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

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Public Guarantees for Small Businesses in Italy during Covid-19

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Abstract

This paper investigates whether banks' information technology (IT) and physical branch presence affect the supply of government guaranteed credit. For identification, we exploit loan level data and the institutional features of the Italian public guarantee scheme during Covid-19. We find that banks with better IT provide more, cheaper and faster guaranteed loans. However, the structure of local banking markets still matters: banks with better IT charge lower rates in less concentrated markets. Moreover, despite the high volume of online loan applications, guaranteed lending remained local: banks lent more in their core markets and where they have a larger market share.

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

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1 Introduction

Covid-19 forced a global business shutdown and caused a liquidity crunch which was especially acute among small businesses (SMEs) that have limited access to capital markets and credit lines to draw upon (Acharya et al., 2021; Chodorow-Reich et al., 2020). To help SMEs overcome the liquidity shock, policymakers in various countries relied on the banking system to act as a conduit of government-backed liquidity through the use of public credit guarantees on private bank loans. In the largest countries of the Eurozone, these programs contributed to increasing the stock of credit to non-financial firms by 8% in 2020 (Panel A of Figure 1). The increase in credit in 2020 is remarkable if compared to previous episodes of large contraction in economic activity, such as the financial crisis of 2008-09, when credit to Eurozone non-financial firms fell by 4% after the collapse of Lehman Brothers (Panel B of Figure 1)[1]. Since credit guarantee programs will likely play an increasingly important role in supporting SMEs' recovery and in future crises, it is of crucial importance to understand how the private sector allocates public guaranteed funds.

In this paper, we study the role of banks and local banking markets in the allocation, pricing and processing time of guaranteed loans. Since applications for guaranteed loans were mostly filed online (i.e. on bank websites or by email) and mobility restrictions limited access to bank branches, we hypothesize that banks with better information technology (IT) systems were better able to provide such loans. However, since SMEs typically rely on lending relationships with local banks (Petersen and Rajan, 1994; Degryse and Ongena, 2005), the bank physical presence through the branch network may still matter. We study these questions exploiting the unique institutional features of the Covid-19 guarantee program in Italy. On April 8^{th}, 2020 the government introduced a public guarantee of 90% for loans up

[1]Many other factors contributed to the growth in credit in 2020. For example, part of the increase in the stock of credit to non-financial companies in 2020 (and in the last months of 2008) is due to draw-downs on existing credit lines, especially from large firms (Li et al., 2020). Targeted monetary policy operations and relaxation of capital requirements also played an important role (Altavilla et al., 2020). There is also evidence that, at least partly, guaranteed lending replaced existing, non-guaranteed lending (Altavilla et al., 2021; Cascarino et al., 2021).

to €5 million and a 100% guarantee for €25,000 loans (increased to €30,000 in June) that requires no fee payment from the borrower and no formal credit assessment by the bank. 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, access to 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 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 was a significant amount of credit, representing about 10% of total lending to the private sector in 2019. At the extensive margin, we find that firms that were ex-ante financially constrained, and hence more likely to suffer from the liquidity shock induced by Covid-19, were also more likely to receive guaranteed loans. Young firms and those with less cash on hand in 2019 had higher take-up rates than other firms. Naturally, larger firms were more likely to obtain partially guaranteed loans, which are above the €30,000 threshold, while smaller firms asked for the 100% guaranteed loans[2]. Importantly, the effect of firm risk, as measured by the Altman et al. (2012) z-score, is non-monotonic: firms in the middle of the risk distribution are much more likely to obtain a guaranteed loan compared to high-risk or low-risk firms. This is consistent with the design of the program, that excluded firms with non-performing exposures, and with the fact that low-risk firms, conditional on the liquidity shock and other observables, are less financially constrained (Altavilla et al., 2021). Given the different institutional setting and relative

[2] The overall take-up rate has been around 16% among all eligible firms in Italy. The take-up rate on government guaranteed loans has been similarly low in Spain and France too. 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.

market size, we also analyze fully guaranteed loans separately from partially guaranteed ones in the remainder of the paper.

We then focus on the factors affecting credit outcomes such as loan rates and loan processing times (i.e. the time between the approval of the guarantee by the FG and the issuance of the loan by the bank)[3]. First, we document that the variation in loan conditions is mostly explained by supply factors (i.e. bank heterogeneity) rather than demand factors. The R^2 of a regression of interest rates or loan processing times on bank fixed-effects is 38-42% compared to 13% with area×4-digit-industry fixed-effects[4]. 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 the ability of the bank to provide guaranteed lending. Banks with better IT systems, as proxied by the Google Playstore review rating on their mobile banking app or overall spending in IT, make 25% more guaranteed loans as a fraction of their total lending compared to banks with low quality IT, charge rates that are 19-23% lower and process guaranteed loans almost twice as fast[5]. 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. While we do not claim causality, as the quality of bank IT is likely to be correlated with other unobserved factors at the bank level, these results underscore the importance of the quality of the digital infrastructure during the pandemic. Importantly, our results hold after controlling for standard bank characteristics, including bank size, which indicates that the quality of IT systems matters beyond economies of scale. Moreover, these effects are not driven by credit demand or a selection of specific borrowers

[3]We believe that this is a good approximation of the time between the loan application and the actual disbursement and show that the actual approval date of the guarantee by the FG does not correlate with bank or demand characteristics.

[4]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 deemed as non-essential, we use fixed-effects for borrower industry and location to capture the most relevant demand factors in this setting.

[5]As proxies for overall spending in IT (He et al., 2021) we use total IT expenses in 2020 and amortization of past IT investments.

with high quality IT banks, as we control for area×4-digit-industry or firm fixed-effects in a short window of time between April and August 2020[6].

Since most applications for guaranteed loans were filed online, one may question the relevance of the bank branch network and of the competition in local banking markets 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 (Kwan et al., 2021). 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). First of all, we find that local banking competition matters for guaranteed loans made by banks with high quality IT: the sensitivity of loan rates to bank IT is lower in more concentrated local markets. In other words, even banks with a good digital infrastructure are affected by local market competition. Second, we find that, even if most applications were filed online, guaranteed lending remained local: 77% of small business borrowers obtained a loan with a bank that has a branch in the same municipality where the firm headquarter is located. Moreover, 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 and pricing conditions of guaranteed lending, despite the growing importance of the bank digital infrastructure.

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 a bank with high quality IT it would receive guaranteed loans faster and at lower rates. In this respect it is notable that local cooperative banks, which are supposed to have a comparative advantage in lending to small businesses (Berger et al., 2017), were

[6]While supply-side heterogeneity matters more than demand heterogeneity to explain credit conditions on guaranteed lending, firm risk is still priced in loan rates. The sensitivity of loan rates to firm risk depends on the guarantee coverage ratio: larger, older, more liquid and less levered firms pay lower rates on 90% guaranteed loans, but there is no statistically significant effect fo fully guaranteed loans.

conspicuously inefficient in providing 100% government guaranteed loans which were meant for the very small firms.

This paper contributes to the growing literature on the effects of public credit guarantees. Earlier studies have focused on the US loan guarantee program from the Small Business Administration (Brown and Earle, 2017; Bachas et al., 2019), the creation of new bank relationships in Chile (Mullins and Toro, 2017), employment and earnings in France (Barrot et al., 2019) or firm performance in the UK (Gonzalez-Uribe and Wang, 2020). Many recent studies have analyzed loan guarantees during Covid-19, in particular the Paycheck Protection Program (PPP) and its impact on employment (Autor et al., 2020; Chetty et al., 2020) or on publicly listed firms (Cororaton and Rosen, 2021; Balyuk et al., 2020).

Furthermore, we contribute to the literature on IT and financial intermediation. D'Andrea et al. (2021) find that the arrival of high speed internet increased credit supply and local market competition, Timmer and Pierri (2020) show that higher intensity of IT-adoption is associated with lower levels of non performing loans and Ahnert et al. (2021) find that bank IT helps spurring entrepreneurship. Kwan et al. (2021) study the impact of the PPP on the adoption of bank digital technologies. In our paper, we use a novel measure of bank IT, the app rating as determined by customers' reviews. As such, our measure is more likely to capture the quality of bank investment in IT compared to measures like the intensity of bank spending in IT (He et al., 2021). Moreover, our measure is more likely to capture a dimension of IT investment that is more salient to banks' customers.

This paper also joins the burgeoning literature studying the impact of the Covid-19 pandemic on financial markets and corporate outcomes. Covid-19 led to the largest increase in demand for credit ever observed by commercial banks (Li et al., 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 (Gourinchas et al., 2020). In this respect, Italy is one of the country most severely affected by the potential future rise in NPLs due to its high share of SMEs (Carletti et al., 2020).

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.

The paper is organized as follows. Section 2 describes the institutional details of public guarantees in Italy and Section 3 the data used in the empirical analysis. Section 4 presents some stylized facts and descriptive evidence about which firms and banks participate in the guarantee program and Section 5 shows the role of bank heterogeneity and local banking markets in explaining credit conditions on guaranteed loans. Finally, Section 6 concludes.

