup>&</sup>lt;sup>6</sup>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

no principal payment, only interest, is due in the first two years of the loan. Crucially, fully guaranteed loans require no application of the credit scoring model typically 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.

Many countries introduced similar programs. For example, in the US the PPP offers government guaranteed loans to small businesses through the SBA. The loans 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 and if firms do not lay off workers or change their compensation. Other European countries, such as France, Spain and the UK have introduced similar measures. Germany has introduced the largest government guarantee program, amounting to  $\notin$ 700 billion. The German scheme also features a 100% guarantee for loans below  $\notin$ 800,000, but subject to a credit approval by the bank for any loan amount and with an interest rate of 3%. Finally, loan guarantees are part of a larger menu of government interventions that include debt moratoria and short-time work programs to support firms during the pandemic.

decreased to 0.6% in August. For loans that are not 100% but only 90% government guaranteed, the interest rate is freely determined by the bank.

## 3 Data

Loan level data on the universe of guaranteed loans are publicly available in Italy.<sup>7</sup> Differently from other guarantee programs, such as the PPP, these loan origination data<sup>8</sup> include basic information on the borrowing firm or 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 guarantee and the type of program (e.g. support for start-up, microcredit, SMEs in the South of Italy). The ability to match individual, private small firms to full balance sheet information is crucial to assess program targeting for financially constrained firms. 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 an anonymous bank identifier.<sup>9</sup> 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 number and value of guaranteed loans extended by every intermediary in Italy. Doing so allows us to recover the names of about 120 lenders that extend 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 2,910,923 entities which filed in either 2018 or 2019. Most firms in Orbis (72%) are private partnerships and sole proprietorships, i.e. unlimited liability companies that

<sup>&</sup>lt;sup>7</sup>The act on data transparency made these data publicly available at https://www.fondidigaranzia.it/amministrazione-trasparente/

<sup>&</sup>lt;sup>8</sup>Loan applications data on guaranteed credit do not exist (fully guaranteed loans are even below the  $\in$  30,000 reporting threshold in the Italian Credit Register). Anecdotal evidence from Bank of Italy and the Parliamentary Committee report filed in late May suggest that banks were able to process about 50% of all the loan applications they received up until then (about 500.000). Banks mentioned the large surge in applications and logistical bottlenecks (the FG did not have a process to automatically approve loan applications until mid-May) as reasons for the delay in the approval process.

<sup>&</sup>lt;sup>9</sup>Disbursement times are not available for all loans because under the current law banks have up to six months to report the data to the FG.

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). We have instead the full financial accounts of 651,797 firms, typically limited liability companies.<sup>10</sup> Within the sample of those that have full financial accounts, we match about 130,000 that obtained the 100% guaranteed loan, 46,000 that obtained 86,000 loans with a partial guarantee (84% on average) while the remaining 456,000 did not obtain any guaranteed loan (the control group) despite being eligible.<sup>11</sup>

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 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 their major role in banks' response to lockdown measures.

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

<sup>&</sup>lt;sup>10</sup>According to the ASIA register, a statistical survey by ISTAT, 935,595 firms were compelled to file a full balance sheet in Italy in 2018. Thus, Orbis coverage of firms with full financial information is quite complete (70%).

<sup>&</sup>lt;sup>11</sup>We analyze firms with 100% or <100% guaranteed loans separately, since the two types of loan guarantees are very different from the institutional point of view. Overall, we thus obtain full financial accounts for 66% of the limited liability companies that appear on the FG data and 43% of private partnerships and sole-proprietorships. While these small, unlimited liability companies 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, the lockdown of non-essential sectors and the local bank branch heterogeneity are robust when we include them too.

deaths between March and April 2020 and March and April 2019 (Excess Deaths 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. These types of government programs were greatly expanded during the pandemic, including among the beneficiaries small business with less than 5 employees.

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<sup>th</sup>, 2020. For example, while agriculture and food processing (codes 011110-017000) were considered essentials and thus could continue to operate, restaurants (code 561011) or construction of residential and non-residential buildings (code 412000) were closed. The availability of this information at the 6-digit sector level yields significant variation even within closely related sectors: for example, while manufacturing of technical glassware for labs and pharmacies was considered essential (code 231910), manufacturing of glassware for watches, optics, lamps and other items (code 231990) was not.

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. Firms that obtained the 100% guaranteed loans are 22.6% of the eligible SME firms in Italy that have full coverage of financial accounts in Orbis, suggesting an overall low level of participation in the program. However, an additional 16% obtained a partially guaranteed loan, which are much larger on average ( $\leq 450,000$  vs  $\leq 23,000$ ). 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  $\notin$ 25,000 have sales lower than  $\notin$ 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 2013 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 with 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,  $\in$ 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  $\in$ 79 billion, representing 10% of the stock of bank credit to non-financial firms in 2019 and 2% of bank total assets. About  $\in$ 18 billions in 100% guaranteed loans were extended to 829,053 borrowers, two thirds of which are private partnerships, sole proprietorships and self-employed individuals, and the remaining  $\in$ 61 billion where received by about 100,000 firms who benefited from an average guarantee of 84% of the value of the loan. Figure 1 - Panel B furthers reveals that the increase in loan

volumes is accompanied by an increase in the number of guaranteed loans, from about 10,000 per month in 2019 to a peak of about 360,000 during the month of May. The increase in both volume and number resulted in a reduction in the average size of the loans: after April 2020 the vast majority (86%) of loans are below &25,000.<sup>12</sup> 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 according to the firm registry in December 2019 (*Movimprese*). 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, more than 20% of firms in the food and accommodation sector have and almost 60% among healthcare and social assistance firms. 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 high in the south of Italy, especially in Sicily and Naples (see Figure A2 in the Appendix). Moreover, it 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

<sup>&</sup>lt;sup>12</sup>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  $\notin$ 50,000 issued in April 2020, 63% are exactly at the  $\notin$ 25,000 threshold compared to 21% before. As the loan threshold was increased from  $\notin$ 25,000 to  $\notin$ 30,000 in late June, a small excess mass appears at that cutoff too. Interestingly however the mode of the distribution remains at  $\notin$ 25,000 even in July, suggesting that the old threshold is more salient to borrowers.

