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

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### Abstract

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

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# 1 Introduction

What is the most effective way to deploy government funds to help the real economy during a crisis? Policymakers worldwide faced this question when Covid-19 forced a global business shutdown and caused a severe liquidity crunch, especially among small businesses (SMEs) that have no access to capital markets. Many countries relied on the private financial sector, and the banking system in particular, to act as a conduit of government-backed liquidity to SMEs through the use of credit guarantees. Since credit guarantee programs will play an increasingly important role in supporting SMEs' recovery and in future crises, it is of crucial importance to understand whether the private sector can deliver the liquidity to the firms who need it or whether existing frictions distort the allocation of public funds.

Governments can lend to non-financial firms either directly or through public guarantees on private credit.[1] Direct government lending has two main shortcomings: first, transaction costs and asymmetric information frictions may prevent governments from setting up lending facilities to small borrowers in a short window of time; second, lending by government-owned banks is typically characterized by inefficiencies emerging from political connections (Sapienza, 2004; Khwaja and Mian, 2005; Carvalho, 2014). For these reasons, governments often prefer to issue public guarantees on private bank loans rather than direct government loans. However, the allocation of public liquidity through banks is not frictionless. For example, if the banking sector is heterogeneous in its ability to disburse funds or if pre-existing relationships determine the allocation of credit, funds may not reach the neediest firms.

We study this question exploiting the unique institutional features of the Covid-19 guarantee program in Italy. On April $8^{th}$, 2020 the government expanded the existing public guarantee scheme for SMEs, increasing the guarantee coverage ratio from 80% to 90% for loans up to €5 million. Moreover, it introduced a 100% guarantee for €25,000 loans (increased to €30,000 in June) that requires no fee payment from the borrower and no formal credit

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

assessment by the bank. Since credit risk is fully absorbed by the government, the Italian guarantee program is ideal to study lenders' incentives to distribute public relief funds to small firms. Moreover loan-level data from the Italian Guarantee Fund (*Fondo di Garanzia*, FG) allow us to distinguish credit supply from demand with a granular set of area×4-digit-industry or firm fixed-effects, exploiting the fact that firms could obtain partially guaranteed loans from multiple banks at the same time. We also match loan-level data to bank and firm balance sheet characteristics, studying how lender and borrower heterogeneity affect the terms of credit on guaranteed loans.

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

We then analyze the factors affecting credit outcomes such as disbursement times (i.e. the time between the approval of the guarantee by the FG and the issuance of the loan by the bank) and interest rates.[3] First, we document that the variation in loan conditions is mostly explained by supply factors (i.e. bank heterogeneity) rather than demand factors. Because of the strong geographic clustering of the pandemic's first wave in Italy, as well as the decision of the government to shut down certain industries because deemed non-essential, we use fixed-effects for borrower industry and location to capture the most relevant demand

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

[3]We do not study loan amounts as a separate credit outcome due the limited variation in the data (60% of guaranteed loans are exactly equal to €25,000).

factors in this setting. The $R^2$ of a regression of disbursement times on bank fixed-effects is 40% (41% for loan rates) compared to 12% (16%) with area×4-digit-industry fixed-effects. Thus, supply-side heterogeneity appears to be the most significant factor to explain the terms of credit on guaranteed loans.

Motivated by the results of the variance decomposition, we investigate the type of bank characteristics that can explain credit outcomes. We find that the bank digital infrastructure has a crucial effect on loan disbursement times. Banks with better information technology (IT) systems, as proxied by the Google Playstore review rating on their mobile banking app or by their expenses on IT, disburse guaranteed loans almost twice as fast as the average bank. This is the case because digitally capable banks were able to handle the surge in online loan applications during the pandemic 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 economies of scale. These effects are not driven by credit demand, as we control for area×4-digit-industry or even firm fixed-effects in a short window of time between April and August 2020. Investigating the impact of supply factors on disbursement times allows us not only to focus on a key policy objective - the speed at which liquidity is distributed to SMEs - but also to contribute to a relatively unexplored topic in the banking literature - the importance of loan origination times for lending standards (Bedayo et al., 2020).

We also find that large banks charge lower rates and disburse guaranteed loans faster than small banks. This is true for fully guaranteed loans, but not for partially guaranteed ones. Large banks may have an advantage in issuing 100% guaranteed loans for two reasons. First, large banks have lower funding costs compared to small institutions, for example due to preferential access to ECB lending facilities. Second, since interest margins on government guaranteed credit are low, especially for small loans (1-2% in gross interest), only large banks that can process a large volume of loans can achieve profitability. Small and cooperative banks, that are traditionally considered to serve small businesses better than large banks,

especially in a crisis (Berger et al., 2017), cannot achieve efficient economies of scale on these loans and are much more reluctant to lend.

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

At the extensive margin, we find that financially fragile firms were more likely to receive guaranteed loans. Smaller firms, those with less cash on hand, higher leverage and those classified as zombies (Acharya et al., 2020) have higher take-up rates in both types of guaranteed loans, with the only natural difference that partially guaranteed loans are obtained by larger firms. Finally, firm risk is priced in loan rates depending on the guarantee coverage ratio: rates on fully guaranteed loans do not vary as a function of firm characteristics, while partially guaranteed loans do. Larger, older, more liquid and less levered firms pay lower rates on 90% guaranteed loans, but not on fully guaranteed loans.

Overall our results indicate that relying on the private sector to distribute public funds may lead to heterogeneous outcomes, depending on the existing bank-firm matches: if a firm was matched with an efficient bank it would receive guaranteed loans faster and at lower rates. Crucially, bad quality of the bank IT infrastructure hampered the process of distributing guaranteed loans, in terms of both pricing and processing times. Notably, local cooperative

banks, which are supposed to have a comparative advantage in lending to small businesses (Berger et al., 2017), were conspicuously inefficient in providing 100% government guaranteed loans which were meant for the very small firms. Cooperative banks charged higher rates compared to other banks (145 vs 119 bps on average) and took almost a week longer to disburse them. However, we also find that the bank branch network still matters for the allocation of guaranteed credit: banks lend more in their core markets and where they have a larger local presence.

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

Furthermore, we contribute to the fast growing literature on the role of IT in financial intermediation. A recent paper by Timmer and Pierri (2020) shows that higher intensity of IT-adoption is associated with lower levels of non performing loans, while Ahnert et al. (2021) show that bank IT helps spurring entrepreneurship. Moreover, Kwan et al. (2021) study the impact of the Covid-19 crisis on banks' digital technology and find that high IT banks are more likely to participate in the PPP program. While these papers rely on measures of intensity of IT adoption, like the number of PCs per employee or the number of communication technologies used, we construct a novel measure: the app rating as determined by customers' reviews. As such, our measure is more likely to capture the quality of bank investment in IT.

This paper also joins the burgeoning literature studying the impact of the Covid-19 pandemic on financial markets and corporate outcomes. Many papers have focused on stock

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

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

The strong heterogeneity in lender participation is a prominent feature of our data too, suggesting that bank supply-side restrictions are relevant for the post-pandemic loan guarantee programs in different countries. A big picture insight of our results is that if low-cost government backed liquidity meant to support small businesses is channeled through the

banking system, the existing lending technology and other local banking market characteristics will determine who gets credit first and at which condition.

## 2   The Role of Public Credit Guarantees

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

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

## 2.1 The Italian Public Guarantee Scheme

The recourse to credit guarantee schemes to alleviate funding constraints for small businesses is not new. These types of government interventions became increasingly popular after the 2007-08 financial crisis (Beck et al., 2010). In Italy, the public guarantees scheme, named *Fondo di Garanzia* (FG), started its operations in 2000 and has supported SME lending massively in the aftermath of both the financial crisis and the sovereign debt crisis (de Blasio et al., 2018). The loan guarantee program in Italy was already quite large compared to other countries even before Covid-19. For example, in 2017 a total of €17.5 billion in new loans to SMEs received a public credit guarantee, compared to €4 billion in France and $25 billion in the US. As required by EU State Aid rules, borrowers 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 8th, 2020 the Italian government approved a law decree, the so-called *DL Liquiditá*, that strengthened the FG capacity to issue guarantees by an additional €400 billion. Of these, €200 billion were dedicated to guarantees for small firms below 500 employees and represent the key novelty of the Italian guarantee fund. First of all, the guarantee coverage was increased from 80% to 90% and eligible loan size went from €1.5 to €5 million.[4] The amount of the loan was capped at one quarter of sales in 2019 or twice annual payroll. Second, for loan amounts up to €25,000 (increased to €30,000 in June), the guarantee is full and free, i.e. no extra-fees are charged to the borrower to obtain it. Moreover, interest rates on small loans were capped at around 2%, but could also be set below the ceiling.[5] The loans have a maturity of 6 years (increased to 10 years in June) and no principal payment, only interest, is due in the first two years of the loan. According to the

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[4]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.

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

law, guaranteed lending need to be new loans, not a replacement of existing credit facilities with the borrower.