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, 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 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 8^{th} 2020 the Italian government approved a law decree, the so-called *DL Liquiditá*, that strengthened the FG capacity to issue guarantees by an additional €400 billion, of which €200 billion to finance guarantees for SME below

500 employees[7]. The guarantees were also greatly expanded in scope and coverage. First of all, the guarantee coverage was increased from 80% to 90% and eligible loan size went from €2.5 to €5 million[8]. 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[9]. The loans have a maturity of 6 years (increased to 10 years in June) and no principal payment, only interest, is due in the first two years of the loan. Finally, firms with pre-existing non-performing exposure as of January 2020 were excluded from the guarantee program, but those with exposures that became non-performing after January 2020 were eligible. That is, firms hit by the Covid shock could apply, but not if they were already in distress before.

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 to the FG), a firm (i.e. the beneficiary), and the FG. First, the firm needs to file a standard loan application with a bank of its 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 €25-30,000, so that SMEs can quickly obtain the needed liquidity. Firms have to complete a self-declaration form (*Allegato 4-bis*), that the bank will forward to the FG, in which they state that their business has been affected by Covid-19, and

[7]Large firms above 500 employees were instead eligible for guarantees issued by SACE, the Italian export credit agency. These loans are not part of our data since the recipients are not SMEs.

[8]An additional 10% guarantee for loans below €800,000, bringing the total guarantee to 100%, can be granted by *Confidi*, a consortium of other guarantee funds. These loans however represent a small category of the overall set of loans.

[9]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.

that they are eligible to receive 100% government guaranteed loans. Over this period, since bank branches were hard to reach to due mobility restrictions, most loan applications were made on bank websites or via email to a local loan officer, with the information provided through dedicated web pages (see the Online Appendix Figure A1 for an example).

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

3 Data

Loan level data on the universe of guaranteed loans are publicly available in Italy[10]. This loan origination data includes basic information on the borrowing firm or the self-employed individual that accessed the guarantee (name, address, sector and the tax identifier), 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)[11]. 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

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

[11] Loan applications data on guaranteed credit do not exist. However, anecdotal evidence from the Parliamentary Committee on the banking system in 2020 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 processed at least two thirds of all applications by the end of May.

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 in 2020 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 and amortization on IT from Orbis Bank Focus in 2020, that we divide by the total of non-interest operating expenses in the same year[12].

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.[13] We calculate the firms' z-score using the updated

[12]IT expenses and amortization are reported by Italian banks under the IFRS9 accounting standard, which was introduced in Italy in 2018. As such, data on IT expenses prior to 2020 are partial and incomplete.

[13]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. 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

methodology in Altman et al. (2012).

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.

4 Stylized facts and descriptive evidence

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 in terms of the volume of guaranteed credit and the type of firms and banks that participate in the guarantee program.

4.1 Amount of credit

We start by describing the amount of aggregate credit credit and take-up rate. Panel A of Table 1 presents the summary statistics for the sample of guaranteed loans. Summary statistics are shown separately for firms with 100% and a 90% guaranteed loans. Partially guaranteed loans are much larger than fully guaranteed loans (€370,000 vs. €20,000), and carry a higher interest rate (2.8% vs 1.1%). It is worth emphasizing that the guarantee program for SMEs in Italy was large even before Covid (Figure 2): from 2013 to 2019, €17-20 billion of loans have received a public guarantee, compared to €4 billion in France (Barrot et al., 2019). However, in the first eight months of 2020 alone, the volume of guaranteed lending increased dramatically, reaching a total of €79 billion or 10% of the stock of bank credit to non-financial firms in 2019. Panel A of Figure 3 further reveals that volume of guaranteed lending is concentrated in the 90% guarantee program (€61 billion) and that 100% guaranteed

these do not enter our estimation sample because they have missing balance sheet information.

loans were issued earlier, especially in May and June. In terms of number of loans, the vast majority (86%) are fully guaranteed, i.e. below €25-30,000 (Panel B of Figure 3)[14].

Fully guaranteed loans were extended to 829,053 borrowers, two thirds of which are private partnerships, sole proprietorships or self-employed individuals and represent about 16% of the universe of registered firms in Italy (*Movimprese*). There are however large differences in the take-up rate across geographic areas. While in some provinces the take-up rate is as low as 7%, in other areas it increases to 26%. Figure 4 shows that the take-up rate is generally higher in the north of the country, where the pandemic hit the hardest (correlation with excess deaths equal to 0.27) or where the share of closed businesses was higher (correlation equal to 0.40)[15]. As one might expect, there are also significant difference in the take-up rate across different sectors (Figure 5). For example, while virtually no firm in agriculture accessed the guarantee program, 25% of firms in the food and accommodation industry and almost 60% in the healthcare and social assistance sector have[16].

4.2 Which firms received guaranteed loans?

We now describe the type of firms that received guaranteed credit. Panel B of Table 1 shows the summary statistics for the sample of firms with full financial accounts in Orbis in 2019, 28% of which obtained a guaranteed loan in 2020[17]. Most firms are rather small and young, with median assets around five million euros and an age of five years since the incorporation

[14] There is also evidence of bunching in the loan size distribution after April 2020 (Figure A2 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.

[15] This is not the case in normal times, as the take-up rate is generally higher in the south of Italy (see Figure A3 in the Online Appendix).

[16] The take-up is especially high in healthcare and social assistance (e.g., nursing homes, dental care and other medical facilities), professional services (e.g., engineering and architecture) and food and accommodation. A similar ranking by sector is found in the US for PPP loans (Wall Street Journal, June 17, 2020: https://www.wsj.com/articles/ppp-small-business-loans-left-behind-many-of-americas-neediest-firms-11592407677.

[17] This number is higher than the 16% mentioned in the previous section because the sample is restricted to firms with full financial accounts in Orbis, which is mostly composed of limited liability companies and thus excludes private partnerships and sole proprietorships.

date. They hold 16% of total assets as cash or other liquid assets and according to the Altman et al. (2012) z-score, 35% can be classified as high-risk and 46% as low-risk.

We analyze the extensive margin of credit, i.e. investigate the types of firms that accessed guaranteed loans, by estimating the following linear probability model:

$$\text{Guarantee2020}_{f,p,s} = \gamma' X_f + \mu_{ps} + \epsilon_{f,p,s} \tag{1}$$

where $\text{Guarantee2020}_{f,p,s}$ is a dummy equal to one if firm f active in province p and 4-digit sector s obtained a guaranteed loan and 0 otherwise. The control group in this estimation consists of firms in Orbis who were eligible for a guaranteed loan (i.e. all SME firms with less than 500 employees or < €50 million in sales or < €43 million in total assets), but did not obtain one. X_f is a vector of firm characteristics and μ_{ps} is a set of province×4-digit sector fixed-effects to control for local demand conditions[18]

The results are presented in Table 2. Firm size and cash-on-hand in 2019 are the most important factors explaining the access to guaranteed loans, with a one standard deviation change in each having an impact of around 25% of the mean uptake rate[19]. Naturally, larger firms seek partially guaranteed loans more than smaller ones, since these loans can be as large €5 million: a one standard deviation increase in total assets decreases the take-up rate of fully guaranteed loans but it increases that of partially guaranteed loans. We also find that younger firms are more likely to obtain a fully guaranteed loan. Importantly, the effect of firm risk on the take-up probability is non-monotonic: medium-risk firms are more likely to apply for a guaranteed loan than both high-risk and low-risk firms. This is consistent with the program design, that excluded firms with ex-ante non-performing exposures as of January 2020 and with the fact that low-risk and more profitable firms are in less need of liquidity (Altavilla et al., 2021; Cascarino et al., 2021).

[18]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 deemed as non-essential, we use fixed-effects for borrower industry and location to capture the most relevant demand factors in this setting.

[19]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.

Overall, the results suggest that firms that are ex-ante more likely to be financially constrained (i.e. younger, smaller and with less cash on hand) are more likely to obtain a guaranteed loan. The program targeting seems to be effective because, conditional on other observables, both high-risk and low-risk firms are less likely to obtain a guaranteed loan than firms in the middle of the risk distribution.

4.3 Which banks issue guaranteed loans?

We conclude the section on the descriptive evidence by showing the type of banks that issue guaranteed loans. There are 104 banks in the sample that extended guaranteed loans and for which we hand-collected information on the app rating from the Google Playstore (Panel C of Table 1). Guaranteed loans in 2020 represent 4% of the overall loan portfolio, two thirds of which are partially guaranteed. Almost 40% of the banks in the sample have a rating of 4 stars or more, with an average rating of 3.7. There is large variation in terms of lender size, which ranges from less than one to more than a hundred billion euros. Banks spend 6.3% of their non-interest operating budget on maintenance and development of their IT infrastructure, and 0.75% in annual amortization of past IT investments.

We then test which type of banks issue more guaranteed loans with a cross-sectional regression at bank-level:

$$\text{ShareGuaranteedLending}_b = \beta_1 HighAppRating_b + \gamma' X_b + \epsilon_b \tag{2}$$

where $\text{ShareGuaranteedLending}_b$ is the share of guaranteed loans over total lending by the bank in 2019Q4 in percentage points. $HighAppRating_b$ is a dummy equal to one if bank b has a 4-5 star rating on its mobile banking app from the Google Playstore and 0 otherwise (i.e. 1-3 stars). Our preferred measure of bank IT is the customer-based satisfaction rating on the mobile banking app, which is a better proxy for the quality of IT investment 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

(Table A1 in the Online Appendix). X_b is a vector of other bank characteristics such as size, capitalization, the quality of the loan portfolio (NPL), profitability and interbank funding[20]. The results are presented in Table 3.