(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 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.

Finally, in Figure A3 in the Appendix we estimate the effectiveness of the guarantee program in addressing firms' liquidity problems. To measure the number of illiquid firms we follow the methodology described in Schivardi and Romano (2020).<sup>13</sup> We find that the number of illiquid firms, absent any intervention, would reach 200,000 firms by the end of the year. Considering the actual uptake of the guarantee (about 14%), the number of illiquid firms is reduced by about 20,000 in each month, but it is still substantial. We find that if all eligible firms had asked and obtained the guaranteed loans, the number of illiquid firms would be reduced by an additional 50,000 units, a reduction of about 50% in the number of illiquid firms as of June 2020.

#### 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

<sup>&</sup>lt;sup>13</sup>The procedure works as follows. Monthly cash flows depend on the initial stock of liquidity and an estimate of the evolution of cash flow month by month in 2020. To obtain the latterm they subtract actual costs times the inputs' elasticity from 2019 sales and assume that 2020 cash flows will change according to forecasts of sales growth at the 2-digit sector from Cerved, a Italian rating agency. Given an initial stock of liquidity, the budget equation determines the stock of liquidity in each month: when this value turns negative, a firm is classified as illiquid. The procedure requires both payroll and costs of material, which we have available for about 400,000 firms.

probability model:

$$Guarantee 2020_{f,p,s} = \beta_1 Covid_p + \beta_2 Essential Sector_s + \gamma' X_f + \epsilon_{f,p,s}$$
(1)

where Guarantee2020<sub>*f,p,s*</sub> is a dummy equal to one if firm *f* located in province *p* and active in the 6-digit sector *s* took a loan in the new 100% guarantee program for loans up  $\in$ 25,000, 0 otherwise. 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.<sup>14</sup> Covid<sub>*p*</sub> 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 June. Essential Sector<sub>*s*</sub> is a dummy equal to one for the 6-digit sectors that remained open between March 25<sup>th</sup> and May 15<sup>th</sup>, 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. bank and long-term debt over assets; and the composition of leverage, i.e. bank debt and overdrafts over short-term liabilities). When we include the Altman Z-score as an alternative measure for firm risk we drop the variables that are already included in the Z-score itself (i.e. leverage). Finally, we use clustered standard errors at the province level.

The results 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 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

<sup>&</sup>lt;sup>14</sup>We restrict the estimation sample to all eligible Italian SME firms (i.e., < 500 employees or  $< \notin 50$  million in sales or  $< \notin 43$  million in total assets) that have a full financial account in Orbis.

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, at least in the overall sample.

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 new guaranteed loan in 2020 in the specification with province  $\times$  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 firms, as measured by total assets, 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  $\notin 25,000$  that obtained a partial loan guarantee (84% on average). The results are presented in Table 3. Interestingly, we find that 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  $\notin 5$  million. On average in fact partially guaranteed loans are about  $\notin 450,000$  with a median of  $\notin 250,000$ . 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. The most noticeable result is that 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.<sup>15</sup> The coefficient is small, but not negligible: for example, a firm located in Bergamo,

<sup>&</sup>lt;sup>15</sup>In Table A2 in the Appendix we use the share of infections at province level 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 varies widely from one region to another. As a matter of fact, we find that the effect of a 1 standard deviation increase in the local infection rate, while positive in

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 A4 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 result suggests that 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 on, as the economic consequences induced by the pandemic and the lockdown measures were fully appreciated in the rest of the country, firms obtained the guaranteed funds. In this respect, Balduzzi et al. (2020) survey Italian firms and find that already in early April those located in areas with more Covid-19 deaths were more pessimistic about their future sales. Potentially these pessimistic entrepreneurs were more likely to apply for a loan earlier on.

The effects of firm characteristics suggest that in June and August the types of firms receiving the guarantee also changed over time. In particular, firms who previously took part to the guarantee program and 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, as the visual evidence in Figure 4 suggested. In July and especially in August, firm level characteristics are precisely estimated but very small, implying that even safer firms obtained a government guaranteed loan.

#### 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

April and May, is not statistically significant. All other coefficients, including the one on the non-essential sectors, are unchanged.

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, the average loan rate is only 2.8%. We then calculate disbursement time as the number of days between the date of approval of the loan by the FG and the date on which banks effectively pay out the loan to the borrower. Notably, disbursement times are negative for 100% guaranteed loans as banks can disburse the loan before the FG approves the guarantee and with no formal credit assessment. Partially guaranteed loans, which are larger and require the application of the rating algorithms from the FG, would instead take longer. In general, we find that the banking sector has been relatively efficient in disbursing the fully guaranteed loans take almost two weeks on average to be disbursed after the FG has approved them. 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), which, as we shall see later, largely depends on bank size and the quality of IT.

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 banks price firm risk: younger, smaller, more levered and with less cash on hand, pay higher interest rates on their guaranteed loans. 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  $\mathbb{R}^2$  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 also 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 other, 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. 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. Much like with interest rates, bank heterogeneity seems to be a key driver of overall disbursement times.