Crucially, fully guaranteed loans require no application of the credit scoring model typically used by the FG to issue the guarantee. Normally, in fact, the public guarantee scheme involves three agents: a bank (i.e. the applicant), a firm (i.e. the beneficiary), and the FG. First, the firm needs to file a standard loan application with the bank of choice. Then, the bank has to verify the firm eligibility for the scheme through a scoring system software provided by the FG (see de Blasio et al. (2018) for further details) and file a separate application to the FG in order to request the public guarantee on the loan. As of April 2020, all these steps have been removed for loans below €25,000, so that SMEs can quickly obtain the needed liquidity. Firms have to complete a self-declaration form, that the bank will forward to the FG, in which they state that their business has been affected by Covid-19, and that they are eligible to receive 100% government guaranteed loans.

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

## 3 Data

Loan level data on the universe of guaranteed loans are publicly available in Italy.[6] This loan origination data includes basic information on the borrowing firm or the self-employed individual that accessed the guarantee (name, address, sector and, most importantly, the

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

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).[7] We also obtained confidential loan-level data from the FG on loan interest rates and, for a subset of the loans, the date in which the loan was actually disbursed to the firm, matched with a bank identifier. We calculate the total number and value of guaranteed loans issued by each intermediary and we match this information with public records from Parliamentary Committee on the banking system, that contain the names of every intermediary in Italy who extended guaranteed loans. Doing so allows us to recover the names of about 120 lenders that extended 95% of total guaranteed credit. We then match the bank names to 2019 balance sheet characteristics from Bureau Van Dijk (BvD) Orbis BankFocus. We also obtain data on location of branches of all Italian banks from the Bank of Italy Supervisory Register.

We hand-collect data on bank IT capabilities 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's Android is the operating system used by more than 80% of smartphones in Italy so its reviews capture the majority of bank customers. Google reviews range from 1 star (very bad) to 5 stars (excellent) and are a customer-based measure of the quality of the bank digital infrastructure. 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. Fu and Mishra (2020) show that both download and usage of finance mobile applications soared in countries more affected by the pandemic, underlying the importance of mobile apps as a measure of IT quality during this period. We complement this information with banks' actual expenses on IT from Orbis Bank Focus in 2020, that we divide by the total of non-interest operating expenses in the same year.[8]

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

[8]IT expenses are reported by Italian banks under the IFRS9 accounting standard, which was introduced in

Next, we retrieve firm-level data from BvD Orbis - a database with the financial accounts for the universe of Italian firms. Most firms in Orbis (72%) are private partnerships and sole proprietorships, i.e. unlimited liability companies that are common legal structures for very small firms, for which we only have basic identifying information (name, tax code, address, sector and date of incorporation). We have instead the full financial accounts of around 600,000 firms, mainly limited liability companies. We then match these firms to the FG data using the firm unique tax code. Within the sample of 600,000 firm with full financial accounts, about 120,000 firms obtained a 100% guaranteed loan, 40,000 obtained 80,000 loans with a partial guarantee, while the remaining did not obtain any guaranteed loan, despite being eligible.[9] We also identify zombie firms in the data in the spirit of Caballero et al. (2008), i.e. low credit quality firms that obtain cheap credit. Following the definition of Acharya et al. (2020) for Amadeus-Orbis data, we classify as a zombie a firm that has below the median interest coverage (EBIT over interest expenses), above the median leverage and below the median cost of credit (interest expenses over outstanding short and long-term debt).

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 is 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 sample of guaranteed loans for which we have full information on interest rate, disbursement time and bank identity from the FG. Summary statistics are shown separately for firms that obtained a 100% and a 90% guaranteed loan. Partially guaranteed loans are much larger than fully guaranteed loans (€390,000 vs. €20,000), and carry much higher interest rates (2.9% vs 1.1%). Disbursement

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Italy in 2018. As such, data on IT expenses prior to 2020 are partial and incomplete.

[9]Overall, we obtain full financial accounts for 66% of the limited liability companies that appear on the FG data. We also match 43% of unlimited liability companies, but these do not enter our estimation sample because they have missing balance sheet information.

times are calculated as the number of days between the approval date of the guarantee by the FG and the date in which the bank effectively hands out the loan to the borrower.[10] Partially guaranteed loans are disbursed on average 11 days after the approval of the guarantee, whereas fully guaranteed loans are disbursed on average 10 days before. The negative average disbursement time indicates the confidence of private banks in the willingness of the FG to approve as many fully guaranteed loans as possible. In both cases there is a significant cross-sectional variation: the standard deviation of disbursement times is larger than the mean.

Panel B collects summary statistics for the 114 banks in the sample that extended guaranteed loans and for which we hand-collected information on the app rating from the Google Playstore. 36% of the banks in the sample have a rating of 4 stars or more, with the average rating being 3.4. Banks in the sample classify 10% of their loan portfolio as non-performing, have 16% Tier 1 capital ratio, and a ROA of 0.11%. Regarding the sample for which data on IT expenses is available in Orbis Bank Focus, banks spend on average 6.5% of their non-interest operating budget on maintenance and development of their IT infrastructure.

Panel C shows the summary statistics for the sample of firms with full financial accounts in Orbis that obtained a guaranteed loan for which we have full information on interest rate, disbursement time and bank identity from the FG. Most firms are rather small, with median assets totalling around 5 million euros. They hold 12% of total assets as cash or other liquid assets, and finance almost 80% of the balance sheet with non-equity-like instruments such as bank debt or trade credit. Around 8% of the firms in our sample are classified as zombies.

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[10]We have data on disbursement times only for about half of guaranteed loans because banks have up to six months to report the data to the FG (the vintage of our FG data is December 2020).

# 4 Results

## 4.1 Stylized facts

Before turning to a more formal regression analysis of the factors influencing credit conditions on guaranteed loans, we describe some general patterns in the data.

First of all, the guarantee program for SMEs in Italy was large even before Covid: from 2013 to 2019, €17 billion of loans per year have received a partial (64%) public guarantee, steadily increasing every year (Panel A of Figure 1). However, in the first eight months of 2020 alone, the volume of guaranteed lending reached a total of €79 billion, representing 10% of the stock of bank credit to non-financial firms in 2019 and 2% of bank total assets. Panel B of Figure 1 further reveals an increase in the number, and not just the volume, of guaranteed loans which resulted in a reduction in the average size of the loans: after April 2020 the vast majority (86%) of loans are below €25,000.[11] These were extended to 829,053 borrowers, two thirds of which are private partnerships, sole proprietorships and self-employed individuals. While numerous, fully guaranteed loans represent only 0.2% of bank total assets.

Second, we document significant heterogeneity in credit conditions for guaranteed loans. Since the maximum loan amount for guaranteed loans is fixed by law (and it is exactly equal to €25,000 for most loans), we study two other margins of adjustment: interest rates and disbursement times. Disbursement times are important because one of the key objective of loan guarantee programs is to distribute liquidity quickly to small firms. Both interest rates and disbursement times vary significantly across lenders. Figure 2 shows that average interest rates and disbursement times at bank level for 100% guaranteed loans are negatively associated with bank size. But size is not the only driver of differences in disbursement times across banks. During the pandemic, most loan applications were made online, through bank

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

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 Figure 3 we show that the entire distribution of disbursement times for banks with highly rated apps is shifted to the left compared to those with low-rated apps.[12]

To further explore whether the heterogeneity is mostly driven by supply or demand factors we decompose the cross-sectional variation of credit conditions into two components: fixed bank characteristics and common borrower variation at the province and (4-digit) sector level. Variation at the province level is important because the first wave of the pandemic in Italy had a strong geographic clustering.[13] Similarly, variation at the sector level captures the decision of the government to shut down some of the businesses deemed as non-essential. As such, variation at the province and sector level is likely to capture a significant part of demand heterogeneity. Formally, we run the following regression at the loan level:

$$Y_{b,ps} = \lambda_b + \mu_{ps} + \epsilon_{b,ps} \tag{1}$$

where $Y_{b,ps}$ is either the interest rate or the disbursement time of a loan made by bank $b$ to a firm active in the 4-digit sector×province $ps$. $\lambda_b$ and $\gamma_{ps}$ are a set of bank and province-sector fixed-effects that proxy for supply and demand heterogeneity, respectively.

Table 2 reports the $R^2$ statistics of the regression in equation (1) including each set of fixed-effects at a time or both. Most of the loan cross-sectional variation in credit conditions is explained by individual bank fixed-effects. Borrower location and industry capture 12% and 16% of the variation in disbursement times and interest rates, respectively, while bank fixed-effects capture about 40%. Adding both together only marginally improves the overall fit of the regression compared to bank fixed-effects only. The high $R^2$ associated to bank fixed-

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[12]The difference in app rating is correlated with size, since large banks tend to have better rated apps, but it is not only explained by that: in Panel B of Figure 3 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. In the regression analysis we will control for the two separately.

[13]In the North the province of Bergamo, the hardest hit in the country, saw an increase in excess deaths of +340%, while other provinces, like Napoli in the South, experienced no increase in excess deaths.

effects suggests that supply-side heterogeneity is the most important driver of heterogeneity in credit conditions on guaranteed loans, which we focus on in the next section.