We find that banks with highly rated apps have 1 percentage point higher share of guaranteed lending over total lending compared to other banks. This is a large effect, equal to 25% of the average share of guaranteed lending by banks in the sample. This effect is not mechanically given by bank size or the number of Google reviews, as we control for both in the specification. Other balance sheet controls are not significantly correlated with the share of guaranteed loans, except for the share of non-performing loans, which suggests that weaker banks with worse quality portfolios are more likely to issue guaranteed loans. Comparing the results across guarantee programs suggests that the effects of bank IT are stronger for 90% guaranteed loans, both statistically and economically: banks with highly rated apps make 33% more partially guaranteed loans and 10% fully guaranteed loans (and the effect is only weakly statistically significant). Thus the evidence suggests that banks with better IT, conditionally on other bank characteristics, are more likely to issue guaranteed loans.

5 Results: loan conditions and local banking markets

5.1 Supply or demand heterogeneity?

We now turn to study how credit conditions vary for guaranteed loans. Since the maximum loan amount for guaranteed loans is fixed by law (and it is exactly equal to €25-30,000 for most loans), we study two other margins: interest rates and processing times[21].

While interest rates for fully guaranteed loans are also capped by law, the rate for 90% guaranteed loans can be freely set by the bank. Loan processing times are calculated as the number of days between the approval date of the guarantee by the FG and the date in which

[20]For ease of comparison with the results at loan-level, the regression models at bank-level are weighted by bank total assets, taking into account that large banks issue a disproportionate amount of guaranteed loans.

[21]We have data on processing 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 November 2020).

the bank effectively hands out the loan to the borrower[22]. As such, loan processing times measure the ability of a bank to disburse guarantee loans, rather than that of the FG to approve them. 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 processing time indicates the confidence of private banks in the willingness of the FG to approve as many fully guaranteed loans as possible.

We document significant heterogeneity in interest rates and processing times across lenders and guarantee programs. During the pandemic, most loan applications were made online, through bank websites (see Figure A1 in the Online Appendix for an example). 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 Panel A of Figure 6 we show that the entire distribution of processing times for banks with highly rated apps is shifted to the left compared to those with low-rated apps[23]. Banks with highly rated apps also charge lower rates on average than banks with low-rated apps (Panel B of Figure 6).

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 (as the visual evidence in Figure 4 confirms). Similarly, variation at the sector level captures the decision of the government to shut down some of the businesses deemed as non-essential (Figure 5). As such, variation at the province and sector level is likely to capture a significant part of demand heterogeneity. Formally, we run

[22] While we do not have the date when the SME filed the loan application with the bank, only when the bank forwarded the application to the FG, we believe that the latter is a reasonable approximation of the former. For example, the actual approval date of the guarantee by the FG does not correlate with individual banks characteristics (see Table A2 in the Online Appendix). In fact, the FG approves banks' applications in batches over the week, with Tuesdays and Fridays accounting for more than 85% of all approvals.

[23] 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 the Online Appendix Figure A4 we show that indeed larger banks have a distribution of processing 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.

the following regression at the loan level:

$$\mathrm{Y}_{b,ps} = \lambda_b + \mu_{ps} + \epsilon_{b,ps} \tag{3}$$

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

Table 4 reports the R^2 statistics of the regression in equation (3) 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 around 13% of the variation in processing times and interest rates, while bank fixed-effects capture 38-42%. 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-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.

5.2 Bank heterogeneity

Motivated by the results from the variance decomposition in equation (3), we now explore which individual bank characteristics matter for guaranteed lending.

While informative, the cross-sectional results at bank level may be affected by differences in the type of borrowers that high IT banks lend to. Therefore, we analyze whether credit conditions vary across different lenders at the loan level, with the following specification:

$$\mathrm{Y}_{f,b,m} = \beta_1 HighAppRating_b + \gamma' X_b + \mu_f + \lambda_m + \epsilon_{f,b,m} \tag{4}$$

where $Y_{f,b,m}$ is either the interest rate or the processing time of a loan made by bank b to firm f in month m. 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 guaranteed loans from different banks. We also include a dummy for the month in which the guaranteed loan was obtained[24]. Finally, standard errors are clustered at the bank level. Results are presented in Tables 5 and 6.

We find that banks with highly rated app (4-5 stars) charge lower rates on guaranteed loans than banks with low rated apps, especially on partially guaranteed ones. Guaranteed loans with 90% coverage issued by banks with highly rated app carry an interest rate which is 67 basis points lower (23% compared to the mean) than banks with low rated apps. Since we control for size and other bank characteristics, the result means that the quality of the IT system is not simply explained by traditional balance sheet factors. Importantly, the coefficient remains strong and positive (19% compared to the mean) once we include firm fixed-effects, focusing on the sample of borrowers with at least two guaranteed loans, either with any type of guarantee coverage (column 4) or with two partially guaranteed loans (column 5), suggesting that province×4-digit industry fixed-effects already capture most of the variation in credit demand. Moreover, banks with higly rated apps disburse both partial and fully guaranteed loans 4-8 days earlier compared to other banks, even to the same firm. This is a sizable effect, since the average fully guaranteed loan is processed 10 days before the approval of the guarantee.

Robustness of bank IT measure The results presented in Tables 5 and 6 are robust to using alternative measures of bank IT. For example, in Table A3 in the Online Appendix we replace the rating on the mobile banking app with the share of IT expenses over total operating costs in 2020, while in Table A4 we use the share of IT amortization over total operating costs, which is a measure of past investment in IT. 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 and amortization from 2020 because

[24] The calendar date when the loan was issued is relevant because the interest rate cap on fully guaranteed loans 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.

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 or amortization process fully guaranteed loans almost one week faster than other banks and charge 17 basis points less on partially guaranteed loans. Moreover, in Table A5 in the Online Appendix we use the full rating scale, from 1 to 5 stars, instead of the dummy for highly rated apps and find very similar results.

Overall, the evidence presented in Tables 3, 5 and 6 and is consistent with a story in which 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.

Residual firm heterogeneity Finally, Table 7 tests whether firm specific heterogeneity matters once bank and province-industry fixed-effects are included. We find limited impact of firm-specific characteristics on processing times. This confirms that bank heterogeneity has a much larger impact on processing times than firm heterogeneity. However, we do find that firm risk is priced in guaranteed loans: smaller, younger, 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 and statistically not significant for fully guaranteed loans (less than a basis point), they are larger and statistically significant for partially guaranteed loans. In particular, firm size appears to be the most significant driver of interest rates differentials once bank and province-industry fixed-effects are included: a one standard deviation increase in total assets decreases the interest rate on partially guaranteed loans by 31 basis points (11% compared to the mean).

5.3 Local banking markets and guaranteed lending

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.

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.

First of all, we find that 77% of borrowers obtained a guaranteed loan with a bank that has a branch in the same municipality as the firm headquarter. This suggests that, despite the online loan applications, most small business owners applied for a guaranteed loan with the nearest branch. Thus, the pre-existing geographical distribution of bank branches affects the allocation of guaranteed credit. We test this hypothesis more formally 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:

$$\log(Lending)_{b,p} = \beta_1 LocalMarketShare_{b,p} + \beta_2 CoreMarketShare_{b,p} + \lambda_b + \mu_p + \epsilon_{b,p} \quad (5)$$

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

5.4 Local banking competition and bank IT

So far, we have shown that the quality of the bank digital infrastructure affects the pricing and disbursement time of guaranteed loans and that the physical presence through the branch network is important to determine the allocation of guaranteed credit to small businesses. In this section we ask whether banks with a better digital infrastructure are affected by local market competition. On the one hand, it is possible that banks with better quality IT apply uniform lending policies across lending markets, basing their decision on borrowers' hard rather than soft information (Petersen and Rajan, 2002). On the other hand, since small business lending has remained local even during the pandemic (Granja et al., 2020), even banks with better IT may be subject to local banking competition[25].

We test this hypothesis more formally by running the following regression on the loan interest rate:

$$Y_{f,b,m} = \beta_1 HighAppRating_b + \beta_2 HighAppRating_b \times HighHHI_p + \gamma' X_b + \mu_f + \lambda_m + \epsilon_{f,b,m} \quad (6)$$

where $HighHHI_p$ is a dummy equal to one if province p has an above the median level of the Herfindahl index (HHI) based on the number of bank branches, 0 otherwise. If high IT banks apply uniform lending policies across banking markets, we expect the coefficient on the interaction β_2 to be not statistically significant, or even negative should high IT banks challenge the incumbents in less competitive banking markets.