## 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 supply side of guarantee loans depends on bank characteristics and on their 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 from unexpected shocks (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 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 big 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, if a firm happens to be located near an underperforming bank it 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  $\notin$ 500 in interest per year, to ensure profitability banks need to decrease average costs per loan by issuing a large volume of loans and automatizing the approval process, since the fixed cost per hour of loan officer 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 leverage on the bank identifier in the confidential FG data, matched with lender names from the Parliamentary Committee report and test whether the pricing and disbursement times of the guaranteed loans granted depend on a number of individual bank characteristics. This allows to control for credit demand conditions by saturating the regression with province×6digit 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.<sup>16</sup> 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:

$$Y_{i,f,b} = \beta_1 AppRating_b + \lambda' X_f + \gamma' X_b + industry \times provinceFE + \epsilon_{f,p,s}$$
(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<sub>b</sub> 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.<sup>17</sup> We also include a dummy for the month in which the

 $<sup>^{16}</sup>$ We focus on reviews and ratings in Google Play Store as in Italy Android (i.e. Google's mobile operating system) had a market share exceeding 80% as of 2019.

<sup>&</sup>lt;sup>17</sup>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

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 7 days 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, suggesting 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 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

less than a quarter of 2019 sales. Results are quantitatively unchanged (Table A3 in the Online Appendix), suggesting that province×6-digit sector fixed-effects are already fully controlling for demand.

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  $\notin 25,000$  loans is about  $\notin 500$  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**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 owner nationwide, banks are not restricted to lend in areas where they have a branch or to their 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 crucial to understand bank lending.

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 (the number of) branches.<sup>18</sup> Formally, we estimate the following:

$$\log(Lending)_{b,p} = \beta_1 Local Market Share_{b,p} + \beta_2 Core Market Share_{b,p} + \lambda_p + \lambda_b + \epsilon_{b,p} \quad (3)$$

where the dependent variable is the log of the total amount of guaranteed credit by bank <sup>18</sup>The amount of deposits or lending in each branch is not publicly available.

b in province p, including both fully and partially guaranteed loans.<sup>19</sup> LocalMarketShare<sub>b,p</sub> is 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 market power of the bank in the province. CoreMarketShare<sub>b,p</sub> 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 7. First of all, we find that banks with higher local market power 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 of market power 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, it will 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

<sup>&</sup>lt;sup>19</sup>We ran the specification separately for each type of guaranteed credit and found very similar results.

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 study the effectiveness of such programs in allocating public funds using the banking system. 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 three distinctive feature: it is free for the borrower; it covers 100% of the loan up to &25,000 and requires no credit check by the bank granting the loan. Moreover, Italian loan-level data on public guarantees allow a full bank-firm match of balance sheet characteristics even for very small firms.

We first show that funds initially flowed to areas most affected by the health crisis and only later went to other areas. Small firms, with less cash on hand, more leverage and bank debt are more likely to participate in the program. Second, we uncover that lender heterogeneity matters both for the pricing and disbursement time of guaranteed loans. In particular, we find that banks with better IT systems, as proxied by the Google review rating on the mobile banking app, disburse loans faster and at lower interest rates. Still, local banking markets are not dead, as banks' pre-existing geographical footprints and the local branch market shares are important determinant of the overall volume of guaranteed credit.

Overall, these results indicate that firms did participate in the new public guarantee program, and funds went to areas, sectors and firms most affected by the pandemic and its economic effects, at least initially. Importantly, bank heterogeneity and the quality of the digital infrastructure matter, suggesting that the banking sector plays an important role in directing such policy stimulus. 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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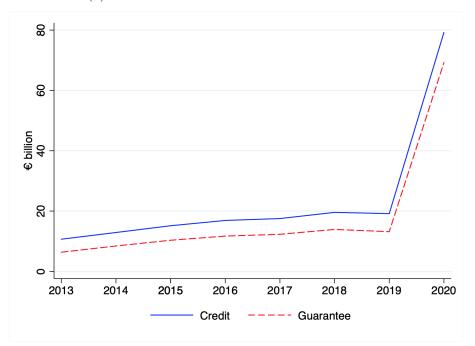
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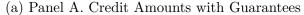
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#### Figure 1: Loan Amounts and Number of Loans with Public Guarantees in Italy

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).





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

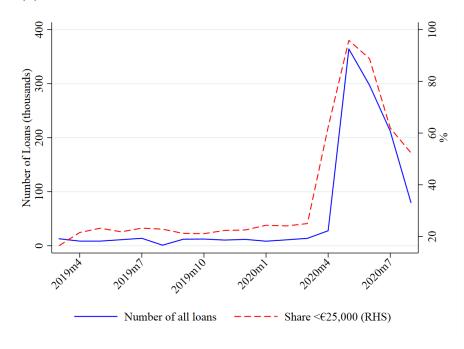
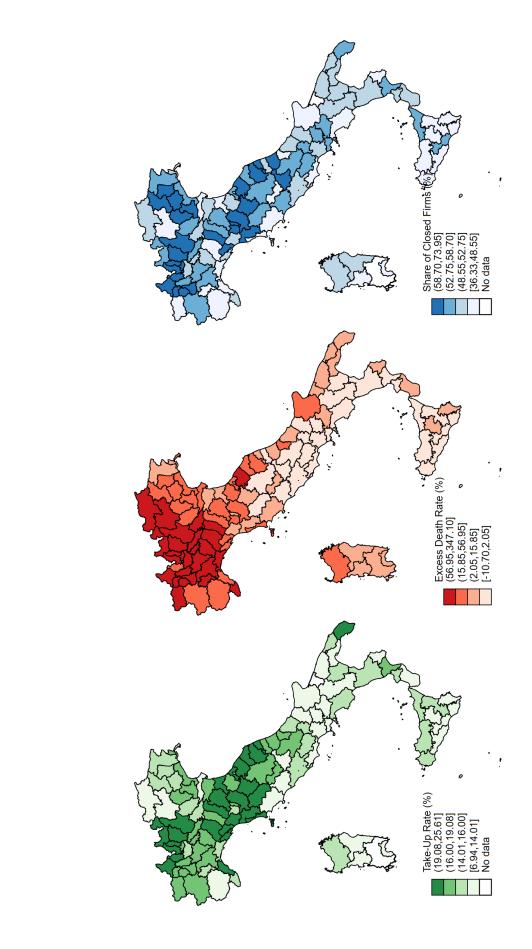