## 4.2 Individual Bank Characteristics and IT systems

Motivated by the results from the variance decomposition in equation (1), we now explore which individual bank characteristics affect the pricing and disbursement times of guaranteed loans. In particular, we run the following specification:

$$Y_{f,b,m} = \beta_1 BankIT_b + \gamma' X_b + \mu_f + \lambda_m + \epsilon_{f,b,m} \tag{2}$$

where $Y_{f,b,m}$ is either the interest rate or the disbursement time of a loan made by bank $b$ to firm $f$ in month $m$. We also run the regressions separately for fully and partially guaranteed loans. $BankIT_b$ is one of two measures of bank IT: a dummy equal to one if bank $b$ has a 4-5 star rating on its mobile banking app from the Google Playstore ($AppRating_b \geq 4$) or the share of IT expenses over total operating expenses. Our preferred measure is the customer-based satisfaction rating on the mobile banking app, which is a better proxy for the quality of IT than the share of IT expenses. In any case, since the development and maintenance of mobile banking apps is the main source of IT costs for banks, the two measures give similar results. $X_b$ is a vector of other 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 4-digit industry×province fixed-effects or firm fixed-effects, exploiting the fact that some firms obtained multiple partially guaranteed loans from different banks. We also include a dummy for the month in which the guaranteed loan was obtained. The calendar date when the loan was issued is relevant because the interest rate cap varies over time with government bond yields and CDS spreads, so that loans issued in April have a higher interest rate cap than those issued over the summer, when market interest rates fell. 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 clustered at the bank level. Results are presented in Tables 3 and 4.

We find that banks with highly rated app (4-5 stars) disburse both partial and fully guaranteed loans 4-8 days earlier compared to other banks. This is a sizable effect, since the average fully guaranteed loan is processed 10 days before the approval of the guarantee. Importantly, the coefficient is stable once we include firm fixed-effects (column 4), suggesting that province×4-digit industry fixed-effects already capture most of the variation in credit demand. Moreover, we control for size and other bank characteristics, which means that the quality of the IT system is not simply explained by traditional balance sheet factors. Bank IT also has a significant effect on loan interest rates for partially guaranteed loans (columns 3 and 4 of Table 4): banks with highly rated apps charge 40-56 basis points less on guaranteed loans, even to the same firm (14-20% less compared to the mean).

Another 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 20 bps less than other banks, an effect of about 20% compared to the mean, and disburse these loans 5 days before other banks. Large banks may have an advantage in issuing 100% guaranteed loans compared to partially guaranteed loans because of the existence of economies of scale. Interest margins on government guaranteed credit are low, especially for fully guaranteed loans (1% on average), and thus only large banks that can process a large volume of loans in an automatized way can achieve profitability. Small banks cannot achieve efficient economies of scale on these loans and therefore end up lending at a slower pace and at higher rates. This in stark contrast to the global financial crisis of 2007-08, where small banks with stable deposit funding could lend more to their customers (Berger et al., 2017; Cornett et al., 2011) while large banks, affected by negative funding shocks, cut their credit supply.

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 share of NPL also process guaranteed loans faster.

Overall, the evidence presented in Tables 3 and 4 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 mentioning that, given that the maximum interest rate on €25,000 loans is about €500 per year, only processing a large number of loans through an automated procedure allows banks to maintain a positive profit margin. If a loan officer had to approve the loans one by one, the fixed cost per loan would probably exceed interest income.[14]

Table 5 provides a robustness test for the effect of bank IT on disbursement times and interest rates by replacing the rating on the mobile banking app with the share of IT expenses over total operating costs. These items are reported under the breakdown of "other administrative expenses" which is mandatory under the new IFRS9 accounting disclosure. We use data on IT expenses from 2020 because this field is scarcely populated in 2019 on Orbis Bank Focus. We find very similar results compared to the app rating: banks with a one standard deviation increase in the share of IT expenses process fully guaranteed loans almost one week faster than other banks and charge 20 basis points less on partially guaranteed loans.

Finally, Table 6 tests whether firm specific heterogeneity matters once bank and province-industry fixed-effects are included. We can do this for a limited sample of loans (about 100,000 compared to 400,000 of the full sample), where we are able to match the firm tax code in the FG dataset to full balance sheet characteristics from Orbis. We find limited impact of firm-specific characteristics on disbursement times: for example, a one standard deviation increase in firm age decreases disbursement times by only half a day. No other coefficient is larger than one, whereas bank characteristics such as size and app rating had much larger

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[14]As a robustness test, we re-estimate the analysis of bank characteristics on interest rates using the full sample of loans for which interest rate information is available, even with no data on disbursement times. Results are presented in Table A1 and are comparable in magnitude, sign, and significance to the main analysis.

coefficients. This suggests that bank heterogeneity has a much larger impact on disbursement times than firm heterogeneity. We also find that firm risk is priced in guaranteed loans, since smaller, younger, more levered firms and those with less cash on hand pay higher rates. Perhaps not surprisingly, the interest rate varies as a function of firm risk depending on the guarantee coverage ratio: while the effects are economically negligible for fully guaranteed loans (less than a basis point), they are large for partially guaranteed loans. For example, a one standard deviation increase in firm size decreases interest rates by 30 basis points, a decrease of 11% compared to mean interest rate. Interestingly, zombie firms obtain partially guaranteed loans with a 10 basis points discount (3.5%) compared to non-zombies. This is consistent with the idea that zombie firms, despite being of low quality, are able to obtain cheap credit from their banks.

## 4.3   Local Banking Markets

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

However, since most applications for guaranteed loans were filed online, one may wonder whether the bank branch network matters at all for the allocation of government guaranteed credit. Since they can easily reach any small business nationwide with online offers, banks

are not restricted to lend in areas where they have a branch or to their own clients. Put it differently, guaranteed loans during Covid-19 provide the perfect setting to test whether lending relationships are sticky (Petersen and Rajan, 1994): if small businesses reach out for new funding only to the banks they normally do business with and banks keep serving only their existing customers, it means that indeed lending relationships are sticky and determine the allocation of guaranteed credit.

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

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

where the dependent variable is the log of the total amount of guaranteed credit by bank $b$ in province $p$, including both fully and partially guaranteed loans.[15] $LocalMarketShare_{b,p}$ is the share of the local branches of bank $b$ in province $p$ relative to all bank branches in province $p$. This measure captures the local presence of the bank in the province. $CoreMarketShare_{b,p}$ is the share of local branches of bank $b$ in province $p$ relative to all 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 presence supply more guaranteed credit in the province: a one standard deviation increase in the local market share increases lending by about 7.7% relative to the mean. We emphasize that this measure is not simply capturing a size effect, i.e. the fact that larger banks both have a larger share of branches and supply more loans, since we either control for bank size (column 1) or include a bank fixed-effect (column 2), exploiting within bank variation only. The coefficient on $LocalMarketShare_{b,p}$ is remarkably stable and it suggests that the structure of

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

local banking market is relevant, even if the applications are filed online. Second, we find that when the local market is important for the bank, i.e. when the province has a large share of the overall branch network, the bank is willing to supply more credit: a one standard deviation increases in $CoreMarketShare_{b,p}$ increases local guaranteed credit by 12%. Once again, the effect is not just driven by large provinces, which are likely to be more important across all banks, or by large banks, which have larger market shares in larger markets, since the specification includes a province and a bank fixed-effect. Third, when we include both market shares together, we find that, while the effect of each diminishes by about 25-30%, they are both positive and significant, indicating that they have an independent effect on the supply of guaranteed credit.

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

## 4.4 Guarantee: Extensive margin

We conclude by analyzing the extensive margin of credit, i.e. investigating the types of firms that accessed guaranteed loans. We do this by comparing firms that obtained a guaranteed loan to those that were eligible but did not. Due to differences in targeting of the two programs, we also separately analyze firms that accessed the full guarantee from those that accessed the 90% guarantee.

At the aggregate level, firms that accessed the new guarantee program after April 2020 represent about 16% of the universe of registered firms in Italy (*Movimprese*), including private partnerships and sole proprietorship. There are however large differences in the take-up rate

both across geographic areas and sectors. For example, while virtually no firm in agriculture has accessed the guarantee, 25% of firms in the food and accommodation industry and almost 60% in the healthcare and social assistance sector have. While in some provinces the take-up rate is as low as 7%, in other areas it increases to 26%.

Figure 4 correlates the participation in the guarantee program in each province to the number of excess deaths or the share of non-essential (i.e. closed) firms. The take-up rate is generally higher in the north of the country, where the pandemic hit the hardest (correlation coefficient equal to 0.27). This is not the case in normal times, as the take-up rate is generally higher in the south of Italy (see Figure A2 in the Appendix). Moreover, the take-up rate in 2020 is higher in provinces with a higher share of closed businesses (correlation coefficient equal to 0.40) which, given the industry structure at the local level, also happen to be more prevalent in the north of Italy. The sectors that have the highest usage intensity of the guarantee are all services, especially healthcare and social assistance (e.g., nursing homes, dental care and other medical facilities), professional services (e.g., engineering and architecture) and food and accommodation (Panel A of Figure 5). 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 5 - Panel B). This reinforces the idea that demand factors are only a part of the picture and supply of guaranteed loans plays a fundamental role in determining the allocation of credit.