The results are presented in Table 9. We find that banks with highly rated apps charge less on guaranteed loans, but the effect is 30% lower in provinces with high local market concentration. That is, the sensitivity of loan rates to bank IT depends on the degree of local market concentration: banks with better IT charge less for guaranteed loans especially in competitive banking markets, suggesting that they too are affected by local competition. Much as with the baseline results in Table 5, the effect of bank IT on interest rates is concentrated on partially guaranteed loans and it is stable to the inclusion of firm fixed-effects in columns (4-5). Results are also robust if we interact bank IT with the HHI index itself rather than the above the median dummy (see Table A6 in the Online Appendix).

[25] The arrival of new communication technology, such as high speed internet, may itself affect the level of local market competition, by increasing the average distance between banks and borrowers (D'Andrea et al., 2021).

6 Conclusion

Several countries worldwide introduced credit guarantees to support small businesses affected by the Covid-19 pandemic. Differently from previous episodes of economic recessions, these programs contributed to a large expansion in total bank credit. 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 which role the banking sector played in the allocation of guaranteed credit. 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 €25-30,000 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 the quality of the digital infrastructure, is a crucial determinant of the quantity, speed and pricing of guaranteed loans. 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, affecting the pricing policies of banks with good digital infrastructure too. In other words, differences in bank characteristics play 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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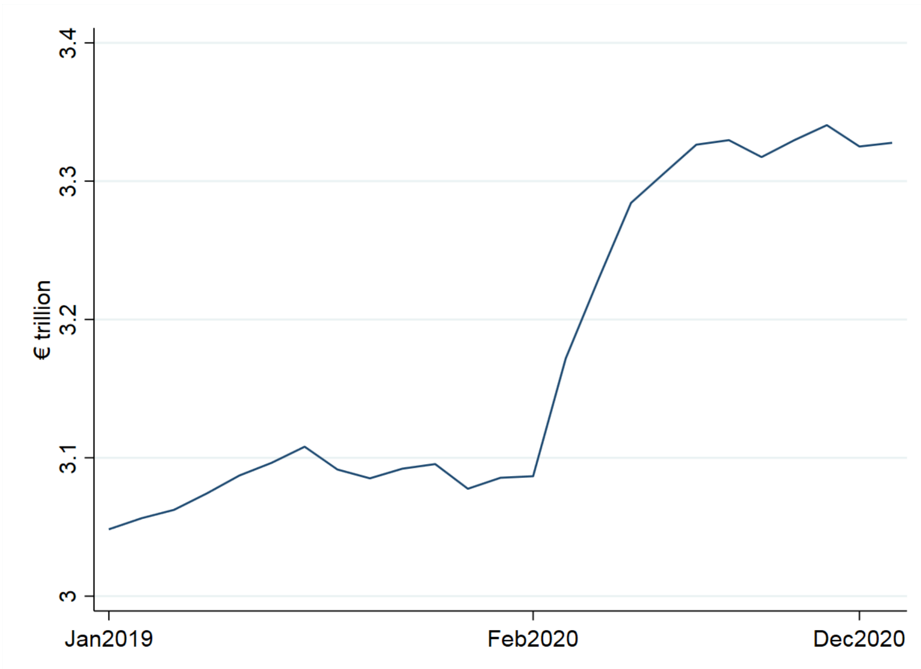
Figure 1: Total Credit to non-financial firms in the Eurozone

This figure plots the stock of total outstanding credit to non-financial companies in France, Italy, Germany and Spain from January 2019 to December 2020 in Panel A and from January 2008 to January 2011 in Panel B. Source: ECB Statistical DataWarehouse (SDW).

(a) Panel A. 2019-2021



(b) Panel B. 2008-2011

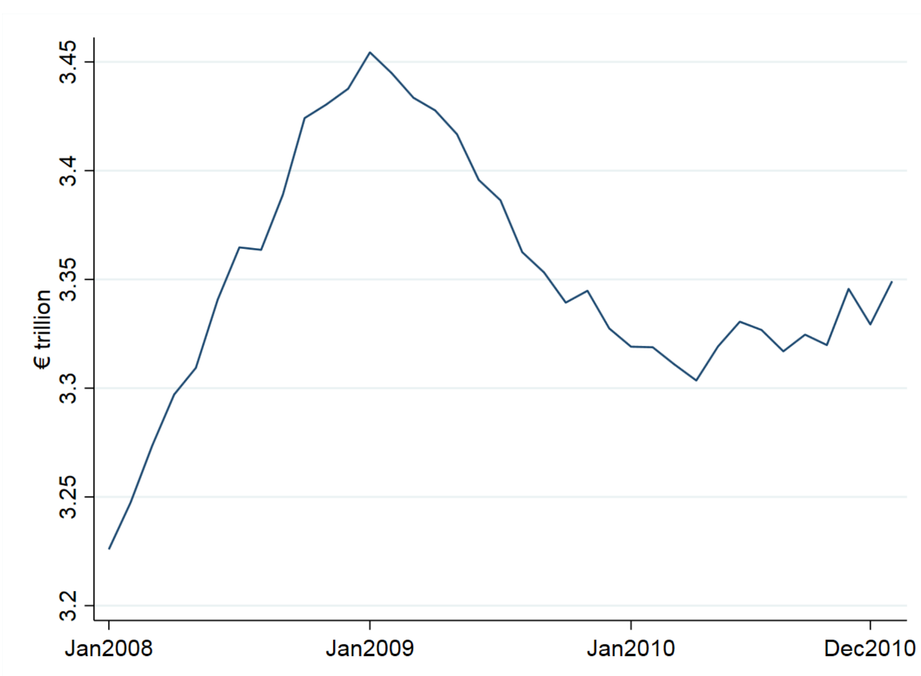


Figure 2: Public guaranteed credit in Italy, 2013-2020

This figure plots total loan volumes and guaranteed amount at a yearly frequency from 2013 to 2020 (up to August 2020) from the Italian Guarantee Fund (FG).

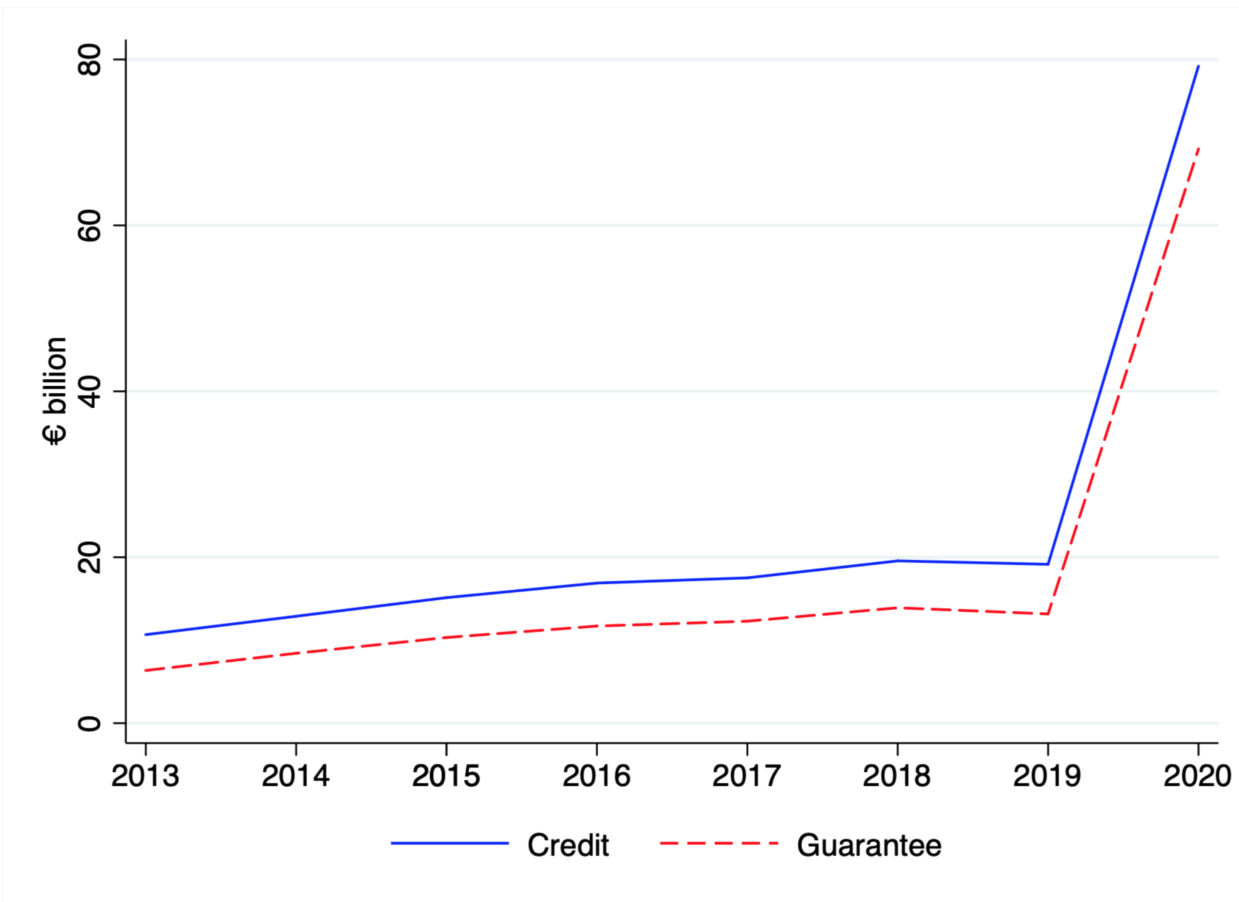
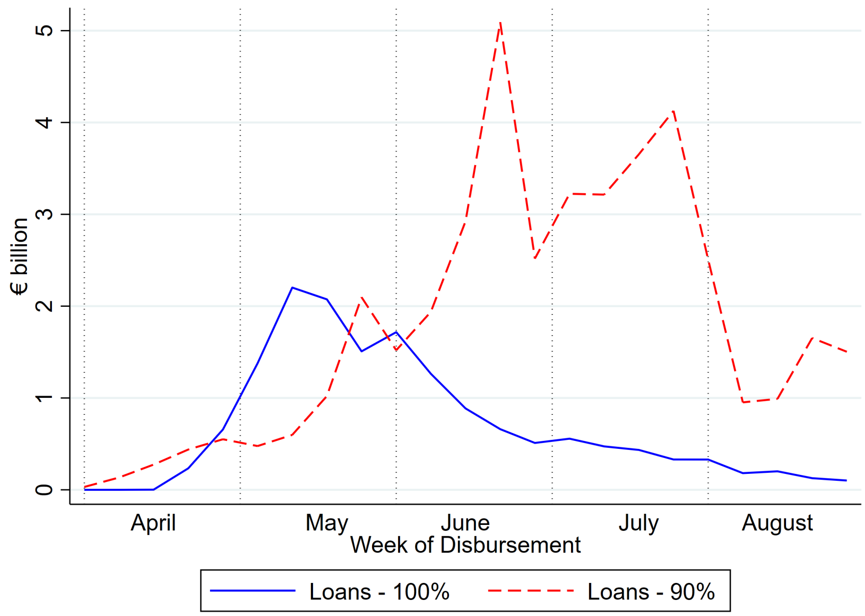