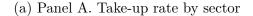
Figure 2: Guarantee, Excess deaths and Closed firms by Province

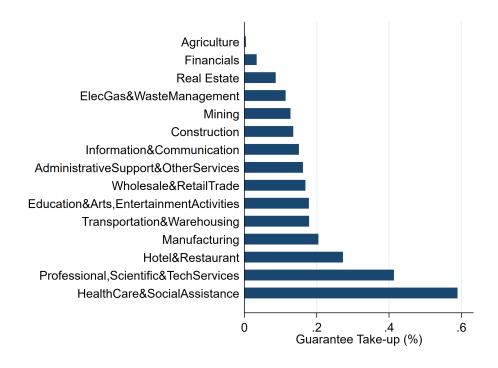
universe of registered Italian firms (Movimprese). The correlation coefficients between the take-up rate and excess deaths or share of closed firms are: This figure plots the share of firms that obtained a loan under the 100% public guarantee scheme from April 2020 over the total number of firms in the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



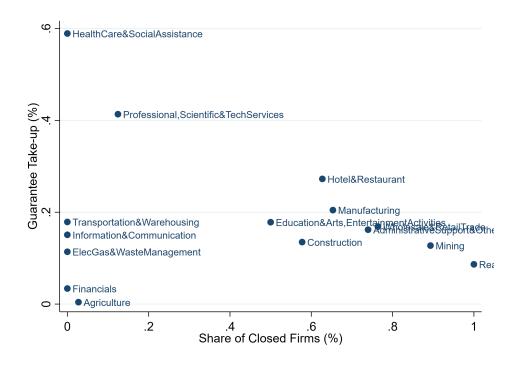
#### Figure 3: Guarantee by Sector

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.





(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.

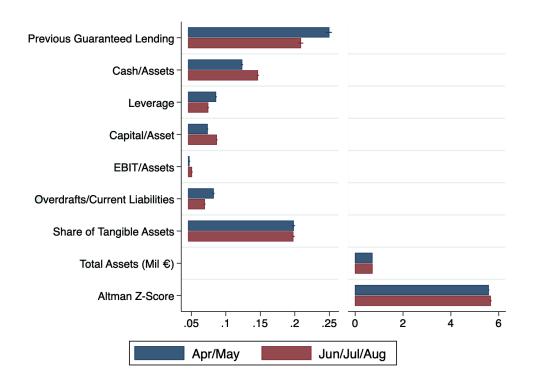
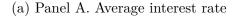
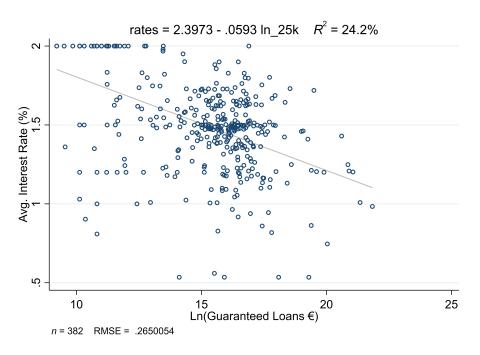


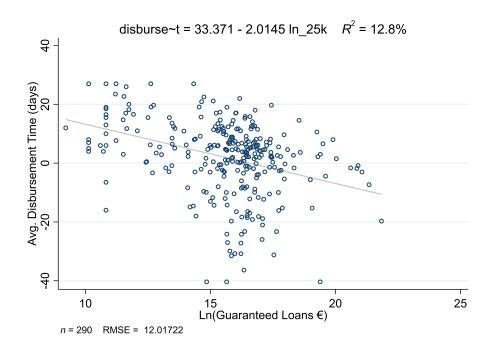
Figure 5: Loan Rates and Disbursement Times by Lender Size (number of loans)

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.



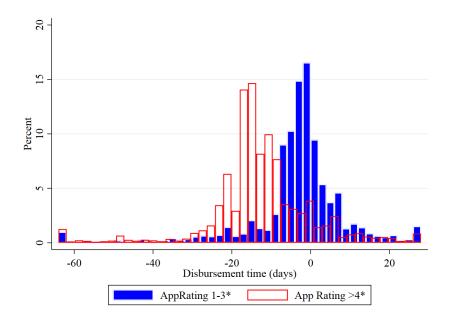


(b) Panel B. Average disbursement time



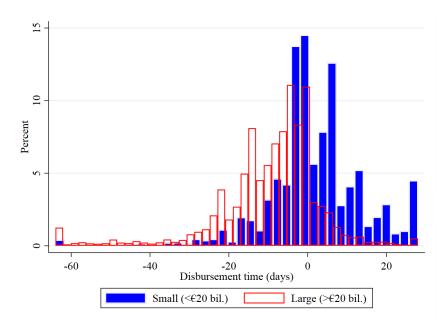
## Figure 6: Bank Heterogeneity in Disbursement Times

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 (> $\in$ 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.





(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 (about 600,000 firms). 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. A 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). Weighted bank variables are local bank balance sheet characteristics where the weights are the share of branches of each bank in the province. Panel D reports bank-level characteristics on the banks that extended government guaranteed loans.