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

$$\text{Guarantee2020}_{f,p,s} = \gamma' X_f + \mu_{ps} + \epsilon_{f,p,s} \tag{4}$$

where $\text{Guarantee2020}_{f,p,s}$ is a dummy equal to one if firm $f$ located in province $p$ and active in the 4-digit sector $s$ took a guaranteed loan after April 2020. We also analyze fully and

partially guaranteed loans separately. The control group in this estimation consists of firms who were eligible (i.e. all SME firms with less than 500 employees), but did not obtain any guaranteed loan.[16] $X_f$ is a vector of firm controls: log of total assets and age; cash and liquid assets over total assets; leverage, i.e. total liabilities over assets; EBIT over assets; and an indicator for whether the firm is a zombie following (Acharya et al., 2020). $\mu_{ps}$ is a 4-digit sector×province fixed-effect. Finally, we cluster standard errors at the province level.

The results are presented in Table 8. We find that smaller and older firms, those with less cash on hand and more debt have 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. All such firm characteristics matter over and above province and sector presence.

Firm size is one of the most important drivers in explaining uptake of guaranteed loans. Naturally, larger firms seek partially guaranteed loans more than smaller ones, since these loans can be as large €5 million. A one standard deviation decrease in total assets increases the take-up rate of fully guaranteed loans by 26% compared to the mean (25% average take-up rate on fully guaranteed loans) and decreases the take-up rate of partially guaranteed loans by 62% (9% average take-up rate on partially guaranteed loans). Moreover, firms with less cash and saddled with more debt, i.e. those with higher leverage, are more likely to participate in both types of guaranteed loans. Lastly, zombie firms are 6% and 70% more likely to participate in fully and partially guaranteed loan programs, respectively. Older and more profitable firms are more likely to obtain fully guaranteed loans, but the effects are quite small for partially guaranteed loans. Overall, the results suggest that small, fully guaranteed loans were obtained by financially weaker firms, while larger loans with a partial guarantee were obtained by larger, yet risky firms. Moreover, partially but larger guaranteed loans seem to encourage zombie lending more, as compared to small fully guaranteed ones.

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

# 5 Conclusion

Several countries worldwide introduced credit guarantees to support small businesses affected by the Covid-19 pandemic. Given the long-term consequences of Covid-19 on SMEs' recovery and the possibility that such measures may be used again in the future, it is crucial to assess whether allocating public funds using the banking system is efficient. Studying the Italian experience has several advantages. First, the credit guarantee program has some unique institutional features: it covers 100% of the loan up to €25,000 and requires no credit check by the bank granting the loan. This makes it ideal to study lenders' incentives to allocate public funds. Second, loan-level data on public guarantees allow a full bank-firm match of balance sheet characteristics even for very small firms.

Our results indicate that bank heterogeneity, in terms of both lender size and the quality of the digital infrastructure, are crucial determinants of the speed and pricing of guaranteed loans. This suggests that the banking sector plays an important role in directing such policy stimulus. The structure of local banking markets and bank branch presence is also relevant, as banks' pre-existing geographical footprints and lending relationships are an important determinant of the overall volume of guaranteed credit. Policy makers should keep this in mind when designing policies that are meant to address firm liquidity shortages during a crisis.

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

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

(a) Panel A. Credit Amounts with Guarantees
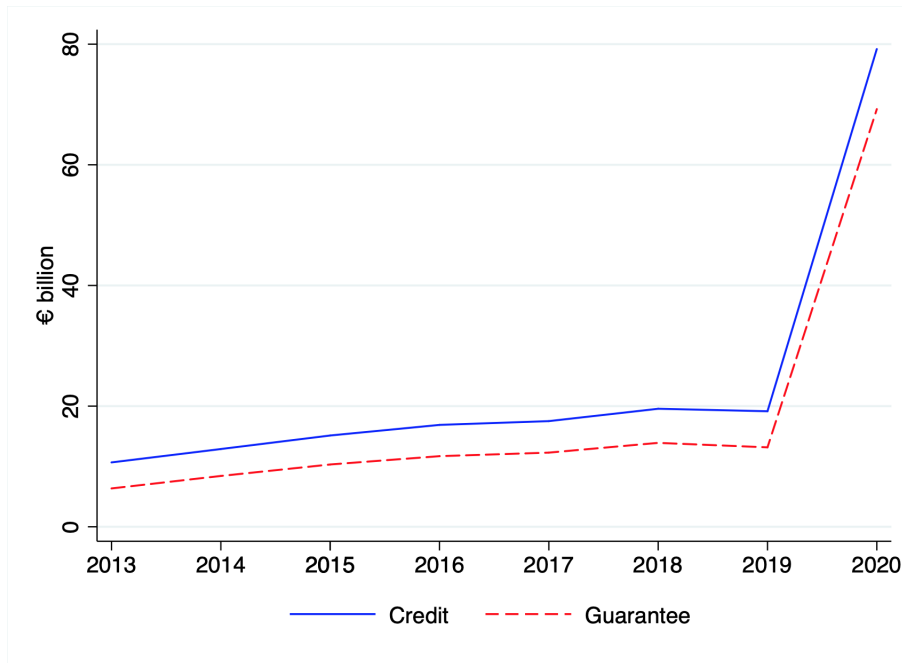


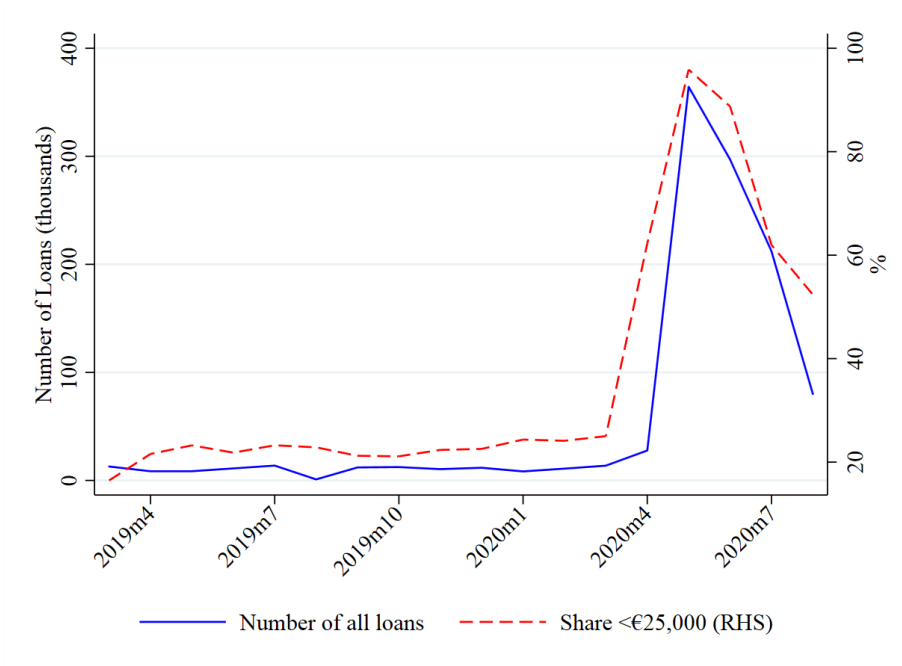(b) Panel B. Number of Loans with Public Guarantee in 2019-2020

Figure 2: Loan Rates and Disbursement Times by Lender Size (number of loans)

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

(a) Panel A. Average interest rate



rates = 2.3973 - .0593 ln_25k    $R^2$ = 24.2%

$n$ = 382    RMSE = .2650054
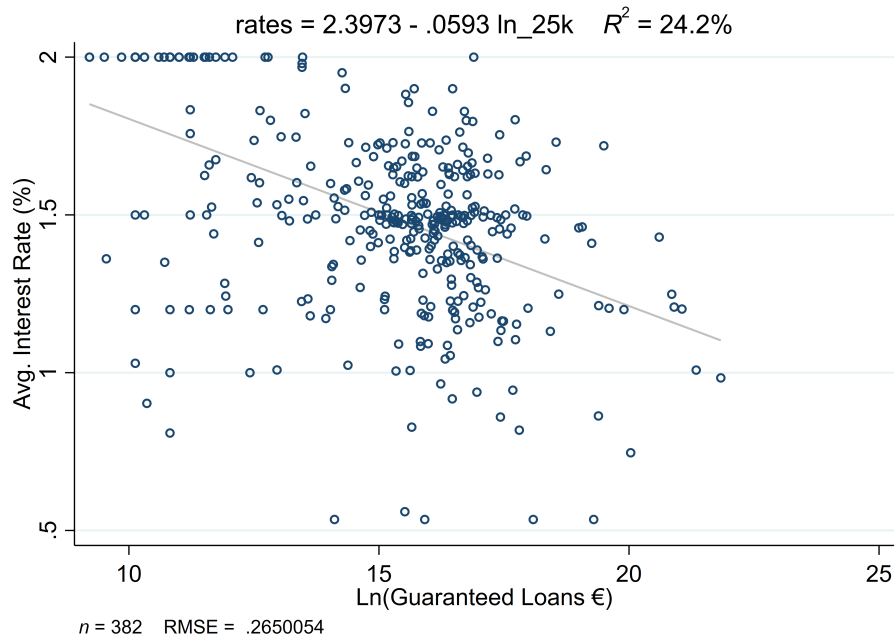
(b) Panel B. Average disbursement time