Figure 3: Public guaranteed credit in Italy in 2020

This figure plots the time series of loans with public guarantees from the Italian guarantee fund, by week of disbursement and type of guarantee. Panel A reports total loan volumes by week of disbursement from April 2020 to August 2020 (vertical lines indicate separate months). Panel B reports the weekly number of government guaranteed loans disbursed from April 2020 to August 2020.

(a) Panel A. Loan Volumes



(b) Panel B. Number of Loans

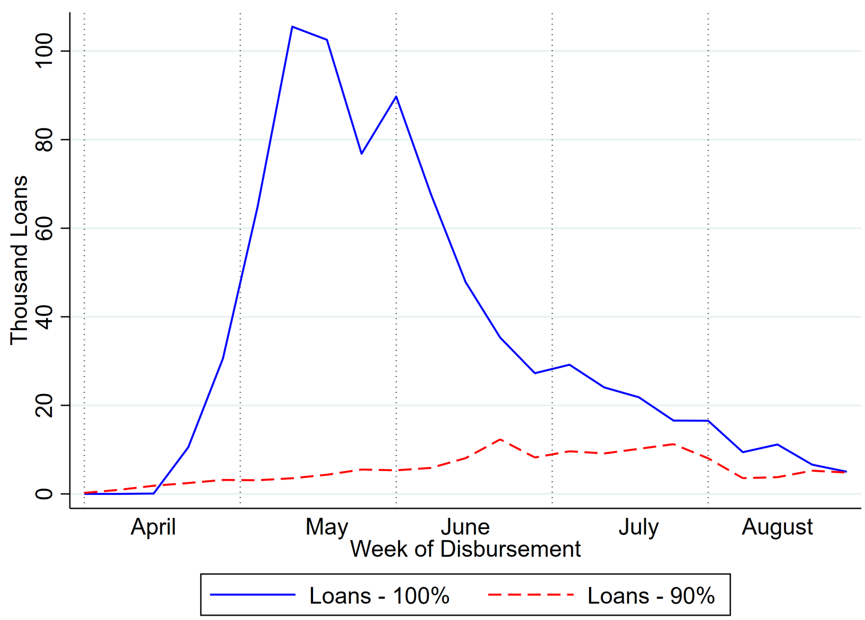


Figure 4: Guarantee, Excess deaths and Closed firms by Province

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.

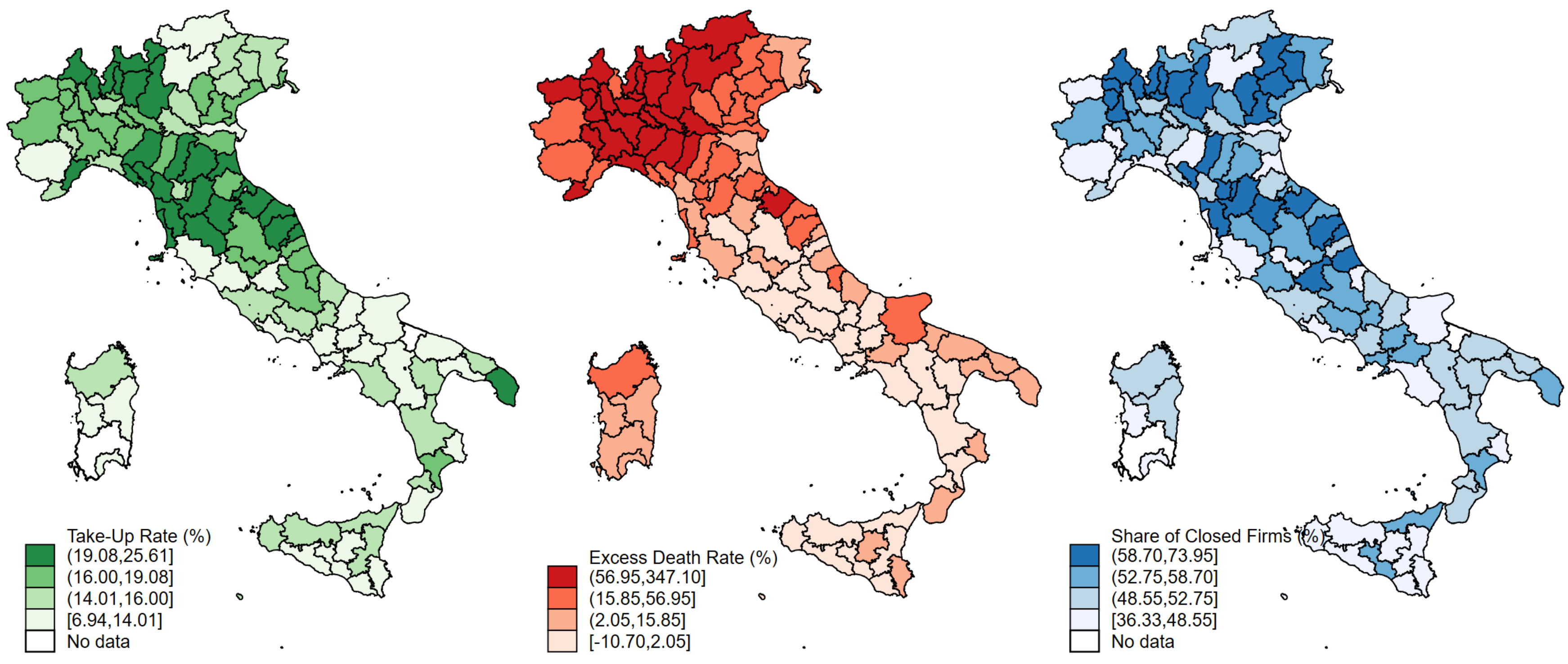


Figure 5: Guarantee by Sector

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.