$\begin{array}{c c c c c c c c c c c c c c c c c c c $		Ν	Mean	Std.Dev.	$5^{th}$ pct.	Median	$95^{th}~{\rm pct.}$
100% Guarantee 2020       586599       0.223       0.416       0       0       1         100% Guarantee Loan (Soles       130241       23.656       4.850       11.300       25       30         100% Guarantee Interest Rate (%)       130241       0.130       0.196       0.013       0.080       0.247         100% Guarantee Interest Rate (%)       130241       1.199       0.356       0.550       1.200       1.750         100% Guarantee Disbursement time (days)       63447       -7.488       14.020       -29       -5       12         <100% Guarantee Loan/Sales	Panel A. Loan level						
100% Guarantee Loan (000 €)       130241       23.656       4.850       11.300       25       30         100% Guarantee Loan/Sales       130241       0.130       0.196       0.013       0.080       0.247         100% Guarantee Interest Rate (%)       130241       1.199       0.356       0.550       1.200       1.750         100% Guarantee Disbursement time (days)       63447       -7.488       14.020       -29       -5       12         <100% Guarantee Disbursement time (days)		586599	0.223	0.416	0	0	1
100% Guarantee Loan/Sales       130241       0.130       0.013       0.080       0.247         100% Guarantee Disbursement time (days)       63447       -7.488       14.020       -29       -5       12         <100% Guarantee Disbursement time (days)						-	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$						-	
100% Guarantee Disbursement time (days)       63447       -7.488       14.020       -29       -5       12         <100% Guarantee Dan (000s €)							
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$							
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	10070 Guarantee Dissuisement time (days)	00111	1.100	11.020	20	0	12
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	<100% Guarantee 2020	550273	0.162	0.369	0	0	1
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$	$<100\%$ Guaranteed Loan (000s $\in$ )	86151	456.29	638.89	39.71	250	1500
$        < 100\% \   Guarantee \   Disbursement \   time \   (days) \  \  34722 \  12.774 \  \  15.155 \  \  -5 \  \  10 \  \  43 \\                             $	<100% Guarantee Loan/Sales	86151	0.117	0.232	0.008	0.058	0.328
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	<100% Guarantee Interest Rate (%)	86151	2.803	2.031	0.75	2	7.3
Essential Sector       593907 $0.388$ $0.487$ $0$ $0$ $1$ Previous Guaranteed Lending       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 $1.4948$ $12.284$ $2$ $11$ $41$ Cash/Assets       593907 $0.689$ $0.213$ $0.001$ $0.079$ $0.654$ EBIT/Assets       586858 $0.043$ $0.169$ $-0.207$ $0.023$ $0.339$ Leverage       593907 $0.689$ $0.325$ $0.106$ $0.754$ $1.061$ Altman Z-Score       593907 $7.447$ $11.377$ $1.076$ $5.464$ $14.619$ Number of employees $353993$ $10.008$ $21.345$ $1$ $4$ $35$ SamE's % of Total Sales $105$ $0.729$ $9.566$ $10.075$ $10.422$	${<}100\%$ Guarantee Disbursement time (days)	34722	12.774	15.155	-5	10	43
Essential Sector       593907 $0.388$ $0.487$ $0$ $0$ $1$ Previous Guaranteed Lending       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 $1.4948$ $12.284$ $2$ $11$ $41$ Cash/Assets       593907 $0.689$ $0.213$ $0.001$ $0.079$ $0.654$ EBIT/Assets       586858 $0.043$ $0.169$ $-0.207$ $0.023$ $0.339$ Leverage       593907 $0.689$ $0.325$ $0.106$ $0.754$ $1.061$ Altman Z-Score       593907 $7.447$ $11.377$ $1.076$ $5.464$ $14.619$ Number of employees $353993$ $10.008$ $21.345$ $1$ $4$ $35$ SamE's % of Total Sales $105$ $0.729$ $9.566$ $10.075$ $10.422$	Panel B: Firm level						
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		593907	0.388	0.487	0	0	1
Total Assets (million €)5939071.5833.1970.0190.4497.408Sales (million €)5939071.1743.1810.0000.2415.132Firm Age (years)59390714.94812.28421141Cash/Assets5939070.6680.2130.0010.0790.654EBT/Assets5868580.0430.169-0.2070.0230.339Leverage5939070.6990.3250.1060.7541.061Altman Z-Score5939077.44711.3771.0765.46414.619Number of employees3539310.00821.3451435Panel C: Province levelExcess Deaths1050.3890.613-0.0560.1641.586Ln(V-A, per Capita) (2017)10512.9410.72111.07312.86814.041Ln(V-A, per Capita) (2017)1050.3760.1890.1920.4630.805Short-time work hours per firm103260.01171.0758.79227.65567.56Weighted Irerl Ratio10515.2502.41412.84114.75318.494Weighted NPL Share1050.1470.0190.1090.1490.172Weighted Banks ROA1050.1360.0780.0770.1150.224Panel D: Bank-level11431.310141.3640.5442.226106.459Tierl Ratio11436.3666.033.625<	Previous Guaranteed Lending	593907	0.075	0.263		0	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		593907	1.583	3.197	0.019	0.449	7.408
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Sales (million €)	593907	1.174	3.181	0.000	0.241	5.132
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Firm Age (years)	593907	14.948	12.284	2	11	41
$\begin{array}{cccccccccccccccccccccccccccccccccccc$			0.168	0.213	0.001	0.079	0.654
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	EBIT/Assets	586858	0.043	0.169	-0.207	0.023	0.339
$\begin{array}{c c c c c c c c c c c c c c c c c c c $		593907	0.699	0.325	0.106	0.754	1.061
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Altman Z-Score	593907	7.447	11.377	1.076	5.464	14.619
$\begin{array}{ c c c c c c c c c c c c c c c c c c c$	Number of employees	353993	10.008	21.345	1	4	35
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Panel C: Province level						
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		105	0.389	0.613	-0.056	0.164	1.586
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Ln(Population) (2019)	105	12.941	0.721	11.973	12.868	14.041
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		105	10.035	0.279	9.566	10.075	10.422
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		105	0.476	0.189	0.192	0.463	0.805
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Short-time work hours per firm	103	260.01	171.07	58.79	227.65	567.56
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Weighted Tier1 Ratio	105	15.250	2.414	12.841	14.753	18.494
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Weighted Ln(Assets)	105	17.380	0.788	15.720	17.474	18.342
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Weighted NPL Share	105	0.090	0.015	0.068	0.089	0.114
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Weighted Interbank/Asset	105	0.147	0.019	0.109	0.149	0.172
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Weighted Banks ROA	105	0.002	0.002	-0.001	0.002	0.004
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	HHI Bank Branches	105	0.136	0.078	0.077	0.115	0.224
$\begin{array}{c c c c c c c c c c c c c c c c c c c $	Panel D: Bank-level						
$ \begin{array}{c ccccccccccccccccccccccccccccccccccc$		114	31.310	141.364	0.544	2.226	106.459
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$		114	16.376	5.918	11.094	14.894	24.229
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	NPL/Loans	114	10.361	6.603	3.625	8.997	20.067
AppRating $\geq 4^*$ 1140.3600.4820.0000.0001.000Number of Reviews (thousand)11416.37024.5770.0114.63237.244		114	0.113	0.594	-0.928	0.247	0.642
Number of Reviews (thousand) $114$ $16.370$ $24.577$ $0.011$ $4.632$ $37.244$		114	14.479	8.160	0.231	14.351	31.997
Number of Reviews (thousand) $114$ $16.370$ $24.577$ $0.011$ $4.632$ $37.244$		114	0.360	0.482	0.000	0.000	1.000
Average App Rating         114         3.388         1.321         -0.090         3.600         4.400		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: Guarantee 2020 and Covid-19 (Excess Deaths)