disburse~t = 33.371 - 2.0145 ln_25k    $R^2$ = 12.8%

$n$ = 290    RMSE = 12.01722

29
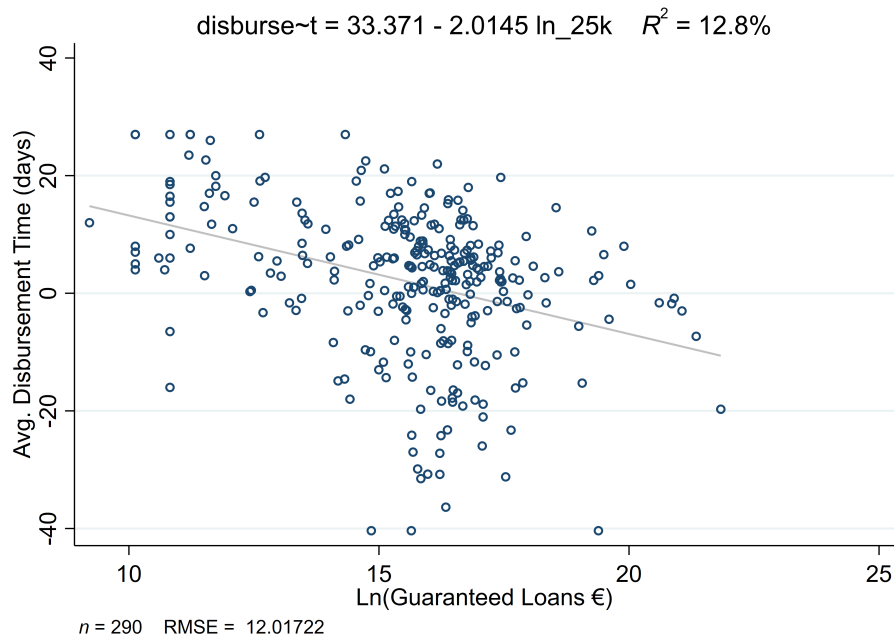
## Figure 3: Bank Heterogeneity in Disbursement Times

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

### (a) Panel A. Mobile Banking App Rating
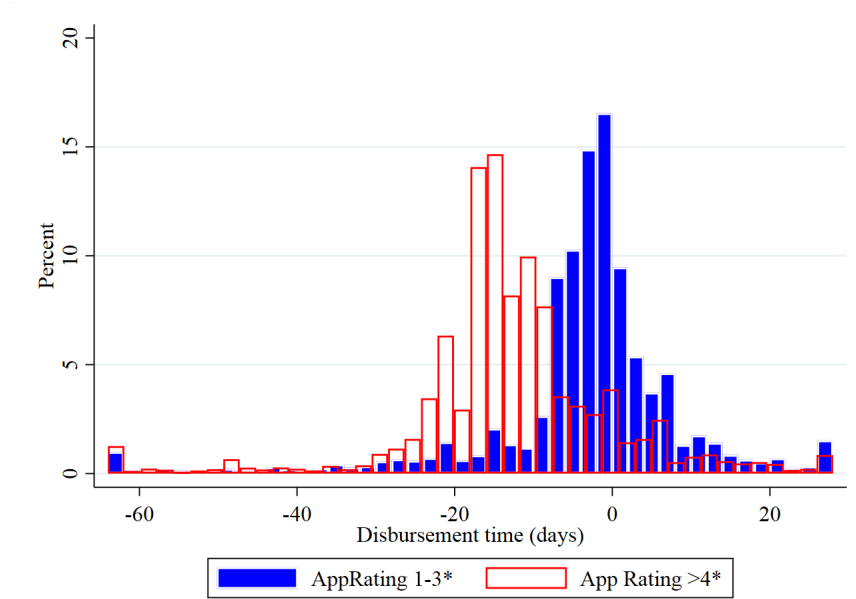


### (b) Panel B. Total Assets
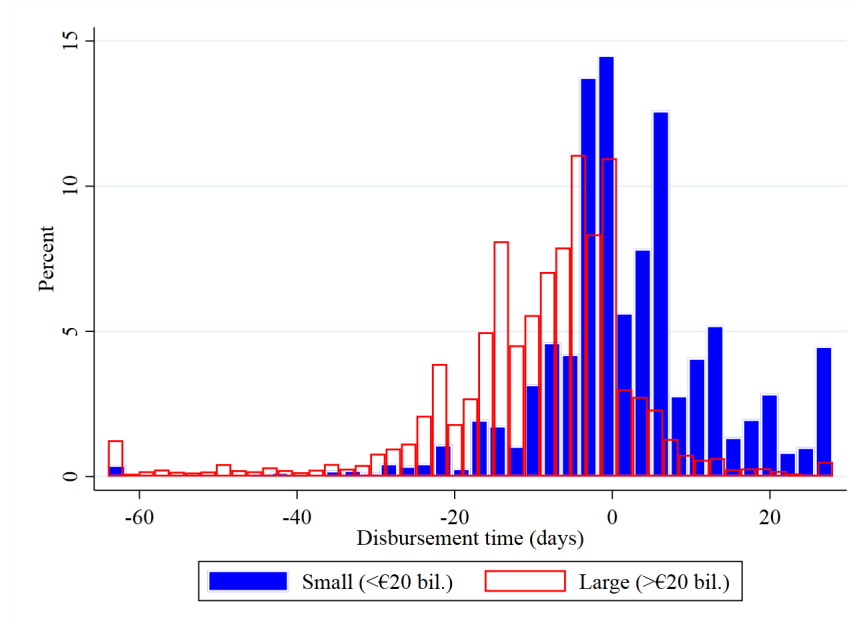
Figure 4: Guarantee, Excess deaths and Closed firms by Province

This figure plots the share of firms that obtained a loan under the 100% public guarantee scheme from April 2020 over the total number of firms in the province, the percentage of excess deaths and the share of closed firms in a province. The total number of firms in a province is obtained from the universe of registered Italian firms (Movimprese). The correlation coefficients between the take-up rate and excess deaths or share of closed firms are: 0.27 and 0.39.
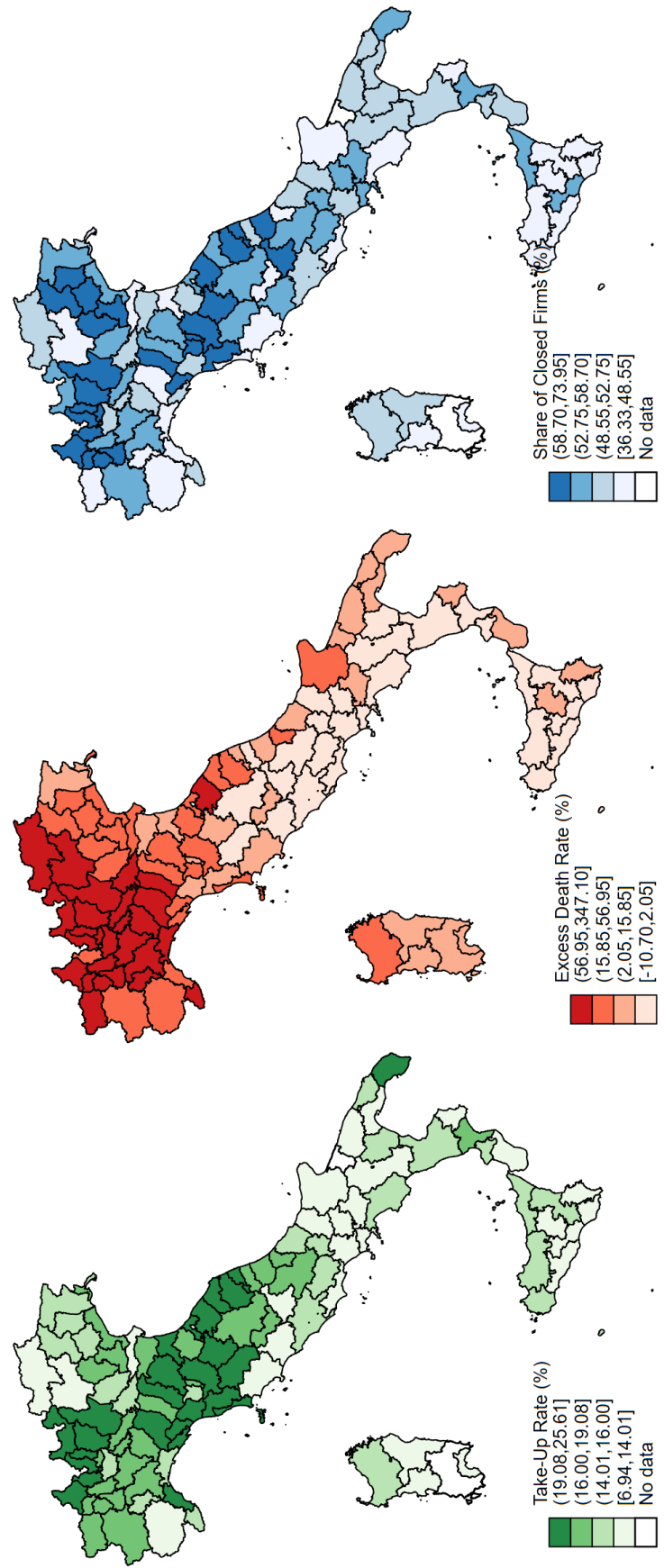
## Figure 5: Guarantee by Sector