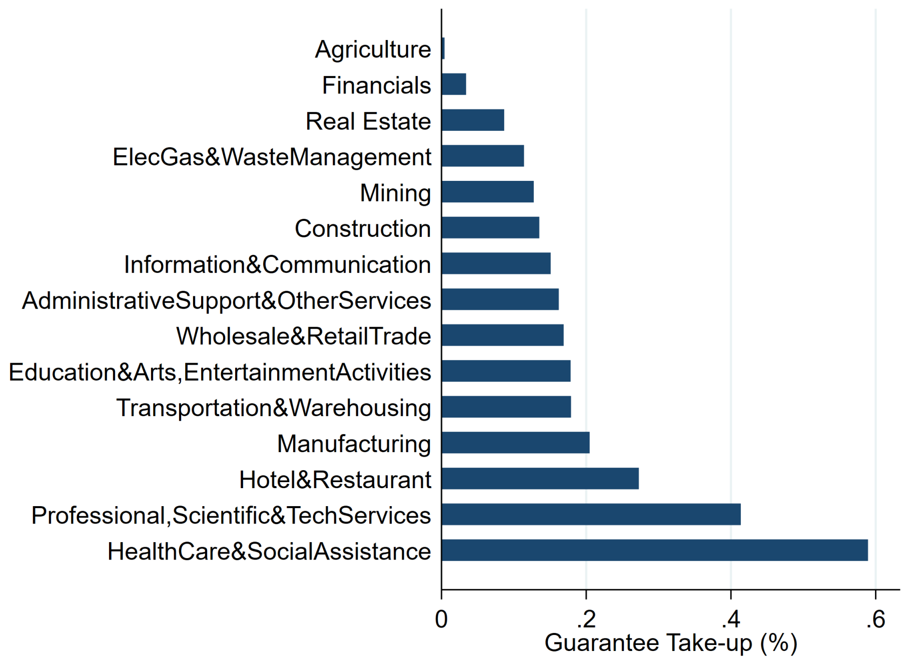
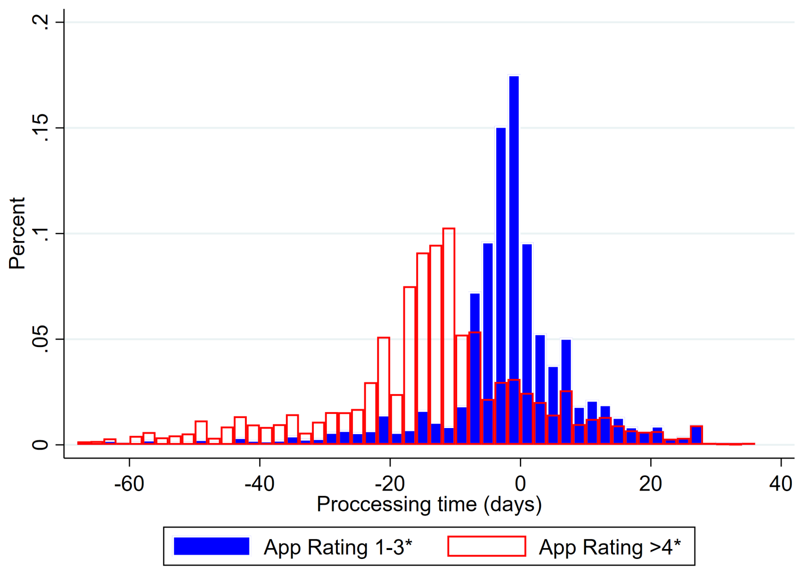


Figure 6: Loan rates and processing times by bank IT

In panel A we report the histogram of processing times on government guaranteed loans for banks with high (4+ stars) and low mobile banking app ratings; Processing times are calculated as number of days between the date of approval of the loan by the FG and the day of processing of the loan to the firm by the bank. In Panel B we present a binned scatter of the average interest rate on government guaranteed loans and rating of mobile apps on Google Playstore of banks.

(a) Panel A. Processing Times



(b) Panel B. Loan Rates

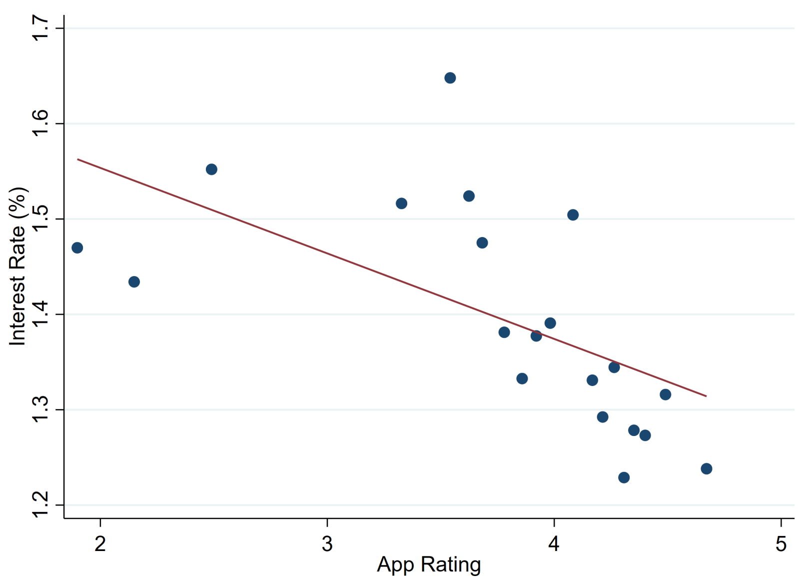


Table 1: **Summary statistics**

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 all firm characteristics from BvD Orbis in December 2019. Panel C reports bank-level characteristics on the banks that extended government guaranteed loans from BvD Orbis Bank Focus in December 2019.

	N	Mean	Std.Dev.	5^{th} pct.	Median	95^{th} pct.
Panel A: Loan level						
100% Guaranteed Loan Amount (000s €)	745489	19.764	7.590	5.000	25.000	30.000
100% Guarantee Interest Rate (%)	745489	1.173	0.334	0.600	1.200	1.750
100% Guarantee Disbursement time (days)	359954	-10.483	16.216	-45.000	-7.000	10.000
90% Guaranteed Loan Amount (000s €)	105385	371.851	563.975	25.000	200.000	1350.000
90% Guarantee Interest Rate (%)	105385	2.808	2.055	0.800	2.000	7.700
90% Guarantee Disbursement time (days)	37998	11.418	12.897	-5.000	9.000	36.000
Panel B: Firm level						
Guarantee 2020 =1	720404	0.285	0.452	0.000	0.000	1.000
Total Assets (million €)	720404	17.656	40.629	0.229	4.525	80.073
Firm Age (years)	720404	15.336	13.870	2.000	11.000	42.000
Cash/Assets	720404	0.166	0.212	0.001	0.076	0.652
Altman Z-score	720404	7.679	12.580	1.230	5.538	14.579
Medium Risk	720404	0.186	0.389	0.000	0.000	1.000
High Risk	720404	0.355	0.479	0.000	0.000	1.000
Panel C: Bank-level						
Guaranteed Loans/Loans	104	0.042	0.029	0.012	0.033	0.090
100% Guaranteed Loans/Loans	104	0.014	0.008	0.004	0.013	0.030
90% Guaranteed Loans/Loans	104	0.027	0.026	0.004	0.020	0.072
HighAppRating	104	0.394	0.491	0.000	0.000	1.000
App Rating	104	3.718	0.717	2.000	3.600	4.400
Number of App Reviews (thousand)	104	17.92	25.20	0.105	4.632	37.24
Total Assets (billion €)	104	34.11	147.76	0.827	2.360	106.46
Tier1 Ratio	104	16.09	5.509	11.09	14.89	23.309
NPL/Loans (%)	104	9.854	4.321	3.959	9.172	16.675
ROA	104	0.154	0.561	-0.799	0.262	0.642
Interbank/Asset (%)	104	14.46	7.494	0.442	14.517	26.723
IT Expenses (%)	104	6.310	3.768	0.677	6.511	11.701
IT Amortization (%)	104	0.753	1.298	0.005	0.103	3.802

Table 2: **Stylized facts: Which firms obtained guaranteed loans?**

This table reports the estimates corresponding to the regression in equation (1). 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. Medium and high risk dummies are defined according to cut-offs on the Z-score as in Altman et al. (2012). 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)	0.015***	-0.035***	0.058***
	(0.004)	(0.004)	(0.002)
Cash/Assets	-0.074***	-0.065***	-0.016***
	(0.003)	(0.002)	(0.002)
Log(Age)	-0.021***	-0.024***	0.003***
	(0.002)	(0.002)	(0.001)
Medium risk	0.071***	0.060***	0.027***
	(0.002)	(0.002)	(0.002)
High risk	-0.001	0.003	-0.005***
	(0.002)	(0.002)	(0.001)
Fixed effects			
Province×4-digit Industry	Yes	Yes	Yes
Observations	720404	662127	556220
R^2	0.162	0.155	0.172

Table 3: **Stylized facts: Which banks issue guaranteed loans?**

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is a bank. The dependent variable is the share of guaranteed lending volume between April and August 2020 over total bank lending as of 2019Q4 (in percentage points). Bank characteristics are balance sheet items from 2019Q4. Regressions are weighted by bank total assets. Standard errors robust to heteroskedasticity in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Share of guaranteed loans		
	All	100%	90%
	(1)	(2)	(3)
HighAppRating	1.059***	0.148*	0.911**
	(0.384)	(0.078)	(0.354)
Log(Number Reviews)	-0.315	-0.001	-0.314
	(0.505)	(0.079)	(0.452)
Log(Assets)	-0.259	-0.223***	-0.036
	(0.282)	(0.065)	(0.246)
Tier 1 ratio	0.092	0.018	0.074
	(0.434)	(0.170)	(0.494)
NPL/Loans	0.948**	0.245**	0.702**
	(0.385)	(0.098)	(0.324)
ROA	0.214	-0.006	0.220
	(0.207)	(0.065)	(0.171)
Interbank/Asset	0.064	-0.147	0.211
	(0.352)	(0.109)	(0.280)
Observations	104	104	104
R^2	0.406	0.611	0.297

Table 4: **Loan conditions: supply and demand factors**

This table reports the R^2 corresponding to the regression in equation (3). 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 processing 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.