The unit of observation is a firm. 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	$-0.003^{*}$ (0.002)		-0.001 (0.001)		
Essential Sector	(0.002) $-0.035^{***}$ (0.004)	$-0.034^{***}$ (0.004)	(0.001)		
Previous Guaranteed Lending	(0.004) $0.156^{***}$ (0.005)	(0.004) $0.157^{***}$ (0.005)	$0.117^{***}$ (0.005)	$0.118^{***}$ (0.005)	$0.118^{***}$ (0.005)
Log(Assets)	$-0.071^{***}$ (0.003)	$-0.069^{***}$ (0.003)	$-0.053^{***}$ (0.003)	$-0.052^{***}$ (0.003)	$-0.051^{***}$ (0.003)
Log(Age)	$-0.011^{***}$ (0.002)	$-0.011^{***}$ (0.002)	$-0.009^{***}$ (0.002)	$-0.010^{***}$ (0.002)	$-0.010^{***}$ (0.002)
Cash/Assets	$-0.046^{***}$ (0.002)	$-0.046^{***}$ (0.002)	$-0.054^{***}$ (0.002)	(0.002) $-0.054^{***}$ (0.002)	$-0.053^{***}$ (0.002)
Leverage	(0.002) $0.048^{***}$ (0.002)	(0.002) $0.048^{***}$ (0.002)	(0.002) $(0.035^{***})$ (0.002)	(0.002) $(0.035^{***})$ (0.002)	(0.002) $0.034^{***}$ (0.002)
EBIT/Assets	(0.002) $0.041^{***}$ (0.001)	(0.002) $0.040^{***}$ (0.001)	(0.002) $0.033^{***}$ (0.001)	(0.002) $0.033^{***}$ (0.001)	(0.002) $0.033^{***}$ (0.001)
Altman Z-Score	$-0.014^{***}$ (0.001)	$-0.014^{***}$ (0.001)	$-0.006^{***}$ (0.001)	$-0.006^{***}$ (0.001)	$-0.006^{***}$ (0.001)
Ln(Population) (2019)	-0.000 (0.002)	(0.001)	-0.003 (0.002)	(0.001)	(0.001)
Ln(V.A. per Capita) (2017)	(0.002) $-0.019^{*}$ (0.011)		-0.014 (0.011)		
SME's $\%$ of Total Sales	-0.004 (0.005)		(0.002) (0.002)		
Short-time work hours per firm	0.000 (0.000)		0.000 (0.000)		
South Dummy	-0.014 (0.010)		-0.012 (0.010)		
Fixed effects	(01010)		(010-0)		
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: <100% Guarantee 2020 and Covid-19 (Excess Deaths)

The unit of observation is a firm. 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.

	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	548815	550562	548812	550559	550273	
$R^2$	0.347	0.350	0.384	0.386	0.477	

The unit of observation is a firm. 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 increase in cumulated deaths in a province between March-April 2020 and March-April 2019 (from ISTAT). Previous Guaranteed Lending 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 firms that either obtained the guarantee in a given month or did not obtain the guarantee at all. Excess Deaths 2020 is the percentage 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 10%, 5%, and 1%, respectively.