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

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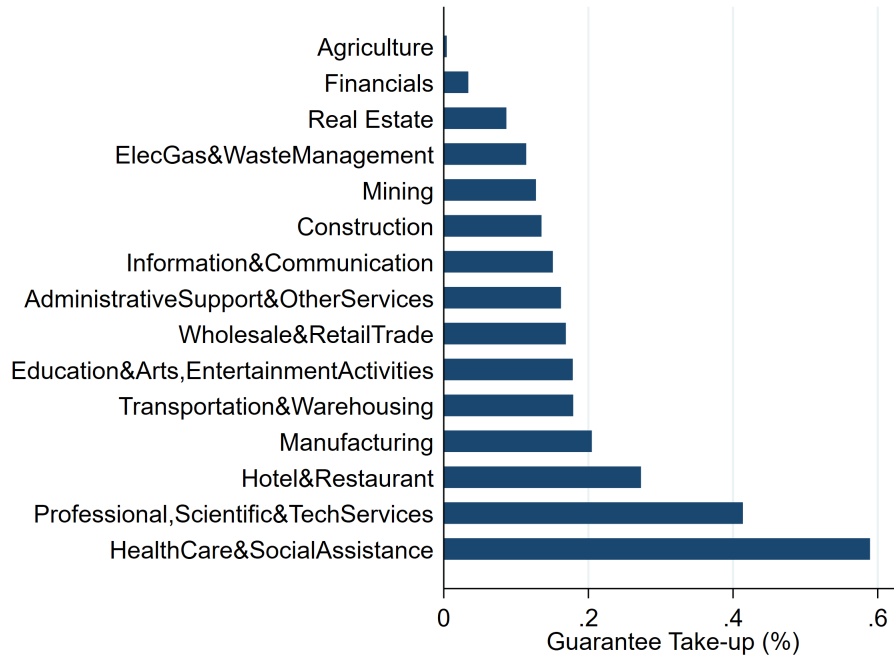


### (b) Panel B. Take-up rate and share of closed businesses

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, by type of guarantee. Panel B reports bank-level characteristics on the 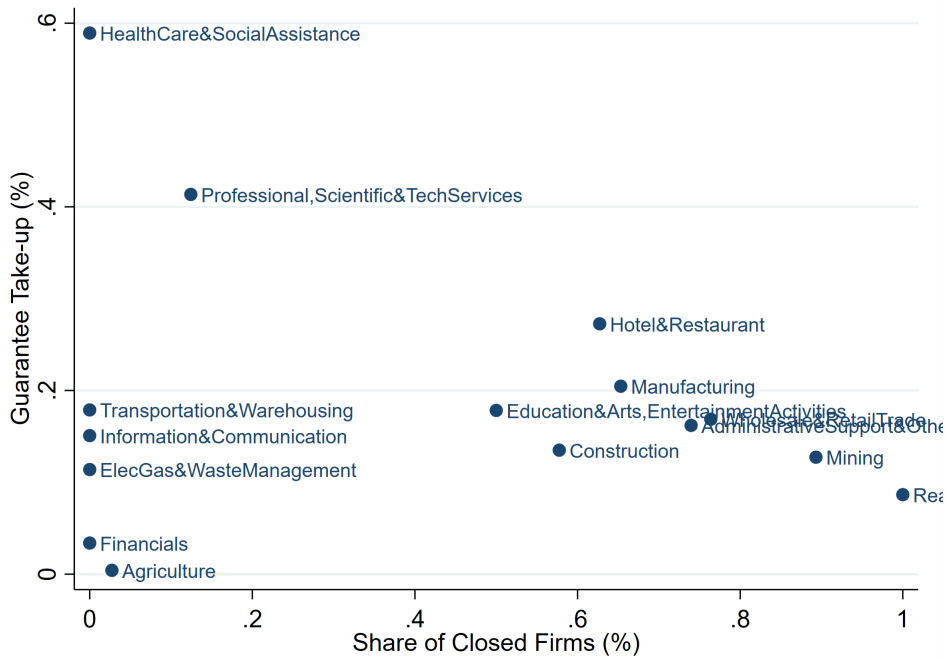banks that extended government guaranteed loans from BvD Orbis Bank Focus in December 2019. Panel C reports all firm characteristics from BvD Orbis in December 2018. Leverage is total liabilities (total assets minus total shareholders' funds) over total assets.

| | N | Mean | Std.Dev. | $5^{th}$ pct. | Median | $95^{th}$ pct. |
|---|---|---|---|---|---|---|
| Panel A: Loan level | | | | | | |
| 100% Guaranteed Loan (000s €) | 360049 | 19.927 | 7.367 | 5.400 | 25.000 | 25.000 |
| 100% Guarantee Interest Rate (%) | 360031 | 1.122 | 0.518 | 0.550 | 1.130 | 1.700 |
| 100% Guarantee Disbursement time (days) | 360049 | -10.545 | 17.078 | -45.000 | -7.000 | 10.000 |
| | | | | | | |
| 90% Guaranteed Loan (000s €) | 38053 | 389.074 | 577.397 | 25.000 | 200.000 | 1450.000 |
| 90% Guarantee Interest Rate (%) | 38050 | 2.872 | 2.133 | 0.785 | 2.000 | 7.750 |
| 90% Guarantee Disbursement time (days) | 38053 | 11.320 | 14.289 | -5.000 | 9.000 | 36.000 |
| | | | | | | |
| Panel B: Bank-level | | | | | | |
| Total Assets (billion €) | 114 | 31.310 | 141.364 | 0.544 | 2.226 | 106.459 |
| Tier1 Ratio | 114 | 16.376 | 5.918 | 11.094 | 14.894 | 24.229 |
| NPL/Loans | 114 | 10.361 | 6.603 | 3.625 | 8.997 | 20.067 |
| ROA | 114 | 0.113 | 0.594 | -0.928 | 0.247 | 0.642 |
| Interbank/Asset | 114 | 14.479 | 8.160 | 0.231 | 14.351 | 31.997 |
| AppRating ≥ 4* | 114 | 0.360 | 0.482 | 0.000 | 0.000 | 1.000 |
| Number of Reviews (thousand) | 114 | 16.370 | 24.577 | 0.011 | 4.632 | 37.244 |
| Average App Rating | 114 | 3.388 | 1.321 | -0.090 | 3.600 | 4.400 |
| IT Expenses | 145 | 6.310 | 3.768 | 0.677 | 6.511 | 11.701 |
| | | | | | | |
| Panel C: Firm level | | | | | | |
| Total Assets (million €) | 83292 | 24.224 | 61.503 | 0.506 | 5.421 | 112.271 |
| Firm Age (years) | 83095 | 14.999 | 12.163 | 2.000 | 11.000 | 41.000 |
| Cash/Assets | 82682 | 0.123 | 0.162 | 0.001 | 0.057 | 0.481 |
| EBIT/Assets | 83008 | 0.048 | 0.128 | -0.120 | 0.028 | 0.276 |
| Leverage | 83291 | 0.773 | 0.220 | 0.338 | 0.821 | 1.001 |
| Zombie Firm | 83292 | 0.078 | 0.268 | 0.000 | 0.000 | 1.000 |

Table 2: **Loan conditions: supply and demand factors**

This table reports the $R^2$ corresponding to the regression in equation (1). The unit of observation is a loan. The sample consists of all the loans taken under the public guarantee program after April 2020 for which disbursement times are available. Fixed effects included are: the interaction of province and 4-digit industry (columns 1 and 4), the bank (columns 2 and 5), or both (columns 3 and 6). The $R^2$ is the adjusted-$R^2$.

|  | Disbursement Time | | | Interest Rate | | |
|---|---|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) | (5) | (6) |
| $R^2$ | 0.120 | 0.402 | 0.455 | 0.162 | 0.410 | 0.489 |
| Fixed effects |  |  |  |  |  |  |
| Province × Industry | Yes | No | Yes | Yes | No | Yes |
| Bank | No | Yes | Yes | No | Yes | Yes |
| N | 453231 | 453231 | 453231 | 453231 | 453231 | 453231 |