	Processing Time			Interest Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.127	0.418	0.473	0.132	0.379	0.440
Fixed effects						
Province × Industry	Yes	No	Yes	Yes	No	Yes
Bank	No	Yes	Yes	No	Yes	Yes
N	452995	452995	452995	994750	994750	994750

Table 5: **Bank heterogeneity: interest rate**

This table reports the estimates corresponding to the regression in equation (4). 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. HighAppRating is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
HighAppRating	-0.182***	-0.083	-0.670***	-0.404***	-0.534***
	(0.055)	(0.066)	(0.193)	(0.132)	(0.148)
Fixed effects and controls:					
Bank Controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	58640
R^2	0.237	0.318	0.411	0.653	0.731

Table 6: **Bank heterogeneity: processing time**

This table reports the estimates corresponding to the regression in equation (4). 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. HighAppRating is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. 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%	All	90%
	(1)	(2)	(3)	(4)	(5)
HighAppRating	-8.387***	-8.088***	-4.238***	-3.460***	-4.729***
	(1.632)	(1.855)	(0.592)	(0.961)	(0.796)
Fixed effects and controls:					
Bank Controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	397952	359954	37998	28108	18952
R^2	0.446	0.470	0.405	0.765	0.758

Table 7: **Firm heterogeneity: disbursement time & interest rate**

The unit of observation is a loan. The dependent variable is either the processing time, in days, or the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. 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.

	Processing Time (Days)		Interest Rate (%)	
	100%	90%	100%	90%
	(1)	(2)	(3)	(4)
Log(Assets)	0.576	0.085	-0.003	-0.312***
	(0.579)	(0.369)	(0.003)	(0.043)
Cash/Assets	0.194**	0.114	-0.004	-0.215***
	(0.079)	(0.163)	(0.002)	(0.034)
Log(Age)	-0.376*	0.034	-0.002*	-0.064***
	(0.226)	(0.219)	(0.001)	(0.012)
Medium risk	-0.172*	-0.319	0.004	0.047**
	(0.101)	(0.237)	(0.002)	(0.024)
High risk	-0.036	0.116	0.005**	0.027
	(0.095)	(0.270)	(0.002)	(0.017)
Fixed effects				
Date of Approval	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	Yes
Bank	Yes	Yes	Yes	Yes
Observations	71534	38932	159153	107947
R^2	0.567	0.492	0.598	0.682

Table 8: **Guaranteed lending and local banking markets**

This table reports the estimates corresponding to the regression in equation (5). 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$_{b,p}$ 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$_{b,p}$	1.030***	1.037***			0.679***
	(0.135)	(0.138)			(0.096)
CoreMarketShare$_{b,p}$			1.967***	1.927***	1.446***
			(0.127)	(0.119)	(0.113)
AppRating $\geq$ 4*	0.386		0.260		
	(0.298)		(0.280)		
Log(Number Reviews)	-0.280		-0.084		
	(0.180)		(0.164)		
Log(Assets)	1.163***		1.713***		
	(0.106)		(0.107)		
Tier 1 ratio	-0.309		-0.056		
	(0.303)		(0.274)		
NPL/Loans	0.060		0.037		
	(0.114)		(0.141)		
ROA	-0.041		-0.163		
	(0.115)		(0.111)		
Interbank/Asset	0.230*		0.140		
	(0.135)		(0.141)		
Fixed effects					
Province	Yes	Yes	Yes	Yes	Yes
Bank	No	Yes	No	Yes	Yes
Observations	2871	2871	2871	2871	2871
R^2	0.574	0.642	0.585	0.662	0.697

Table 9: **Bank IT and Local Banking Markets**

This table reports the estimates corresponding to the regression in equation (6). 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. HighAppRating is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. HighHHI_p is a dummy equal to one if the province-level branch-HHI is above the median, 0 otherwise. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
HighAppRating	-0.203***	-0.084	-0.738***	-0.458***	-0.582***
	(0.053)	(0.065)	(0.202)	(0.141)	(0.158)
HighAppRating × HighHHI_p	0.072**	0.003	0.274**	0.185***	0.167*
	(0.030)	(0.018)	(0.115)	(0.071)	(0.097)
Fixed effects and controls:					
Bank Controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	58640
R^2	0.237	0.318	0.412	0.653	0.731

Online Appendix

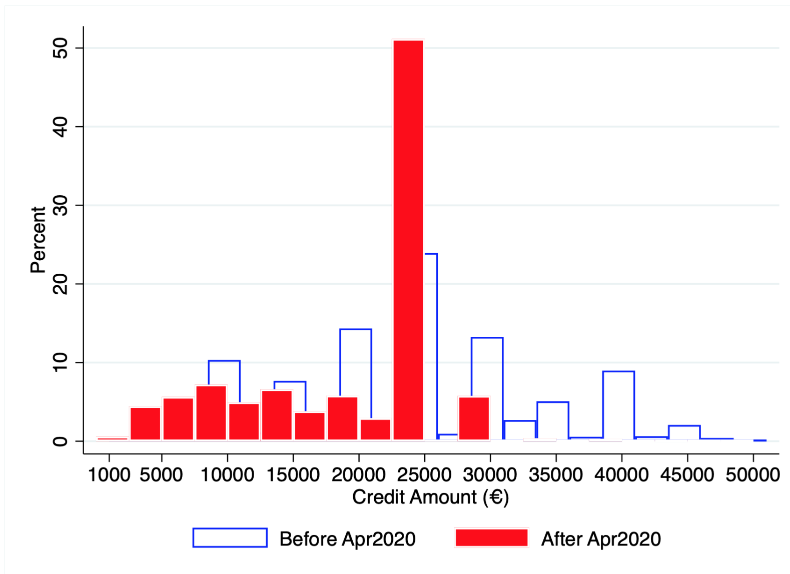
Figure A1: Example: Guaranteed Loan Application Website

This figure reports the web page of a large Italian bank with the information on how to file an online application for a guaranteed loan (in Italian).

Figure A2: 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 between January 2018 and August 2020, splitting the sample before and after April 2020, while Panel B shows the distribution of loan amounts below €50,000 between April and August 2020, splitting the sample before and after July 2020.

(a) Panel A. January 2018 - August 2020



(b) Panel B. April - August 2020

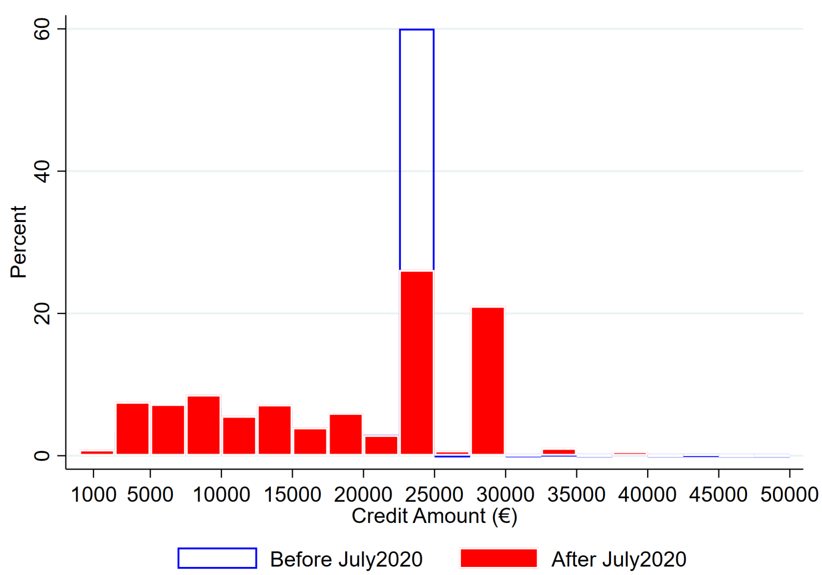


Figure A3: Guarantee Uptake in 2018-19

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).