	Apr-May	May	Ju	June	Jr	July	BuA	August
	(1)	(2)	(3)	(4)	(5)	(9)	(2)	(8)
Excess Deaths	$0.002^{*}$		$-0.004^{***}$		-0.003***		$-0.001^{***}$	
	(0.001)		(0.001)		(0.001)		(0.00)	
Essential Sector	$-0.024^{***}$		$-0.018^{***}$		-0.006***		$-0.001^{**}$	
	(0.002)		(0.002)		(0.001)		(0.00)	
<b>Previous Guaranteed Lending</b>	$0.121^{***}$	$0.095^{***}$	$0.061^{***}$	$0.045^{***}$	$0.035^{***}$	$0.028^{***}$	$0.015^{***}$	$0.012^{***}$
	(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)	(0.00)	(0.001)	(0.00)	(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)	(0.00)	(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)	(0.00)	(0.00)	(0.00)	(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)	(0.00)	(0.00)	(0.00)	(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)	(0.00)	(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)	(0.00)	(0.00)	(0.00)	(0.000)
Fixed effects								
Province controls	$\mathbf{Yes}$		Yes		$\gamma_{es}$	ı	$\mathbf{Yes}$	ı
Province×6-digit Industry	No	$\mathbf{Y}_{\mathbf{es}}$	No	$\mathbf{Y}_{\mathbf{es}}$	No	$\mathbf{Yes}$	No	Yes
Observations	517940	516961	492285	490260	472866	470051	460830	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 unit of observation is a firm. The sample is restricted to firms that took out a 100% guaranteed loan in Panel A and a <100% 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.

	Int	terest Rate (	. /	Disburs	sement Time	e (Days)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. 100% Guaranteed Loa	ans					
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(	(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( 0 )	(0.002)	(0.002)	(0.001)	(0.084)	(0.089)	(0.060)
Cash/Assets	-0.008***	-0.006***	-0.003***	$0.263^{***}$	0.301***	$0.316^{***}$
7	(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
<u> </u>	(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. $<100\%$ Guaranteed L						
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	V		V		V	
Province controls	Yes	- V	Yes	- V	Yes	- V
Month	Yes	Yes	Yes	Yes	Yes	Yes
Province×6-digit Industry	No	Yes	Yes	No N-	Yes N-	Yes
Bank	No 70014	No 70014	Yes 70014	No 20420	No 20420	Yes
Observations $P^2$	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 unit of observation is a firm. The sample is restricted to firms that obtained a 100% guarantee loan in Panel A and <100% 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.

	Int	erest Rat	e (%)	Disburs	sement Time	(Days)
Panel A. 100% Guaranteed	(1) Loans	(2)	(3)	(4)	(5)	(6)
AppRating $\geq 4^*$	-0.059	-0.042	-0.094	$-7.808^{***}$ (2.283)	$-5.839^{***}$	$-5.490^{***}$
Log(Number Reviews)	(0.084)	(0.087) -0.034 (0.059)	(0.067) $0.128^{**}$ (0.050)	(2.283)	(1.670) -3.134*** (1.138)	(1.435) -2.710** (1.318)
Bank - $Ln(Assets)$		(0.059)	(0.030) $-0.153^{***}$ (0.021)		(1.136)	(1.518) $-2.508^{***}$ (0.682)
Bank - T1 Ratio			(0.021) 0.104 (0.083)			(0.002) 3.901 (2.597)
Bank - NPL share			0.098 (0.060)			$-7.387^{***}$ (2.232)
Bank - ROA			0.025 (0.024)			(1.281)
Bank - Interbank/Asset			-0.032 (0.027)			(0.493) (1.722)
Observations $R^2$	$108005 \\ 0.191$	$108005 \\ 0.197$	$108005 \\ 0.369$	$48416 \\ 0.359$	$\begin{array}{c} 48416\\ 0.385\end{array}$	$\begin{array}{c} 48416\\ 0.454\end{array}$
Panel B. $< 100\%$ Guarante	ed Loans					
AppRating $\geq 4^*$	-0.380 (0.307)	-0.262 (0.313)	$-0.566^{***}$ (0.163)	$-6.274^{***}$ (0.557)	$-4.425^{***}$ (0.673)	$-4.349^{***}$ (0.787)
Log(Number Reviews)	(0.501)	(0.515) $-0.222^{*}$ (0.124)	(0.103) 0.177 (0.142)	(0.001)	(0.010) $-2.730^{***}$ (0.454)	(0.101) $-1.950^{***}$ (0.690)
Bank - Ln(Assets)		(0)	(0.194) (0.162)		(0.101)	-0.695 (0.464)
Bank - T1 Ratio			(0.072) (0.398)			$-3.559^{**}$ (1.561)
Bank - NPL share			-0.038 (0.182)			0.532 (0.682)
Bank - ROA			$-0.407^{*}$ (0.237)			$0.327 \\ (0.547)$
Bank - Interbank/Asset			$-0.594^{**}$ (0.296)			-0.025 (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
$\begin{array}{c} \text{Observations} \\ R^2 \end{array}$	59882 0.426	59882	59882	22420	22420	22420
<u></u>	0.426	0.433	0.473	0.438	0.453	0.455

		Log(1+	Guaranteed	lCredit)	
	(1)	(2)	(3)	(4)	(5)
$LocalMarketShare_{b,p}$	1.045***	1.006***			0.682**
- )F	(0.137)	(0.132)			(0.086)
$CoreMarketShare_{b,p}$	× /	× /	$1.666^{***}$	$1.623^{***}$	1.235**
- 75			(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

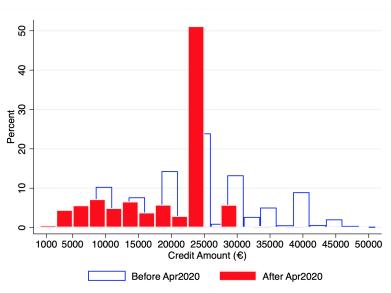
### Table 7: Guaranteed Lending and Local Banking Markets

The unit of observation is a bank-province pair. The dependent variable is the log of total guaranteed lending by bank b in province p. LocalMarketShare<sub>b,p</sub> is the share of branches of bank b in province p relative to the total number of bank branches in province p. CoreMarketShare<sub>b,p</sub> 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. \*,