Table 3: **Bank heterogeneity: disbursement time**

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is a loan. The dependent variable is the disbursement time, in days, of the loans taken under the public guarantee program after April 2020. AppRating $\geq 4$* is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

|  | Disbursement Time (Days) | | | |
|  | All | 100% | 90% | |
|  | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| AppRating $\geq 4$* | -8.201*** | -7.821*** | -4.736*** | -4.958*** |
|  | (1.662) | (1.885) | (0.660) | (0.822) |
| Log(Assets) | -3.993*** | -4.254*** | -0.376 | -0.227 |
|  | (1.097) | (1.157) | (0.684) | (0.775) |
| Log(Number Reviews) | -2.792* | -2.778* | -2.034** | -2.037*** |
|  | (1.535) | (1.641) | (0.795) | (0.632) |
| Tier1 Ratio | 1.190 | 1.254 | -1.439** | -1.453* |
|  | (1.202) | (1.254) | (0.691) | (0.871) |
| NPL share | -4.785*** | -5.774*** | -0.358 | 0.032 |
|  | (1.310) | (1.544) | (0.421) | (0.468) |
| ROA | 0.384 | 0.323 | 0.026 | 0.090 |
|  | (1.248) | (1.369) | (0.577) | (0.678) |
| Interbank/Asset | -0.303 | 0.387 | 0.350 | -0.329 |
|  | (1.292) | (1.452) | (0.546) | (0.628) |
| Fixed effects |  |  |  |  |
| Month | Yes | Yes | Yes | Yes |
| Province $\times$ Industry | Yes | Yes | Yes | - |
| Firm | No | No | No | Yes |
| Observations | 403771 | 360049 | 38053 | 18996 |
| $R^2$ | 0.405 | 0.423 | 0.394 | 0.748 |

Table 4: **Bank heterogeneity: interest rate**

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is a loan. The sample is limited to loans with known disbursement times. The dependent variable is the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. AppRating $\geq 4^*$ is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

| | Interest Rate (%) | | | |
| --- | --- | --- | --- | --- |
| | All | 100% | 90% | |
| | (1) | (2) | (3) | (4) |
| AppRating $\geq 4^*$ | -0.177*** | -0.062 | -0.564*** | -0.382** |
| | (0.059) | (0.051) | (0.196) | (0.152) |
| Log(Assets) | -0.257*** | -0.200*** | -0.454* | -0.203 |
| | (0.055) | (0.036) | (0.244) | (0.275) |
| Log(Number Reviews) | 0.056 | 0.050 | 0.188 | 0.102 |
| | (0.051) | (0.050) | (0.185) | (0.182) |
| Tier1 Ratio | 0.038 | 0.029 | 0.279 | 0.448* |
| | (0.071) | (0.035) | (0.217) | (0.229) |
| NPL share | 0.077 | 0.030 | -0.037 | -0.077 |
| | (0.053) | (0.046) | (0.122) | (0.099) |
| ROA | 0.064 | 0.066 | -0.262 | -0.435* |
| | (0.056) | (0.041) | (0.231) | (0.246) |
| Interbank/Assets | -0.109* | 0.023 | -0.296 | -0.167 |
| | (0.064) | (0.037) | (0.222) | (0.191) |
| Fixed effects | | | | |
| Month | Yes | Yes | Yes | Yes |
| Province × Industry | Yes | Yes | Yes | - |
| Firm | No | No | No | Yes |
| Observations | 403771 | 360049 | 38053 | 18996 |
| $R^2$ | 0.287 | 0.200 | 0.541 | 0.800 |

Table 5: **Bank heterogeneity: robustness (IT expenses)**

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is a loan. The dependent variable is the disbursement time, in days, and the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. IT Expenses are measured in 2020 as a percentage of total operating expenses. Bank characteristics are balance sheet items from 2019Q4. All bank controls including IT Expenses have been normalized to have a mean of zero and standard deviation of one. Fixed effects for the interaction of province and industry (4-digit) of the firm are added. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

| | Disbursement Time (Days) | | | | Interest Rate (%) | | | |
|---|---|---|---|---|---|---|---|---|
| | All | 100% | 90% | 90% | All | 100% | 90% | 90% |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| IT Expenses | -6.463*** | -6.547*** | -1.824** | -2.147*** | -0.102** | -0.063* | -0.200 | -0.193* |
| | (1.022) | (1.053) | (0.726) | (0.620) | (0.039) | (0.033) | (0.125) | (0.104) |
| Fixed effects | | | | | | | | |
| Month | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Province × Industry | Yes | Yes | Yes | - | Yes | Yes | Yes | - |
| Firm | No | No | No | Yes | No | No | No | Yes |
| Bank Characteristics | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 398391 | 355842 | 36993 | 18444 | 398391 | 355842 | 36993 | 18444 |
| $R^2$ | 0.406 | 0.435 | 0.377 | 0.746 | 0.297 | 0.205 | 0.561 | 0.805 |

Table 6: **Firm heterogeneity: disbursement time & interest rate**

The unit of observation is a loan. The dependent variable is either the disbursement time, in days, or the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. AppRating $\geq 4$* is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google Playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4. All firm characteristics are dated December 2019 and have been normalized to have a mean of 0 and a standard deviation of 1. Fixed effects for the bank and the interaction of province and industry (4-digit) of the firm are added. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

| | Disbursement Time (Days) | | Interest Rate (%) | |
| --- | --- | --- | --- | --- |
| | 100% | 90% | 100% | 90% |
| | (1) | (2) | (3) | (4) |
| Log(Assets) | 0.803 | -0.096 | -0.012** | -0.298*** |
| | (0.637) | (0.317) | (0.006) | (0.043) |
| Log(Age) | -0.582*** | -0.026 | 0.004 | -0.083*** |
| | (0.206) | (0.230) | (0.006) | (0.023) |
| Cash/Assets | 0.250*** | 0.173 | -0.005*** | -0.198*** |
| | (0.066) | (0.168) | (0.002) | (0.034) |
| EBIT/Assets | -0.191*** | -0.492** | 0.001 | -0.091*** |
| | (0.040) | (0.226) | (0.001) | (0.026) |
| Leverage | -0.094 | -0.278 | 0.007*** | 0.137*** |
| | (0.065) | (0.188) | (0.002) | (0.012) |
| Zombie Firm | -0.033 | -0.104 | 0.006 | -0.098** |
| | (0.297) | (0.308) | (0.007) | (0.039) |
| Fixed effects | | | | |
| Month | Yes | Yes | Yes | Yes |
| Province × Industry | Yes | Yes | Yes | Yes |
| Bank | Yes | Yes | Yes | Yes |
| Observations | 66359 | 39435 | 66355 | 39428 |
| $R^2$ | 0.544 | 0.486 | 0.430 | 0.721 |

## Table 7: **Guaranteed lending and local banking markets**

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

|  | Log(GuaranteedCredit) | | | | |
|---|---|---|---|---|---|
|  | (1) | (2) | (3) | (4) | (5) |
| LocalMarketShare$_{b,p}$ | 1.045*** | 1.006*** |  |  | 0.682*** |
|  | (0.137) | (0.132) |  |  | (0.086) |
| CoreMarketShare$_{b,p}$ |  |  | 1.666*** | 1.623*** | 1.235*** |
|  |  |  | (0.102) | (0.092) | (0.079) |
| AppRating $\geq$ 4* | 0.083 |  | 0.001 |  |  |
|  | (0.150) |  | (0.158) |  |  |
| Log(Number Reviews) | -0.279** |  | -0.203 |  |  |
|  | (0.133) |  | (0.136) |  |  |
| Log(Assets) | 1.158*** |  | 1.691*** |  |  |
|  | (0.101) |  | (0.102) |  |  |
| Tier1 ratio | -0.185 |  | -0.083 |  |  |
|  | (0.272) |  | (0.205) |  |  |
| NPL share | 0.205 |  | 0.209 |  |  |
|  | (0.143) |  | (0.161) |  |  |
| ROA | 0.086 |  | 0.026 |  |  |
|  | (0.115) |  | (0.118) |  |  |
| 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 8: **Extensive margin**