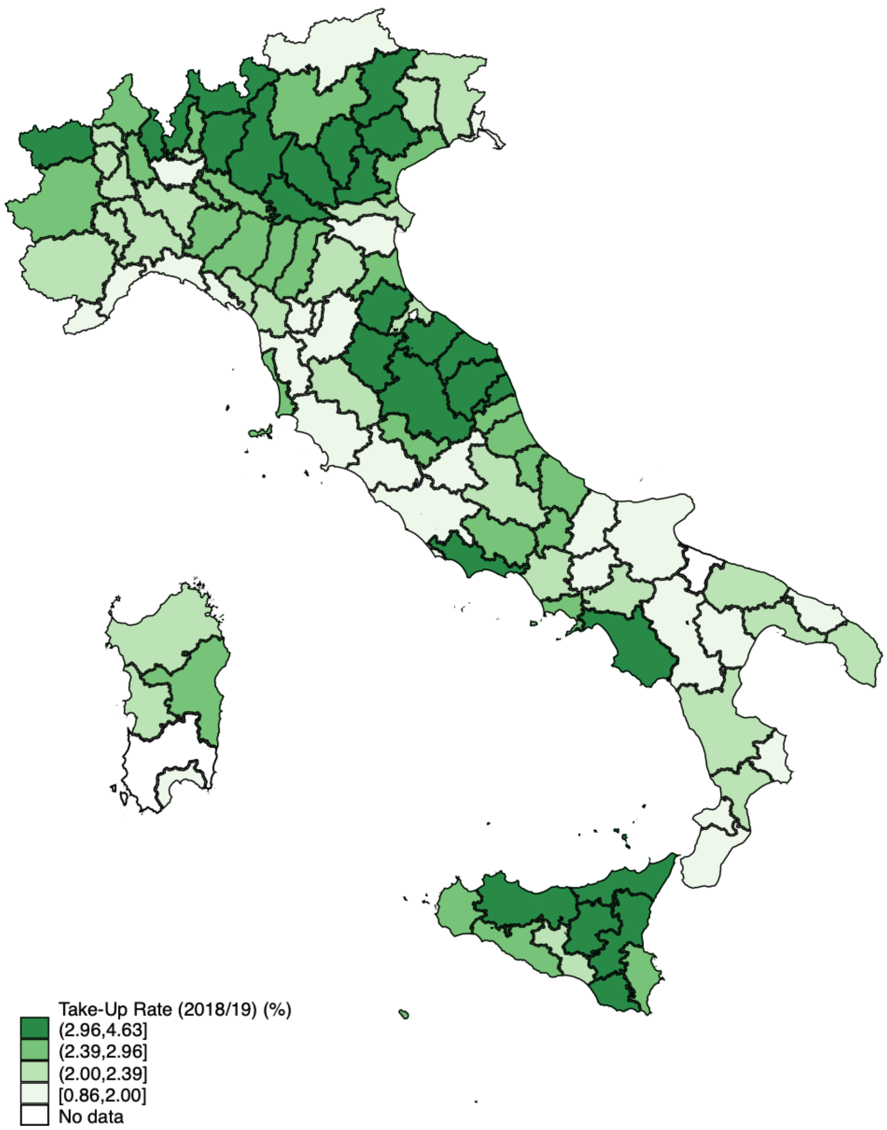


Figure A4: Processing times by bank IT

We report the histogram of processing times on government guaranteed loans for large banks (>€21 billion in total assets, according to the Bank of Italy definition, found here) vs. small banks Processing times are calculated as number of days between the date of approval of the loan by the FG and the day of processing of the loan to the firm by the bank.

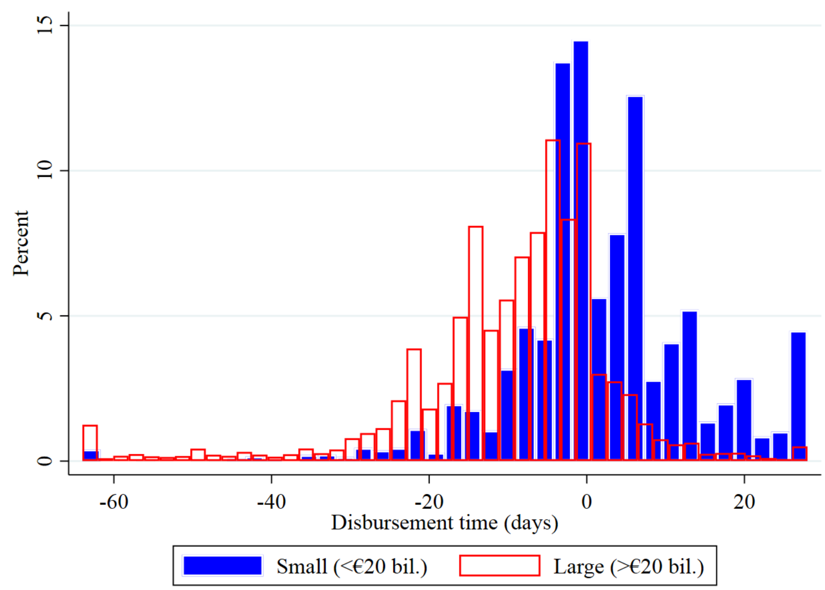


Table A1: **Which banks issue guaranteed loans: robustness (IT expenses and amortization)**

This table reports the estimates corresponding to the regression in equation (2). The unit of observation is a bank. The dependent variable is the share of guaranteed lending volume between April and August 2020 over total bank lending as of 2019Q4 (in percentage points). Bank characteristics are balance sheet items from 2019Q4. Regressions are weighted by bank total assets. Standard errors robust to heteroskedasticity in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Share of guaranteed loans		
	All	100%	90%
	(1)	(2)	(3)
IT Expenses (%)	0.572*	-0.073	0.645**
	(0.320)	(0.059)	(0.304)
Observations	104	104	104
R^2	0.289	0.658	0.184
Bank Controls	Yes	Yes	Yes
	All	100%	90%
	(1)	(2)	(3)
IT Amortization (%)	0.351***	0.036*	0.314***
	(0.096)	(0.019)	(0.083)
Observations	104	104	104
R^2	0.413	0.603	0.313
Bank Controls	Yes	Yes	Yes

Table A2: **Bank Heterogeneity: Date of approval**

The unit of observation is a loan. The dependent variable is the date opf approval by the FG of the loans taken under the public guarantee program after April 2020. Fixed effects for the interaction of province and industry (4-digit) and the bank are added. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Date of approval		
	(1)	(2)	(3)
R^2	0.092	0.087	0.164
Fixed effects			
Province × Industry	Yes	No	Yes
Bank	No	Yes	Yes
N	994750	994750	994750

Table A3: **Bank heterogeneity: robustness (IT expenses)**

This table reports the estimates corresponding to the regression in equation (4). The unit of observation is a loan. The dependent variable is the processing 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 controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Processing Time (Days)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
IT Expenses (%)	-6.383***	-6.495***	-1.572*	-1.268*	-1.932**
	(0.978)	(1.023)	(0.609)	(0.547)	(0.581)
Observations	397952	359954	37998	28108	18952
R^2	0.440	0.480	0.385	0.765	0.756
	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
IT Expenses (%)	-0.044	-0.043	-0.185**	-0.064	-0.173**
	(0.027)	(0.030)	(0.091)	(0.056)	(0.068)
Fixed effects and controls:					
Bank controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	58640
R^2	0.244	0.286	0.423	0.675	0.745

Table A4: **Bank heterogeneity: robustness (IT amortization)**

This table reports the estimates corresponding to the regression in equation (4). The unit of observation is a loan. The dependent variable is the processing time, in days, and the interest rate, in percentage, of the loans taken under the public guarantee program after April 2020. IT Amortization is measured in 2020 as a percentage of total operating expenses. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Processing Time (Days)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
IT Amortization (%)	-4.193***	-4.171***	-2.519***	-1.780**	-2.307***
	(1.111)	(1.175)	(0.606)	(0.585)	(0.437)
Observations	397952	359954	37998	28108	18952
R^2	0.416	0.446	0.403	0.765	0.757
	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
IT Amortization (%)	-0.049	-0.016	-0.235	-0.111	-0.196
	(0.051)	(0.029)	(0.274)	(0.164)	(0.174)
Fixed effects and controls:					
Bank controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	58640
R^2	0.223	0.277	0.414	0.649	0.728

Table A5: **Bank Heterogeneity: robustness (Google Playstore rating)**

This table reports the estimates corresponding to the regression in equation (4). The unit of observation is a loan. The dependent variable is the processing time, in days, and the interest rate,in percentage, of the loans taken under the public guarantee program after April 2020. Playstore rating is the number of stars the mobile banking app has the Google playstore, from 1 to 5. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and1%, respectively.

	Processing Time (Days)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
Playstore rating	-2.950	-2.037	-4.809***	-4.297***	-5.036***
	(2.443)	(2.695)	(0.736)	(0.683)	(0.680)
Observations	397952	359954	37998	28108	18952
R^2	0.421	0.444	0.409	0.766	0.759
	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
Playstore rating	-0.071	0.019	-0.459*	-0.399***	-0.494**
	(0.077)	(0.081)	(0.252)	(0.145)	(0.201)
Fixed effects and controls					
Bank controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	No	No
Firm	No	No	No	Yes	Yes
Observations	850874	745489	105385	103487	58640
R^2	0.233	0.309	0.406	0.653	0.731

Table A6: **Bank IT and Local Banking Markets: robustness (HHI index)**

This table reports the estimates corresponding to the regression in equation (6). 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. HighAppRating is a dummy variable equal to one if the mobile banking app has a 4-5 star rating on the Google playstore, 0 otherwise. Bank controls as of 2019Q4 include: the log of the number of Google reviews, log of bank total assets, Tier 1 capital ratio, share of NPL over total loans, return on assets and interbank funding over total assets. Standard errors clustered at the bank level in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1%, respectively.

	Interest Rate (%)				
	All	100%	90%	All	90%
	(1)	(2)	(3)	(4)	(5)
HighAppRating	-0.229***	-0.091	-0.886***	-0.560***	-0.728***
	(0.057)	(0.066)	(0.236)	(0.154)	(0.196)
HighAppRating × HHI_p	0.039*	0.007	0.185*	0.129*	0.161*
	(0.020)	(0.017)	(0.099)	(0.067)	(0.092)
Fixed effects and controls:					
Bank controls	Yes	Yes	Yes	Yes	Yes
Date of Approval	Yes	Yes	Yes	Yes	Yes
Province × Industry	Yes	Yes	Yes	-	-
Firm	No	No	No	Yes	Yes
Observations	850422	745037	105385	103462	58640
R^2	0.237	0.318	0.412	0.653	0.731

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