# 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  $\notin$ 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)

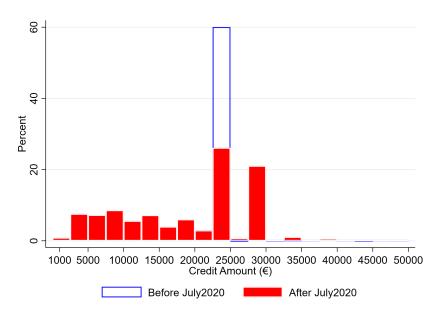
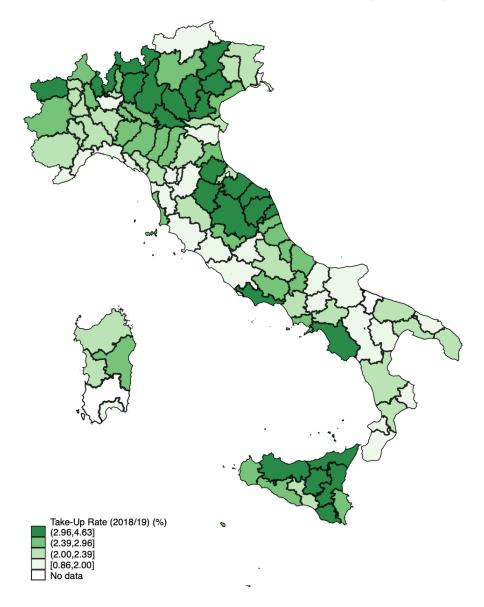


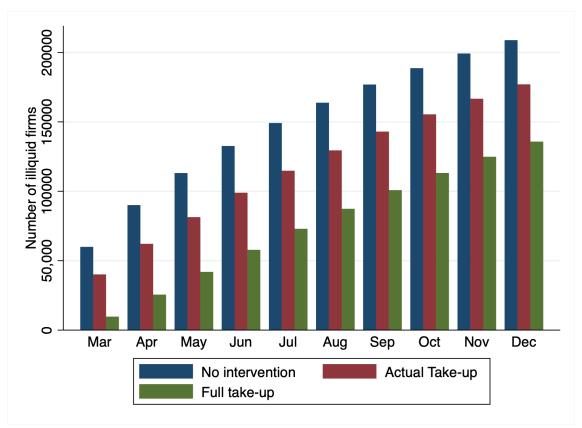
Figure A2: Guarantee Uptake in 2018-19

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).

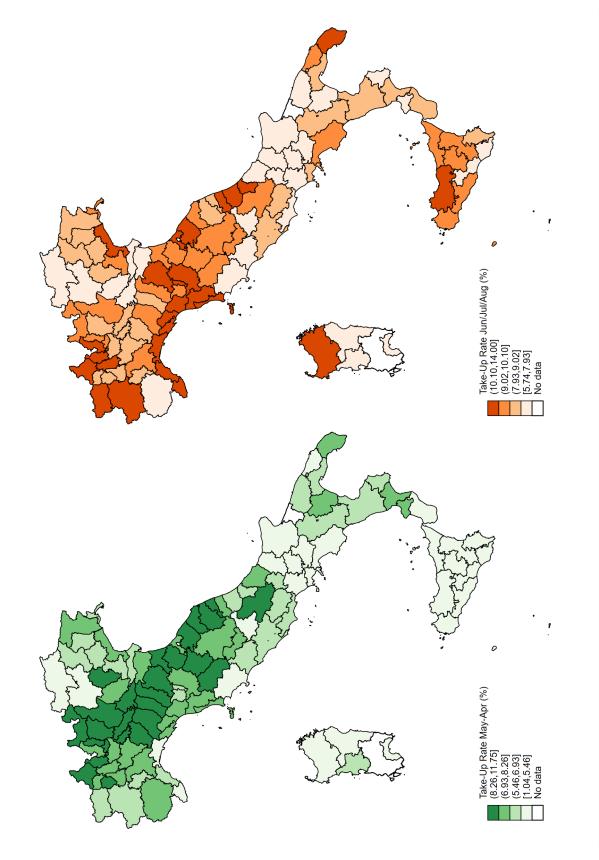


## Figure A3: Number of illiquid firms in Italy

This figure plots the number of illiquid firms using the methodology in Schivardi and Romano (2020) in three scenarios: one with no government intervention; one where we include the government guaranteed loans for the firms that actually obtained them and one where we assume that all eligible firms receive the guaranteed loan.







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

The unit of observation is a firm. 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)
	0.000	0 00 04 4 4	0 000**	0 001 ***	0 000***
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 unit of observation is a firm. 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 Lo	All Loans		June	July	August
	(1)	(2)	(3)	(4)	(5)	(6)
COVID19 Cases per Capita	$-0.004^{*}$ (0.002)	-0.001 $(0.002)$	0.003 (0.002)	$-0.002^{*}$ (0.001)	$-0.002^{**}$ (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: Within Firm Variation

The unit of observation is a loan between April and August 2020. The sample is restricted to firms taking out more than one partially guarantee loan. The dependent variables are the interest rate (in percentage) and disbursement times in days of <100% 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)
	(1)	(2)
	0 500**	
AppRating $\geq 4^*$	-0.532**	-5.016***
	(0.132)	(0.726)
Log(Number Reviews)	0.204	-1.676**
	(0.126)	(0.685)
Bank - Ln(Assets)	-0.182	-0.612
	(0.145)	(0.538)
Bank - T1 Ratio	0.165	-3.211*
	(0.379)	(1.770)
Bank - NPL share	-0.037	0.801
	(0.151)	(0.586)
Bank - ROA	-0.432**	0.456
	(0.211)	(0.581)
Bank - Interbank/Asset	-0.571**	-0.878
	(0.245)	(1.054)
Fixed effects		
Firm	Yes	Yes
Month	Yes	Yes
Observations	39388	13226
$R^2$	0.702	0.758