The unit of observation is a firm. The sample is restricted to eligible SME firms. The dependent variables are dummies equal to one if the firm obtained a loan under any guarantee program, the full, or the partial guarantee programs after April 2020, 0 otherwise. All firm 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 a the province level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.
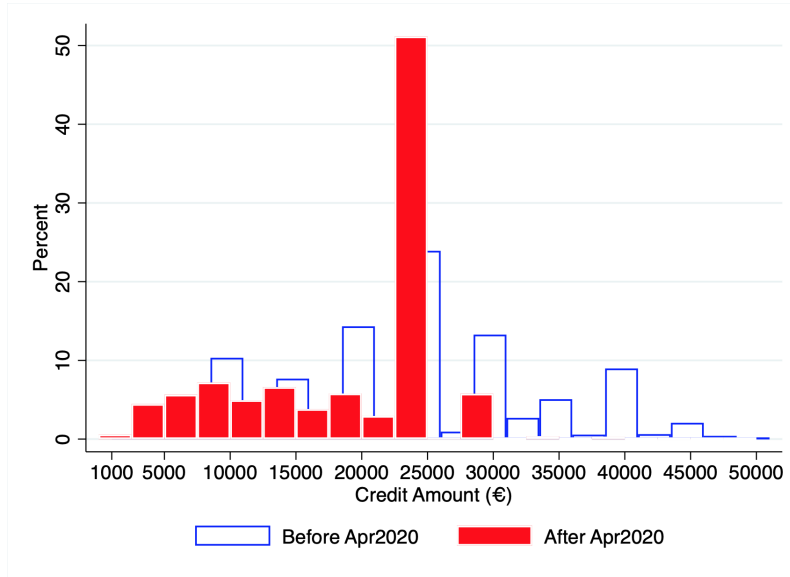
| | Guarantee 2020 = 1 | | |
| --- | --- | --- | --- |
| | All | 100% | 90% |
| | (1) | (2) | (3) |
| Log(Assets) | -0.016*** | -0.064*** | 0.056*** |
| | (0.003) | (0.003) | (0.002) |
| Log(Age) | 0.019*** | 0.025*** | -0.002** |
| | (0.001) | (0.001) | (0.001) |
| Cash/Assets | -0.054*** | -0.053*** | -0.010*** |
| | (0.002) | (0.002) | (0.001) |
| Leverage | 0.049*** | 0.043*** | 0.014*** |
| | (0.002) | (0.001) | (0.001) |
| EBIT/Assets | 0.036*** | 0.035*** | 0.003*** |
| | (0.001) | (0.002) | (0.000) |
| Zombie firm | 0.055*** | 0.015*** | 0.063*** |
| | (0.005) | (0.004) | (0.004) |
| Fixed effects | | | |
| Province× Industry | Yes | Yes | Yes |
| Observations | 628232 | 584308 | 494364 |
| $R^2$ | 0.157 | 0.161 | 0.176 |

# Online Appendix

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

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

(a) Panel A. Credit Amounts below €50,000 (2018-2020)



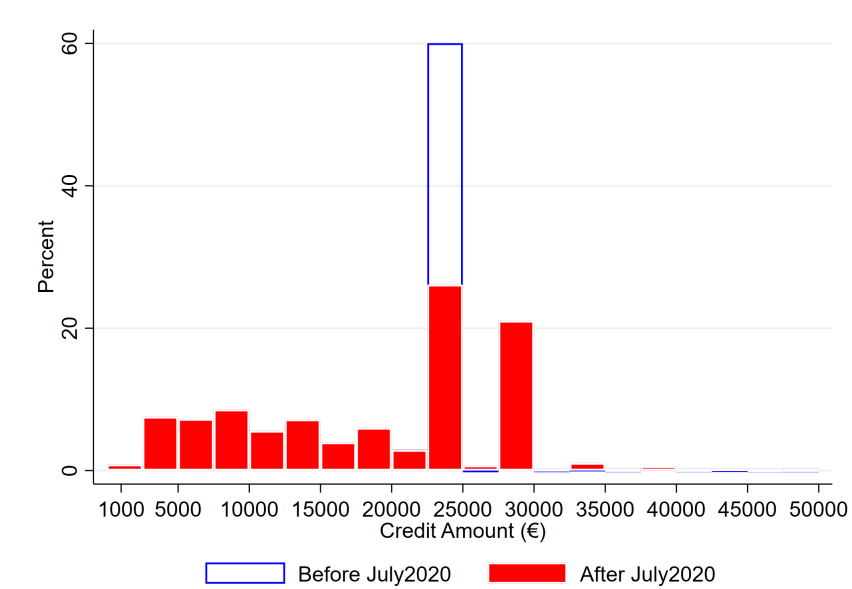(b) Panel B. Credit Amounts below €50,000 (2020)

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).



Take-Up Rate (2018/19) (%)
(2.96,4.63]
(2.39,2.96]
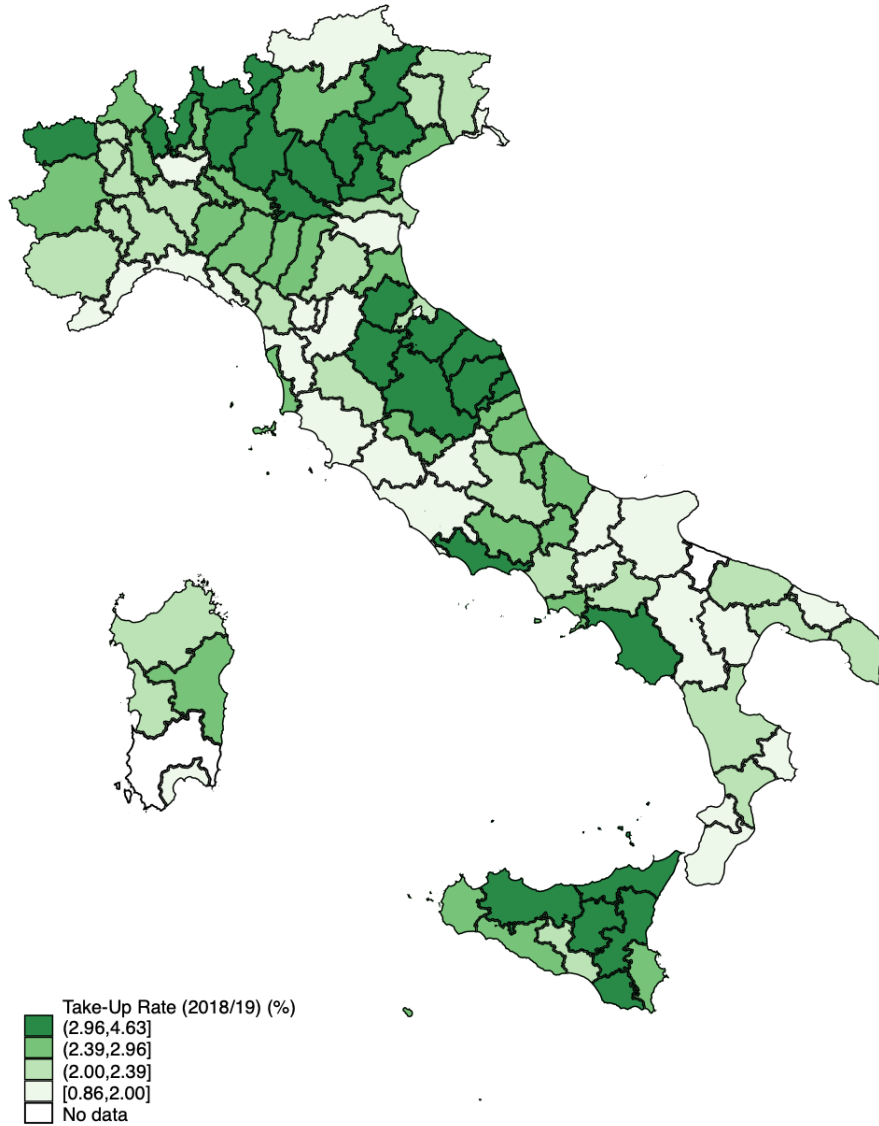(2.00,2.39]
[0.86,2.00]
No data

Table A1: **Robustness: Interest Rate**

The unit of observation is a loan. The dependent variable is the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. AppRating $\geq 4^*$ is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Log(Number Reviews) is the log of the number of Google reviews. Bank characteristics are balance sheet items from 2019Q4. Fixed effects for the interaction of province and industry (4-digit) of the firm are added. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

| | Interest Rate (%) | | | |
|---|---|---|---|---|
| Guarantee | All | 100% | 90% | 90% |
| | (1) | (2) | (3) | (4) |
| AppRating $\geq 4^*$ | -0.110 | 0.005 | -0.657*** | -0.527*** |
| | (0.104) | (0.122) | (0.202) | (0.150) |
| Bank - Ln(Assets) | -0.280*** | -0.224*** | -0.452 | -0.287 |
| | (0.055) | (0.042) | (0.273) | (0.246) |
| Log(Number Reviews) | 0.093 | 0.083 | 0.266 | 0.225 |
| | (0.059) | (0.059) | (0.162) | (0.144) |
| Bank - T1 Ratio | 0.093 | 0.104 | -0.099 | 0.016 |
| | (0.074) | (0.081) | (0.211) | (0.198) |
| Bank - NPL share | 0.028 | 0.038 | -0.056 | -0.036 |
| | (0.039) | (0.044) | (0.140) | (0.106) |
| Bank - ROA | -0.013 | -0.012 | -0.317 | -0.396* |
| | (0.035) | (0.036) | (0.228) | (0.235) |
| Bank - Interbank/Asset | -0.067 | 0.007 | -0.536** | -0.413** |
| | (0.048) | (0.033) | (0.243) | (0.188) |
| Fixed effects | | | | |
| Month | Yes | Yes | Yes | Yes |
| Province $\times$ Industry | Yes | Yes | Yes | No |
| Firm | No | No | No | Yes |
| Observations | 858823 | 745780 | 105600 | 58878 |
| $R^2$ | 0.130 | 0.077 | 0.394 | 0.722 |